The London School of Economics and Political Science

Essays in Environmental Economics: Innovation and Economic Performance of Firms, and Distributional Questions

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated otherwise.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of approximately 80,200 words.

Statement of co-authored work

I confirm that Chapter 1 was jointly co-authored with Antoine Dechezleprêtre, Tomasz Koźluk, Daniel Nachtigall and Alain de Serres. I contributed 40% of this work.

I confirm that Chapter 2 was jointly co-authored with Myra Mohnen, Peter Pope and Misato Sato. I contributed 70% of this work.

I confirm that Chapter 3 was jointly co-authored with Myra Mohnen and Misato Sato. I contributed 90% of this work.

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Abstract

This thesis consists of two parts within the field of environmental economics. The first part contributes to the literature on the relationship between firms' environmental and economic performance. The second part investigates distributional questions within environmental economics.

The first part of this thesis consists of three co-authored chapters. Chapter 1 provides a systematic and detailed literature review on the relationship between firms' environmental and economic performance. It is an introductory and scene-setting chapter to the subsequent two chapters. Chapter 2 examines how diversifying production towards low carbon goods and services impacts the financial performance and market valuation of firms. Using new data on firms' revenues that are generated from the production of green goods and services, we are able to measure shifts from non-green to green activities at the firm level. The paper provides novel insight into the relationship between such green revenues and a comprehensive set of accounting- and market based economic performance measures. Chapter 3 uses event study methodology to assess the impact of the Paris Agreement on stock returns. We show that green firms, have experienced significant positive abnormal returns in the week following the agreement compared to the overall market. In addition, we show that emissions-intensity appears to be a less precise determinant for firms' stock performance.

The second part consists of two single-authored chapters. Chapter 4 examines distributional preferences for international climate finance. Understanding public preferences for climate policies is crucial to ensure and increase public support for such policies. Using a choice experiment on a representative sample of the UK population this chapter elicits preferences with respect to distributional dimensions of adaptation finance. The findings provide new insights into preferred payment mechanisms and support the adoption of egalitarian policy mandates among international climate adaptation funds. Chapter 5 contributes to the literature on distributional outcomes of natural resource wealth. We use panel regression techniques as well as the quasi-experimental synthetic control method at the country- and US state-level to estimate the effect of an oil price boom on income inequality. The paper does not find strong evidence for a significant relationship. It discusses challenges in empirically identifying effects on aggregate inequality metrics.

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Introduction

This thesis consists of two parts. The first part (chapters 1, 2, and 3) examines the relationship between environmental and economic performance at the firm level. The second part explores distributional questions within environmental economics.

The thesis is structured as follows. Chapter 1 reviews the extensive literature on the relationship between environmental and economic performance indicators at the micro-level. It provides the background for the first part of this thesis. A shortcoming of the existing literature is that it has relied largely on cross-sectional data, binary environmental performance variables, or limited sector coverage. Chapter 2 builds upon this review and is able to overcome some of the limitations of the prior literature. It uses a novel continuous variable capturing firms' revenue share generated from producing 'green' goods and services. It allows us to explore the relationship in a multi-year panel across a broad group of sectors for listed firms covering approximately 98% of global market capitalisation. In particular it examines the relationship between green revenues and a comprehensive set of profitability indicators as well as firms' market valuation. We draw on the financial accounting literature and offer novel insights on the relationship between the individual profitability indicators. We show that producing green goods and services is positively associated with firms' operative profit margins across a broad group of sectors. Such higher operative profit margins do however not necessarily increase firms' overall profitability. Producing green goods and services tends to entail higher investment requirements, which impose a downward drag on their overall profitability. In terms of market based performance, higher green revenues are neither punished nor rewarded by investors, except for utility sectors, which tend to face unique regulatory settings. We show that important heterogeneities exist across sectors. The findings suggest that public policies can support the transition towards low-carbon technologies by facilitating cheaper access to capital for investments into low-carbon technologies and by helping to create and expand markets for green goods and services. Sector-specific R&D support can also be important in helping to reduce costs for low-carbon technologies.

Chapter 3 uses event study methodology to examine whether financial markets reward environmental activities of firms. We use the Paris Agreement as it created a large, discrete and plausibly exogenous shift in the reward for being green to identify the effect. The paper shows that green firms have significantly outperformed the market in the week following the Paris Agreement. The greenest firms experienced approximately 10% higher returns over the week following the agreement. We show that the effect exists both at the extensive and intensive margin of firms' green revenue share. Moreover, the results suggest that firms' emissions-intensity is a less clear-cut determinant for their stock performance following the agreement. While some emissions-intensive sectors have experienced negative abnormal returns, we show that emissions-intensive electricity generating firms have actually outperformed the market following the agreement. By combining the green revenue and emissions-intensity data we observe that these emissions-intensive electricity-generating firms also generate sizeable shares of renewable electricity. The findings suggest that investors value particularly the growing opportunities for firms active in green technologies following the Paris Agreement. This chapter provides novel insight into the reaction of financial markets to a detailed green product-based measure. Moreover, it allows us to assess investors' perception of the post-Paris policy landscape, and of the perceived credibility of the Paris Agreement with respect to the anticipated diffusion and adoption of low-carbon technologies.

The second part of the PhD begins with chapter 4, which examines distributional preferences in the context of climate finance. Understanding public preferences for climate policies is crucial to ensure sustained public support for such policies over the long run. Previous research has shown that in particular the distributional outcomes of policies determine their overall acceptability. The chapter is motivated by the observation that collecting and allocating international climate adaptation finance will involve difficult moral judgements with respect to such distributional dimensions. For this chapter, I conducted a discrete choice experiment on a representative sample of the UK population, a large donor for climate finance. I elicit distributional preferences in particular with respect to (1) the preferred burden sharing principles among UK individuals, as well as (2) the allocation of resources among eligible recipients. The chapter provides novel insights on the preferred design for climate adaptation policies. It shows that individuals tend to prefer an 'ability-to-pay' approach over a 'polluter-pays' principle in the context of climate adaptation. This is contrary to previous findings for preferred climate mitigation policies and suggests that respondents see a less direct link between individual emissions and a potential responsibility to contribute to climate change adaptation. Hence, using carbon pricing to collect revenues for a global adaptation fund would likely be less popular compared to a progressive fee based on income levels. Moreover, the chapter reveals distributional preferences with respect to the allocation of funds to the most vulnerable individuals, which supports the adoption of egalitarian allocation criteria among international climate funds. The results also suggest that adopting a communication strategy that focuses on benefits to donor country residents may be a promising avenue. Overall, the findings reveal that public support for climate adaptation payments is vastly insufficient in light of the overall requirements, highlighting the importance of further work in this field.

Chapter 5 contributes to the literature on the impacts of natural resource booms on socio-economic outcomes. It examines the impact of the shift from a low- to a high oil price regime on income inequality for resource dependent countries and US states using panel data. The chapter specifically contributes to the literature in two ways. First, it applies a quasi-experimental methodology to study distributional outcomes of the oil price shock post 1998 at the country-level, which to the best of my knowledge has not been done before. Second, this is the first paper to provide evidence of the effect of this oil price boom on income inequality within US states. We analyse the relationship for a time period that is characterised by particularly high levels of inequality, for which outcomes may systematically differ from earlier low-inequality periods. By adopting panel regression techniques, as well as the quasi-experimental synthetic control method, we are able to show average effects across all resource rich units, as well as identify unit-specific effects, which allows for a more detailed insight. Overall we do not find strong support for an effect of the post-1998 oil price boom on income inequality within resource dependent countries or US states. The chapter discusses challenges in empirically identifying effects using the available inequality metrics.

The thesis concludes with a brief chapter summarising the findings and providing some suggestions for further research and for policymakers.

I would like to explain why this thesis consists of two parts. It reflects the learning journey over the past years. When I embarked on my PhD, I was keen to investigate distributional questions within environmental economics. The motivation for this part of my thesis was driven partly by the work of Thomas Piketty (Piketty, 2013), Joseph Stiglitz (Stiglitz, 2012) and others that showed how high levels of inequality can be detrimental to societies. If high levels of inequality can reduce societal cohesion and have negative impacts on the willingness to pursue public goods, it may provide an additional barrier in mitigating climate change and managing other environmental problems. The management of environmental and natural resources may in itself also influence such socio-economic inequalities. Similarly, the way the international community manages climate change and its consequences will have distributional implications, which need to be managed carefully to ensure public support.

For my chronologically first paper I contribute to the literature on the relationship between natural resource wealth and inequality (chapter 5). In this paper I use income inequality data to examine the relationship between natural resource booms and income distribution. One limitation of secondary distributional data is that it is typically only available for monetary metrics such as income or wealth. Distributional outcomes and preferences may however be highly context specific and thus may require case-specific elicitation using primary data. Hence for chapter 4 I collected primary data on distributional preferences using a choice experiment. The chapter provides specific distributional preferences in the context of climate adaptation finance that can help to inform policy design.

Halfway through my PhD my focus and interest shifted towards topics of low-carbon innovation and firm-level analysis in particular. I began this part of my PhD by conducting an extensive literature review on the relationship between environmental and economic performance variables at the firm-level (chapter 1). The review paper as well as initial analysis on a newly developed dataset, which captures the production of 'green' goods and services at the firm-level, sparked my interest in the topic. I therefore decided to pursue this avenue further for my thesis. Chapter 2 builds upon the review and explores the relationship between firms' involvement in green technologies and their financial performance as well as market valuation. The third chapter examines investors' perceptions of green technologies following a climate policy announcement.

This second part of the thesis is motivated by the observation that the international community requires a substantial increase in investments into climate compatible infrastructure and low-carbon technologies to limit global warming to 1.5°C or well below 2°C (OECD, 2017). The private sector needs to play a crucial role in mobilising the financial resources and in reducing the costs of the transition (CPI, 2018). Therefore, it is important to understand the market environment for low-carbon technologies to design potentially new policies. Furthermore, financial markets can provide a useful platform to assess the credibility and potential effectiveness of already existing climate policies.

Chapter 1

Do Environmental and Economic Performance go Together? A Review of micro-level empirical evidence from the past decade or so.

Abstract

This article reviews the empirical literature combining economic and environmental performance data at the micro-level, i.e. firm- or facility-level. The literature has generally found a positive and statistically significant correlation between economic performance, as measured by profitability indicators or stock market returns, and environmental performance, as measured by emissions of pollutants or adoption of international environmental standards. The main reason for this finding seems to be that firms that reduce their material and energy costs experience both better economic performance and lower emissions. Only a small and recent literature analyses the joint causal impact of environmental regulations on environmental and economic performance. Interestingly, this literature shows that environmental regulations tend to improve environmental performance while not weakening economic performance. However, the evidence so far is limited to a handful of environmental regulations that are not extremely stringent, so the result cannot be easily generalised. More research is needed to assess the joint effects of environmental regulations on environmental and economic performance, to explore the heterogeneity of these effects across sectors, countries and types of policies, and to understand which policy designs allow improving environmental quality while not coming at a cost in terms of economic performance of regulated businesses.

1.1 Introduction

The emergence of green growth as a new paradigm has come in part in response to the recognition that environmental challenges could not be addressed seriously, or at least not effectively, unless they were fully integrated in the development of comprehensive growth-enhancing policy strategies. Governments have long been concerned with environmental issues but "green" and "growth" objectives and policies were essentially pursued by different ministries and agencies operating for the most part in silos. This has often resulted in policy incoherence and a low degree of effectiveness in the pursuit of environmental objectives. The push for the wider adoption by governments of green growth strategies as a means to better pair the objectives of growth with those of environmental sustainability gained more traction in the aftermath of the global financial crisis. The desire to reduce the negative impact of the crisis in a way that could simultaneously meet environmental and economic objectives created a context more favourable to policymakers being receptive to adopting a green growth approach to economic recovery.

One direct implication of the joint pursuit of growth and green objectives in development strategies is the acknowledgement of policy trade-offs and synergies. The existence of trade-offs is predicated on the assumption that the transition to green growth necessarily imposes constraints on the optimal allocation of resources, thereby raising production costs and reducing productivity. The aggregate costs of pursuing environmental objectives have often been reported in the form of economy-wide GDP losses measured against a business-as-usual scenario whereby output growth is assumed to continue unabated, based on a production process and assumptions that largely ignore the environmental constraints (i.e. both the constraints to reduce pollution externalities and the adverse feedback effects from environmental degradation on output). One major OECD study looking at the economic impact of climate change mitigation highlighted how the adoption of cost-effective measures coordinated at the international level could limit the size of such costs to a relatively small amount, especially in comparison to the estimated costs arising from climate change-related damages and required adaptation (OECD, 2009).

One strand of literature has gone even further, calling into question the assumption that environmental policies necessarily entail a short-run trade-off by raising production costs and reducing efficiency. The challenge to conventional wisdom has been originally laid-out in a landmark paper by Porter and van der Linde (1995) , who have argued that improving a company's environmental performance can result in better economic or financial performance, without necessarily leading to higher costs (Ambec and Lanoie, 2008). The authors made the case based on the notion that by pushing firms out of their comfort zones, environmental policies can act as a catalyst for investment in innovation that might not have taken place in the absence of the regulatory constraint. Such investment can result in an improvement in both the environmental and business performance. What became referred to as the Porter Hypothesis stimulated a large amount of research, both to provide theoretical underpinnings and to assess whether it can be supported by empirical evidence.

The growing importance of this debate in policy circles has sparked a large empirical literature that analyses the relationship between economic and environmental performance at the level of firms, and assesses the joint impact of environmental regulations on these outcomes. The objective of this chapter is to provide an up-to-date review of this empirical literature that combines economic and environmental performance data at the micro-level[1]. In this review, we focus largely on GHG emissions, air pollution and toxic release emissions as environmental performance variables[2]. For each of the papers surveyed, we discuss the pros and cons of the data used and present the empirical approach taken by the authors. A comprehensive table summarises these micro-level studies that combine environmental- and economic performance variables (see Appendix A.1)[3]. Compared to ex-post analysis based on more aggregated data at sectoral, regional or national level, or to ex-ante Computable General Equilibrium models, analyses based on micro-data have several advantages. Sample sizes are typically much larger, allowing for more precisely estimated effects, smaller biases due to unobserved heterogeneity (for example, through the inclusion of firm-level fixed effects) and exploration of heterogeneous impacts across time or sectors. More generally, micro databases allow for a more credible identification of the treatment effects of a given regulation. In particular in combination with quasi-experimental techniques, they provide a robust approach to identify causal impacts of environmental policies (List et al., 2003; Greenstone and Gayer, 2009; Calel and Dechezleprêtre, 2016). For example, the European Union Emissions Trading System, which regulates the carbon emissions of around 12,000 industrial sites and power generating facilities across Europe, only regulates installations above a certain threshold in terms of production capacity. Therefore, it is possible to construct a control group of unregulated installations the size of which falls just below these administrative thresholds, but which are very similar to regulated installations in terms of all other observable characteristics. With a "treated" and a "control" group that are statistically identical before the introduction

[1] Note that the existing literature predominantly covers evidence from the United States and Western Europe due to greater availability of micro-data in these regions.

[2] Regulations targeting e.g. solid waste, water pollution, contaminated sites, biodiversity, or livestock (and associated firm performance along these variables) are therefore not covered.

[3] The inclusion criteria for papers covered in the summary table are that they use both environmental and economic performance variables at the micro-level (i.e. that they use firm- or plant-specific observations for both outcome variables).

of the regulation, it is possible to identify the causal effect of the policy on regulated entities after the introduction of the regulation (Dechezleprêtre and Sato, 2017).

Analyses based on micro-datasets also have drawbacks, however. In particular, they are ill-equipped to capture general equilibrium effects. For example, it is not possible, using the sort of quasi-experimental methods mentioned above, to analyse the potential impact of the EU ETS on unregulated firms facing higher energy prices because they purchase electricity from regulated firms.

The chapter is organised along two main strands of the literature. The first section reviews the literature that analyses the direction of the correlation between environmental and economic performance at the firm level. The key feature of this literature is that it generally abstracts from the drivers of environmental performance, which could be induced by environmental regulations but could also come from voluntary efforts of companies. Because high environmental performance could be driven by profit-enhancing motivations (for example, improving energy efficiency to reduce input costs), one should not necessarily expect a negative relationship between environmental and economic performance. The second section focuses on the literature that analyses the impact of environmental regulations on environmental outcomes and economic performance, with a focus on papers that simultaneously evaluate the impact of environmental policies on both outcomes. Here, basic economic theory predicts regulations to improve environmental performance while weakening economic performance, but alternative theories related to the Porter Hypothesis claim that a different outcome is possible.

1.2 Does it really pay to be green? Micro-level evidence on the correlation between environmental and economic performance

There is a large literature on the relationship between environmental performance and economic performance at the firm level. However, this literature usually focuses on establishing correlations and does not properly address causality, i.e. the vast majority of studies cannot say with confidence whether improvements in firms' environmental performance cause improvements in firms' economic performance. This is an important limitation because good environmental and economic performance could be driven by unobserved factors such as good management practices or the quality of the workforce, in which case the solution to improve both environmental and economic performance could reside in implementing policies in the non-environmental domain, for example education policies.

Still, establishing the sign of the correlation between environmental and economic performance at the micro level is interesting in its own right, as it can shed light on the widespread concern that there is a systematic negative relationship between the two. The main upshots from the literature focusing on this issue are summarised in this section. Most of the literature focuses on the energy production and manufacturing sectors, as firms in these sectors tend to be the main source of pollution across countries. In comparison, the services sector is an understudied area.

1.2.1 Environmental performance and economic performance: Friends or foes?

Numerous papers have analysed the correlation between environmental and economic performance and several surveys and meta-analyses are available, including Wagner (2001); Blanco et al. (2009); Horváthová (2010); Albertini (2013); Crifo and Sinclair-Desgagé (2013); Crifo and Forget (2015). Different measures of economic performance are used, including return on assets (ROA), return on sales (ROS) and return on equity (ROE). Measures of investors' valuation are also used to express expectations of future profitability (e.g. Tobin's Q)[4]. Environmental performance measures include toxic release inventory (TRI) emissions, greenhouse gas (GHG) emissions, environmental management certification (e.g. ISO 14001)[5] and the adoption of other international environmental standards.

Overall, the literature surveys tend to conclude that better environmental performance is associated with greater financial performance, although there is some variation in the results across studies. For example, Ambec and Lanoie (2007) survey 12 studies that rely on regression analysis of financial performance on environmental performance across multiple years. Nine studies showed that better environmental performance is associated with better economic performance. Two studies show no impact, while one concluded that a negative relationship exists. Similarly, Horváthová (2010) reports that about 55% of studies find a positive effect and 15% of studies find a negative effect. Blanco et al. (2009) focus on manufacturing firms and conclude on a prominent absence of penalty for being green. However, this result is affected by the typology of the firm, the methods utilised for implementing environmental initiatives, the intensity

[4]Tobin's Q is often measured as market capitalisation divided by assets. It is a measure to capture investors' valuation of a firm relative to the replacement costs of its assets. Hence, it is used to indicate market expectations of future profitability of the firm. Since it requires a value of firms' market capitalisation it can typically only be computed for firms listed on a stock exchange.

[5]ISO 14001 is a standardised environmental performance system that covers many aspects of environmental management such as life-cycle assessment and environmental performance indicators.

of the abatement efforts and stockholders' valuation of green firms.

Particularly in earlier studies, which use cross-sectional data or pooled regression analysis, it remains unclear whether it 'pays to be green' or whether profitable companies decide to engage in green activities. Telle (2006) illustrates in detail the potential omitted variable problems existing in earlier studies using a sample of Norwegian manufacturing plants. Starting with a pooled regression, controlling for observable plant characteristics such as size or industry, the author confirms results of earlier papers that find a positive association between environmental and economic performance. However, when controlling for time-invariant unobservable plant characteristics (such as time-invariant quality of management, or employee motivation) using plant fixed effects, the effects become insignificant, meaning that environmental performance is not significantly associated with firms' financial performance. Consequently, the author cautions against premature conclusions based on these early pooled regression analyses. He concludes that future emphasis should be placed on analysing the necessary conditions and the specific industries or plants for which it may pay to be green.

In the following subsections, we examine to what extent heterogeneous findings in the literature are due to actual heterogeneities across samples or are simply a result of using different outcomes and explanatory variables. We categorise studies according to (a) the type of environmental performance variable (e.g. adoption of standards, emissions, pollution abatement investments), (b) the time-horizon of the effect, and (c) the economic performance variable (profitability and investors' expectations of future profitability).

(a) Environmental Performance Variables

Adoption of standards and environmental management systems

A crude measure of environmental performance is provided by international environmental management standards such as ISO 14001. The implementation of an environmental management standard does not provide information on the actual environmental outcomes, which remain unobserved and may be pure signalling of confounding issues, such as management quality. Moreover, such an indicator is binary: within firms having adopted the standard, it is not possible to rank firms according to their performance, while there is also heterogeneity in the environmental performance of firms not adopting the standard. Bearing these limitations in mind, Hibiki et al. (2003) find that the introduction of the ISO 14001 certification system is associated with a statistically significant increase in the market value by 11% to 14%, based on a sample of 573 Japanese publicly-listed firms in the manufacturing industry listed at the Tokyo Stock Exchange. A similar finding is reported by Jacobs et al. (2010).

An alternative proxy for environmental performance is the implementation of an environmental management system (EMS) at the firm level. Wagner and Blom (2011) examine nearly 500 firms from the UK and Germany and find that the implementation of an EMS is only positively associated with firms' financial performance for already financially well-performing firms. A negative association exists for financially less-well performing firms. Yet, a limitation of their approach is that the implementation of the EMS does not provide information on the actual environmental outcomes, which remain unobserved.

Emissions releases: Toxic releases and greenhouse gases

Emissions releases can be broadly divided into two types of groups: local pollutants such as toxic releases and waste and global pollutants such as greenhouse gas emissions.

Using toxic release inventories allows for an accurate measurement of environmental performance, and many studies have used this indicator. One of the most cited is by Konar and Cohen (2001), who use a sample of 321 (mostly) manufacturing firms in the S&P 500 and relate the market value to toxic chemicals emitted relative to the firm's revenue. After controlling for variables traditionally thought to explain firm-level financial performance, they find that poor environmental performance - as measured by toxic chemicals emissions - is negatively correlated with the intangible asset value of firms. The average 'intangible liability' for firms in their sample is USD 380 million, which equals 9% of the replacement value of tangible assets in their sample. The authors conclude that toxic chemicals, even if legally emitted, have a significant impact on the intangible asset value of publicly listed firms. A 10% reduction in emissions of toxic chemicals is associated with a USD 34 million increase in market value. The effect is heterogeneous across industries. Traditionally polluting sectors experience larger losses. A similar result is reported by King and Lenox (2001).

Other studies have obtained similar results based on improved methodologies, such as Al-Tuwaijri et al. (2004) who analyse the relationship between environmental and economic performance based on a cross-sectional dataset of 198 US firms. They find that better environmental performance is associated with significantly better economic performance. This is consistent with the idea that investors view good environmental performance as an intangible asset. To measure environmental performance, they use the ratio of toxic waste recycled to total toxic waste generated. They measure a firm's economic performance using an industry-adjusted annual return, which is calculated as the change in stock price during the year (adjusted for dividends), scaled by the beginning-of-year stock price minus the industry median return (based on two-digit SIC codes). This annual industry-adjusted stock return thus represents a measure of the firm's current-period economic performance relative to other firms in the same industry (they find a similar result when directly using stock price as a measure of economic performance).

A couple of papers have found evidence of a non-linearity of the relationship between environmental performance and economic performance by adding quadratic terms in their regressions. For example, Fuji et al. (2013) examine the relationship between environmental performance - as measured by chemical emissions relative to sales - and economic performance in Japanese manufacturing firms. ROA, ROS and Capital Turnover (CT) are used as indicators of economic performance. They demonstrate a significant inverted U-shaped relationship between toxic releases and ROA and CT. While Fuji et al. (2013) solely analyse manufacturing industries, Trumpp and Guenther (2017) include service industries as well. In a global dataset of 2,361 firm-years with 696 unique firms, they find a U-shaped relationship between carbon performance and profitability as well as between waste intensity and profitability. Hence, the level of environmental performance affects the direction of the relationship between the two variables. Trumpp and Guenther (2017) conclude that only after passing an environmental performance threshold it starts to 'pay to be green'.

While studies using toxic emissions as a measure of environmental performance report a positive relationship between environmental and economic performance, this might not be the case for other environmental outcomes. We might expect heterogeneous effects across pollutants, as investors might value reductions in toxic releases more strongly as they reduce the risk of environmental liabilities and lawsuits and reputational damage to the company. Yet, with the emergence of carbon trading systems and penalties associated with non-compliance with GHG regulations, these effects across pollutants might have converged recently. Few papers look at GHG emissions as an environmental performance indicator, but a notable exception is Fuji et al. (2013) who use CO_2 emissions alongside chemical emissions. They show that environmental performance measured by CO_2 emissions contributes positively to ROA.

Most papers in this literature rely on secondary data collected through official government surveys or mandatory reporting. An exception is a 2003 OECD survey, which contacted 4,188 facility managers from seven OECD countries (Canada, France, Germany, Hungary, Japan, Norway, the United States) (Darnall, 2009). It examines the relationship between self-reported firm-specific environmental performance and self-reported profitability. Environmental performance is measured as a change in environmental impacts per unit of output in the last three years, separately for six environmental impacts: natural resource use, solid waste, waste-water effluent, air pollution, GHG emissions, and overall environmental impact. Financial performance is measured as changes in the facility's profits over the past three years. Furthermore, facility managers were asked to rate the environmental policy stringency to which they were subject. They find a positive relationship between environmental performance and financial performance and observe a negative correlation between facility-specific perception of policy stringency and profits. Yet, a limitation of this approach remains the reliability of the managers' responses, as well as the cross-sectional nature of the study, which does not allow an assessment of the direction of the effect.

Pollution abatement investments

Investments in pollution abatement technologies have been used as a proxy for firms' environmental performance, relying on the assumption that such investments result in actual pollution abatement. One concern of such investments is that they may reduce firms' productivity, particularly when a specific abatement technology is prescribed by an environmental regulation. The empirical evidence finds that pollution abatement investments have not had a strong influence on productivity.

Gray and Shadbegian (2003) and Shadbegian and Gray (2005) find insignificant effects for the relationship between firms' pollution abatement investments and productivity. Gray and Shadbegian (2003) examine 116 US pulp and paper plants between 1979 and 1990 and observe that the effect of pollution abatement investments on productivity differs substantially by plants' technology. On average, they observe that plants with higher abatement costs have lower productivity levels. Yet, this negative relationship between higher abatement costs and lower productivity levels is largely driven by mills, which incorporate a pulping process. For mills without such technology, the impact is negligible. Similarly, Shadbegian and Gray (2005) examine the contribution of pollution abatement expenditure to firms' productivity for 68 paper mills, 55 oil refineries and 27 steel mills. In their sample, they are able to distinguish between productive and pollution abatement expenditures for each production input. They find little evidence that abatement inputs contribute to production with nearly all coefficients being insignificant.

Ayerbe and Gorriz (2001), Broberg et al. (2013), and Sanches-Vargas et al. (2013) find modest negative relationships between firms' environmental performance and productivity. Ayerbe and Gorriz (2001) examine whether pollution abatement investments designated for compliance with environmental performance- and technology standards impact firms' productivity. In their sample of 53 large Spanish companies, they find a weak negative relationship with firms' productivity. Yet, the authors conclude that this finding might be specific to their small sample and the specific pollution abatement technology.

Broberg et al. (2013) use a stochastic frontier model to estimate the relationship between environmental protection investment and technical efficiency in five Swedish manufacturing industries. Environmental protection investments are again used as a proxy for environmental performance, assuming that such investments result in actual environmental protection. They observe a weak negative relationship between environmental investments and technical efficiency. Sanches-Vargas et al. (2013) use a 2002 cross-sectional dataset of 900 Mexican manufacturing plants to identify nonlinearities in the relationship between plants' pollution abatement expenditure and productivity. They find an overall negative relationship between pollution abatement expenditure and plants' productivity. However, the relationship is nonlinear and depends on plant size: the negative effect is larger for small plants and nearly negligible for larger ones.

(b) Short-term vs. long-term performance

An important question in understanding the relationship between environmental and economic performance is whether improving environmental performance induces costs in the short run but benefits in the longer run. A few studies seem to confirm this hypothesis. Khanna and Damon (1999) evaluate the impact of the US Environmental Protection Agency's (EPA) 33/50 program on the economic performance of firms in the US chemical industry relative to non-participants. The 33/50 Program is a voluntary initiative launched by the EPA in 1991. It encourages firms to cut their emissions of 17 high-priority toxic chemicals. Of the firms emitting at least one of these 17 chemicals in 1988, 14% had pledged their participation in the program by 1993. After controlling for the effects of firm-specific factors, the authors obtain two separate findings. An increased probability of participation in the program is significantly associated with a decline in return on investment, implying a negative effect on short run profitability. However, it is also associated with an increase in market valuation variables (measured as the excess of market value over the book value of assets normalised by sales). Hence in the short run, participation in the programme is associated negatively with profits relative to non-participants. In the long run participating companies are however expected to be more profitable, which is reflected in the higher market valuation (Khanna and Damon, 1999).

Similarly, Horváthová (2012) distinguishes between short- and longer-run effects. Using a sample of 136 Czech firms observed over several years, she finds that better environmental performance decreases financial performance in the subsequent year, but increases financial performance after two years. The net (cumulative) effect seems to be negative, but the author does not test whether it is statistically significant. The study's indicator of environmental performance is a composite indicator constructed using the European Pollutant Release and Transfer Register (E-PRTR), which provides data on 93 pollutants releases to air, water and land, as well as off-site transfers of waste and of pollutants in waste water from industrial facilities in the European Union Member States. Economic performance is measured using ROA and ROE. Rassier and Earnhart

(2011) also focus on the inter-temporal effect of environmental performance on financial performance. They study U.S. firms and measure the environmental performance by permitted wastewater discharge limits and use the returns on sales as the financial performance measure. In contrast to Horváthová (2012), they find that lower emissions levels improve firms' financial performance both in the short and the long run with a stronger effect in the long run.

(c) Profitability and investors' valuation

The theoretical channels through which environmental performance impacts short-term profitability (ROA, ROE, ROS) are somewhat different from the drivers of investors' valuation of a firm, as measured by Tobin's Q. For the former effect to exist there must be a tangible impact on firms by either increasing their income or reducing costs. The latter is driven by investors' expectations of future profitability. It captures how the market values a firm relative to the replacement value of its assets. It is common to observe firms which receive a high valuation by investors even though they do not operate profitably over a period of time. Consequently, it is necessary to separate the two channels and we might expect different effects across these variables.

In a series of studies, Rassier and Earnhart (2010b,a, 2015) analyse the extent to which firm-specific limitations on emissions have heterogeneous effects on firms' actual profitability and investors' expectations on firms' future profitability[6]. Across all studies, they examine the effects of facility-specific wastewater discharge limits regulated by the US EPA[7]. Although the authors do not observe actual emissions, the enforced facility-specific discharge limits are used as a close proxy for facilities' emissions.[8] Using ROS as their financial performance measure, Rassier and Earnhart (2010b) use quarterly data on 59 firms and annual data of 73 firms to examine the relationship between financial performance and discharge limits. For both datasets, they find a negative relationship between clean water regulation and firms' actual profitability. A 10% reduction in the average permitted discharge leads to a decline in the return on sales of between 0.8% and 2.7%.

In a separate paper, Rassier and Earnhart (2010a) examine the effect of permitted wastewater discharge levels on future expected financial performance of 54 manufacturing firms in the US using annual data. They find that tighter permitted discharge

[6]For a comprehensive summary on the differences between the studies see Table C.1 in Rassier and Earnhart (2015).

[7]All of their three papers use wastewater discharge limits for biochemical oxygen demand (BOD) and total suspended solids (TSS). These are conventional and highly prevalent pollutants, which receive regulatory scrutiny by the EPA.

[8]The facility-specific discharge limits are based on state-or industry-level water quality standards. These state water quality standards differ across water bodies and time. Moreover, the discharge limits differ across facilities and time since the assimilative capacity of water bodies differs across location and time (Rassier and Earnhart, 2015, p.133).

limits significantly decrease the market's expectations of future profits. In a more recent paper, Rassier and Earnhart (2015) build upon their earlier studies and estimate the effects on actual and expected profitability jointly using a sample of 740 observations from 47 unique firms using quarterly data. They are able to improve upon their earlier work by including additional control variables. Their results on actual profitability are consistent with the Porter Hypothesis indicating that tighter clean water discharge limits are positively associated with profitability. However, their results on expected profitability suggest that investors appear to expect a negative relationship between clean water discharge limits and profitability. This finding suggests that investors do not value the positive effect of regulation on firms' profitability, but instead seem to expect a negative impact on firms' profitability from tighter regulation. The authors explain these results with behavioural biases and lack of information among investors.

Summing up

Overall, most studies have focussed on toxic releases or pollution abatement investments and their short-run effects on economic performance variables. This emphasis is at least partly driven by data availability. To observe firms' environmental management systems (EMS) over time, regular industry surveys would be necessary. Firms might also not be willing to share detailed data on their management systems, which limits further analysis on EMS. The lack of long panel data has limited the possibilities to study long-run profitability effects, although more data is becoming available. The most extensive evidence is found for reductions in toxic release emissions which seem to be positively related with firms' valuation and profitability, although contrary findings exist as well. Similarly, pollution abatement investments do not seem to hurt firms' productivity significantly. Most of the evidence covers the power generation or the manufacturing sector. Moving beyond these sectors to incorporate service industries remains an important avenue for future research. Similarly, most of the evidence covers firms located in one or a small group of developed countries. Hence, further work focussing on developing countries is necessary to assess the generalisability of the results.

1.2.2 Understanding the drivers: why environmental performance can go hand in hand with economic performance

The vast literature that has looked empirically at the relationship between environmental and economic performance overall points to a positive correlation. This section tries to understand why such a positive relationship may emerge empirically.

1.2.2.1 Theoretical background

While the conventional wisdom regarding environmental protection is that it comes at an additional cost imposed on firms, which should thus lead to weaker economic performance, this plausible prediction has been challenged over the past two decades following the famous paper by Porter and van der Linde (1995), who argued that improving a company's environmental performance can result in better economic or financial performance without necessarily increasing costs (Ambec and Lanoie, 2008). Porter and van der Linde (1995) did not provide any strong theoretical motivation for that prediction, but many authors have subsequently provided theoretical grounding for it.

Ambec and Lanoie (2008) argue that there are at least seven ways in which improving a company's environmental performance can lead to better economic performance (see Figure 1.1). This could happen through either an increase in revenue or a reduction in production costs. Better environmental performance could lead to an increase in revenues through three channels: (a) better access to certain markets; (b) differentiating products; and (c) selling pollution-control technology. Better environmental performance can lead to a reduction in costs in four categories: (a) risk management and relations with external stakeholders; (b) cost of material, energy, and services; (c) cost of capital; and (d) cost of labour (Ambec and Lanoie, 2008, pp.46-47). In the following sub-sections we present the empirical literature that has analysed these potential determinants of the mostly positive relationship between environmental and economic performance uncovered by studies reviewed in section 1.2.1.

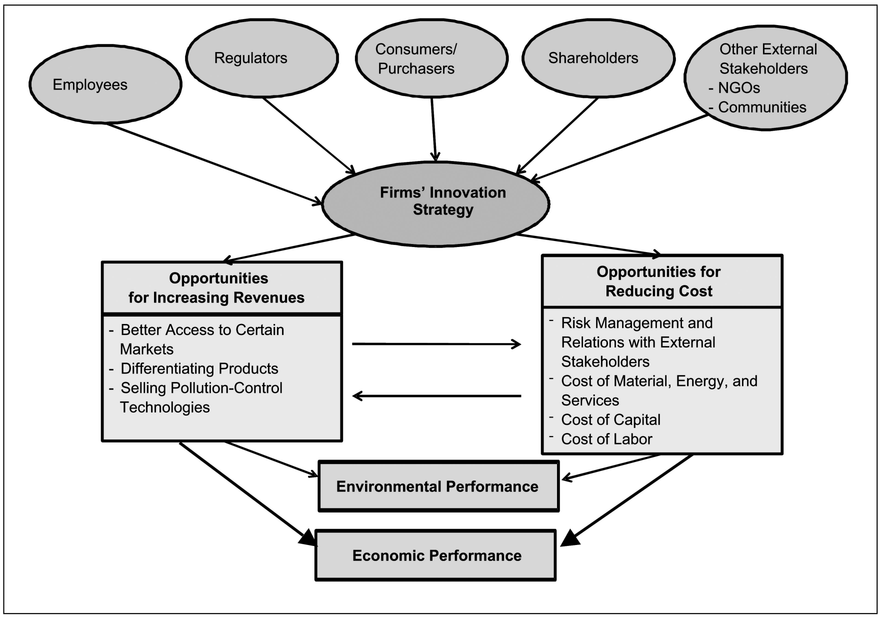


Figure 1.1: Potential positive links between environmental and economic performance (Source: Ambec and Lanoie (2008, p. 47)).

1.2.2.2 Better economic performance through increased revenues

The empirical evidence on environmental performance providing better access to certain markets is usually available from case studies with small samples. An exception is the paper by Antweiler and Harrison (2003), which tests the prediction that 'environmentally-leveraged' firms with consumer market exposure experience larger emission reductions. Indeed, they find that companies that are relatively more exposed to final consumers and that have a greater diversity of emissions across products (thus, are more "environmentally-leveraged") reduce their releases to air and transfers of wastes off site most strongly. Interestingly, they also increase relatively more their less visible releases to subsoil via underground injection. The authors obtain these findings by making use of firms' responses to the publication of Canada's National Pollutant Release Inventory (NPRI) between 1993 and 1999. NPRI covers around 2,500 facilities which have to report their emissions of 192 pollutants into the air, water, land, and subsoil. The main problem faced by the authors is that they do not observe purchases from households and businesses at a sufficiently high level of disaggregation and they cannot link products to individual plants. Thus, they rely on the idea that, if consumers use the NPRI to identify facilities with high levels of pollution and to identify the companies that own them, the only way they can then punish these firms is by not buying any products from these firms since they cannot link products to particular facilities. Therefore, multi-product firms will experience a "spillover" effect through which high-emission products will negatively impact sales of low-emission products.

Only a handful of papers analyse the correlation between the introduction of green products and firms' economic performance. This small literature has mostly focused on the relationship between introduction of new green products and employment growth. Rennings and Zwick (2002) and Rennings et al. (2004) examine the determinants of employment changes due to the introduction of new environment-friendly products. The data stem from telephone surveys in five European countries. Some 1,594 interviews were conducted with environmentally innovative establishments from both the industry and services sectors. The authors classify environmental innovations of these establishments into new products and services, new processes, adoption of end-of-pipe technologies, and enhanced recycling. Based on results of discrete choice models, they show that if the most important environmental innovation is a product or a service innovation, i.e. the introduction of a new green product or service, then this has a positive and statistically significant effect on the probability that the firm increases its number of employees. However, if the most important environmental innovation is an end-of-pipe innovation, this increases the likelihood that the firm decreases its employment base.

While both studies use cross-sectional data, similar results are obtained using a panel dataset (Horbach, 2010). Firms in the environmental sector that developed new or modified products from 2002 to 2003 significantly increased their employment from 2003 to 2005. Furthermore, the magnitude of the impact of innovation on employment seems to be larger than in non-environmental fields. The empirical analysis is based on the establishment panel of the Institute for Employment Research (Nuremberg) and includes 900 firms operating in environmental sectors and 12,400 firms operating in non-environmental fields. The authors explain that the effect may be more pronounced in environmental fields due to the fact that environmental technologies and products are characterised by an earlier market development phase compared to other innovative products connected with higher employment dynamics.

A recent study conducted by Palmer and Truong (2017) examines the relationship between the introduction of new products based on green technologies and firm profitability. According to their definition "new technological green products" include "any new product that builds on technological advances to limit or lower its environmental footprint or that of other products, for instance, through improved energy efficiency or waste management" (Palmer and Truong, 2017, p. 87). While past studies have mostly used survey-based questionnaires to capture firms' new green products, Palmer and Truong (2017) use the press releases of actual new product introductions instead of relying on respondents' reporting which may be less reliable and less objective. The sample consists of 1,020 technological green new product introductions (NPIs) covering 79 global firms between 2007 and 2012. The authors find a positive correlation between technological green NPIs and firm profitability, as measured by turnover or return on total capital. Since the authors do not control for new product innovations in general, this result could simply reflect the impact of new product innovations in general. However, when the authors use as an alternative explanatory variable the ratio of technological green NPIs to the total number of NPIs, they interestingly still find a positive effect, although only statistically significant at the 10% level, suggesting that there might be extra profitability associated with a higher proportion of green products. Overall, the findings suggest that some financial incentives for firms already exist to use green technologies to limit the environmental impact of new product introductions.

1.2.2.3 Improved economic performance through reduced cost of inputs

While there is so far only limited empirical evidence to back the hypothesis that increased environmental performance could be associated with an increase in revenue, or this evidence is based on small samples from which no general conclusion can be made, much more evidence is available on the cost side.

Energy and materials

Perhaps the most natural way in which better environmental performance could be associated with greater economic performance is through reduced cost of inputs, and in particular of energy. The empirical evidence available confirms this prior. Existing studies examine this question often through measures of firms' productivity (Total Factor Productivity or TFP). This captures the effect on firms' output from the introduction of an environmental regulation with a constant set of production inputs. According to the Porter Hypothesis, regulation may increase productivity, as it reduces firms' wasteful energy inputs. Firms facing some costly regulation may also react by improving the productivity of other inputs such as labour. The opposing view is that regulation reduces firms' productivity as it poses additional constraints on their production. Overall, the empirical literature shows that environmental regulations do not appear to be a major driver of firms' productivity.

A number of studies examines the relationship between energy- and emissions-intensity and overall production efficiency. Overall, results are mixed, yet, the most robust studies tend to find positive effects. Using a sample of 68 US paper mills, Shadbegian and Gray (2003) find that plants with lower emissions are also generally more efficient: plants with 10 percent higher productivity have 2.5 percent lower emissions. This indicates that productive efficiency and pollution abatement efficiency are complements. Better managers are better at both production and abatement (rather than substitutes, with managers concentrating on the efficiency of production at the expense of their pollution abatement performance). Shadbegian and Gray (2006) also report a positive correlation between production efficiency and pollution abatement efficiency in the US paper, oil, and steel industries, even after controlling for observable factors.

Bloom et al. (2010) examine how much the energy intensity of firms (energy costs per unit of output) and total factor productivity correlate with the quality of management, by matching firm-level information on management practices to production and energy usage data from the UK census for the establishments owned by these firms. They find that firms with good management practices are less energy-intensive while being more productive. Thus, lower energy intensity is associated with better economic performance as measured by TFP. In terms of magnitude, improving the quality of management practices from the 25th to the 75th percentile is associated with a 17.4% reduction in energy intensity and with a 3.7% increase in TFP. Martin et al. (2012) report a similar result when focusing specifically on management practices related to climate change for 190 randomly selected manufacturing plants in the UK. The authors interviewed the managers of these plants to derive measures for the companies' practices in the areas of energy use and climate change and combined their responses with energy consumption data from the Annual Respondents Database (ARD) and economic performance data from official business microdata. They find that climate-friendly management practices, as measured by an index constructed from survey responses, are associated with lower energy intensity and higher productivity.

Similarly, Horbach and Rennings (2013) show that the introduction of cleaner production process innovations leads to higher employment of firms. Noticeably however, end-of-pipe technologies (in particular air and water process innovations) have a negative impact on employment. This confirms an earlier result by Pfeiffer and Rennings (2001) who show that cleaner production processes are more likely to increase employment compared to end-of-pipe technologies. Van-Leeuwen and Mohnen (2017) obtain similar results from a panel of Dutch manufacturing firms for the period 2000-2008. They show that only production process innovations are positively correlated with firms' productivity, whereas end-of-pipe innovations are negatively correlated. Kumar and Managi (2010) also find a positive relationship between environmental and economic performance. They analyse the US emission allowance trading scheme for SO_2 emissions, which was introduced as part of the 1990 US Clean Air Act Amendment (USCAAA). Again, as in the case of the EU ETS, participation in the SO_2 trading scheme is not a direct measure of environmental performance. However, since these companies face a price on their firm-specific SO_2 emissions, they should emit less than in the absence of the trading scheme. They find that between 1995 and 2005 electricity-generating plants are able to increase electricity output and reduce SO_2 emissions due to the allowance trading scheme.

Alongside papers based on regression analysis of past data, a new literature is emerging that uses experimental data to assess the environmental-economic performance of firms. Gosnell et al. (2017) implemented an experiment in partnership with Virgin Atlantic Airlines (VAA) in order to test the impact of various incentives (monitoring, performance information, personal targets, and prosocial incentives) on fuel efficiency of their captains in three key flight areas: pre-flight (aircraft fuel load), in-flight (fuel-efficiently between take-off and landing), and post-flight (taxi). They find that, by simply informing the captains that the academic researchers and VAA Fuel Efficiency personnel overseeing the study are measuring their behaviours, captains considerably reduce fuel consumption: captains in this experimental group significantly increased the implementation of Efficient Flight and Efficient Taxi by nearly 50 percent from the pre-experimental period. These behavioural changes generated more than 7,700 tons of fuel saved for the airline over the eight-month experimental period (i.e. \$6.1 million in 2014 prices), which translates to approximately 24,500 tons of CO_2 abated. Moreover, monitoring and targets also induce captains to improve efficiency in all three key flight areas. The study provides the lowest ever calculated marginal abatement cost per ton of CO_2, at negative \$250 (i.e. \$250 savings per ton abated), showing that airlines can improve both environmental as well as economic performance at the same time. Experimental studies of this sort are only emerging, but constitute a fruitful avenue for future research.

Labour costs

Some authors have also argued that better environmental performance can lead to a reduction in the cost of labour, because environmentally-friendly companies are able to attract and retain motivated employees who work harder for lower wages. Indeed, if people prefer their employer to be socially responsible, they will, if faced with a choice between two otherwise identical job offers with equal pay, choose the employer they perceive to be more responsible. Therefore, the less responsible employer should offer a higher wage to make those people indifferent (Nyborg and Zhang, 2013). There is empirical support for the idea that social responsibility of firms is valued by employees. For instance, job satisfaction is considerably higher when top management is regarded as supporting ethical behaviour. Lanfranchi and Pekovic (2012) use data on 11,600 employees at 7,700 French firms and find that employees of firms that have adopted voluntary environmental standards report a considerably, and statistically significantly, higher feeling of usefulness at work.

Nyborg and Zhang (2013) carried out a survey on 100,000 Norwegian employees and show that firms with higher Corporate Social Responsibility (CSR) pay substantially, and statistically significantly, lower wages. Three studies using data for French firms and employees find that employees are more likely to work uncompensated overtime hours for firms that have adopted voluntary environmental standards (Lanfranchi and Pekovic, 2012; Nyborg and Zhang, 2013), labour productivity is higher (Delmas and Pekovic, 2013), and difficulties with recruitment are smaller (Grolleau et al., 2012). It is not clear, however, whether this is driven by self-selection of more productive and motivated employees into CSR firms or whether working for a socially responsible employer in itself increases motivation at work. This literature is still in its infancy and future research might enable to shed light on this issue.

Cost of capital

Better environmental performance could be associated with a lower cost of capital, in particular because of lower exposition to environmental risk and liabilities. For example, El Ghoul et al. (2011) examine the effect of CSR on the cost of equity capital for a sample of around 2,000 US firms. They find that firms with better CSR scores exhibit cheaper equity financing. Attig et al. (2013) find that credit rating agencies tend to award relatively high ratings to firms with good social performance. Cheng et al. (2013) show that firms with better CSR performance face significantly lower capital constraints. Goss and Roberts (2010) use a sample of 3,996 loans to US firms and find that firms with social responsibility concerns pay between 7 and 18 basis points more than firms that are more responsible. A common limitation to all these studies is that they use indicators of CSR that include not only environmental performance but also other measures of social responsibility, such as responsible practices towards employees. Therefore, it is not possible to determine whether the relationship stems from better environmental performance or better performing or more committed employees.

1.2.3 Summing up

While numerous measures of environmental performance are used, the measure of economic performance usually applied is financial performance based on market value data. While market data has the advantage of being widely available, it is also - by definition - restricted to listed firms and, as such, the results may be affected by a sample selection bias and might not be representative of the population of firms, in particular of smaller firms that are typically not listed. Moreover, this literature generally abstracts from the drivers of environmental performance, which could come from voluntary efforts of companies or be induced by environmental regulations. Because high environmental performance could be driven by profit-enhancing motivations (for example, improving energy efficiency to reduce input costs), it is perhaps not surprising that many studies report a positive relationship between environmental and economic performance.

Ambec and Lanoie (2008) suggest two main theoretical channels through which environmental performance can impact economic performance positively: (1) increasing revenues or (2) reducing costs of inputs. The empirical evidence on the revenue channel is relatively scarce. This is at least partly due to a lack of sufficiently disaggregated data of new green product introductions at the firm level and suitable control groups to take into account non-green product introductions. Yet, the existing studies suggest that a positive association may exist between environmental and economic performance through an increase in revenue. More evidence is available on the cost side: The cost channel suggests that environmental performance can improve economic performance by reducing costs of inputs. Overall, the empirical evidence finds support for this channel. The majority of studies focused on energy- and material inputs for which a positive relationship is observed. Yet, the effect seems to be limited to cleaner production process innovations. For end-of-pipe innovations, which maintain the same production process but reduce emissions through installing additional filters, most studies do not find a positive effect on economic performance. In addition, the results of some papers suggest that firms with better environmental performance also have lower costs of labour and have access to cheaper financing.

1.3 The separate impact of environmental policies on economic outcomes and environmental performance

Positive economic and environmental outcomes can go hand in hand, particularly when environmental performance is aligned with a firm's profit-enhancing strategy such as investments in energy or material efficiency to reduce costs. While this suggests that firms might benefit from better environmental performance in economic terms, it does not imply that (exogenous) environmental regulations aiming at improving firms' environmental performance would improve firms' economic outcomes.

Environmental regulations are accused by some of jeopardising economic activity but are viewed by others as potential drivers of economic growth. The traditional thinking among economists has been that environmental regulations add costs to companies and slow down productivity, because they divert resources away from productive investments such as investments in research and development and towards pollution-control activities (Rose, 1983; Schmalensee, 1993; Walley and Whitehead, 1994; Jaffe et al., 1995). Since it is reasonable to assume that firms would have reduced pollution in the absence of environmental regulation if it was profitable for them to do so, any environmental regulation is likely to come at a cost for businesses. If the stringency of policies differs across countries or regions, then environmental regulations may not only add costs to businesses, but may also affect the competitiveness of the domestic industry, putting some companies at a competitive disadvantage vis-*à*-vis their foreign competitors (Levinson and Taylor, 2008). Discussions about the effects of environmental regulations on competitiveness are often framed in terms of 'jobs versus the environment' (Morgenstern et al., 2002). This applies particularly in countries and regions where employment in manufacturing sectors has been decreasing, making environmental regulation a contentious political issue (Dechezleprêtre and Sato, 2017).[9]

However, a different view of the world has been articulated since the 1990s, with what has become widely known as the Porter Hypothesis (Porter, 1991a; Porter and van der Linde, 1995). The basic idea is that environmental regulations should foster innovation in environmentally-friendly technologies which would not have been developed otherwise, and the adoption of these new technologies could well, in the medium run,

[9] For instance, aggregate manufacturing jobs declined by 35 percent in the United States between 1998 and 2009. Over the same time period total manufacturing sector production grew by 21 percent (Kahn and Mansur, 2013; Dechezleprêtre and Sato, 2017).

improve firms' productivity or allow regulated firms to achieve technological leadership.

Ambec et al. (2013) illustrate the main causal links involved in the Porter Hypothesis (see Figure 1.2). If an environmental regulation is well-designed and sufficiently flexible, it may not only lead to improved environmental performance, but it may also lead to innovation offsets. These offsets can partially, or sometimes more than fully, offset any additional costs from the regulation, thereby increasing firms' business performance. Thus, according to the Porter Hypothesis, while effective environmental regulation improves the environmental performance of firms, well-designed regulation could also improve business performance.

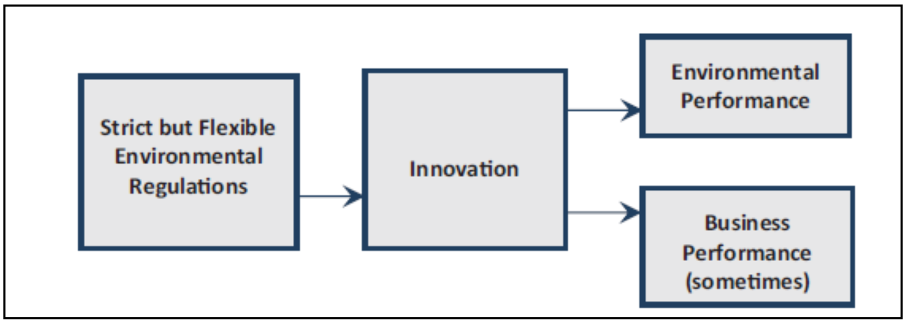


Figure 1.2: Causal links involved in the Porter Hypothesis (Source: Ambec et al. (2013, p. 3))

The Porter Hypothesis can take different forms according to the strength of the effect and the type of regulation (Jaffe and Palmer, 1997). The 'weak' version states that regulation will spur innovation. Thus, firms respond by innovating to reduce their costs from the environmental regulation (i.e. the first causal link in Figure 1.2). Yet, this weak version does not indicate if this innovation is good or bad for a firm's economic performance. The 'strong' version says that the regulation induces firms to find new products or processes that increase profits while complying with the regulation. According to this strong version, the benefits of the regulation more than offset its costs. This would make the regulation socially desirable even when ignoring any environmental improvements arising from it. The 'narrow' version of the Porter Hypothesis states that only certain types of regulation (e.g. flexible instruments) will encourage innovation.

The regulation needs to be sufficiently flexible and focus on the outcome (i.e. the emission reduction) rather than the process (i.e. the technology firms need to adopt) to induce innovation. Market-based regulations (taxation, emission trading schemes) would therefore be preferable to command-and-control regulations (Ambec et al., 2013). The firm-level empirical literature tends to fall into one of two categories: studies testing the weak version (i.e. the link between environmental regulation and innovation activity), and those testing the strong version (i.e. the impact of environmental regulation through innovation on business performance). The former is often assessed through R&D expenditures or the number of registered patents. The latter is often assessed through effects on productivity, profits or stock market returns.

The Porter Hypothesis was initially criticised for its lack of theoretical foundation, as it rests on the idea that firms ignore opportunities to improve their business performance. Following Porter and van der Linde (1995) a sizeable literature has emerged to provide the theoretical basis for the hypothesis, by highlighting the existence of additional market failures (beyond the environmental pollution externality). Examples for such market failures include asymmetric information within firms (Ambec and Barla, 2002), learning-by-doing (Mohr, 2002), and market power (Greaker, 2003). For example, in a theoretical model, Mohr (2002) assumes that the existence of knowledge spillovers prevents the replacement of an old polluting technology by a new one even if it is cleaner and more productive. Second-mover advantages benefit firms that wait for other firms to adopt the technology first. In this case, additional environmental regulation can induce firms to adopt a new, and cleaner technology. This example illustrates that the strong version of the Porter hypothesis is theoretically possible. Regulation can improve environmental quality and ultimately increase productivity (Dechezleprêtre and Sato, 2017).

The growing importance of the debates over the many consequences of pollution on health, biodiversity loss, climate change, and so on, and the potential negative consequences of environmental regulations on economic performance has led to a large number of studies that aim to empirically quantify the impact of environmental regulations on the economic and the environmental performance of businesses. Multiple dimensions of economic performance of regulated businesses have been analysed, including productivity, innovation, employment, profitability, output and trade (Calel et al., 2017). Similarly, numerous environmental performance indicators have been used, including energy consumption, carbon emissions, emissions of various local pollutants (NO_x, SO_x, etc.) as well as composite indicators. These are typically used based on absolute values (e.g. emissions in tonnes, energy consumption in kWh) or relative values (e.g. energy intensity).

1.3.1 The impact of environmental policies on economic outcomes

The empirical literature on the effects of environmental policies on economic outcomes - such as growth, trade, investment, productivity and employment - is well developed. Most investigations have focused on the impact of environmental policies in the context of corroborating fears of the losses of competitiveness and productivity - broadly related to the so-called Pollution Haven Hypothesis[10] - and hopes of reaping potentially overlooked productivity gains in the context of the so-called Porter Hypothesis (Dechezleprêtre and Sato, 2017).

The richness of this literature also implies that it has been extensively reviewed. In particular, a series of recent reviews (Dechezleprêtre and Sato, 2017; Cohen and Tubb, 2017; Koźluk and Zipperer, 2014) does a thorough job and our intention is not to attempt to replicate that. Instead, we summarise the findings of these reviews, complemented by most recent papers. Empirical papers tend to look at outcomes such as innovation, productivity, profits, sales, employment, entry and exit, and trade and FDI. Most papers are within-country studies, focusing on the effects of the introduction or increase in the stringency of a specific environmental policy.

A broad interpretation of the results of the empirical literature is that the cost-burden of environmental regulation has been found to be rather small. However, effects of more stringent environmental policies are context-specific and existing analyses focus on short-term and partial equilibrium effects. Effects on economic outcomes tend to be statistically insignificant in general (though a large amount of studies finds positive effects too), but environmental regulations can also result in statistically significant adverse effects on economic performance in the short-run, particularly in pollution- and energy-intensive sectors, for which the environmental or energy regulatory costs are substantial (Dechezleprêtre and Sato, 2017). However, a general consensus seems to be that these adverse effects tend to be "small" relative to other changes going on in the economy (e.g. changes in transport costs, proximity to demand, potential to cost-pass-through etc.) and often depend on firm or industry characteristics. Moreover, evidence of the "weak" version of Porter's hypothesis - i.e. that environmental policies tend to induce innovation - seems well established (Bellas and Lange, 2010; Calel and Dechezleprêtre, 2016; Dechezleprêtre and Sato, 2017), while there seems little reason to believe that this innovation leads to overall better economic performance, as would be in the case of the "strong" version of the Porter Hypothesis (Dechezleprêtre and Sato, 2017; Koźluk and Zipperer, 2014).

The "small" nature of the effects is further confirmed in more recent cross-country panel studies such as Albrizio et al. (2017) for productivity growth. This paper tends to find heterogeneous effects across firms depending on how far away they are from

[10]The so-called Pollution Haven Hypothesis (PHH) suggests that when the costs of pollution increase, environmental policies provide industries with incentives to relocate some parts of their production to jurisdictions with less strict environmental regulations or to source inputs from them (for reviews, see Brunnermeier and Levinson (2004); Copeland and Taylor (2004); Jaffe et al. (1995)). As a result of costs induced by stringent environmental policies, jurisdictions that introduce them are seen as potentially loosing competitiveness against those that maintain laxer regulation. For comprehensive reviews of the empirical literature on such claims see Dechezleprêtre and Sato (2017) and Koźluk and Timiliotis (2016).

global industry leaders in terms of productivity. Moreover, it finds heterogeneous effects across time - with (small) short-term effects, eventually disappearing.

The recent literature on economic effects of environmental policies tends to be more preoccupied with causality - benefitting from more advanced micro-econometric methods and better data availability. On the one hand, micro studies exploiting thresholds and policy discontinuities are now the most popular approach, allowing the identification of causal effects. The downside is that they are difficult to generalise - as any event studies - and it is difficult to control for other local or concurring policies and developments. Micro studies by nature tend to be partial equilibrium, and would tend to be better placed to capture the direct "costs" - i.e. the negative effects, particularly as they often focus on energy and pollution intensive industries - than to capture the second order benefits, such as those coming from a cleaner environment or healthier workers, which may generally be more difficult to be appropriated by a firm. Finally, a general feature of these studies is a fairly loose approach to the timing of effects - many studies would not attempt to distinguish potentially different short and longer term effects. However, the distinction can be crucial due to the way competitiveness and costs are measured. For example, environmental policies that induce increased investment (in capital and innovation) or increased employment (e.g. R&D staff) can show up as reduced profits and productivity resulting in losses of competitiveness in the short term. However, such investments can in principle have offsetting beneficial effects over the longer term - hence increasing economic outcomes of firms.

To address the shortcomings of micro studies, a strand of literature looks at effects from a cross-country perspective, allowing better control for national policies and circumstances, better generalisation of results, but being generally less clean on causality. As cross-country natural policy experiments are scarce, such studies tend to use more recently available environmental policy stringency proxies, such as the OECD's Environmental Policy Stringency (Botta and Koźluk, 2014) or international and sectorial variation in energy prices (Sato et al., 2015). As such policy proxies tend to be available at the national level, an identification strategy similar to Rajan and Zingales (1998) is commonly applied, whereby effects on global value chains (Koźluk and Timiliotis, 2016), on investment (Dlugosch and Koźluk, 2017) and on FDI (Garsous and Koźluk, 2017) are analysed.

Going back in time, the first significant review of the literature on the impact of environmental policies on economic outcomes, Jaffe et al. (1995), found little evidence of large resulting losses in competitiveness. It is fair to say, that over two decades later, and notwithstanding the caveats discussed above, this view tends to be confirmed - environmental policies generally do not tend to have large negative effects on economic activity.

1.3.2 The impact of environmental policies on environmental outcomes

In principle, the main objective of environmental policies is to enhance environmental quality. Yet, the empirical evidence on the environmental performance of environmental policies is surprisingly shallow - i.e. de facto, the environmental effectiveness, at the firm level, tends to be more assumed than investigated. The epidemiology literature predominantly researches the link between pollution levels and public health, but puts less attention on the precise origins of the changes in pollution levels. Economists, on the other hand, tend to focus on environmental policies' effects on economic outcomes such as competitiveness. Since - as argued in the previous section - most papers concerned with economic effects such as loss of competitiveness, tend to find small, if any, negative effects of environmental policies, the scarcity of empirical evidence on the policies' environmental effectiveness is even more surprising. Understanding the environmental effectiveness of environmental policies is crucial for answering the basic question: Do we see hardly any negative impact on competitiveness because environmental policies are a red herring - i.e. they do not have much environmental impact either? Or is it that they are more of a free lunch - i.e. they can provide substantial benefits in terms of environmental protection without harming the pure economic performance?

Evaluating the impact of environmental policies on pollution levels in a causal manner is still challenging. One reason is the nature of environmental policies. Many of them have an exhaustive coverage, covering a population of operating entities in the respective state or country. This prevents researchers from observing a credible counterfactual, i.e. how emissions would have evolved in the absence of the policy. For others, where discrete changes in policies - such as different stringency applying to different facilities - are analysed, the selection into treatment is based on endogenous characteristics of the facility, making the disentangling of such effects cumbersome.

Another key reason for the lack of analysis is the scarcity and nature of environmental performance data. Data on emissions is often gathered through ambient monitoring - and hence reported on an aggregated country or regional level or for a given location - without the attribution of the origins of the emissions. Sectoral and facility level data is often not monitored directly, but estimated - based on industry and technology specific parameters - again making monitoring the actual effects problematic. Some registries, such as the European Union Transaction Log or the national Pollution Release and Transfer Registers (PRTRs), provide micro data, but cover only installations that are affected by the respective policy, or above certain thresholds.

Nevertheless, the progress in collection of environmental data such as data from monitoring stations recording air pollution or installation-level data from PRTRs has become increasingly available in the last two decades, allowing researchers to make advances in the understanding of effects of policies. Policies analysed in empirical studies using micro data include the Clean Air Act and the SO_X Trading Scheme in the United States, the European Union's Emission Trading Scheme and more recently British Columbia's carbon tax in Canada.

1.3.2.1 The effectiveness of command and control regulations

The US Clean Air Act and its Amendments (CAAA) is one of the most extensively studied command and control regulations. It defines federal guidelines to reduce emissions, but leaves much of its implementation and enforcement to the county level. If a county exceeds a federally set emissions ceiling for a certain pollutant, it is in 'non-attainment' status and, hence, faces incentives to introduce regulations for reducing emissions, which counties in attainment do not face. These incentives include more stringent regulations for new manufacturing firms, stricter requirements to reduce source emissions for existing firms, and submissions of plans how to be brought into attainment. The majority of studies on the CAAA make use of monitoring stations and analyses the effect of the policy on ambient emissions (Ozone, SO_2, PM_{10}) using temporal variation of counties' compliance status to proxy environmental stringency[11]. Overall, they find that being assigned non-attainment status under the CAAA results in a decline of ambient emissions. Yet, recent studies suggest that counties put particular effort in reducing pollution around monitoring stations rather than improving the overall air quality. This finding reveals a key limitation of relying exclusively on monitoring stations for policy analysis and shows a key advantage of source-based micro-data (Auffhammer et al., 2009, 2011; Bento et al., 2015).

Firm- or plant-level micro data allow for a more precise attribution of policies' effects because changes in ambient emission levels might also be caused by other factors, which are not always controlled for (e.g. weather conditions, traffic or changes in population demographics and consumption patterns). Greenstone (2003) uses data from the U.S. Toxic Release Inventory (TRI) to analyse the impact of CAAA's air pollution standards between 1987 and 1997, focussing on the iron and steel sector. Using a differences-in-differences (DiD) approach, this study finds that plants in non-attainment counties reduced their total emissions from lead by 7.1% relative to instal-

[11] Henderson (1996), Greenstone (2004), Chay and Greenstone (2003), and Chay and Greenstone (2005). Researchers have also used the CAAA as an instrument to estimate the impact of pollution on infant mortality (Chay and Greenstone, 2003; Sanders and Stoecker, 2015) housing prices (Chay and Greenstone, 2005; Grainger, 2012), distributional aspects of environmental policy (Bento et al., 2015), worker reallocation (Walker, 2011), and worker productivity (Isen et al., 2017).

lations in attainment counties (PM: 3.5%; VOC's: 5.6%). Focussing on the chemical industry, Gamper-Rabindran (2009) finds that VOC emissions decreased by 21% between 1988 and 2001 using the same methodology as Greenstone (2003). More recently, Gibson (2018) expands Greenstone's approach by including all industries. He finds that treated plants reduced their PM_{10} emissions by between 33 and 38% relative to non-treated plants. This reduction is much higher than the 11 to 14% reduction reported in Auffhammer et al. (2011) for ambient concentrations - potentially because of the limited direct contribution of industrial emissions.

Combining pollution data from the Canadian National Pollution Transfer and Release Inventory with financial data on the firm level from the Annual Manufacturing Survey, Najjar and Cherniwchan (2018) analyse the impact of air pollution regulation in Canada on pollution levels and pollution intensities. Much like the CAAA, the Canada Wide Standards for Particulate Matter and Ozone (CWS) divides the counties into attainment and non-attainment counties, but also explicitly address 'targeted industries' that were subject to stricter regulations. This allows for exploiting variation in the stringency of regulation across regions, industries, and time. Using plant-level data from 2004 to 2010, they find that the CWS is associated with a 15% reduction in $PM_{2.5}$ emissions and a 33% reduction in NO_X emissions. Overall, Najjar and Cherniwchan (2018) conclude that the CWS explains up to 61% of the clean-up of the Canadian manufacturing.

1.3.2.2 The effectiveness of environmental taxes

Most papers of the empirical ex-post literature analyse the impact of carbon taxes using sector-level or country-level data on CO_2 emissions (for example: Li and Lin (2011); Elgie and McClay (2013); Rivers and Schaufele (2015)). Examining the environmental effectiveness of the British Columbian carbon tax, Ahmadi (2017) provides one of the first assessments using plant-level GHG emissions. He uses data from the Annual Survey of Manufacturing (ASM) to estimate the causal effect of the BC carbon tax on emissions using more than 20,000 plant-year observations[12]. Combining the data for plant-level fuel purchases from the ASM with fuel prices and embodied GHG emissions of each fuel type, the author is able to calculate plant-specific GHG emissions. The analysis is complicated by the fact that the economic recession starting in 2009 seems to have affected Canadian provinces in a different way. To address this concern, Ahmadi (2017) exploits the variation in exposure to the carbon tax and assigns only BC installations with high exposure, proxied by high emission intensity, as treatment

[12]Besides Ahmadi (2017), Martin et al. (2014) is currently the only paper that assesses the impact of a carbon tax using micro-data. This paper is reviewed in the next section.

group. To control for unobserved time-varying province-specific heterogeneity, he estimates a triple difference regression that compares the differential change in emissions for plants with high and low emission intensity in BC before and after implementation of the carbon tax, to the same differential change in the counterfactual plants in other provinces. While the standard DiD approach points to a significant reduction of CO_2 emissions in the order of 8%, the triple difference method yields a 2% reduction which is not statistically significant from zero. Yet, the emission-intensity of plants declined significantly by 7%. The lack of a decline in carbon emissions could be due to the revenue-neutral design of the policy. In parallel with the carbon tax, corporate tax rates were lowered to reduce negative impacts on competitiveness. The author concludes that firms appear to have increased their output as a response to the decline in the corporate tax rates, which prevented a decline in emissions, but in combination with the carbon tax resulted in a decline in emissions intensity.

Most studies using firm-level data do not explicitly evaluate the impact of carbon or energy taxes, but focus on the relationship between energy prices and energy demand, assuming that more stringent environmental regulation will translate directly or indirectly into higher energy prices. These papers usually set up factor demand models to estimate the own-price elasticity and the cross-price elasticities for energy, labour, and capital. Pioneering works on panel data and cross-section estimations have been performed by Woodland (1993) on Australian firms, Nguyen and Streitwieser (1999) on US firms, and Bjørner and Jensen (2002) on Danish firms, all of which report own-price elasticities of energy to be negative in the range between -0.4 to below -3.8. More recent studies report similar results for Denmark (-0.45, Arnberg and Bjørner (2007)), Ireland (-1.5, Haller and Hyland (2014)), and Italy (-1.13, Bardazzi et al. (2015)).

Few papers look at non energy-related environmental taxes with micro data. Millock and Nauges (2006) analyse the effect of the French tax on air pollutants (SO_2, NO_X, HCI, and VOC) based on a sample of 226 plants from the chemical, coke and iron and steel sector. Estimating a fixed effects model without control group, they find that the elasticity of emissions with respect to the tax to be between -0.21 and -2.67 depending on the pollutant and economic sector. The Swedish nitrogen oxide tax with refund payments has been studied most extensively. Although this literature does not provide a direct estimate of the effectiveness regarding emission reductions, it provides evidence that plants have invested in advanced abatement technologies (Isaksson, 2005), using a variety of different technologies (Sterner and Turnheim, 2009), thereby reducing the emission intensity. Ancev et al. (2012) evaluate the load based licencing (LBL) scheme for NO_X emissions in New South Wales on NO_X emissions based on a sample of 85 industrial plants between 2000 and 2009. They exploit the variation of the pollutant fee, which originates from area-specific emission rates varying over time, to identify the impact of the LBL on NO_X emissions. Their results suggest that the LBL had a negative, but statistically not significant effect on reducing emissions, potentially due to the relatively low levels of the fee (the Swedish tax on NO_X emissions is 100 times higher). This result is confirmed by Contreras et al. (2014) who do not find a significant impact of the LBL on emission intensities of NO_X, PM, and Fine Particulate Matter for electricity generating units.

1.3.2.3 The effectiveness of emissions trading schemes

Emissions trading schemes have become more and more popular in the last years, in particular for mitigating climate change. The basic idea is that a central authority sets the maximum level of pollution, i.e. the cap, while polluters are required to hold permits equal to the amount of their emissions. Polluters can trade the permits among each other, thereby guaranteeing to achieve the given environmental target at the least cost.

By far the biggest market for tradable emission permits is the European Union Emissions Trading System (EU ETS), implemented in 2005 and covering the GHG emissions of more than 12,000 power plants and industrial facilities in 31 countries. A comprehensive review on ex-post evaluations of the EU ETS on emission reductions is provided by Martin et al. (2016). As for any comprehensive environmental regulation, assessing the effectiveness of the EU ETS requires to know the counterfactual emissions. Counterfactual emissions have been estimated based on aggregate emissions, and based on firm or plant-level data.

McGuinnes and Ellerman (2008) use power plant-data from the United Kingdom in order to estimate the effect of the EU ETS on abatement for the first phase. Based on a fuel switching model, they estimate that natural gas utilisation increased by about 22 percent while coal utilisation decreased by 17 percent, resulting in annual emission reductions between 13 and 21 Mt CO_2. Six other studies until now have used installation-level data to provide causal estimates of the effect of the EU ETS on regulated installations' carbon emissions. As these studies also shed light on the economic performance of ETS-installations, they are reviewed in the next section.

Another local carbon market, established in 2009, is the Regional Greenhouse Gas Initiative (RGGI) that covers the emissions of fossil-fuelled power plants in 10 northeastern U.S. states. Fell and Maniloff (2018) estimate the impact of the RGGI program on reducing emissions using daily and yearly generator-level data from 2004 to 2012. They use a DiD design to estimate the causal effect of the programme on power generation capacity, focusing in particular on coal plants. Their findings suggest that the RGGI program led coal fired power plants to reduce their capacity utilisation by 10 percentage points and that the generation was not compensated by gas-fired generation in the same regulated region. Thus, they examine possible leakage to non-regulated regions and observe that power generation capacity increased in neighbouring unregulated regions. However, the leakage increased the capacity of relatively cleaner plants so that overall emissions still declined as a result of the policy.

The SO_2 trading program (Acid Rain Program) in the US was the first large experiment with a cap-and-trade mechanism. In Phase I (1995 - 1999), the 263 most SO_2-emission intensive units were covered, while Phase II covered virtually all generating units (Stavins, 2005). The bulk of the literature assumes that the SO_2 trading was effective in reducing emissions (Schmalensee et al., 1998). Most reduction estimates rely on EPA's projections of the counterfactual, but this projection is complicated by major uncertainties with respect to the remaining lifetime of existing facilities, the rates of adoption of clean production processes and the growth in electricity demand (Chestnut and Mills, 2005). EPA (2015) reports that units covered by the Acid Rain Program reduced annual SO_2 emissions in 2015 by 13.5 million tons or 87 percent relative to 1990.

The design, the performance, and the challenges of other emissions trading schemes are reviewed in Schmalensee and Stavins (2017). Two papers use a quasi-experimental study design to estimate the impact of trading schemes on emissions reductions in a causal manner. Deschênes et al. (2017) analyse the NO_X Budget Trading Program (NBTP) that operated between 2003 and 2008 covering around 2,500 electricity generating units in eastern and mid-western states in the US. Since the NBTP aimed at reducing ozone pollution, which typically reaches its highest levels in summer, the market operated only between 1 May to 30 September. Hence, Deschênes et al. (2017) make use of a triple difference technique comparing the emission levels between participating and non-participating states, before versus after, and summer versus winter. Using unit-level data, they find that the NBP led to a statistically significant reduction between 391,000 and 521,000 tons NO_X in each summer, which translates into a decrease of the mean summer ozone by about 6 percent. Fowlie et al. (2012) examine the Southern California REgional CLean Air Incentive Market (RECLAIM) that started in 1994 and included 392 industrial NO_X and SO_2 emitters. They exploit the fact that RECLAIM covers only facilities in Southern California, whereas all other Californian installations continue to be regulated under command-and-control. Using installation-level data and applying a matched DiD study design they estimate that RECLAIM facilities have reduced their NO_X emissions by 20% relative to non-regulated installations in the first 10 years of RECLAIM.

1.3.2.4 Summing up

In the last ten years, this literature strand has seen much progress by using more advanced estimation techniques such as matched DiD study designs and by making use of new micro datasets that allow for establishing a causal relationship between environmental policies and its impact on environmental quality. This trend is likely to continue in the future as more and more environmental data from various sources becomes available. However, some challenges in the evaluation of environmental policies will remain. The comprehensive coverage of environmental policies exacerbates the policies' assessment in a causal manner. Hence, making use of randomised controlled trials, that are increasingly used in other policy areas such as labour market policies and welfare programmes (Gueron and Rolston, 2013), would certainly facilitate the evaluation of the effectiveness of environmental policies.

Across the board - regardless of the environmental policy instrument analysed - most of the reviewed papers find a significant reduction of emissions as a result of the policy.

As shown above, both command and control policies and emission pricing are effective environmental instruments. At the same time, it is often argued that pricing instruments provide incentives to reduce emissions in a cost-effective way since economic agents internalise the emissions price in their abatement decisions. Although this insight dates back to Pigou (1920), environmental taxes only have become popular in the last three decades and emission trading schemes are even more recent (OECD/IEA, 2017). To what extent they actually deliver on the expectation is an empirical question that can only be addressed when looking at the environmental and economic effects jointly.

1.3.3 The joint impact of environmental regulations on environmental and economic performance

Most studies have so far assessed the impact of environmental regulations on environmental and economic performance separately (for reviews, see Ambec et al., 2013; Arlinghaus, 2015; Cohen and Tubb, 2017; Dechezleprêtre and Sato, 2017; Endrikat et al., 2014; Friede et al., 2015; Iraldo et al., 2011; Jaffe et al., 1995; Koźluk and Zipperer, 2014; Lankoski, 2010; Martin et al., 2016). However, a critical input for policy makers implementing environmental regulations is an understanding of how such policies will impact both environmental quality and local businesses' economic performance. As a consequence, some recent studies have started to jointly analyse these dimensions.

A large literature has analysed the impacts of environmental regulations on environmental performance, while another strand of the literature - somewhat less rich - has looked at the consequences on economic performance. Ideally, we would like to know whether environmental policies were effective in environmental terms and whether or not they were accompanied by detrimental economic effects. Observing only one of the two dimensions does not allow for a comprehensive evaluation of the respective policy. Yet, despite some progress in the last years the empirical literature regarding the joint economic effects and the environmental outcome is still very scattered. This makes it hard to draw conclusions about the joint environmental and economic impact of specific environmental policies because the respective results originate from studies using different datasets, focussing on distinct countries and/or economic sectors. Notably, the key papers have focused on climate change regulations, and within this literature, most papers analyse the effect of the European Union Emissions Trading System (EU ETS).

1.3.3.1 The joint impact of the EU ETS on carbon emissions and firm performance

In 2005, the EU ETS - the EU's flagship climate change policy - was launched in 24 countries across Europe. The policy regulates the carbon emissions of around 12,000 installations, together representing approximately 40% of the total greenhouse gas emissions in the EU, by allocating pollution permits to these installations, which can then be freely traded on an international permit market. The objective of this cap-and-trade programme is to achieve a set reduction of aggregate CO_2 emissions at minimal cost. Across Europe, power stations and industrial plants were categorised by their primary activity such as: combustion, cement, pulp and paper, among others. The EU ETS provides a unique context to examine the causal impact of environmental policy on both environmental and economic performance. It is the first and largest environmental policy initiative of its kind anywhere in the world up to now (Calel and Dechezleprêtre, 2016; Martin et al., 2016; Calel et al., 2017).

Importantly, to reduce administrative costs, the EU ETS covers only large installations. This is an important characteristic of the regulation, which can be exploited for identification in empirical research. Size thresholds of the EU ETS are defined specifically for each primary activity and determine whether an installation is included in the regulation. For example, the regulation only covers combustion installations, which have an annual thermal input exceeding 20 MWh. Smaller installations are not included in the regulation (Calel and Dechezleprêtre, 2016). Researchers can therefore use these inclusion criteria at the installation-level to compare firms or installations with similar environmental and economic performance prior to the introduction of the EU ETS, as long as some installations are regulated since 2005 and some other are not. This allows researchers to apply quasi-experimental methods, to examine the causal impacts of environmental policies (List et al., 2003; Greenstone and Gayer, 2009; Calel and Dechezleprêtre, 2016; Calel et al., 2017).

The main outcome of interest for the EU ETS are CO_2 emissions. Yet, confidential business surveys, maintained by statistical agencies, are the only source for representative emissions data for both EU ETS and non-EU ETS plants. Access to these datasets is restricted and subject to disclosure control. This is one of the explanations for why few studies have so far examined the impact of the EU ETS on the economic and environmental performance of regulated installations by using plant-level data. To date, four studies have explored the joint effect of the EU ETS on firms' and installations' environmental and economic performance, respectively in France, Germany, Norway and Lithuania (Horbach, 2010; Calel et al., 2017).

France

Wagner et al. (2014) use comprehensive plant-level data for around 9,500 French manufacturing firms to explore the economic and environmental response of plants to the introduction of the EU ETS. The analysis is based on a combination of energy consumption and economic performance data at the facility and firm level. The EACEI (Enquete Annuelle sur les Consommations d'Energie dans l'Industrie) is a survey conducted annually in France. It provides quantities and values of energy consumed by energy type (electricity, vapour, natural gas, coal, lignite, coke, butane, propane, fuel oil, heating oil, wood, etc.). About 12,000 establishments are part of the sample: all industrial establishments employing 20 employees or more in the most energy consuming sectors, all establishments with more than 250 employees, and a sample of establishments with employment between 20 and 249 employees in sectors that are not energy intensive. Fuel consumption information at the plant level is then converted into carbon emissions based on widely available carbon content data on the various fuels consumed. This dataset is combined with EAE (Enquête Annuelle des Entreprises), which collects balance-sheet data at the firm level on turnover, employment, capital, and aggregate wages, as well as information about firm location and industry classification. The data are available for all firms with more than 20 employees and all the plants of those firms. Finally, the data is matched on the European Union Transaction Log, which contains the list of all installations regulated under the EU ETS. Notably, in France, the national registry is managed by the Caisse des Dépôts and their website provides a link between the EUTL permit identifier (GIDIC) and the French unique firm identifier SIREN, allowing a quasi-perfect matching of the two databases (Horbach, 2010).

To examine the causal effect of the EU ETS on environmental and economic performance, Wagner et al. (2014) combine matching with difference-in-differences. For each EU ETS-regulated plant, they use propensity score matching to identify the most similar non-EU ETS plant (nearest neighbour), which becomes part of the control group and helps determining what would have been the behaviour of regulated plants, had they not been regulated. Ideally, one would want to directly use the production capacity of the plants to create such pairs, since it is production capacity pre-EU ETS that determines inclusion into the system. However, this variable is not observed by the researchers. Therefore, they use carbon intensity of each plant in the year 1999, the year in which the EU ETS was announced, as the main matching variable. They also match each plant exactly on sector at the NACE two-digit level. This means that each EU ETS plant is compared with a non-EU ETS plant operating in the same two-digit sector and having the same carbon intensity before the announcement of the EU ETS. A potential problem is the absence of size variables in the matching process, which might induce the authors to compare plants of different sizes and thus different on unobserved characteristics as well (see also Horbach, 2010).

Their results imply that ETS-regulated manufacturing plants in France reduced emissions by an average of 15%. The analysis shows no effect of the EU ETS during Phase I (2005-2007) and a 15% reduction in emissions during Phase II compared to unregulated plants. Having facility level data, Wagner et al. (2014) can explore if there is any evidence of within firm leakage for firms with both unregulated and regulated facilities. It might be easier for such firms to shift emissions to unregulated plants as they are experiencing lower transaction costs compared to firms which have no existing links with unregulated facilities (Horbach, 2010). However, they do not find any evidence for such within-firm carbon emissions reallocation effects. Instead, the reduction in emissions appears to be driven mostly by reductions in the carbon-intensity of production. In particular, about half of the reduction in emissions is due to an increase in the share of gas, which is less carbon intensive than coal and oil. In terms of economic outcomes, Wagner et al. (2014) do not find any statistically significant results on employment. This suggests that the EU ETS reduced emissions of regulated plants without a significant effect on domestic jobs in France (see also Horbach, 2010; Calel et al., 2017).

Germany

Petrick and Wagner (2009) analyse the causal impact of the EU ETS on German manufacturing firms using comprehensive panel data from the German production census. Contrary to Wagner et al. (2014) who use data on French plants, their analysis is conducted at the firm level. They are able to match 1,658 EU ETS facilities to the German AFiD company database, a database comprising official firm-level data from the German Federal Statistical Office. They use propensity score matching to select a group of comparable but unregulated firms, and base this on a comparably much richer set of observable pre-treatment characteristics: CO_2 emissions, gross output, export share of output, number of employees, average wage, the squares of all these variables, and dummies for two-digit industry (WZ classification) and state (Bundesland) wherein the firm is located.

Petrick and Wagner (2009) show robust evidence that the second phase of the EU ETS caused treated firms to reduce their emissions by a substantial margin of around 25 to 28 percentage points compared to non-treated firms. In parallel, carbon intensity declined between 18 and 30 percentage points faster at EU ETS firms than at the control firms. This suggests that firms responded to the introduction of the EU ETS mainly by changing the carbon intensity of production, not the scale. Furthermore, firms were found to have reduced their carbon emissions by switching from high-carbon fuels (natural gas and oil) to low-carbon fuels (electricity) (see also Calel et al., 2017, for a discussion of the results).

Turning to economic outcomes, Petrick and Wagner (2009) find no statistically significant effects of the EU ETS on employment. In a word, putting a price on carbon does not seem to come at the expense of domestic job destruction. As for gross output, they estimate that the EU ETS increased gross output at regulated firms by a statistically significant amount of between 4 and 7 percent. While this allows the authors to reject the hypothesis that the EU ETS caused firms to reduce the scale of production, the positive effect on gross output is surprising and consistent with both firms producing more or charging higher prices. Unfortunately, they cannot distinguish between these two responses because they lack a measure of physical output. Similarly, they reject the hypothesis that the EU ETS caused regulated firms to reduce their overall exports, but they even find that the EU ETS increased total exports by 6% to 11% for phase I and by 7% to 18% for phase II. Again, it is not clear whether the increase in exports reflects an increase in the volume of shipments or a price increase, or a combination of both.

Norway

In a panel study of Norwegian plants, Klemetsen et al. (2016) analyse the effect of the EU ETS on emission levels and intensity (defined as emissions divided by man hours). Their results show marginally significant evidence that regulated plants reduced emissions by a substantial amount (-30%) in the EU ETS' second phase, and a lack of evidence that emission intensity decreased in any of the phases. This suggests that during the second phase of the ETS, participating firms reduced emissions by reducing output rather than emissions intensity.

The authors use plant level data from the Norwegian Environment Agency for the period 2001 to 2013 on annual emissions of all Norwegian plants regulated by the Norwegian ETS or the Norwegian Pollution Control Act, including emissions of CO_2, N_2O and PFCs (measured in CO_2 equivalents). It allows them to identify which plants were regulated by the EU ETS. Their sample includes 665 plants of which 150 plants are regulated by the EU ETS. They consider two measures of economic performance: First, value added at factor prices, which is the plant's annual gross production value minus the cost of intermediates plus subsidies and minus taxes (except VAT). Second, labour productivity, which is measured as value added at factor prices per man hour. For the second phase of the EU ETS, the authors find positive and significant effects for both value added and productivity of around 25%. These surprising effects could arise due to the free allocation of permits or cost pass-through and their effect on value added (Calel et al., 2017).

Propensity score matching techniques are used to construct a control group of similar but unregulated plants. Exact matching is done on type of pollutant (CO_2, N_2O or PFCs) and on industry classification at two-digit level. Continuous matching variables include emissions levels of emissions (as a proxy for capacity limit) and number of employees (as a measure of plant size) in the pre-treatment year 2001. Not all EU ETS regulated plants can be matched, hence the final matched sample includes 152 plants of which 72 plants are regulated by the EU ETS. However, it is notable that the control group still appears quite different from the treatment group even after matching with, for example, an average CO_2 intensity of 62.1% in the treatment group and only 6.8% in the control group. Therefore, it is questionable how comparable the treated and control groups are in this study.

Lithuania

Finally, Jaraite and Di Maria (2016) analyse the effect of the EU ETS on carbon emissions and firm profitability in Lithuania for the years 2005-2010 using plant-level data. They compare 41 EU ETS firms with 312 non-EU ETS firms matched through propensity score-matching. They find no reductions in emissions and a slight improvement in emissions intensity in 2006-2007, but their data does not allow them to study effects on emissions beyond 2007. With respect to economic performance, Jaraite and Di Maria (2016) find no significant impacts of the EU ETS on Lithuanian firms' profitability (see also Calel et al., 2017, for a discussion of the results).

Pan-European studies

At present, only two papers have analysed the joint effect of the EU ETS on CO_2 emissions and economic performance based on data from more than one country of the European Union. Abrell et al. (2011) use data on 2,101 firms across Europe representing around 60% of EU ETS regulated emissions to assess reductions in CO_2 emissions induced by the transition from Phase I to Phase II of the programme, which occurred in 2008. They find that emission reductions were 3.6% higher between 2007 and 2008 than between 2005 and 2006, a difference which they attribute to the increased stringency of the regulation. This finding is robust to controlling for turnover, employment, profits, and industry and country trends, suggesting that the reduction in emissions is due to the change in stringency from Phase I to Phase II (i.e. the lower allocation of permits) and not to a decline in production. Abrell et al. (2011) then apply a nearest-neighbour matching procedure to their sample of EU ETS firms and show that the policy caused a small but statistically significant decrease in employment of approximately 0.9 percent between 2004 and 2008. One limitation of the matching procedure is that, as Martin et al. (2014) explain, taking control firms only from non-regulated sectors is problematic. The regulated sectors within the EU ETS were possibly not selected at random. Hence the study may suffer from selection bias at the sector level (Martin et al., 2016; Calel et al., 2017).

More recently, Dechezleprêtre et al. (2018) combine two sources of data. First, they take carbon emissions data at the installation level from the national Pollutant Release and Transfer Registers (PRTR) from France, Netherlands, Norway and the United Kingdom, complemented with data from the European PRTR. Second, financial data and other firm-level performance data such as employment, fixed assets, profits, and revenues come from the global financial database Orbis, which includes all 31 countries covered by the EU ETS. Using the European Union Transactions Log (EUTL), they can identify installations and firms covered and not covered by the EU ETS.

They employ a matching procedure in which each treated installation and firm is matched to the closest installation and firm operating in the same economic sector and country and similar in all other observable characteristics before the introduction of the EU ETS. This control group combined with a difference-in-differences estimation allows to estimate the policy's causal impact on installations' emissions and on firms' revenue, assets, profits and employment. Dechezleprêtre et al. (2018) find that the EU ETS has led to carbon emission reductions of around -10% between 2005 and 2012 while not having any adverse impact on firms' economic performance. The EU ETS has not had any negative effect on regulated firms' revenue, profits, fixed assets or jobs. In fact, the EU ETS rather seems to have led to an increase of revenues and fixed assets of regulated firms - contrary to what could have been expected. Dechezleprêtre et al. (2018) argue that one explanation for these results is that the EU ETS induced regulated firms to increase investment - likely in carbon-saving technologies - which, in turn, may have increased productivity.

1.3.3.2 The joint impact of the UK Climate Change Levy on carbon emissions and firm performance

The UK Climate Change Levy (CCL) is a carbon tax associated with a scheme of voluntary agreements (called Climate Change Agreements) available to plants in selected energy intensive industries. Upon joining a CCA, a plant adopts a specific target for energy consumption or carbon emissions in exchange for an 80% discount on the tax liability under the CCL. Martin et al. (2014a) analyse the impact of the CCL on energy use, emissions and economic performance of regulated plants for the period 2001-2004 based on micro-level data.

The identification strategy of the paper is to compare changes in outcomes between fully-taxed CCL plants and CCA plants which pay the reduced tax rate. Since plants self-select themselves into a CCA, it is not possible to implement a straightforward DiD strategy. However, a key feature of eligibility for CCAs is that plants needed to emit pollutants subject to environmental regulation under the Pollution Prevention and Control (PPC) act which pre-dated the CCL. This variation in eligibility across plants can hence be used as an instrument for CCA participation. Indeed, since eligibility is based on pollution intensity, many energy intensive industries are ineligible for the tax discount. Martin et al. (2014) state that textile wet processing was an eligible activity thanks to its high pollution emissions. Yet dry processing, which is also energy intensive, emits no pollution regulated under PPC. Similarly, both the production and the recycling of glass containers are energy-intensive. However, only the former is pollution-intensive, which is the reason why the latter (glass container recycling) was not eligible for CCA participation. This characteristic of the policy design induces exogenous variation in the probability of treatment even within narrowly defined, energy-intensive industrial sectors (Martin et al., 2014).

The core dataset is the Annual Respondents Database (ARD), an annual production survey that covers about 10,000 plants in the manufacturing sector. Energy use comes from the Quarterly Fuels Inquiry (QFI), a survey among a panel of about 1,000 manufacturing plants which can be matched to the ARD. Information on CCA participation comes from both the Department for Environment, Food and Rural Affairs (DEFRA) and HM Revenue and Customs (HMRC) websites. Finally, data for the instrumental variable comes from the European Pollution Emissions Register (EPER). The final dataset includes 6,886 plants, among which 1,079 have detailed information on fuel consumption by type.

Instrumental variable estimations show that the CCL had a strong negative impact on energy intensity (-18%), particularly for larger and more energy intensive plants. The results are mainly driven by a reduction in electricity use, which results in a decline in CO_2 emissions. The results suggest that firms substituted labour for energy and increased output prices in response to the energy price increase. In contrast, the authors do not find any statistically significant impacts of the tax on employment, revenue or total factor productivity. Similarly, no evidence is found that the CCL accelerated plant exit.

1.3.3.3 The joint impact of energy prices on economic and environmental performance

To examine more generally the effect of energy prices on firms' environmental and economic performance, Marin and Vona (2017) use three rich datasets provided by the French Statistical Office covering the period 1997 to 2010: the EACAI survey for establishment-level energy purchases and consumption, DADS (Déclaration Annuelle des Données Sociales) for data on employment and wages, and FARES-FICUS for information on firms' balance sheets. By combining these datasets they can use differences across establishments in energy intensities, -prices, and -mixes. Hereby, energy intensities provide a proxy for establishments' exposure to energy price changes, and the energy mix (i.e. the use of electricity versus natural gas and other fuels) indicates establishments' technology and the relative exposure to price changes for the respective energy source. Energy use and CO_2 emissions capture firms' environmental impact, and employment, wages and productivity are used as economic outcomes.

To estimate the effect of electricity prices on firms' environmental and economic outcome variables Marin and Vona (2017) use both a simple fixed effects model, as well as an Instrumental Variable (IV) specification. The latter is important to address concerns of endogeneity due to non-observed variables, which could bias the results of the simple fixed effects model. Such variables could be firm-specific demand shocks or technological change as a response to changes in energy prices. These variables are likely to be correlated with both the outcome variables and energy prices, resulting in a biased estimation of the model. To overcome this concern the authors require an instrumental variable that is correlated with the exogenous variation in energy prices but not related to establishment-specific technological responses to changes in energy prices. They use a combination of the nationwide price of energy with a fixed firm-specific energy mix, which does not change over time (shift-share instrument). Changes in nationwide prices are uncorrelated with firm-specific demand shocks dealing with the first concern. Since most endogenous technological change operates through changes in the mix of energy sources, holding fixed the energy mix addresses the second source of potential bias.

In their preferred specification with the Instrumental Variable, Marin and Vona (2017) identify a trade-off between environmental and economic goals: A 10% increase in establishment-level energy prices, leads to a reduction in energy consumption and CO_2 emissions by 6.4% and 11.5% respectively. Yet, the same increase in energy prices also leads to a modest negative effect on employment (-2.6%), wages (-0.4%) and firm's productivity (-1.1%). The negative employment impacts differ across sectors with energy-intensive and trade-exposed sectors experiencing the largest decline. However, preliminary evidence shows a substantial reallocation of production inputs between establishments of the same firm as a response to energy price changes. This gives reasons to believe that the estimated employment impacts are upper bounds. Some of the employees that are observed as losing their job at one establishment are simply relocated to another establishment within the same firm (Marin and Vona, 2017).

1.3.3.4 The joint impact of environmental regulation on environmental and economic performance through innovation

The Porter Hypothesis suggests a causal link from environmental regulation to firm's innovation, and profitability. Many studies have studied this chain of causality. They observe that although there is a positive impact of innovation on economic performance, it is typically not sufficient to compensate entirely for the negative effect of the regulation (Lanoie et al., 2011; Dechezleprêtre and Sato, 2017). Hence, environmental regulation can come at a cost. Yet, for the total cost calculations it is crucial to also include the possibility of cost-reductions through innovation. Hence, the total costs are less than the direct costs of an environmental regulation. Innovation that is induced by regulation can improve firms' resource efficiency with respect to energy or material usage, which in turn increases profitability (Rexhäuser and Rammer, 2014; Dechezleprêtre and Sato, 2017).

This does not preclude the possibilities that environmental regulations induce new green technology leaders higher up the supply chain, but to our knowledge no study has looked at effects of such regulation on the entire supply chain. Yet, some evidence suggests that environmental regulation can trigger innovation from technology suppliers (Bellas and Lange, 2010; Bellas et al., 2013). Further research could jointly look at the environmental and economic performance taking into account the whole supply chain.

Porter and van der Linde (1995) also argue that in the long run environmental regulation can result in a competitive advantage for domestic firms, if foreign firms will be exposed to the same or a similar regulation in the future. Hence, firms that innovated to adjust to a regulation will be able to benefit as soon as more firms become subject to similar types of regulations due to their first-mover advantage. So, while regulations may imply costs in the short run, they can benefit regulated firms over longer time horizons. However, to the best of our knowledge, this link between first-mover advantages and a potential increase in competitiveness has not been studied empirically (Dechezleprêtre and Sato, 2017).

1.3.3.5 Summing up

Because economists traditionally think of environmental regulations as forcing firms away from the optimum by requiring them to implement costly abatement activities that divert resources away from productive investments, it is all the more interesting that this literature - scarce as it is - finds that environmental regulations tend to improve environmental performance while hardly weakening economic performance. The evidence on the EU ETS suggests that in particular Phase II of the policy causally induced reductions in GHG emissions in regulated plants in the range of 15-30% relative to non-regulated plants. At the same time the regulation has not resulted in loss of employment and might have even increased gross output of regulated plants. These findings might be specific to the EU ETS design and due to the overallocation of emission permits, which have resulted in windfall profits for regulated plants. Whether these results hold in a stricter policy environment without a surplus in permits will need to be tested. At the same time, these findings also show that relatively weak environmental regulation can lead to substantial reductions in emissions without hurting competitiveness. Similarly, the existing studies on energy-price regulations in the UK and France suggest that such pricing policies are effective at reducing firms' energy-intensity and GHG emissions with at worst small negative impacts on employment and competitiveness.

So far, no study confirms the so-called strong version of the Porter hypothesis, which proposes that environmental regulations can improve at the same time environmental and economic performance. Yet, it is important to note that Porter and van der Linde (1995) were referring to particular types of 'well-designed' environmental regulation. These regulations would need to be sufficiently flexible and incorporate a market-based mechanism with clear and reliable price signals that provide incentives for innovation. Moreover, they would need to cover a comprehensive set of pollutants and economic sectors moving away from "piecemeal solutions" (p.111). Given the existing deficiencies in environmental regulations (e.g. exemptions for particular industries, over-allocation and a low permit price in the EU ETS) it might not be surprising that we do not yet observe effects confirming the strong version of the Porter Hypothesis.

1.4 Conclusion

There is still a widespread belief among economists of a trade-off between economic performance and environmental outcomes of firms, claiming that good environmental performance would jeopardise business activities by adding costs and diverting resources from more productive use, thereby slowing down productivity and reducing international competitiveness. This article has reviewed two strands of the available empirical literature, combining economic and environmental performance data at the micro-level: First, is the issue of whether economic and environmental performance can go hand in hand, and where the main finding is that the majority of studies report a positive relation between environmental performance and economic outcomes. This finding is probably not very surprising because good environmental performance could be driven by profit-enhancing motivations of firms.

Addressing the potential reverse causality in these findings is an important, albeit challenging avenue for future research. Moreover, expanding the scope to industries beyond manufacturing and energy generation would be valuable to assess the generalisability of current findings. Improved environmental performance indicators at the firm-level would also offer promising avenues for future research. These could for example focus on the 'greenness' of firms' supply chains, production processes, their product mix or investment decisions. Most studies reviewed here focused on GHG emissions and toxic release emissions. Further work is required on different environmental performance variables such as firms' impact on biodiversity.

The second issue reviewed is about the impact of environmental regulations on firms' environmental and economic outcomes. The conclusion of Jaffe et al. (1995), who find little evidence of adverse economic impacts of environmental regulation, has become even more robust in the last ten years through numerous studies using different datasets from different countries and sectors while applying more advanced econometric techniques. This is an important finding for policy-makers, which needs to be communicated more effectively. It remains crucial that environmental policies allow sufficient flexibility for firms to adjust. Environmental taxes or market based mechanisms fulfil these requirements and have the potential for Porter-type effects. Redistributive mechanisms and revenue-neutrality of pricing policies can play an important role in increasing the political acceptance and in cushioning socio-economic impacts for particularly affected groups. The political acceptance and the political economy of environmental policies play an increasingly important role and should be considered when designing and implementing new policies.

The vast majority of studies on the impact of environmental regulation focus on economic impacts, while abstracting from the effectiveness in environmental terms. In fact, environmental effectiveness is often assumed, but not investigated in more detail. Given the evidence from studies finding only small, if any, adverse impact of environmental policies on economic outcomes, the question of whether environmental policies are improving environmental performance is even more pressing. In the last ten years, this strand of literature has seen much progress, particularly as more and more environmental data has become available. The recent evidence suggests that both command and control policies and economic instruments lead to a statistically significant improvement of the environmental performance. While economic theory suggests that pricing an environmental bad reduces emissions in a cost-effective way, the empirical literature on the cost-effectiveness of different environmental policy instruments still lacks evidence and is one avenue for future research.

Another avenue for future research is to continue the evaluation of the economic and environmental performance of environmental policies by making use of new (micro) datasets in different contexts and countries to update and reassess the existing evidence. Most of the evidence originates from studies that analyse the impact of environmental policies on economic and environmental outcome separately. Ideally, we would like to know the impact of the same environmental instrument in the same regulatory context on both firms' environmental performance and their business activities. Only the joint analysis of both outcomes is appropriate for this kind of evidence and, thus, should be followed further.

The joint analysis of economic and environmental performance is still in its infancy and has obvious limitations. Most studies have used a single policy experiment, the EU ETS, and focus on a single country. They rely on relatively small samples, and tend to cover a very narrow subset - of albeit important - environmental policy instruments. This has some key implications, limiting the ability to distinguish e.g. short versus longer term effects or finding counterfactual references. Only two multi-country studies are currently available, while cross-country studies would enable researchers to determine which combination of public policies (instruments for environmental policy, innovation policy, fiscal policy, etc.) works best at inducing the greatest benefits in terms of improved environmental performance, while implying the smallest costs or, potentially, the greatest improvements in terms of economic performance.

Still, while the generalisation is difficult, the relative freshness of this literature means that it tends to at least attempt to look for causal effects, which is hardly the case in the earlier studies of effects of environmental policies. Because the implementation of environmental regulations can sometimes be claimed to be exogenous (this is in particular the case for the EU ETS, which uses arbitrary administrative thresholds to determine inclusion), this allows for more confidence in the identification of causal links.

Establishing causal relationships between environmental regulations and firms' outcomes will remain the gold standard in the empirical literature. However, the comprehensive coverage of most environmental policies exacerbates the compliance with this standard. This calls for policy designs that allow for a more robust evaluation of the effectiveness of regulations, including the phase-in of new regulations in different regions at different points in time or the use of randomised controlled trials. In fact, randomised controlled trials are already successfully used in other policy areas such as labour market policies and welfare programmes. Making use of these policy designs in combination with new data sources such as pollution data of point sources gathered from satellites would significantly improve the available evidence on the impact of environmental policies on both environmental and economic outcomes.

Chapter 2

Green Revenues, Profitability and Market Valuation: Evidence from a Global Firm Level Dataset.

Abstract

Substantial private investments in low carbon technologies and capital assets are necessary to meet climate change mitigation targets. This paper examines how diversifying production towards low carbon goods and services impacts the profitability and market valuation of firms. Using new and unique data on firms' revenues that are generated from the production of green goods and services, we are able to measure shifts in firms' commercial focus towards green activities over time. Our dataset is comprehensive, covering approximately 98% of global market capitalisation for the period 2009-2016. We show that operating profit margins tend to increase with higher shares of revenues generated from green goods and services. However, higher operating profit margins do not necessarily increase profits per unit of investment, because the production of green goods and services tends to entail higher asset requirements. In terms of market valuation, higher green revenue shares are neither rewarded nor punished by investors on the stock market, except in utilities, hence investors generally do not value green firms more compared to non-green counterparts. Our findings suggest that governments can support driving forward a market-led low-carbon transition across the broad economy by, for example, facilitating cheaper environmental capital expenditures and helping the creation and expansion of markets for green goods and services.

2.1 Introduction

Responding to environmental problems and policies as well as changing demand towards low-pollution or energy efficient products, a growing number of firms are changing commercial focus towards the production of environmental goods and services. According to FTSE Russell (2018) the "green economy", at 6% of the globally listed equity market, was worth as much as the fossil fuel sector in 2018. This paper explores how a shift from non-green to green activity affects the financial and market performance of these frontier firms in the green economy.

The question of whether environmental performance and economic performance can go hand in hand has been around, ever since the major environmental policies were enacted in the 1970s. The conventional view is that, because firms are perfectly rational and have already exhausted all profitable opportunities, any additional effort to provide public goods by reducing pollution necessarily has to come at a cost (Palmer et al., 1995). These arguments are used to oppose stringent unilateral environmental policies on the grounds that there is a trade off-between environmental performance (social benefits) and the economic performance of regulated firms (private costs). This rather static view was challenged by Porter (1991b) and Porter and van der Linde (1995) who argued that firms in fact do not always make optimal choices and that continual opportunities for resource efficiency and technological improvements exist, because of incomplete information, organisational inertia and other problems that plague the real world. Under this view – what has become known as the Porter Hypothesis – the trade off can be relaxed with well designed and stringent environmental policy, for example, by reducing uncertainty around investments and stimulating innovation that improves resource productivity and economic performance. Porter and van der Linde (1995) also argue that as consumers become more sophisticated and green market segments open up globally, the early-mover "clean" companies can gain a lasting competitive edge.

A vast empirical literature has put these conflicting predictions to the test. There is general agreement that the introduction of environmental policies has led to higher pollution abatement costs (as share of business capital expenditures) (Pasurka, 2008), but firms typically do not face the full burden of regulatory costs due to exemptions and compensation measures (Ekins and Speck, 1999; Stavins, 2003). Moreover, environmental regulation can signal companies about inefficiencies and induce technical change (as measured by R&D or patents) (Calel and Dechezleprêtre, 2016; Fabrizi et al., 2018), especially with market-based instruments (Ambec et al., 2013). Having established that firms can innovate in response to environmental policies, the secondary question is, how this affects firms' bottom line. The Porter Hypothesis focuses on whether the regulatory cost can be partly, fully or more than fully recovered by the "innovation offsets". A number of studies explicitly test this question, but the evidence remains inconclusive according to recent reviews (e.g. Ambec et al., 2013; Cohen and Tubb, 2017).[1]

The majority of empirical studies contributing to the evidence base for the Porter Hypothesis instead tackle smaller pieces of the puzzle. Ambec and Lanoie (2008) distinguish two channels through which environmental innovation can impact firms' environmental and economic performance: the "cost channel" whereby firms reduce input costs through improving efficiency and mitigating risk, and the "revenue channel" whereby firms increase revenues by developing new, cleaner products in response to changing customer preferences and capturing market share (Ambec and Lanoie, 2008). So far, most studies test the former channel and find on the whole that policy induced innovation can lead to reduced costs through improving energy efficiency (Bloom et al., 2010; Kumar and Managi, 2010; Gosnell et al., 2017) or productivity (Van-Leeuwen and Mohnen, 2017). Meta-analyses on the relationship between firms' environmental and financial performance find that overall, the relationship is positive (Endrikat et al., 2014; Horváthová, 2010; Albertini, 2013)[2] but that this effect is heterogeneous, for example according to their initial level of financial performance (Wagner and Blom, 2011). Studies on stock market impacts usually find that *dirty* firms tend to be punished by investors and suffer negative abnormal returns for example following disclosure of emissions data (Baboukardos, 2017; Lourenço et al., 2012b), whereas the effect of being *clean* or being perceived to be committed to sustainability (for example with adoption of environmental management systems, Corporate Social Responsibility (CSR) announcements or being included in a sustainability stock index) could be positive (Flammer, 2015; Song et al., 2017) or negative (Oberndorfer et al., 2013).

Fewer studies examine the "revenue channel". In theory, shifting commercial focus towards environmental goods and services could lead to higher profitability for firms because a) they result from a long-term investment plan in research and development which allows for more product differentiation and can lead to higher price premiums and lower competition (Berrone et al., 2013), b) green product differentiation is more visible than internally-driven green activities and thus hold higher commercial value

[1] Ambec et al. (2013) finds that the positive effect on innovation are realised with some time lag, and that generally, it does not outweigh the negative costs of environmental regulation, thus supporting the *weak* version of the Porter hypothesis. On the other hand, a meta analysis by Cohen and Tubb (2017) finds that a positive effect of environmental policies is more likely at the country level rather than the firm level, supporting the "strong" version of the Porter hypothesis i.e. that environmental policies induce innovation and increase competitiveness over time.

[2] Horváthová (2010) finds that negative relationships between environmental and financial performance tends to be found in studies using less sophisticated methods, whereas a positive effect tends to be found when more advanced methods (panel data estimation with reduced omitted variable problems) and better data with longer time frames are used.

(Dangelico and Pontrandolfo, 2010) or c) company reputation improves through marketing (González-Benito and González-Benito, 2005; Driessen et al., 2013). Examining whether diversifying into the environmentally friendly market space is privately rewarded is important, as it can inform policy designs to harness market forces to stimulate innovation and foster a profit-driven response to environmental problems. This can keep the costs of the low carbon transition down and is politically appealing especially in the context of market economies.

This study builds on the handful of studies that empirically test the "revenue channel" - whether orienting production towards low carbon goods and services contributes to market value creation, or if not doing so is penalised. In terms of financial performance, González-Benito and González-Benito (2005) finds that ecological product design has no impact on return on assets using a cross sectional regression on a sample of 186 Spanish companies, Jabbour et al. (2015) finds that green product development has a positive influence on firm performance on a variety of measures (marketing, operational and environmental) for a sample of 62 Brazilian companies, while Palmer and Truong (2017) find higher net income in firms that introduce green new products using a sample of 79 global firms using OLS regression. In terms of stock market performance, few studies explicitly examine the effect of market-oriented environmental activities. Dechezleprêtre et al. (2017) uses the share of clean patenting to capture firms' strategic focus on low carbon innovation and analyses knowledge spillovers from clean and dirty technologies using patent citations. They show that clean-patented inventions have higher spillovers, and also observe a positive relationships between more spillovers from clean patents and Tobin's Q, suggesting investors attribute a higher value to green technologies compared to non-green counterparts.

While the evidence is not conclusive, they largely point to the difficulty in rejecting the Porter Hypothesis. The possibility prevails, that a well-designed, stringent environmental policies could simultaneously reduce environmental impact and enhance economic performance of firms, such that the provision of public goods from the private sector results in a "win-win". However, the question still remains, how can private sector investments in low carbon technologies be accelerated on a greater scale? Indeed to address the looming climate emergency (IPCC, 2018), it is estimated that each year trillions of US dollars of investment are required to drive the low carbon transition (Stern, 2015b; OECD, 2017)[3]. Given the scale of the challenge, both public and private sector investments are needed. Yet private sector investments will be key to drive forward low carbon innovation and keep the costs down, as was seen in the earlier IT revolution (Mazzucato et al., 2015; CPI, 2018). Thus it is important to understand how

[3] The OECD (2017) estimates for instance that approximately 7 trillion US dollars are required annually until 2030 in infrastructure investments to comply with the Paris Agreement, half of which in the energy sectors.

policy design can be improved to enhance the economic viability of "going green" such that large scale private sector low carbon investments can be mobilised.

This paper contributes to the evidence on the "revenue channel" by exploiting the variation across firms in the degree to which they have already shifted company attention to "green" activities in recent years. The fact that growth in low carbon innovation and new green markets is observed (Popp, 2019) indicates that environmental policies are working to some extent and in some sectors, to correct market failure and harness the ability of markets to deliver public goods. We examine if these strategic moves into new markets for low carbon goods and services[4] by frontier firms pays off, and if they are rewarded or punished by investors. We aim to shed light on how policy can be fine-tuned to unblock barriers to mainstreaming shifts into the low carbon economy.

We use newly constructed firm level data that records green revenue shares, key firm characteristics and firm financial performance variables. Our dataset includes information on over 16,000 global publicly listed firms across 48 countries operating from 2009 to 2016 in a wide range of industries.[5] We identify over 3,500 firms which derive revenues from production and sale of green goods and services. Using this data, we are able to test if changes to the share of green revenues affect the financial and market performance of firms, overcoming a number of key limitations in the previous literature. First, our green revenue share variable is able to capture within-firm strategic shifts away from the non-green and into the green economy. Indicators of the degree of firms' environmental efforts are hard to come by, particularly for a large sample of firms spread across geographically. We use a unique firm level dataset from FTSE Russell which, to our knowledge, is the first database that provides comprehensive and detailed information into the environment-focused commercial activities of publicly listed firms, tracking the share of revenues generated through green goods and services over time.

Second, we overcome the external validity issue present in previous studies that were typically limited in geographic or sectoral scope - the dataset we construct covers global publicly listed firms representing approximately 98% of global market capitalisation over an eight year panel across 48 countries. Third, we examine the impact of firms' green revenue shares on a range of financial performance variables including both accounting based and market based measures, capturing both current and expected profitability. For accounting based measures, we examine both operating profit margin

[4]These are either produced with technologies that economise on exhaustible resources and emit less greenhouse gases, for example electricity produced by renewables, or emit less carbon during its use phase whilst providing similar functions as conventional goods and services, for example hybrid and electric cars.

[5]The raw data is provided for the years 2008-2017. We limit the analysis to the years 2009-2016 due to data quality concerns in the first and last year.

(how successful the management is in creating profits from its sales) but also more comprehensive measures of profitability that capture return on investments, such as return on assets and return on equity. An important contribution of this paper is to show the linkages between the variables. Fourth, an important limitation of existing studies is that potential selection bias is largely ignored, even though the group of "treated" frontier firms that move into the green space early are likely to differ from the non-green group. We show that indeed green firms tend to be on average larger and more profitable and employ inverse propensity score weighting (Guadalupe et al., 2012) to address this selection bias. Lastly, we disaggregate our results by sectors, providing new insights into sectoral heterogeneities. Our estimates provide the first comprehensive empirical assessment of the impact of diversifying towards green goods and services on financial and market performance.

Our results provide a number of new insights with clear policy implications. We find that across all industries, increasing the share of revenue generated from the sale of green goods and services is associated with higher operative profit margins. This suggests higher price premiums can be yielded from proactive moves into the environmentally friendly market space. Hence an important role that public policy can play to accelerate and harness, private sector low carbon investments is to ensure the level of firms' "green effort" is known to consumers and investors, for example through the provision of information or clear labelling. Why then is a rapid and broader shift into the production and sale of low carbon goods and services not observed? Interestingly, we find that higher operating margins do not translate to higher return on investments, except in the utilities sectors. We show that this is in part due to the higher asset requirements of engaging in the production of green goods and services as shown by Hirth and Steckel (2016). High asset requirements pose a barrier for firms to shift into the green space. Hence policy should tackle this barrier to make green shifts more economically viable across a broader range of sectors, and mobilise large scale private sector investments, for example by facilitating cheaper access to green capital through reduced interest rates or risk sharing through public-private partnerships.

In addition to accounting based measures of current profitability, we also assess expected profitability using market-based measures to assess how a change in commercial focus towards green affects how investors in stock markets value firms. We find that an increase in firms' green revenue share affects investors expectations positively, again largely only for utilities. These findings deliver a cautionary note because meeting the climate goals requires switches to low carbon alternatives across a broad set of sectors. While utilities, and electricity generation in particular, are key for the low-carbon transition, policies need to increasingly target non-utility sectors to achieve a broad diffusion of green technologies.

In line with the Porter Hypothesis, our results suggest that the environment - competitiveness trade-off could be relaxed with well designed and targeted environmental policies. Important sectoral heterogeneities exists in the relationships between producing green revenues and firms' economic performance. The automobile sector plays a distinct role, as the manufacturing of hybrid- and electric vehicles is associated with lower earnings-margins. The finding is supported by industry reports, which state that higher component costs, especially for battery technology, reduce operating margins for hybrid- and electric vehicles compared to vehicles using combustion engines. Additional R&D subsidies, such as tax credits, may be necessary to accelerate the cost decline for these technologies. The observed heterogeneities across sectors and economic performance indicators can help in explaining the often inconclusive findings in the existing literature and can guide policy design.

This paper proceeds as follows. In Section 2.2, we provide further background by elaborating on the previous literature, focusing on a) the limitations in existing performance measures that capture firms' efforts to reduce their environmental impact and b) the choice of financial performance variables. In Section 2.3, we familiarise ourselves with the data including the new measure of firms' green revenue share and describe the changing size and composition of the green economy in recent years. We set out the different measures of current and expected profitability and provide descriptive statistics. We then turn to empirically assessing the impact of green revenue shares on current profitability in Section 2.4. In Section 2.5 we begin by reporting the average results for our full sample. We then discuss their robustness and disaggregate the effects by sectors in Sections 2.5.3 and 2.5.4. We examine in detail the heterogeneous effects for utilities and non-utilities, as well as the largest manufacturing sectors. We discuss the findings and conclude in Section 2.6.

2.2 Greening of firms, financial performance and market performance

2.2.1 Measures of firms' green activities

One of the key challenges when assessing the impact of engaging in the green economy on firms' performance has been the difficulty to precisely measure how much firms shift from non-green to green activities. This is rarely measured and good proxies are hard to obtain, not least because of the lack of precise and widely accepted framework for defining and measuring production of goods and services that have a positive environmental outcome (OECD and Eurostat, 1999), but also because all human activities have an impact on the environment hence efforts to reduce environmental impact relative to other activities is inherently difficult to measure (de Melo and Vijil, 2016).

Previous studies have used a number of indicators to capture internally-driven environmental efforts that are relevant to the "cost channel", but they are often crude, binary measures such as the adoption of voluntary environmental management systems as an indicator of firms' environmental performance (Wagner and Blom, 2011; Hojnik and Ruzzier, 2017; Jacobs et al., 2010; Yin and Schmeidler, 2009), whether or not a firm is included in a green stock index (Ziegler, 2012; Oberndorfer et al., 2013), or the announcements of philanthropic gifts for environmental causes (Jacobs et al., 2010).[6] One problem with these variables is that it is not clear that the control group firms are untreated (makes no environmental effort), hence there is likely to be considerable measurement error. Alternatively, studies have used pollution intensity data such as CO_2 emissions and toxic chemical substance emissions (e.g. Fuji et al., 2013)), toxic waste (Al-Tuwaijri et al., 2004), water waste (Rassier and Earnhart, 2015) and other waste (e.g. Trumpp and Guenther, 2017). A major constraint with using many of these measures is that the sample size is restricted because such information is usually obtainable only for a few companies in a few sectors[7] in a single country. Moreover, a meta analysis by Horváthová (2010) shows that the pollutant type for environmental performance indicator affects the environmental-financial performance relationship, hence a composite pollution indicators is preferred (Horváthová, 2012).

On measures of the level of attention a firm pays to the environment that are more relevant to the "revenue channel", one main data source is the number of patent applications. Specifically, studies have looked at the share of "green" or "clean" patents relative to total patents, to capture firms' strategic shift towards low carbon markets (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Veugelers, 2012; Dechezleprêtre et al., 2017). While patent counts and their citations offer a relatively homogeneous measure of technological novelty and are available for a long time series, they also have well known drawbacks as indicators of firm innovation activity. Not all innovations are patented, different technologies are differently patentable, and the propensity to patent innovations varies considerably across types of firms, sectors and countries (Malerba and Orsenigo, 1995). Granted patents capture only successful innovations, therefore representing only a fraction of innovation activity (Lychagin et al., 2016). Moreover, they mainly capture inventions and do not capture the diffusion or adoption of new technologies. Finally, given that some sectors rely more on patents than others, using patent data may lead to a biased view of the green economy. Alternatively, studies

[6]For detailed reviews see (Blanco et al., 2009; Albertini, 2013; Ghisetti and Rennings, 2014; Endrikat et al., 2014; Crifo and Forget, 2015; Friede et al., 2015; Dechezleprêtre et al., 2019).

[7]Usually energy sector, traditional environmental sectors such as water and waste, or energy intensive sectors

have utilised information on green innovation and green product introductions through questionnaires (Rennings and Zwick, 2002; Rennings et al., 2004; Bloom et al., 2010; Martin et al., 2012; Jabbour et al., 2015) or analysis of press releases (Palmer and Truong, 2017) to capture firms' commercial shifts towards environmental products. Robust statistical analysis is difficult when using these indicators not least because sample size tends to be small (external validity is also threatened because of limited sectoral and geographical coverage) but also because there is usually no time variation. It is more difficult to obtain data that captures within firm variation in environmental effort over time, but such variables enable panel data analysis which is strongly preferable for assessing how shifting towards green activities affects firm performance. Fixed effects can be used to control for unobserved heterogeneity at the firm, time, or sector level. This is important because, environmental effort may be driven for example by firm specific characteristics such as corporate culture or time specific shocks such as an introduction of regulation.

This study uses a unique measure, tracking the share of revenues derived from green goods and services over time at the firm level, using data from FTSE Russell. This database provides detailed information into the environment-focused commercial activities of publicly listed firms, thus capturing firms' decision to shift towards the low carbon economy over time. This dataset covers firms across a broad range of sectors, thus acknowledging the fact that environmental goods and services are provided not only by firms belonging to the narrowly defined environmental sector (See section 2.3 for detail). In the analysis, we are able to control for time invariant sector fixed effects and the results can be interpreted as a general effect across the economy. This is important because both the propensity of firms to generate revenues from environmental goods and services, and how that shift affects profitability is likely to vary considerably by sector, for example due to the role of technology or policies. This data is particularly suited for assessing the "revenue" channel through which changing commercial focus towards the production of environmental goods and services may impact financial and market performance. Its panel structure and wide coverage capturing within variation in green activities of a firm allows us to circumvent many limitations in previous analysis highlighted above. Lastly, it also allows us to explore sector-specific heterogeneities.

2.2.2 Unpacking firm level financial performance measures

Changes in the share of green revenues occur at the level of a firm, and we link this data to firm level financials to construct a panel of firm level green and financial data. Reflecting the fact that changing focus towards green activities may affect firms' current profitability or their expected profitability in the future, the literature has assessed the link between environmental and financial performance, using a wide range of measures. Current profitability is typically captured by accounting-based variables such as net income (e.g. Palmer and Truong, 2017), return on sales (ROS) (e.g. Wagner and Blom, 2011; Ghisetti and Rennings, 2014), return on assets (ROA) (e.g. Fuji et al., 2013; Trumpp and Guenther, 2017) and return on equity (ROE) (e.g. Przychodzen and Przychodzen, 2015). Expected profitability is instead captured by market-based variables including market value of equity (e.g. Moliterni, 2018), total shareholder return (e.g. Trumpp and Guenther, 2017), or Tobin's Q (e.g. Hibiki et al., 2003; Rassier and Earnhart, 2015).

Horváthová (2010) argues that the type of financial variable used is likely to influence the results when quantitatively assessing the link between firm environmental and financial performance, primarily focusing on the distinction between financial variables that contain market expectations vis-á-vis accounting-based measures. No study in this literature has yet explained further the differences in what the various profitability measures capture and in what way the results are expected to differ. We therefore start to unpack the key financial performance measures and show the linkages between them to aid our choice of dependent variables and estimation strategy, as well as the interpretation of our results.

Accounting based measures of current profitability

Current profitability measures are largely grouped into two: those capturing operating profit margins (how much profit is being produced per dollar of sales) and those capturing return on investments (how efficient a firm is at using its assets or equity to generate earnings). The former group typically use Returns-on-Sales (ROS) or earnings ratios (Ebit- and Ebitda-margin).[8] The latter group represents more comprehensive measures of profitability, that set earnings against investments. Common variables in this group are Return-on-Assets (ROA) and Return-on-Equity (ROE), which take into account firms' asset- or equity resource requirements respectively, and in essence measure how efficient a firm can generate profits given the capital investment entrusted to it. These indicators are related through the DuPont decomposition (Equation 2.1 to 2.3) (see e.g.

[8]These may also be referred to as the operating margin. Both terms are used interchangeably. Ebit-margin is measured as Earnings before Interest and Taxes (EBIT) divided by Revenues. Ebitda-margin is measured as Earnings before Interest, Taxes, Depreciation & Amortization (EBITDA) divided by Revenues. The ebit-margin and ROS are often used interchangeably, the main difference being that the nominator of the Ebit-margin (EBIT) includes non-operating income and non-operating expenses which are not in the nominator of ROS (Operating Income). Non-operating income (expense) includes for example interest or tax income (payments). Operating Income is: gross income - total operating expenses. Ebit is: pre-tax income + interest expense + tax expense. We use all three variables in our analysis.

Fairfield and Yohn, 2001; Soliman, 2008):

$$ROS = \frac{\text{Operating Income}}{\text{Sales}} \tag{2.1}$$

$$ROA = \frac{\text{Net Income}}{\text{Assets}} = ROS \cdot \frac{Sales}{Assets} \tag{2.2}$$

$$ROE = \underbrace{ROS \cdot \frac{Sales}{Assets}}_{ROA} \cdot \frac{Assets}{Equity} \tag{2.3}$$

If a higher share of revenues derived from green goods and services is associated with higher ROS, this indicates that going green increases operative efficiency. In other words, a higher share of "green" sales can be turned into profits. As shown in Equation 2.2, ROA is the ratio of net income to total assets, or ROS multiplied by the inverse asset requirement ($Sales/Assets$, also known as asset turnover). Certain sectors or activities may exhibit higher asset requirements, for example capital intensive industrial production, or innovative processes that require higher initial investments. ROE is similar to ROA, but also takes account of debt or equity requirements. The term $Assets/Equity$ is known as the equity multiplier and captures the amount of leverage used by a firm to operate i.e. the proportion of a firm's assets that has been financed by equity rather than debt. Even though it is the most comprehensive measure, assessing firms' profitability using ROE alone can be potentially misleading - it is possible that a firm's ROE increases due to higher equity multipliers implying that a firm is increasing its debt level (potentially increasing its default risk), rather than achieving higher operative efficiency or asset turnover.[9] The decomposition into its components is therefore important and provides additional insight into the drivers of firm profitability.

Market based measures of expected profitability

An arguably more interesting question to ask is whether increasing the share of revenues derived from green goods and services changes market expectations of a firm's expected profitability. A large, closely related literature explores, using various financial modelling methods, how investors' respond to companies' voluntary environmen-

[9] High dept ratios can be perceived as more risky since they require firms to have relatively stable cash flows to be able to pay off debt. A low ratio indicates that a business has been financed in a conservative manner, with a large proportion of investor funding and a small amount of debt.

tal efforts including improving Corporate Social Responsibility (CSR), announcements about sustainability commitments, inclusion in sustainability stock indexes or by Environmental Social and Governance (ESG) scores. These environmental efforts more closely relate to reducing in-house environmental impacts and are thus more relevant to the "cost channel". The evidence has been mixed but studies using more recent data tend to find that investors penalise firms that do not embrace sustainability and climate mitigation (Moliterni, 2018). In these studies, expected profitability is typically captured by market value of equity or market capitalisation (see e.g. Moliterni, 2018; Lourenço et al., 2012a), or Tobin's Q (see e.g. Hibiki et al., 2003; King and Lenox, 2001; Ziegler, 2012; Rassier and Earnhart, 2015), which are measured as:

$$\text{Market Capitalisation} = \text{Share Price (End of Year)} \cdot \text{Number of Shares Outstanding} \tag{2.4}$$

$$\text{Tobin's Q} = \frac{(\text{Market Capitalisation} + \text{Total Assets} - \text{Common Equity})}{\text{Total Assets}} \tag{2.5}$$

Market capitalisation (or market value of equity) is simply the aggregate market value of a firm at a point in time. In contrast, Tobin's Q is a more comprehensive measure that also takes firms' assets into account. The denominator here is the total value of a firm's assets. This is important as it scales the market capitalisation relative to the total assets that are available for distribution in case of firm liquidation. Building upon the Efficient Market Hypothesis,[10] Tobin's Q isolates the perceived value of the firm beyond its assets, and reflects investors' expectations about expected profitability (Fama, 1991; Ball, 1995; Bharadwaj et al., 1999). Tobin's Q is measured as the market capitalisation plus the book value of debt (which is computed as the difference between the book value of assets and the book value of equity), divided by total assets (see e.g. Claessens and Laeven, 2003; Klapper and Love, 2004)[11]. Another way of interpreting the measure is by separating firms' assets into tangible and intangible ones. For firms without any intangible asset value, Tobin's Q equals 1, as the market value equals the replacement value of the firms tangible assets (Konar and Cohen, 2001). It is important to note that any analysis using Tobin's Q requires firms' to have a share price and a related market capitalisation. Thus any analysis using this measure is limited to listed firms.

[10]This is a hypothesis in financial economics that states that financial markets fully and immediately reflect all available information.

[11]The book value of common equity measures common shareholders' investment in the company

2.3 Data and Descriptives

We combine two main datasets for the analysis: FTSE Russell Green Revenues and Thomson Reuters Worldscope. Merging the two results in a panel of approximately 16,500 firms for which we can determine the annual level of green activity in addition to information on their economic and financial performance. This database provides comprehensive and detailed information into the green activities and the financial and economic performance of global publicly listed firms.

2.3.1 Green Revenues

The FTSE Russell Green Revenues is a proprietary dataset from the financial services company, which records detailed information on listed firms' annual revenues attributable to "green" goods and services. It covers global publicly listed firms across 48 countries representing approximately 98% of global market capitalisation for the period 2008 and 2017. Due to missing data in the first and last year, we limit our sample period to 2009-2016. To estimate each firm's contribution to the green economy, FTSE Russell (2010) first define the green economy, using what is called a Green Revenues classification model. Ten broad green sectors and 60 green sub-sectors are identified (See Table B.1 in Appendix). It covers a wide range of activities related to the environment, both goods and services. This includes sectors traditionally know as green, such as low carbon energy generation, energy efficiency equipment, and waste- and natural resource management, but also sectors that are not traditionally classified as green, such as finance and investment, railways operation, smart cities design and engineering. Thus it recognises that the green economy spreads across many sectors in the economy, and it comprise of firms of different shades of green.

Having defined the green sectors, taking all globally listed companies as the sample, a team of analysts search through firms' annual reports for evidence of engagement in any of these green subsectors. Revenues that are attributed to that green subsector are reported where available. For each firm and year, the sum of sub-sector green revenues is divided by total revenues to express a firm-year level green revenue share with values between 0 and 100.

A unique feature of this dataset is the level of detail, with information on each firm's annual green revenue by sub-sectors. However, there are many cases where firms report being engaged in a green sub-sector but the exact revenue attributed to that activity is not disclosed. In these cases, the data provider reports a possible range of values – a minimum and maximum value – of the green revenues by sub-sector. The minimum is typically zero where the green subsector revenue is unreported, hence the overall minimum green revenue share is highly skewed towards zero in the dataset. This issue affects a large proportion of the dataset. Approximately 70% of the minimum green revenue share at the firm level is less than 1% (see Figure B.2 in the appendix).

We address this issue in the following way. In our most conservative estimates, we use the minimum green revenue value where clearly the estimated effect is underestimating the true effect (see section 2.5.3). For our base-line estimation, we instead utilise the information on the relative importance of a sector within a firm. To illustrate, imagine a large automobile company generates 95% of its revenues from passenger cars and 5% from financial and other services. Of their passenger cars, an undisclosed share of their revenues are derived from electric and hybrid cars. In this case the potential range of green revenues reported for the firm is 0-95%. In order to improve on this range, we impute the missing subsector green revenue share using yearly averages of firms in the automobile sector - say on average, green vehicles account for 5% of total automobile revenues in this sector. We then use this value, such that the green revenue share range for this firm is narrowed to 0-4.75%[12]. This is possible because a company's sector revenues are never missing in the data, and the relative importance of a sector within a company is always known (for further details see Appendix B.2). It is important to note that the imputation is conducted at the company sub-sector level, hence there is no threat of introducing additional endogeneity issues into our estimates.[13]

The green revenue measure allows us to provide the first comprehensive overview of the size and composition of the global green economy among publicly listed firms. We observe that global green revenues among listed firms account for approximately US$1.6 trillion in 2016 (up from about US$ 1 trillion in 2009) (Figure 2.1)[14]. According to (Forbes, 2018) the global revenue of the largest two thousand firms accounts for about US$39 trillion. A back-of-the-envelope estimation suggests that green revenues account for approximately 4% of total turnover globally among listed firms. Furthermore, we can assess the green revenue composition by industry. It is important to note that non-listed firms such as small-and medium enterprises (SMEs) that also contribute to the green economy are not in our sample, hence our analysis provides a lower-bound of the true size.

[12] Based on the calculation $0.95 \cdot 0.05 = 0.0475$

[13] When referring to "green revenues" we refer to the green revenue measure after applying the sub-sector imputation. We also refer to this measure as "estimated green revenue" or "augmented" green revenue variable. When referring to the "minimum green revenue" we refer to the 'raw' FTSE Russell lower-bound minimum green revenue.

[14] This is based on the green revenue measure after sub-sector level imputation

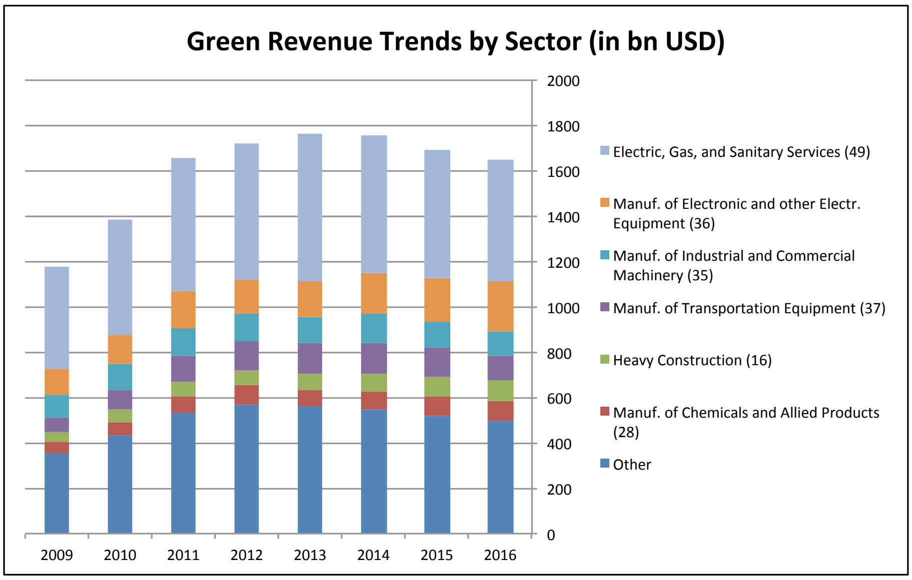


Figure 2.1: Green Revenue Trends by Sectors

Approximately 3,500 of the overall sample of 16,500 firms have some green revenue during the sample. Overall, the average minimum green revenue share increased from 1.8% in 2009 to 2.4% in 2016. For the subset of firms that have positive green revenues during the sample period, the average minimum green revenue increased from 11.5% in 2009 and 13.4% in 2016, representing an overall increase of approximately 16% over seven years.[15] Figure 2.2 shows the distribution of green revenue shares is highly skewed, even after the imputation at the sub-sector level[16]. In Figure 2.2 the first bar indicates that a little over 30% of firm-year observations in this sub-sample report low levels of green revenues between 0 and 2.3%[17].

Figure 2.3 shows the green revenue shares and absolute US dollar amounts aggregated at the 2-digit sector level. We see that the green economy spreads across many sectors but is focussed in energy and manufacturing. Across most sectors we observe that the revenue share ranges roughly between 2 and 15%. Green revenues and shares are highest in Electricity, Gas, & Sanitary Services, which generates approximately 25% of revenues from green goods and services on average. This sector consists largely of renewable electricity generation, as well as water- and waste-management. Significant green revenues are also generated by manufacturing sectors. The four largest manufacturing sectors in terms of green revenues (manufacturing of electronics, industrial commercial machinery, transport equipment and chemicals) together generate approximately USD 550 billion (Figure 2.3) (see Appendix B.3 for green revenue decomposition by 3-digit SIC codes).

[15]The imputed green revenue increased from 2.4% to 3.2% between 2009 and 2016. For the firms that have some green revenue during the sample it increased from 15.1% to 17.5%, equivalent to a 16% increase.

[16]See Figures B.2 and B.3 for a comparison of distributions before and after the imputation

[17]About 25% of the firm-year observation in this sub-sample do not report any green revenue.

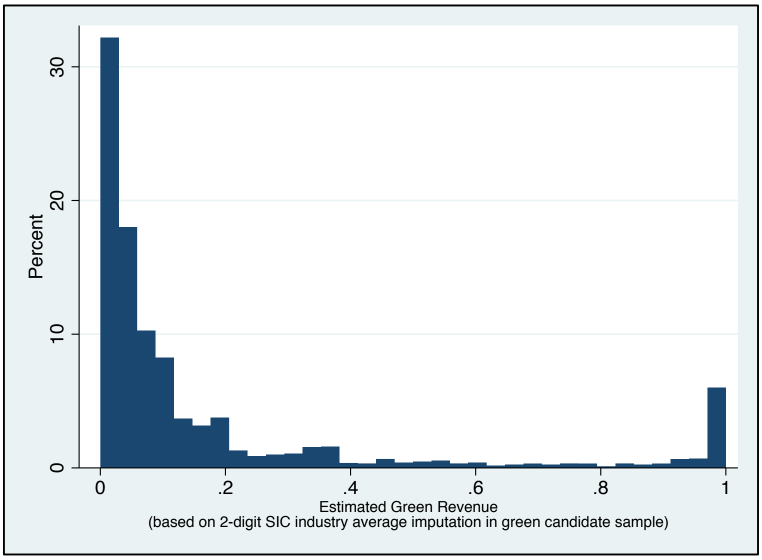


Figure 2.2: Distribution of Green Revenue based on augmented Green Revenue variable

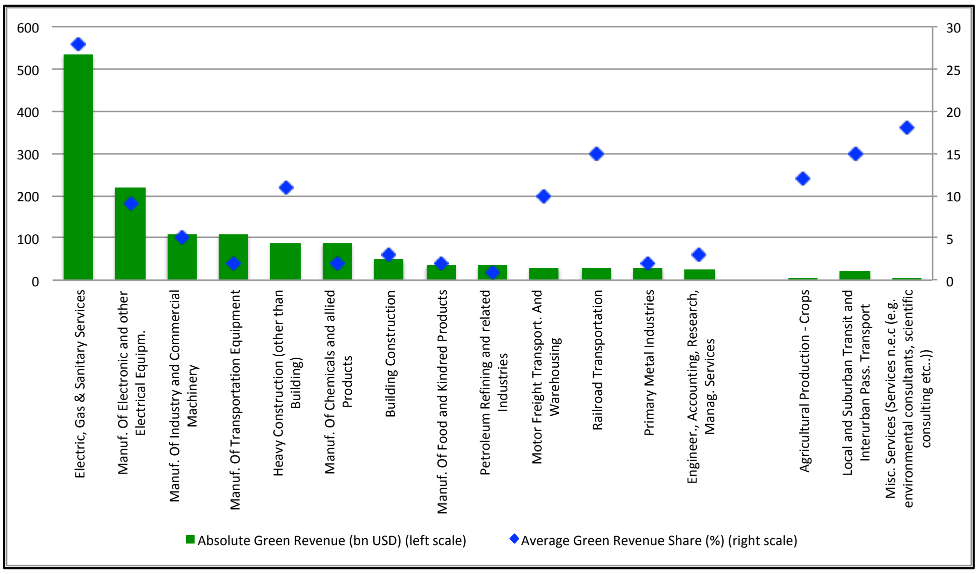


Figure 2.3: Green Revenue and Average Green Revenue Share by Industry (2-digit SIC) in 2016

2.3.2 Financial Performance Variables

Firm-level economic variables are obtained from Thomson Reuters Worldscope.[18] As variables are expressed in local currency units, we convert to USD using the annual official exchange rate obtained from the World Development Indicators provided by the World Bank (The World Bank, 2018).

We draw on the financial economics literature for rules on sample restrictions to im-

[18] At an early stage of the analysis we compared the number of observations to Orbis, which had up to 20% fewer observations on most control variables for our sample compared to Worldscope.

prove the robustness of our analysis.[19] Such rules are applied when using large global firm-level samples across the universe of industries. We exclude financial firms (SIC 6000-6999) as is conventionally done in financial economics. Firms in these sectors tend to have statutory capital requirements and the leverage of financial firms has a different meaning than for non-financial firms (see e.g. Fama and French, 1992; Faulkender and Petersen, 2006). Utility firms (SIC 4000 - 4999) are also often excluded, as they may face different types of regulations. However, since this sector accounts for (by far) the largest share of green revenues (in particular electricity generating firms), we keep them in our main specification. In our assessment into sector heterogeneity (Section 2.5.4) and robustness checks (Section 2.5.3), we will examine in detail, to what extent effects might be driven by utilities. This allows us to examine in detail systematic differences between utility- and non-utility sectors and derive different sets of policy conclusions across sectors.

We also draw on the financial economics literature for restriction criteria to ensure results are not driven by three specific factors: (1) accounting anomalies in the data, (2) specific corporate events (e.g. corporate reorganisations), and (3) extreme values. There is much debate on these restrictions - while some papers impose few restrictions on the data (e.g. Fama and French (1992); Khanna et al. (1998); Anderson et al. (2012); Mollet and Ziegler (2014)), others apply more restrictive exclusion criteria. Being too restrictive in excluding observations is problematic as the sample-selection may drive results and can reduce the external validity of the findings. It can also increase the likelihood of a type 2 error, which implies failing to reject a null hypothesis (of no difference), even though a true difference exists. We follow the approach by, among others, Opler et al. (1999), Vermoesen et al. (2013), and Liu et al. (2014) and exclude all firm-year observations with negative equity or sales. Negative equity implies that firms' liabilities exceed their assets, which can be driven by large accumulated losses over multiple time periods, which become liabilities on firms' balance sheets. These are exclude to avoid that results are driven by firms in severe financial distress. Negative revenues capture anomalies in the data or possible errors and are commonly excluded. Beyond these restrictions, we also exclude all firm-year observations with a change in total assets greater than 100%, following Duchin et al. (2010) and Vermoesen et al. (2013). Such large jumps typically indicate major events such as mergers and acquisitions or other corporate reorganisations. By excluding these observations we aim to avoid that such corporate restructuring events drive our results. We winsorize all continuous variables symmetrically at the top and bottom 1% to avoid that any

[19] Papers in the environmental economics literature often ignore sample restrictions that need to be applied to examine firm-level economic performance. Some closely related papers do not apply any sample restrictions (e.g. Palmer and Truong, 2017; Trumpp and Guenther, 2017). These papers are however based on much smaller samples, which might make further restrictions not possible.

remaining outliers drive the results (following Clarkson et al. (2015) among others).

Table 2.1 presents the descriptive statistics of our sample. We see that our sample contains relatively large firms with an average (median) of about 11,000 (2,600) employees. The median firm reports short-term profitability indicators of 8% (ROS), 5% (ROA), and 9% (ROE). The mean values tend to be lower as the distribution of these indicators tends to be skewed to the left (see minimum and maximum values in Table 2.1). The share of green revenue is on average 3%. The mean (median) Tobin's Q is 1.89 (1.37), meaning that the median firm is valued higher by the market than the replacement cost of its assets, which is in line with previous literature (e.g. Duchin et al., 2010; Jermias, 2008)[20].

When comparing descriptive statistics for firms that have positive green revenue shares vis-à-vis firms with no green revenues (see Appendix B.5), green firms emerge on average to be larger and more profitable than non-green firms, yet have on average lower values of Tobin's Q. This indicates that frontier firms in the green economy are systematically different. This has important implications (e.g. selection bias, endogeneity concerns) for our empirical strategy, which will be discussed in Section 2.4.1.

We report the pairwise correlation coefficients between the profitability indicators in Table 2.2. Appendix B.4 shows the correlation coefficients between our explanatory variables. It shows high correlations between different measures of operating profitability, i.e. the Ebit-, and Ebitda-margin, and ROS. ROA and ROE are somewhat less (but positively) correlated with the operating profitability measures, but are highly correlated between each other. This reflects the difference in operating profit margin and financial resource-based profitability indicators. Hence, we might also expect to see relatively similar results for the indicators within these two groups and some heterogeneity across the groups. Each of the components of Tobin's Q (Market Capitalisation, Total Assets, Common Equity) have respectively relatively low correlations with the profitability indicators. Similarly, we observe low correlations between Tobin's Q and the short-term profitability indicators. We see small negative correlations with operating profit margin and small positive correlations with ROA and ROE. Investors would typically be more concerned about these financial resource-based profitability indicators, as they indicate how efficient a firm is at using investments. However, the low correlations show that other variables beyond profitability matter for firms' market valuation and that profitability does not linearly translate into market valuation. This also emphasises the importance of studying accounting- and market-based firm performance separately.

[20]Duchin et al. (2010) report a mean Tobin's Q of 1.77. Jermias (2008) report a mean of (log) Tobin's Q of 0.615, which is equivalent to 1.85 in Tobin's Q.

Table 2.1: Descriptive Statistics

	Median	Mean	Std. Dev.	Min.	Max.
Ebit-margin	0.08	-0.05	1.06	-9.05	0.73
Ebitda-margin	0.13	0.03	0.94	-7.98	0.88
Return-on-Sales (ROS)	0.08	-0.07	1.12	-9.77	0.53
Return-on-Assets (ROA)	0.05	0.03	0.14	-0.73	0.32
Return-on-Equity (ROE)	0.09	0.05	0.29	-1.50	0.84
FTSE Min Green Revenue	0	0.03	0.14	0	1
Green Revenue Share (after imputation)	0	0.04	0.14	0	1
# employees	2636	10935	25243.88	7	170953
Log(Assets/Sales)	0.30	0.43	0.88	-1.27	3.87
D(R&D>0)	0	0.40	0.49	0	1
Leverage	0.04	0.12	0.17	0	0.74
Dividends per Share (USD)	0.01	0.27	0.59	0	3.6
Sales Growth	0.06	0.11	0.34	-0.69	1.98
Tobin's Q	1.37	1.89	1.49	0.51	9.50
Log (Sales/Assets)	-0.30	-0.44	0.96	-11.54	1.27
Log (Assets/Equity)	0.69	0.80	0.56	0.03	2.93

Table 2.2: Pairwise Correlations of Profitability Indicators

	Ebit	Ebitda	ROS	ROA	ROE	TQ	MC	TA.	CE.
Ebit-margin	1								
Ebitda-margin	0.99	1							
ROS	0.94	0.94	1						
ROA	0.62	0.63	0.56	1					
ROE	0.49	0.48	0.43	0.88	1				
Tobin's Q (log) (TQ)	-0.06	-0.07	-0.08	0.07	0.06	1			
Market Cap. (MC)	0.05	0.05	0.05	0.10	0.11	0.07	1		
Total Assets (TA)	0.04	0.05	0.04	0.04	0.05	-0.08	0.72	1	
Com. Equity (CE)	0.04	0.05	0.04	0.05	0.05	-0.07	0.77	0.89	1

2.4 Empirical Strategy

Our aim is to assess firms' incentives to engage in green activity. In particular we are interested in the relationship between producing green goods and services and firms' current profitability, and their expected profitability. Most past studies use cross-sectional data, which does not allow the use of firm fixed effects (e.g. Konar and Cohen, 2001; Hibiki et al., 2003; Rexhäuser and Rammer, 2014). In our eight year panel, firm fixed effects absorb any time-invariant firm-level characteristics, which would need to be proxied by additional control variables in cross-sectional studies. Additionally, we are also able to control for industry-by-year dummies, which absorb any industry- and year-specific effects. Since the literature and theoretical frameworks on the relationship between firms' environmental activities and economic performance are not consolidated on the correct choice of control variables, we prefer to take a rather simple specification and make use of firm fixed effects and industry-by-year dummies as well as robustness checks with different specifications.

In our first specification we focus on the relationship between green revenue shares and various measures of current profitability. We estimate the following model:

$$Y_{it} = \beta_1 GR_{i,t-1} + \beta_2 V_{it}' + \beta_3 SIC_{it} + \alpha_i + \varepsilon_{it} \qquad (2.6)$$

where i and t index the firm and year respectively. Y_{it} is a variable of financial performance (EBIT-, EBITDA-margin, ROS, ROA, or ROE). $GR_{i,t-1}$ is a continuous measure of green revenue share. We have incorporated a one year lag-structure to minimise the possible concerns about reverse causality. We also include a vector of firm-specific controls V_{it}' including the number of employees (log), the (log) assets-to-sales ratio, a dummy variable indicating whether a firm invests in R&D, and (log) leverage (debt divided by asset). We use the number of employees as a proxy for firm size following Telle (2006) and Fuji et al. (2013).[21] The assets-to-sales ratio captures capital-intensity or capital requirements for production. In addition, it also proxies entry-barriers since in markets with high assets-to-sales ratios, entry is more difficult due to higher capital requirements and potentially sunk costs. (O'Brien, 2003; Rexhäuser and Rammer, 2014). We include an R&D variable to control for the innovative activity of a firm. One challenge in controlling for R&D expenditure is that it is not a mandatory or standardized reporting item for firms. More importantly, firms face substantial incentives to strategically misreport their R&D expenditure. Knowledge of competitors' R&D expenditure allows insight into firms' short-and long-term strategy and operations (Li,

[21] We include employees rather than total assets as our control for firm size to reduce issues of multicollinearity with our other control variables in particular the assets-to-sales ratio.

2016). Empirical evidence has shown that firms systematically misreport R&D expenditures (Beatty et al., 2013; Li, 2016). Since such misreporting is likely to be correlated with our dependent and independent variables it is likely to induce bias in our estimation. Thus, we use a dummy variable taking the value of 1 if a firm has reported positive R&D expenditures and we exclude advertising expenditures. We consider this approach to be more reliable and less likely to result in biased estimation.

We also include Leverage (Debt/Assets) to control for firms' level of debt and their financing structure (of debt versus equity financing). The importance of leverage in models explaining firm performance has been widely discussed in financial economics beginning with the landmark paper by Modigliani and Miller (1958). The subsequent literature has underlined and shown empirically the importance of firms' financing structure for their profitability and valuation (see also Myers, 2001).[22] This has not received the same level of attention in environmental economics where few papers control for firms' leverage-ratio, some exceptions including Konar and Cohen (2001) and King and Lenox (2001), which control for firms' debt or leverage in cross-sectional settings.

The vector *SIC* represents 3-digit industry-by-year dummies that account for unobserved year-specific effects. α_i are firm-fixed effects that soak up all time-invariant firm level characteristics such as initial commitment to "going green" or initial productivity. Finally, ε_{it} is an idiosyncratic error term. We cluster the standard errors at the firm level to account for correlation in unobserved components of the outcomes within a firm.

[22]Following Modigliani and Miller (1958), many studies investigated the relationship between firms' financing structure and economic performance and show that existing capital markets are not sufficiently perfect and that the type of financing and firm leverage impact their economic performance. This literature has examined the impact of financing on both accounting-based profitability (e.g. ROS, ROA, ROE), as well as market based profitability such as Tobin's Q (see e.g. Berger and di Patti, 2006, for a discussion). A number of theories have been developed to explain the impact of financing decisions on firm performance. One view focuses on tax advantages of debt over equity financing. Interest (paid on debt) is often tax-deductible, which implies that an additional dollar of interest paid is partly offset by lower taxes, making debt financing relatively cheaper. Hence, financing with debt rather than equity should improve firms' overall performance. Moreover, financing with equity has substantially higher transaction costs, in large parts due to fees paid to the underwriting bank (i.e. the "spread"), as well as other legal and auditing costs (Myers, 2001; Chod and Zhou, 2014). These effects alone would point in the direction of complete debt financing, which is however not observed in reality. Counteracting effects have been identified, of which the trade-off theory suggests that higher levels of debt-financing increase the risk of bankruptcy, implying a cost of financial distress. The threat of default can impact firms' operating and investment decisions, as it may delay or deter otherwise profitable investments. Such "underinvestment" problems arising from deterring effect from high leverage-ratios can reduce firms' economic performance (Myers, 1977, 2001). Debt can also function as a tool to discourage managers from taking excessive risks or from using financial resources inefficiently through the threat of liquidation (Margaritis and Psillaki, 2010) (For a detailed review see also Modigliani, 1982; Myers, 2001; Chod and Zhou, 2014). Due to the potentially counteracting effects, the net effect of firms' leverage-ratio on their economic performance remains unclear and may be case-specific, yet it is an important control variable in models of firms' economic performance (Margaritis and Psillaki, 2010).

To investigate the market valuation of engaging in green activity, we examine the Tobin's Q of firms (Hall et al., 2005). We use a similar fixed-effects specification as in the case of short-term profitability. However, the set of control variables differs based on theoretical considerations. Based on the Efficient Market Hypothesis (Fama, 1991; Ball, 1995; Bharadwaj et al., 1999), it is assumed that all information is immediately priced into firms' stock price. Hence, there is no time lag between engaging in green activities and firms' market valuation. We estimate the following equation:

$$\text{Tobin's Q}_{it} = \beta_1 GR_{i,t} + \beta_2 W'_{it} + \beta_3 Div_{it} + \beta_4 SIC_{it} + \alpha_i + \varepsilon_{it} \tag{2.7}$$

where Tobin's Q is measured as specified in Equation 2.5, and $GR_{i,t}$ is the continuous measure of the green revenue share at time t. We include a vector of firm-specific controls W'_{it}. We again control for the number of employees as our measure of firm size following Telle (2006) and Fuji et al. (2013) [23]. We use assets-to-sales as our variable of firms' capital intensity following O'Brien (2003), as well as the dummy variable indicating whether a firm invests in R&D. We also add dividends per share to the specification (Div_{it}) which is relevant for investors' valuation of a firm. Firms' dividend pay-out policies can affect their Tobin's Q, as firms with high dividend payments may have higher market values and lower book values relative to low dividend firms since investors receive an additional income from their investment (Jermias, 2008).[24]

As with current profitability, the type of financing can impacts firms' valuation. Financing with debt rather than equity should increase market value because it increases the after tax return to investors due to the tax deductibility of interest payments (Myers, 2001). Yet, increasing debt ratios also increase the risk of bankruptcy and the associated cost of financial distress, implying a moderating effect on debt financing. Since the threat of default can impact firms' operating and investment decisions towards deterring profitable investments, high debt-to-asset ratios can also impose a downward effect on firms' market valuation (Myers, 2001). Similar to accounting-based prof-

[23] Papers in this literature also use the total book value of assets as a size indicator. However, this may induce issues of multicollinearity between the independent variables, in particular with the assets-to-sales ratio.

[24] Parts of the existing literature using Tobin's Q include advertising expenditure as a control variable. These papers are typically limited in geographical scope to one country, often the US (e.g. Konar and Cohen, 2001). The Compustat database provides information on firms' advertising expenditure for US companies only. Reliable data at the global level to capture advertising expenditure of firms is unavailable. The variable is neither available in Worldscope nor in Orbis. More importantly, it has been emphasised that advertising expenditure is likely measured with substantial error and is subject to significant strategic misreporting as firms do not want to disclose business and marketing strategies to competitors (Salinger, 1984; Beatty et al., 2013; Li, 2016). This systematic measurement error would likely bias our results as the misreporting error would be correlated with our dependent and independent variables. In addition, the estimated coefficient for advertising intensity in Konar and Cohen (2001) is small and only weakly significant at 10%.

itability, the net effect of leverage is ambiguous, but it is an important control for the model.[25] Some papers within the literature also suggest that firms' growth opportunities, as measured by revenue-growth, can be a relevant determinant for market valuation (see e.g. King and Lenox, 2001; Rassier and Earnhart, 2015). Yet, again there is no consensus on the variable's importance within Tobin's Q models. For instance it is not included in Jermias (2008), it is highly insignificant in the model of (Rassier and Earnhart, 2015)[26] and only marginally significant in Khanna and Damon (1999). The cost of including sales-growth in a panel fixed-effects specification is that automatically one year is dropped from the analysis. Our panel only contains eight years, and to accommodate this trade-off, we test for the robustness of our results by once controlling for sales-growth and once without this control.

The vector *SIC* represents 3-digit industry-by-year dummies that account for unobserved industry- and year-specific effects. α_i are firm-fixed effects that soak up all time-invariant firm level characteristics. Finally, ε_{it} is an idiosyncratic error term. We cluster the standard errors at the firm level to account for correlation in unobserved components of the outcomes within a firm.

2.4.1 Propensity Score Weighting

Our descriptive statistics revealed that comparing firms that generate some green revenue with those that don't engage in any green activities can be problematic. There may be unobserved variables associated to both the green activity and current profitability or market valuation. Failure to account for these confounders can result in a biased effect estimate that conflates the true effect of engaging in green activity. In particular, selection may be driven by lagged firm characteristics and investment decisions that could be correlated with expected profitability or market valuation. To better control for selection on pre-sample observable time-invariant characteristics of firms, we combine a fixed effect regression with an inverse propensity score weighting (IPSW) strategy. This allows us to fit a regression line not on the overall sample, but to obtain an more localised regression coefficient after restricting the sample to a more similar set of firms based on pre-sample characteristics. Propensity score methods, proposed by Rosenbaum and Rubin (1983), have gained widespread popularity for balancing dissimilar groups with respect to baseline covariates.

[25] It has been noted that a challenges in controlling for leverage is that firm-specific financing strategies exhibit low-levels of variation. With short panels, fixed-effects models may face difficulties in estimating the coefficient on leverage, which may be a reasons for why it has been omitted in some of the previous papers (O'Brien, 2003).

[26] In their fixed- and random effects specifications sales growth has a p-value of 0.43 and 0.92 respectively.

In our setting, the propensity score is defined as the probability of engaging in green activity (i.e. having green revenues) as a function of the respective control variables. We estimate the propensity score on the pre-sample averages (2005-2008) of all control variables, except for the R&D-dummy.[27] We consider firms that generate a positive green revenue share at any point in the sample as being "treated" and firms that never generate any positive green revenue share as the pool of controls (Guadalupe et al., 2012). We use the pre-sample averages of the control variables as well as 3-digit industry dummies to estimate the propensity score $\hat{p}$ within each industry. We apply exact matching at the industry-level to ensure that the propensity score for firms is generated separately within each industry.[28] The estimated propensity scores are then used to weight firms, thus creating a sample that is similar with respect to the propensity score distribution (Lechner, 1999; Dehejia and Wahba, 2002; Guadalupe et al., 2012; Busso and McCrary, 2014). Specifically, the weight for each "green" firm is $\frac{1}{\hat{p}}$ and the weight for each control firm is $\frac{1}{(1-\hat{p})}$ (also known as inverse probability weighting (IPW)). In the subsequent results section, we compare results with and without IPW restricting the sample to firms with the common support. We winsorize the weights symmetrically at 1% following Guadalupe et al. (2012).

Figures B.8 to B.14 in the Appendix point to the different variable distributions in the initial sample and improvements following the reweighing. Prior to the weighting, firms generating green revenues tend to be larger and on average more profitable. It is important to note that this does not mean that the coefficient on green revenue after re-weighting should be interpreted as causal effects of going green. There remains selection based on unobservables.

[27] We exclude the R&D dummy from the propensity score estimation as we are worried it might introduce additional bias. It is the least precisely measured variable and a 0 in the dummy variable can either mean that a firm does not have any R&D expenses, does strategically not report its R&D expenses, or that the data point is missing for other reasons. Hence, we exclude it from the propensity score estimation.

[28] Exact matching at the industry-level is important, as the propensity score would otherwise be estimated for firms across industries with similar SIC codes. Since the proximity in SIC-codes is not a meaningful characteristic, approximate matching on industry codes can induce bias as it treats the sector-codes as a continuous variable. In other words, a closer proximity in SIC codes does not imply a more similar or comparable business activity compared to more distant SIC codes. Since we control for 3-digit industry-by-year dummies in the regressions, failing to impose exact matching at the 3-digit industry level could induce bias in the propensity score and the corresponding weights

2.5 Results

2.5.1 Current Profitability

We first present our results on the complete sample across all sectors. They represent the average effects across the entire sample. Starting with measures of operating profit margins in table 2.3, we observe positive and significant relationships between the green revenue share and ebit-, ebitda-margin, and returns-on-sales (ROS). The effects are significant at the 5% level in columns 1-3 which shows results for the full sample without inverses propensity score weighting, and columns 7-9 with the weighting. We show also in columns 4-6, the results without weighting where we restrict the sample to the weighting sample, to show the impact of the weighting vis-à-vis the smaller common support sample. Here, the effects are similar in magnitude, but are only significant at 10%.

To interpret the magnitude of the coefficients and to be able to compare them across models, we standardise the effects by using standard deviations. A one standard deviation increase in the green revenue share, which is equivalent to an increase of 13 percentage points, is associated with a 0.03 standard deviation increase in return-on-sales. Hence, for the median firm, with a ROS of 0.08, a one standard deviation increase in Green Revenues is associated with a 0.039 point increase in ROS, equivalent to a 49% increase[29]. Regarding the control variables, we observe that larger firms (measured by number of employees) are more profitable. Both the coefficients on the assets-to-sales ratio and the leverage are negative. The coefficients highly significant for the assets-to-sales ratio and marginally significant for leverage. This indicates that higher levels of assets (per sale) and debt (per asset) are associated with lower profitability.

Moving on to more comprehensive measures of current profitability that measure return on investments, we see in Table 2.4 that there is a significant and positive relationship between green revenue and return-on-assets (ROA) and return-on-equity (ROE), albeit small in magnitude on the aggregate sample. For ROA, we observe a coefficient of 0.03, an order of magnitude smaller than the coefficients of the operating profit margin indicators. A one standard deviation increase in green revenue (13 percentage points), is associated with a 0.03 standard deviation increase in ROA. However, since the standard deviation of ROA is lower than for ROS, this is equivalent to a 0.004 point increase in ROA. For the median firm with a ROA of 0.05, this is equivalent to an 8%

[29]This calculation is based on $\beta_{sROS} = \beta \cdot \frac{sd_{GR}}{sd_{ROS}}$. In our setting, $0.30 \cdot \frac{0.13}{1.12} = 0.03$. A 0.03 standard deviation increase in ROS is equivalent to 0.039 increase in ROS points based on $0.03 \cdot 1.12 = 0.039$. For the median firm, an increase in 0.039 ROS points is equivalent to 49% based on $(0.039/0.08) \cdot 100 = 49\%$

increase in ROA.[30] In the case of return-on-equity, a one standard deviation increase in green revenue is associated with a 9.6% increase in ROE for the median firm. Overall we observe a substantially larger increase in operating profit margin associated with generating revenues from producing green goods and services, compared to the more comprehensive asset- or equity- based profitability indicators.

To make sense of our result, we refer to the DuPont Decomposition (Equations 2.2 and 2.3). Recall that ROA is the product of ROS and the inverse asset requirement ($Sales/Assets$). ROE is similar but has an additional term, $Assets/Equity$, the equity multiplier. Thus a positive ROS is compatible with a relatively low effect on ROA or ROE if the sales to assets ratio is negative, or in the case of ROE the equity-multiplier is negative. Therefore, we investigate the relationship between leads and lags of green revenue and sales/assets. Results are reported in Tables B.4 and B.5 for sales-to-assets requirement and Tables B.8 and B.9 for the equity-multiplier. We find that sales-to-assets are significantly negatively associated to green revenues for the current and the next (green revenue) time period (the correlation remains negative up to two years, but is not significant in the second year). This implies that firms' generating green revenues require more assets (per sales) for up to two years.[31] We do not observe significant relationships with firms' equity multiplier ratios.[32] This suggests that engaging in green activities is associated with higher asset requirements (per sales) for up to two full years prior to producing green goods and services. This might be the case as firms need to purchase additional machinery or plants to be able to produce green goods. Firms' financing decisions (between debt and equity financing) are not significantly associated with their decisions to produce green goods and services.

These results provide insight into the performance effects of engaging in green activities. On the one hand, firms that decide to engage in green activities increase their ability to earn income. This suggests that firms are moving into the green space in sectors where green goods and services can be differentiated and consumers are willing to pay a premium for them. Green markets also tend to be less mature, which could indicate less competition resulting in higher markups and higher earnings per sale. These

[30] The calculation is based on $\beta_{sROA} = \beta \cdot \frac{sd_{GR}}{sd_{ROA}}$. In our case $0.30 \cdot \frac{0.13}{0.14} = 0.03$. A 0.03 standard deviation increase in ROA is equivalent to a 0.004 point increase in ROA based on $0.03 \cdot 0.14 = 0.0042$. For the median firm (with a ROA of 0.05) an increase in ROA of 0.0042 points is equivalent to 8.4% based on $(0.0042/0.05)100 = 8.4\%$.

[31] To keep the tables on the sales-to-assets ratio consistent with our main specifications, we expressed them as correlations in which green revenues is the 'independent' variable and the sales-to-assets ratio is the 'dependent' variable. This allows us to adopt the same econometric specification as in our main results. B.4 shows that generating green revenues in the next period (1-year lead) is negatively associated with (sales-to-assets) in the current period. This is equivalent to saying that generating green revenues in the current period is associated with a higher assets-to-sales ratio in the previous time period.

[32] One outlier result suggests a significant negative correlation for the correlation with 3-year green revenue lead. We interpret this as an outlier occurring due to chance (with a 5% probability).

factors contribute to higher earnings per sales of firms. On the other hand, engaging in green markets is associated with additional asset and investment requirements. The cost of additional assets required imposes a downward drag on firms' overall return on investment, as measured by return-on-assets and return-on-equity. This provides a dampening factor, so that we observe relatively lower impacts on these profitability indicators.

Table 2.3: Regressions of current profitability (operating profit margins)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.42**	0.36**	0.31**	0.34*	0.35*	0.21	0.35**	0.34**	0.29**
	(0.17)	(0.15)	(0.12)	(0.20)	(0.19)	(0.14)	(0.16)	(0.15)	(0.12)
Employees	0.04**	0.03**	0.03	0.06***	0.06***	0.04**	0.07***	0.06***	0.05***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.54***	-0.44***	-0.66***	-0.38***	-0.30***	-0.51***	-0.39***	-0.31***	-0.52***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
D(R&D>0)	0.02**	0.02**	0.02*	0.02**	0.02**	0.02*	0.03*	0.03**	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Leverage	-0.01*	-0.01*	0.00	-0.02***	-0.02***	0.00	-0.01	-0.01	0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.15	-0.05	-0.00	-0.41***	-0.32***	-0.12	-0.41***	-0.33**	-0.16
	(0.13)	(0.12)	(0.13)	(0.15)	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)
R^2	0.722	0.767	0.829	0.753	0.744	0.825	0.716	0.708	0.777
Nb. of obs.	51,498	51,444	52,653	35,233	35,212	35,721	35,233	35,212	35,721
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs. All models incorporate a full set of firm fixed effects and 3-digit industry-by-year dummies. In columns 4 to 6 we estimate the model on the common support sample without any weighting. In columns 7 to 9 we weight the sample by the inverse propensity score.

Table 2.4: Regressions of current profitability (return on assets and equity)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.03***	0.06*	0.04***	0.07**	0.03**	0.06*
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Employees	-0.00	0.00	0.00	0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Assets/Sales	-0.04***	-0.08***	-0.03***	-0.06***	-0.02**	-0.05***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
D(R&D>0)	-0.00	0.00	0.00	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Leverage	-0.01***	-0.02***	-0.01***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.04***	0.04	-0.01	-0.08*	-0.04**	-0.15***
	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.05)
R^2	0.729	0.650	0.691	0.606	0.662	0.590
Nb. of obs.	51,814	51,617	35,549	35,506	35,549	35,506
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs. All models incorporate a full set of firm fixed effects and 3-digit industry-by-year dummies. In columns 3 and 4 we estimate the model on the common support sample without any weighting. In columns 5 and 6 we weight the sample by the inverse propensity score.

2.5.2 Expected profitability - Tobin's Q

Our results for investors' expectations of future profitability are presented in Table 2.5. We broadly find positive and significant coefficients of around 0.1, between the green revenue share and Tobin's Q across the different specifications, with the aggregate sample (columns 1-3) and when controlling additionally for revenue growth (columns 4-6). This implies that a one standard deviation (13 percentage points) increase in green revenues is associated with a 0.02 standard deviation increase in (log) Tobin's Q.[33] For the median firm, a one standard deviation increase in green revenues is associated with a 3.8% increase in Tobin's Q. Thus, generating revenues from producing green goods and services is positively and significantly associated with firms' market valuation in the overall sample.

Focusing on the controls, we again observe negative and significant coefficients for assets/sales and the leverage ratio. This suggests that higher investments (per sales) and higher debt financing are negatively associated with investor valuation. The negative coefficient for leverage is in line with the theoretical prediction that higher debt increases the risk of bankruptcy, the cost of financial distress, and may result in constrained investment activities. In our sample, this effect appears to dominate any offsetting effects arising from lower cost of debt financing. In line with expectations we observe consistently positive and significant coefficients for dividend payments. We observe significantly negative coefficients for the number of employees and our R&D indicator variable. The relationship between the number of employees and firm performance is ambiguous as it may capture larger firms, but also more labour-intensive production, which might be valued negatively by investors. Similarly negative coefficients for employees have been observed by Telle (2006) for instance. While the R&D variable captures innovation activity the coefficient suggests that innovation activity can be associated with additional costs in the current period and uncertain future benefits. These effects are negatively associated with investor valuation.

[33] This is based on the calculation: $0.1 \cdot \frac{0.13}{0.58} = 0.02$. This 0.02 standard deviation increase in (log) Tobin's Q is equivalent to a 0.012 point increase in (log) Tobin's Q ($0.02 \cdot 0.58 = 0.012$). In other words, a 1 standard deviation increase in green revenue is associated with a 0.012 point increase in (log) Tobin's Q. For the median firm with a (log) Tobin's Q of 0.32, a 0.012 point increase is equivalent to a 3.8% change in (log) Tobin's Q ($\frac{0.012}{0.32} * 100 = 3.75$). This can be converted back to non-logged Tobin's Q through: $(e^{0.037} - 1) * 100 = 3.77\%$. Hence, for the median firm a 13% point increase in green revenue is associated with a 3.77% change in (non-logged) Tobin's Q.

Table 2.5: Regressions of expected profitability (Tobin's Q)

	(1)	(2)	(3)	(4)	(5)	(6)
	log (Tobin's Q)					
Green Revenue	0.07*	0.11**	0.13***	0.06	0.10**	0.08*
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Employees	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets/Sales	-0.13***	-0.14***	-0.14***	-0.12***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D(R&D>0)	-0.06***	-0.08***	-0.08***	-0.02***	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends per Share	0.11***	0.11***	0.11***	0.11***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sales-Growth	/	/	/	0.08***	0.07***	0.07***
				(0.01)	(0.01)	(0.01)
Constant	0.86***	0.81***	0.82***	0.81***	0.75***	0.77***
	(0.06)	(0.07)	(0.08)	(0.06)	(0.08)	(0.09)
R^2	0.843	0.839	0.836	0.862	0.859	0.858
Nb. of obs.	57,354	40,141	40, 141	50,582	34,819	34,819
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

2.5.3 Robustness checks and limitations

We perform a number of robustness checks to test the sensitivity of the results to the use of different variables, as well as the exclusion of particular sectors. First, we control for loss-making firms, because the reporting and valuation of firms with negative profitability can differ systematically from profit making firms (see e.g. Jiang and Stark, 2013; Darrough and Ye, 2007).[34] We include a dummy variable taking the value of 1 if a firms' operating profit margin (measured by ROS) is negative in a given year. The magnitude and significance of the effects remain fairly stable (Tables B.10, B.11, and B.12 in the Appendix). In particular the coefficients for operating profit margin, ROA, and Tobin's Q remain significant. The coefficients for ROE are more sensitive to this additional variable and are largely not significant anymore. As expected we observe a negative and significant coefficient for the dummy variable on negative profitability.

Second, we examine the sensitivity of our results to the imputed green revenue measure. We replicate our results using the raw FTSE Minimum Green Revenue variable, which provides the most conservative estimate. The results hold in magnitude and significance (Tables B.13, B.14, and B.15). We observe similar coefficients for operating profit margin (around 0.3), ROA (around 0.03), ROE (around 0.05), and Tobin's Q (around 0.1). We also observe similar coefficients (in magnitude and significance) for the control variables in this model. Hence, we are confident that our results are not driven by the imputation of missing values in the green revenue variable.

Third, we test if the results are driven by electricity generating firms, which is by far the largest 3-digit SIC sub-sector accounting for about 400 billion USD in green revenues in 2016 on its own (See Figure B.6). Renewable electricity generation has received substantial subsidies over the past decade and may therefore have experienced a unique economic performance (e.g. IEA, 2017). Hence, we exclude electricity generation as an additional robustness check to examine if results might be driven by this particular sector (Tables B.16, B.17, and B.18).[35] The results for our profitability indicators remain stable. We observe a decline in significance for the results on Tobin's Q, after controlling for revenue growth. This suggests that once controlling for firms' growth opportunities, the relationship between green revenues and market valuation is at most marginally significant for the sample without electricity generating firms.

[34] In the particular the role of firms' assets is different for loss-making firms and their valuation. Assets tend to be valued systematically stronger for loss-making firms, as they provide an indication of the value of the firm in the case of liquidation. They have also been used as proxies for firms expected future earnings. Furthermore, the role of carry forward losses to reduce tax payments on anticipated future profits may lead to systematically different outcomes (Ohlson, 1995; Jiang and Stark, 2013).

[35] In addition to SIC 491 (Electric Services), we also exclude SIC 493 (Combined Electric, Gas, and other Utility) to avoid that the effects might simply be driven by firm classification since primarily electricity generating firms can also be classified as SIC 493. This is a conservative approach as we exclude a larger set of firms.

The relationship between green revenues and profitability holds for both the operating profit margin and return on investment indicators after excluding electricity generation.

Lastly, we exclude all utilities from our sample (SIC 4900-4999), which covers a broad group of sub-sectors including electricity generation, gas production and distribution, waste management, water supply and sanitary services among others. Utilities collectively account for a large amount of green revenues in the database and hence excluding them provides a substantial restriction to the variation in our main independent variable. We observe that the positive effect on the operative profitability margins persists for non-utility firms (Table B.19). However, the effects on return on investments (ROA, ROE) and Tobin's Q are largely insignificant after applying this sample restriction (Tables B.20 and B.21). Utilities tend to be endowed with a degree of market power. They can be natural monopolies or can be otherwise protected through price control for instance. As a consequence they operate in unique regulatory settings, in which they are often sheltered from market forces. (see e.g. Filbeck and Gorman, 2004; Wolak, 2008). The relationship between green revenues and economic performance may therefore be different for utilities compared to non-utility firms. Utilities contain however also a quite heterogeneous group of sectors. Hence it may be important to also distinguish between different types of utilities as we do in the following section 2.5.4.1.

Our findings suggest that the most generalisable and strongest relationship for green revenues exists with firms' operative profitability margins. Even after excluding all utilities from the sample, which account for a large share of green revenues, we observe positive and significant relationships between green revenues and firms' operative profitability (on the full sample and after applying the weighting). Non-utility firms are able to obtain higher earnings-per-sales from producing green goods and services. However, the higher operative margins are not transmitted into higher return on investment (ROA, ROE). This is supported by the observation that the negative relationship between green revenues and firms' sales-to-assets ratio is more pronounced for the sample of non-utility firms than for the sample of utility firms (Tables B.6 and B.7). Non-utility firms have higher assets-to-sales ratios in the current period and the period prior to generating green revenues, requiring up to two years of higher investments to produce green goods and services. The effect for utilities only exists in the current period. For non-utility firms the additional investment requirement imposes a relatively strong downward drag on their return on investment and their higher operative margins do not translate into higher ROA or ROE.[36]

This paper makes significant advances in terms of data and empirical methods that reduce potential bias in estimates, nonetheless, the associations we find between en-

[36]In addition, the coefficients on operative profitability for the non-utility sample are also smaller in magnitude (around 0.2) (Table B.19) compared to the aggregate sample (around 0.3) (Table 2.3).

vironmental and financial performance of firms cannot be interpreted as causal effects. A number of potential threats to identification remain, in particular, the most likely source of endogeneity comes from potentially reverse causal effects, meaning that better accounting- or market performance may increase the likelihood of investing in green technologies. We partially address this using a one-year lag structure in our green revenue variable. Yet this may still be endogeneous if the decision to invest in green technologies was taken even earlier. Using further lags would not fully resolve this concern as the true lag in firms' decision making is unknown and may always be partly endogeneous. Our relatively short panel makes it difficult to adopt further lag structures because it reduces the sample size and increases the likelihood of a type 2 error.[37]

Additionally, the Stable-unit-treatment-value assumption (SUTVA) might be violated in this context. The most relevant SUTVA assumption here is that the observed decision (to generate green revenues) is independent of decisions of other firms i.e. there are no general equilibrium effects across firms. This may be violated, as firms' decision to invest in green technologies may be conditional on other firms, for instance due to the fear of falling behind in a growing market or by exploiting second-mover advantages. This is not an uncommon threat to identification in empirical economic analysis (e.g. Lechner, 1999). Lastly, even after applying the inverse propensity score weighting the coefficients may be biased by selection on unobservables. Compared to previous studies using cross sectional data, the panel data in this study allows us to reduce omitted variable bias considerably, by using firm fixed effects to absorb any time-invariant firm characteristics, and 3-digit industry-by-year dummies that account for unobserved industry- and year-specific effects.

2.5.4 Sector Heterogeneity

In the previous section we tested the robustness of our aggregate results to the use of additional controls and to omitting specific sectors. In this section we further examine how the effect of green revenues on profitability and market valuation differs by sector. To do so, we estimate our models individually for the sectors that account for the largest amounts of green revenues. The smaller sample sizes in estimations by sector reduces the power of statistical tests, making the coefficients less stable across specifications and increasing the likelihood of type 2 errors.[38] First, we report the results individually

[37] Since the green revenues data is provided at the global level of firms and linked to their 'consolidated' global accounts, we are also not able to exploit potentially exogenous variation in energy prices across countries as done for instance by Marin and Vona (2017) using an instrumental variable approach.

[38] A Type 2 error occurs if we fail to reject a null hypothesis (of no difference), even though the null hypothesis is false.

for each of the largest sectors. We then summarise the conclusions from the sector-specific analysis at the end of this section.

2.5.4.1 Utilities

We begin our sector-specific estimation with utilities (SIC 4900-4999), as they account for the largest quantity of green revenues in absolute terms (at the 2-digit SIC sector level; see Figure B.4). As mentioned, firms classified as utilities consists of a broad and heterogeneous group including electricity generation, gas production and distribution, water-and waste management, and sanitary services among others. The heterogeneity in business models across these sub-sectors might lead to different responses to the production of green revenues.

For utilities as a whole, we observe marginally significant positive coefficients for operating income, as well as a significant relationship with ROA (Table B.22 and B.23). On market valuation, we obtain positive and consistently significant effects for green revenues on Tobin's Q (Table B.24). Even though the operating income of 'green' utilities is only marginally higher than for non-green counterparts, the effects persist for ROA. Utilities generating green revenues are able to obtain significantly higher levels of ROA compared to utilities not active in green technologies. They are also valued significantly higher by investors compared to non-green counterparts.

When utilities are further disaggregated at the 3-digit SIC level, some interesting differences occur. For electricity generation, which accounts for more than 70% of the green revenues within the utilities sector,[39] increasing green revenue shares (largely from renewable electricity generation) is associated with higher levels of operating profit margin (Table B.25) and marginally significant positive effects on ROA (Table B.26) but no significant effect on Tobin's Q (Table B.27). These results reinforce the observation that effects of green revenues on operative profitability are the most robustly observed across specifications and sub-samples.

What is driving the positive and significant effect of the green revenues share on Tobin's Q for overall utilities are non-energy related utilities (i.e. water-, and waste management, and sanitary services (SIC 494-497)). For non energy related utilities, we observe strong positive and significant coefficients (Table B.30) while the effects for energy-related utilities (electricity-, and gas production and distribution, SIC 491-493) are insignificant (Table B.31). However, for current profitability measures, we see re-

[39] See sectoral distribution in Figures B.4 and B.6. As for the robustness checks, we combine sectors 491 (Electric Services) and 493 (Combined Electric, Gas, and other Utilities) together to estimate the effect for electricity generating firms. Primarily electricity generating firms can be classified in either of the two classifications.

verse effects. Green revenues of non-energy utilities are not significantly associated with profitability in any model (Tables B.28 and B.29). For energy-related utilities we observe consistently positive and significant coefficients on the operating income and return-on-assets (Tables B.32 and B.33).

In short the higher profitability of green energy-related utilities is not transmitted into a higher market valuation. Green non-energy utilities have higher market valuations despite no difference in profitability. This suggests that investors expect growing business opportunities for non-energy related utilities. Firms in these sectors have among the highest sector-level averages of green revenue shares already (Figure B.7: Water Supply 72%, Sanitary Services 45% average green revenue shares). Yet the positive and significant relationship between green revenues and Tobin's Q still persists after controlling for firms' revenue growth, suggesting that investors anticipate further growth from more specialisation in "green" core activities, for example recycling of solid waste or water supply- and treatment.[40]

2.5.4.2 Manufacturing Sectors

After utilities, the largest green revenues in absolute terms are attributable to Manufacturing of Motor Vehicles and Equipment (SIC 371), and Manufacturing of Electronic Components and Accessories (SIC 367) (See Figure B.6 for sectoral distribution of green revenues at the 3-digit level). For firms in Manufacturing of Motor Vehicles and Equipment (SIC 371), we observe negative coefficients for the effect of green revenues on operative profitability (Table B.34 and B.35). Green revenues in these sectors are largely produced from manufacturing and selling hybrid- and electric vehicles. Our findings suggest that the earnings margins for such vehicles are lower compared to fossil-fuel based vehicles. This is backed by industry reports, which state that battery technology still tends to be more expensive compared to internal combustion engines. The average cost of production of an electric vehicle still exceeds a comparable combustion engine car by twelve thousand US dollars on average in 2019. Higher component costs, particularly of battery technologies, and limited take-up exert downward pressure on firms' operative margins (McKinsey & Company, 2019). The car manufacturer Volvo estimates for instance that its earnings-margins for electric vehicles will only match those of its combustion engine cars by 2025 (Reuters, 2019). Similar struggles have been reported by other car manufacturers as well (Reuters, 2018).[41] Our findings are in line with these observations. Car manufacturers that shift more aggres-

[40] Since an increase in business activities results relatively directly in an increase in green revenues for these sectors, it is important to note that the effect persists after controlling for revenue growth. Thus, the effect persists beyond a simple effect arising from an increase in business activities.

[41] See also Forbes (2019) for comments on limited take-up of electric vehicles in Europe.

sively towards hybrid- and electric vehicles production yield lower operative margins. Perhaps since the difference in earnings margins are expected to disappear by the mid 2020s and the hybrid- and electric vehicle markets are projected to grow rapidly into the future, firms' market valuation are not hampered by lower operative margins today (McKinsey & Company, 2019). We also do not observe significant relationships between green revenues and market valuations for manufacturers of motor vehicles (Table B.36).[42]

Manufacturing of Electronic Components and Accessories (SIC 367) accounts for the third largest quantity of green revenues in absolute terms. Green activities in this sector contain the manufacturing of electronic components for energy efficiency improvements, as well as the manufacturing of electronic components for renewable energy generation among others. For this 3-digit sector, we observe positive and significant coefficients for the Tobin's Q models (in the specifications without revenue-growth) (Table B.39), and no significant results for any of the profitability models (Tables B.37 and B.38). We are concerned that the sensitivity of the results might partly be due to the relatively small sample size, increasing the likelihood of a type 2 error. Therefore, we also examine the corresponding 2-digit sector SIC 36 (Manufacturing of Electronic and other Electrical Equipment and Components except Computer Equipment), which is the second largest sector at the 2-digit level (See Figure B.4).[43]

For the 2-digit sector SIC 36, we also do not observe significant relationships with respect to any of the profitability indicators (Tables B.40 and B.41), but we observe marginal significance in the Tobin's Q models (Table B.42). Hence, the effect at the 3-digit level (SIC 367) persists, albeit weakened, at the 2-digit level (SIC 36). One possible interpretation of these effects is that the sector is expected to benefit from future growth in renewable energy generation by providing equipment and components (see e.g. IEA, 2018, for renewables growth forecasts). With growth in renewable energy generation the suppliers of equipment and components are also expected to benefit, potentially increasing their market valuation. Moreover, investors expect large growth potentials for energy-saving electrical equipment (e.g. McKinsey & Company, 2010). Energy-efficiency technologies are considered to be one of the most important and cost-effective components in the low-carbon transition, by reducing energy consumption. Yet, numerous well-known barriers dampen the wide-spread uptake of such technologies. These include among others split incentives, high up-front costs, uncertainty about the amortisation time (see e.g. McKinsey & Company, 2010; Du

[42]We also do not observe significant relationships between green revenues and firms' return on investments as measured by ROA and ROE Table B.35.

[43]We also analysed the effects for the third largest 2-digit sector SIC 35 (Manufacturing of Industrial and Commercial Machinery). We do not observe any significant relationship with any of the profitability indicators nor with Tobin's Q. The results are therefore omitted.

et al., 2014; Diaz-Rainey and Ashton, 2015; Nehler and Rasmussen, 2016). The data does not allow us to precisely attribute our findings to particular barriers or policy interventions. Yet, the combination of anticipated growth potentials in combination with limited uptake could help explain the positive impacts on firms' market valuation despite no effect on their current profitability.

2.5.5 Summary of results

Our analysis shows that frontier firms that currently comprise the global green economy and generate revenues from the sale of green goods and services are highly concentrated in a few sectors. While there is sector heterogeneity in the impact of moving into the environmentally friendly market space on financial and market performance of firms, some generalisable results that hold for a broad group of sectors can be derived thanks to the comprehensive nature of this analysis. Overall, we found that firms shifting commercial focus towards green goods and services are typically able to obtain higher earnings per sales. This suggests that firms are moving into the green space in markets where premiums can be charged for green goods and services through, for instance, product differentiation. This result is robust across different model specifications and is generalisable across most sectors, as it holds even when all utility-sectors are excluded from the sample. The exception is the automobile manufacturing sector, where a shift towards clean vehicles (increasing the share of hybrid- and electric vehicles production) is associated with lower operating profit margins. This is in line with auto industry reports that show that higher component costs, in particular for battery technology, exert downward pressure on operating profit margins.

While most firms are able to increase profits per unit of sales by increasing their green revenue share, this does not necessarily increase profits per unit of investment (as measured by ROA and ROE). This is because the production of green goods and services tends to entail higher investments (per sale). This higher asset requirements impose a downward drag, such that going green does not significantly improve the ability to generate profits relative to capital investments entrusted to the firm. One exception is the utilities sector, and in particular the energy-related utilities, where return on assets increase with green revenue shares. For the rest of the economy, however, we find that increasing the green revenue share does not increase return on investments, hence the economic viability of such green shifts is ambiguous.

We also found evidence of sector heterogeneity in how investors value firms' decision to diversify into markets for green goods and services. Our analysis shows that the higher market valuation for increased green specialisation is largely limited to the non-energy related utilities sectors, where the green revenue share is associated positively with Tobin's Q. In other sectors, we find no robust evidence of firms being punished or rewarded by investors.[44]

2.6 Conclusion and discussion

With the growth in low carbon innovation and new green markets in the recent decades, this paper set out to assess how decisions to diversify production into green goods and services affects firms financial and market performance - whether it is a good investment that pays off for firms, or is rewarded or punished by investors. Prior analyses on the relationship between firms' environmental and economic performance found mixed results, and were often performed on poor quality or small sample sized data using for example, binary environmental performance indicators, cross-sectional data, or small datasets with limited sectoral- and country-coverage. This study makes a marked advancement to the literature on several dimensions including data, methodology, empirical findings and policy implications.

We construct a new firm level dataset recording green revenue shares, key firm characteristics and firm financial performance variables, that allows the use of better econometric techniques. The dataset is global, covering approximately 16,500 global publicly listed firms across 48 countries operating from 2009 to 2016 in a wide range of industries, representing approximately 98% of global market capitalisation. This dataset enables us to run estimations using panel fixed-effects specifications and exploit within-firm variation over time. This is possible thanks to the green revenue share variable that captures firms' strategic shifts away from the non-green and into the green economy over time at the firm level. We overcome a number of key limitations in the previous literature including selection and omitted variable bias. We evaluate impacts on firms' ability to earn income (using operating profit margin measures such as return-on-sales, ebit-, and ebitda-margins) as well as ability to generate profits relative to the capital investments entrusted to firms (using return-on-assets and return-on-equity). Linkages between these variables give additional insight into how going green affects firms' finances and into the current market environment for green technologies.

Our first main finding is that firms are typically able to obtain higher earnings per sales (operating profit margin) by moving into the environmentally friendly market space. This is consistent with Palmer and Truong (2017)'s findings using a much smaller sample, and our results can be interpreted in a much broader context in terms of geography

[44] Since the results on Tobin's Q for Manufacturing of Electronic and other Electrical Equipment disappear after controlling for Sales Growth, we are more cautious in the interpretation of this relationship and consider it to be less robust.

and sectors. This suggests that firms are moving into green activities in sectors where a green premium can be charged. Hence policies that help create clearly distinguished markets for green goods (e.g. through labelling, other information provision or green public procurement) may further encourage diversification into green markets. The automobile sector is an exception, as manufacturing of hybrid- and electric vehicles is associated with lower operating profit margins. This suggests that additional policy measures may be justified to accelerate the development and sale of low carbon cars. Carbon emissions from transportation account for about one quarter of global energy-related carbon emissions and continue to grow rapidly, even in advanced economies (IEA, 2017). Even though the costs for hybrid- and electric vehicle technologies have been declining, targeted R&D subsidies such as R&D tax credits and research grants or cheaper access to green capital could help to accelerate the decline in component costs.

The second main finding is that higher operating profit margins do not necessarily increase profits per unit of investment. We find that consistent with the DuPont Decomposition, this is because the production of green goods and services tends to entail higher asset requirements, which may be in the form of new machinery or specialised production facilities. We not only show how a positive effect on profitability as expressed as operating profit margin can be reconciled with a no effect on profitability as expressed by return on assets or equity, but highlight how the choice of profitability measure matters when examining impacts of environmental performance on economic performance, and how comparing results of studies using different profitability measures can be problematic.

Why would frontier firms move into the green space if higher profit margins are not yielding higher return on investments? A number of arguments can be put forward. González-Benito and González-Benito (2005) find that while ecological product design has no impact on return on assets, it is at times associated with better operational performance such as quality, reliability and volume flexibility. It may be argued that wile investors care about returns on assets (and equity), firm managers may focus (at least in the short run) on identifying opportunities to increase their operating profits, hence engage in green activities where they can earn higher returns per sale. Frontier firms moving into the production of green goods and services may also be driven by other factors such as environmental regulations (e.g. emission standards for vehicles) or expectations about green markets in the future. In order to mobilise large scale private sector investments and achieve a much broader low carbon transition rapidly, additional policy support will be necessary to ensure that diversifying into green markets is a sufficiently attractive business strategy. In particular, generating green goods and services demands a higher asset requirement, hence facilitating cheaper access to green capital through reduced interest rates, or risk sharing through public-private partnerships could encourage further private sector investment into these sectors.

A third main finding is that in general, firms' decisions to move into the environmentally friendly market space are neither rewarded or punished by investors on the stock market, except in the utilities sector. This indicates that for our sample time period (2009-2016) global stock markets did on average not anticipate significant growth opportunities for green goods and services in non-utility sectors. Thus, despite higher operating profit margins, investors do not value green firms more compared to non-green counterparts. This is consistent with the lack of a positive and significant impact of green revenue shares on return on investment (ROA, ROE), as investors are predominantly interested in firms' return on the capital they provide. Thus, they care about firms' efficiency of using assets and equity to generate returns. A higher operative margin is therefore on itself not sufficient to attract further investment. The findings suggest a cautionary tale on the current policy and investment landscape for low-carbon technologies. Since the international community requires large-scale investments into such technologies to meet the climate targets, additional financial resources are necessary (OECD, 2017; CPI, 2018). Therefore investors need to find it sufficiently profitable to invest in such technologies. Providing subsidies on 'green capital' to dampen the effect of additional assets (per sales) and to relatively improve firms' ROA and ROE, could help increase green firms' market valuation and attract additional investment. Such additional policies may be necessary to create the necessary investment environment to channel funds into green technologies.[45] [46]

A fourth main finding is around sector heterogeneity. For utilities, which tend to provide relatively homogeneous goods, the provision and diffusion of green technologies is largely driven by the supply side. Government regulation has been key to increase the supply of renewable electricity through renewable quotas and financial incentives

[45]Adopting the view of entirely efficient capital markets, the results can also be interpreted as meaning that there is no mispricing in the market based on firms' green revenue share. This view assumes that stocks are always and immediately priced correctly and that investors cannot find stocks that are either under- or overvalued (see e.g. Wall, 1995; Mollet and Ziegler, 2014). Empirical evidence however suggests that capital markets are not sufficiently efficient for this strict view to hold. Stocks and portfolios have been shown to experience systematic mispricing based on environmental performance and other indicators (see e.g. Hong and Kacperczyk, 2009; Edmands, 2011; Eccles et al., 2014).

[46]We would also like to note that it can be argued that by excluding all utilities from the sample, the likelihood of a type 2 error increases. This might occur as we drop the sectors with a large amount of variation in the main independent variable. In other words this may increase the likelihood of not observing an effect, even though a true effect exists. We would fail to reject the null hypothesis (of no difference) even though it is false (see e.g Ziegler, 2012). If our results on the restricted non-utility sample were due to a type 2 error, the overall policy implications would however remain largely unchanged. The negative impact of additional asset requirements on firms' comprehensive performance also exists for the sample with utilities. To meet the climate targets large-scale additional investments into low-carbon technologies are required over the next decades. To accelerate such investments our findings suggest (across non-utility and utility samples) that reducing the costs for green investments is an important factor.

for renewable energy generation (IRENA, IEA, and REN21, 2018). Indeed our results show that going green is already an economically viable move in the utilities sectors, and is rewarded by the stock market. To a large degree this may be attributable to the low-carbon policy support for these sectors in many countries. For example, as is well known, significant public investments have gone into driving down renewable energy costs, both through price based instruments such as feed in tariffs and technology support policies such as R&D tax credits or public research grants (see e.g. Bloom et al., 2019). Our results highlight that in contrast to utilities, for the rest of the economy, policy support is less strong and likely insufficient given the urgency and size of the challenge to decarbonise the economy over the next decades (e.g. IPCC, 2018). Specifically, we show that supporting financing costs for green investments can help firms to convert higher earnings-margins into higher return on investments, which may therefore induce more investment in green technologies. For non-utilities, motives for the adoption and diffusion of green technologies are different because they are more exposed to international competition. Producers can capture greater global market shares by responding to changing demands with product differentiation (e.g. Robinson, 2018). For example in energy efficient appliances or electric vehicles, consumers may have a different willingness to pay for green and non-green products (e.g. Jovanovic and Rob, 1987; OECD, 2011; Antonnen et al., 2013). Supply side policies, such as emissions- or energy efficiency standards help drive technologies and demand forward, as do demand side policies such as subsidies for electric vehicles.

Overall our findings highlight important shortcomings of current policy and investment landscape for low-carbon technologies. Large-scale investments to develop, deploy and diffuse low carbon technologies are imperative for meeting the climate targets (OECD/IEA, 2017). It appears that so far, public policies are making some head way in reducing environmental impact and enhancing economic as well as market performance of firms, but only in utility sectors. On the one hand this is encouraging news, as it demonstrates that policy support can correct market failures and harness the ability of markets to deliver public goods. On the other hand, it highlights that much more policy intervention across a broader spectrum of the global economy is needed to align incentives such that developing new, cleaner products and services in response to changing customer preferences improves not only firms' environmental performance but also financial and market performance, through the 'revenue channel'.

Chapter 3

Do International Agreements Matter for Financial Markets? New Evidence from the Paris Agreement.

Abstract

The Paris Agreement is considered a landmark of international efforts to mitigate climate change, yet it is unclear if it can actually deliver meaningful outcomes since it is largely built upon voluntary pledges. We use event study methodology to examine if the Paris Agreement actually mattered for investors and financial markets. In particular we show that firms, which generate revenues from producing "green" goods and services have experienced significantly positive abnormal returns in the week following the agreement relative to the overall market. We show that this effect exists both at the extensive and intensive margin of firms' green revenue share. The effect is not limited to electricity generation, but holds for a larger group of sectors. Secondly, we show that emissions-intensity is a less clear-cut determinant for firms' financial performance following the Paris Agreement. While we observe negative returns for some emissions-intensive firms, the effect is highly heterogeneous across sectors. Interestingly, the most carbon-intensive electricity generating firms observe positive abnormal returns. Combining the emissions-intensity and green revenue data, we show that the most emissions-intensive electricity generating firms are also, and sometimes quite heavily, engaged in green technologies with substantial renewable electricity shares. Investors appear to value in particular the growing opportunities for firms active in green technologies following the Paris Agreement.

3.1 Introduction

International cooperation to mitigate climate change has a long history beginning with at least the Rio Conference in 1992 to the Conference of the Parties (COPs) in Kyoto, Copenhagen and Paris among others. Yet, the past experience of climate negotiations, and in particular the unsuccessful 2009 Copenhagen conference, led many observers to disbelieve in the multilateral process. Against this background, the Paris Agreement offered a breakthrough in climate diplomacy (Falkner, 2016). Commentators described the passing of the agreement as a "landmark" (Davenport, 2015) (*The New York Times*) and "milestone" (Tompkins and Levin, 2015) (*World Resources Institute*) of international climate negotiations. Moreover, it is considered as "breaking new ground" (Falkner, 2016, p.1107) and a "turning point" (Stern, 2015a) in international climate diplomacy. While the unanimity of the agreement has been praised, shortcomings in particular with respect to its stringency and enforceability have been raised subsequently.

Compared to previous climate summits, the Paris Agreement adopted a new strategy allowing countries to set their own targets (Nationally Determined Contributions or NDCs) in combination with an international review process that would scrutinise the ambitions of individual pledges. This "pledge and review" process will determine the actual ambition of the agreement and will to some extent depend on the outcome of a "naming and shaming" process that encourages countries to gradually strengthen their targets (Falkner, 2016, p.1107). Thereby, COP-21 and the Paris Agreement shifted away from requiring mandatory emissions reductions from countries, which had been a major barrier in past negotiations. The non-mandatory approach and the flexibility, through which countries can determine their own ambition has likely provided the breakthrough in the negotiation process (Falkner, 2016). It has been argued that such a decentralised approach may be a promising avenue for global cooperation. It can facilitate the gradual building of trust among countries and may lead to incremental strengthening of cooperation and coordinated emission reductions. Such decentralised coalitions might therefore result in more effective mitigation action compared to mandatory targets, which have deadlocked negotiations in the past (Bernauer, 2013; Keohane and Victor, 2016). Game theoretic and experimental work have also increasingly focused on the potential benefits from non-mandatory international cooperation. Instead of the required emissions-reductions, the NDC approach might facilitate small-scale coalitions, which may encourage laggards to follow and gradually adopt more ambitious emission reduction goals (e.g. Bosetti et al., 2017; Marchiori et al., 2017). So, one potential avenue for the Paris Agreement to gradually strengthen its emission reductions is through the formation of coalitions of ambitious countries which encourage others to follow.

Nevertheless, it remains unclear whether an international agreement largely built upon voluntary pledges can actually deliver ambitious emissions reductions and can facilitate the transition towards a low-carbon economy.[1] Since climate mitigation is a global public good, individual incentives to reduce emissions are limited. It remains unclear whether other countries would follow once some countries start reducing emissions and adopt a low-carbon development path. The incentives for free-riding and the absence of a supranational authority provide a major barrier to meaningful international cooperation to mitigate climate change (Hardin, 1968; Barrett, 2006). Since the pledges are voluntary, a particular concern is that observed effects might not go beyond business-as-usual emission reductions (e.g. due to gradual efficiency improvements). The concern is reinforced by recent work of UNEP (2018) showing that the current NDCs imply a global warming of about 3°C, rather than the intended 1.5°C. Similarly, a survey among 600 experts from the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC) reveal a low level of confidence among experts in voluntary pledges to deliver ambitious emission reductions (Dannenberg et al., 2017). The US announcement to withdraw from the agreement provided a major setback, even though the withdrawal may only take effect the day after the next presidential election in 2020 (see for example Mooney, 2017). Lastly, global greenhouse gas emissions have risen again in 2018 and are estimated to continue rising in 2019 (Global Carbon Project, 2018; Met Office, 2019). Thus, it remains to be seen if the voluntary commitment approach of the Paris Agreement is at all credible.

In addition to agreeing on the NDC approach and the submission of reduction targets, the international community also agreed to making international "finance flows consistent with a pathway towards low greenhouse gas emissions and climate resilient development" (UNFCCC, 2016, p.22). Thus, the ambition of the agreement goes beyond emission reductions, but aims to redirect and restructure financial flows towards a low-carbon and climate resilient economy. Again, it is however unclear if a non-binding international agreement based on voluntary pledges is able to deliver such an ambitious goal. Hence, in addition to assessing the immediate impact on carbon emissions, it is important to assess whether the agreement is credible and effective at providing the right policy-framework and incentives for a transition towards a low-carbon economy. One way to assess the credibility is by examining the reaction of the financial markets

[1] We refer to the agreement as voluntary and non-binding since countries are only legally obliged to submit a Nationally Determined Contribution, but the level of ambition of this NDC is entirely voluntary. Furthermore, large parts of the agreement are either non mandatory or non enforceable. This is to be regarded separately from the discussion in environmental law on whether the agreement, or parts of it, are "legally-binding" (See for example Bodansky (2016a,b), which refers largely to the legal nature of the NDCs).

to the agreement. In particular by analysing the potentially heterogeneous responses for "green" and "dirty" portfolios. It is important to note that this does not assess the credibility with respect to emission reductions, but rather the credibility with respect to the technology diffusion and adoption of "green" or low-carbon technologies, which are essential to achieve emission reductions.[2] Similarly, it provides insight into the anticipated use of relatively "dirty" or carbon-intensive technologies, which need to be faced-out to achieve the emissions reductions targets and to remain well below 2°C (e.g. UNEP, 2018).

In addition to contributing to the discussion on the credibility of international climate agreements, we also contribute to the debate within environmental economics on whether financial markets actually respond to firms' environmental performance. So far the literature has provided mixed results. Some evidence suggests that investors value firms' improvements in environmental performance when it is related to reductions in risk from future liabilities or potential future regulations. Khanna and Damon (1999) show for instance that voluntary participation in the US EPA 33/50 programme to reduce toxic release emissions is positively valued by investors. Clarkson and Li (2004) find evidence that investors use environmental performance information to assess potential future abatement spending for firms in the pulp and paper industry. Some studies have however also shown that firms' voluntary commitment to improve their environmental performance is negatively related to stock performance. Fisher-Vanden and Thorburn (2011) show that membership in voluntary environmental programmes is negatively associated with stock returns for the period 1993-2008. Similarly negative effects are found by Cañon-de Francia and Garcés-Ayerbe (2009) for the voluntary adoption of the ISO 14001 norm between 1996-2002. Oberndorfer et al. (2013) identify significantly negative returns for firms being included in a sustainability index between 1999-2002. These studies conclude that voluntary measures to improve the environmental performance tend to impose unproductive costs and may be a reaction to institutional pressures. Such additional voluntary costs can therefore lead to negative stock returns.

Even though it is difficult to identify a time-trend from previous findings because of different data and study contexts, it is interesting to note that some of the most recent studies suggest that such negative effects may be reversing. By disaggregating year-by-year effects Moliterni (2018) shows that firms' commitment to reduce emissions has become significantly positively related to their market valuation in the more recent years of the sample (2013-2016), while it was not significantly related in the earlier

[2]Green technologies include low-carbon technologies, but also other technologies which help reducing the overall impact on the environment and that may not be directly linked to greenhouse gas emissions. These include technologies in water management or resource efficiency technologies among others.

years (2010-2012). Lourenço et al. (2012b) shows that membership in a sustainability index is positively associated with firms' stock performance for the years 2007-2010. Matsumura et al. (2014) find that voluntary disclosure of carbon emissions is positively associated with firm value and that higher carbon emissions are punished by investors for the period 2006 to 2008. Even though heterogeneities in the findings exist, they seem to suggest that in more recent years, in particular since the mid-2000s, the effect may be changing towards a positive relationship between firms' voluntary commitment to improve their environmental performance and market valuation (see also Moliterni, 2018, for a discussion of time trends across studies).

A number of limitations exist across the present studies. First, studies have largely been limited to binary measures, such as the inclusion in a sustainability index, the implementation of an environmental management system or the self-reported commitment to reduce emissions (e.g. Cañon-de Francia and Garcés-Ayerbe, 2009; Ziegler et al., 2011; Ziegler, 2012; Lourenço et al., 2012b; Oberndorfer et al., 2013; Moliterni, 2018). Such results are therefore limited to extensive margin effects and may hide variation in the actual commitment level. Second, the inclusion in a sustainability index for instance is not only determined by firms' environmental performance, but may also depend on other factors such as its past stock performance, which may make it difficult to isolate the effect of the environmental performance. Third, in addition to the above binary indicators, some studies examine firms' environmental performance with respect to emissions, i.e. a by-product of firms' business activity, which is linked to firms' production costs (e.g. Khanna and Damon, 1999; Clarkson and Li, 2004; Rassier and Earnhart, 2015). Emission reductions can be valued because they capture efficiency improvements in the material or energy input use and not because of their environmental benefits. These findings are linked to the "cost channel", through which firms are able to improve their economic performance through efficiency improvements, which in turn result in better environmental performance (see Ambec and Lanoie, 2008, for a detailed discussion of the cost and revenue channels). While these effects are clearly important they are limited to capturing the productive efficiency of firms. Fewer studies have analysed the "revenue channel" through which firms can improve their economic performance by shifting their business activities towards producing "green" goods and services. Rennings and Zwick (2002) and Rennings et al. (2004) use binary information on whether firms have introduced new green products using a telephone survey. They find positive associations with firms' subsequent employment levels in a cross-sectional analysis. Similar results are obtained by Horbach (2010) in a panel from 2002-2005. Palmer and Truong (2017) find that green product introductions are positively associated with firms' accounting profitability using a panel of 79 global firms between 2007-2012. These results are however limited to employment levels or accounting based profitability. A related paper by Kruse et al. (2019) (Chapter 2) examines the relationship between green goods and services and both accounting and market based indicators using a panel regression. In their panel setting they are however unable to identify a causal effect.

We are able to overcome some of these limitations by using a continuous measure of firms' "green" revenue share. It captures the share of revenues from the production of green goods and services. This allows us to construct portfolios based on a continuous variable, capturing the intensity of firms' green activities. To the best of our knowledge this is the first event study to examine the reaction of financial markets to a detailed green product-based measure. It allows novel insight into the market's perception of growth opportunities for green goods and services. An advantage of using event study methodology is that it allows us to identify a plausibly causal effect arising from firms' green revenue share on their market valuation. This is typically not possible in similar papers using panel regressions or portfolio analysis (as for example in Ziegler et al., 2011; Lourenço et al., 2012b; Kruse et al., 2019). We use the Paris Agreement as it created a large, discrete, and plausibly exogenous shift in the reward for being green. Without such a discrete event it would be difficult to attribute any change in financial returns to preferences for financing such firms because the choice of investing in green firms is endogenous and there are many other factors influencing decision making in financial markets.

In this paper we examine whether and to what extent, financial markets reward green goods and services and whether they might punish carbon-intensive firms following the Paris Agreement. This allows us to provide novel insight on the credibility of the Paris Agreement with respect to the diffusion and adoption of green goods and services. More generally, it allows us to asses investors' perception of the post-Paris policy landscape. We show that financial markets respond to environmental activities of companies. In particular they reward the share of revenues from the production of "green" goods and services. Importantly, the effect exists both at the extensive and intensive margin of firms' green revenue share. The emissions-intensity of firms is however a less clear-cut determinant for market reactions following the Paris Agreement. The remainder of this paper is structured as follows: In Section 3.2 we review the related event study literature. Section 3.3 explains the methodology and the different data sets we use for our analysis. Section 3.5 presents the results and Section 3.7 discusses the findings and concludes.

3.2 Event Study Literature

Short-term event studies are particularly common in financial economics. They are commonly applied to examine the effect of mergers and acquisitions, earnings announcements, or the effect of new regulation (MacKinlay, 1997).[3] Event studies have recently also become more popular within environmental economics. Oberndorfer et al. (2013) examines the effect of the inclusion of nearly 30 German firms into a sustainability stock index between 1999 and 2002. They find that the inclusion is penalised by the market and results on average in a relative decrease of stock returns (-2% on average). The authors conclude that such inclusions appear to be regarded as a reaction to institutional pressures that mandate firms to invest in corporate sustainability activities and result in unproductive costs. A similar finding is obtained by Cañon-de Francia and Garcés-Ayerbe (2009) who examine investors' responses to firms' voluntarily adoption of the ISO 14001 environmental certification. They show that adopting the norm has generated negative abnormal returns for firms. Similarly, they argue that investors perceive the voluntary adoption of an environmental standard to be unproductive and as a response to institutional pressures. Hence, productive resources are diverted to complying with the certification instead of being invested in productive activities.

In the closely related branch of natural resource economics, event study methodology has been applied to examine effects of anticipated or actual regulation on carbon-intensive firms. Lemoine (2017) identifies Green Paradox effects due to a suggested strengthening of legislation in the US Senate. The discussion of strengthening environmental policy led to an increase in carbon emissions due to inter-temporal leakage and firms maximising profits prior to the anticipated regulation. Sen and von Schickfus (2019) study two large coal-intensive German electricity providers. Using the gradual development of a German climate policy aiming at phasing out coal, they show negative abnormal returns for German electricity providers. These effects are however dampened by anticipation of financial compensation. They find that the German climate levy and coal phase-out scenarios imply substantial losses for these energy providers and resulted in 4% negative average abnormal returns over a five day window around the respective events. A slightly different approach to examine investors' perceptions of stranded asset risks is adopted by Griffin et al. (2015). They use a 2009

[3] We focus on short-term event studies since they are considered to be more robust compared to long-term studies. Long-term studies typically examine event-horizons over multiple years (e.g. Lyon et al. (1999)). Long-term event studies are methodologically similar to portfolio analyses, which typically compare the development of returns over multiple years (e.g. Mollet and Ziegler (2014)). Trade-offs exists in the respective approaches. While portfolio analyses can provide insight into the relative performance of stock returns over long time horizons they can typically not establish causality. We leave such long run studies for future research.

article published in *Nature* and the subsequent media coverage. The *Nature* article argues that a large share of global fossil fuel reserves is ‘unburnable’ when aiming to remain below 2°C of global warming. They find that the publication and the subsequent media coverage lead to a 1.5-2% decline in average stock prices for a sample of 63 US oil and gas firms.

A related paper by Mukanjari and Sterner (2018) examines the effect of the Paris Agreement on coal and renewable energy Exchange Traded Funds (ETFs). They find no significant effects of the Paris Agreement on coal ETFs. Furthermore, they find no strong significant effect for renewable and non-renewable energy ETFs except for solar energy. They argue that the coal industry has already been declining in many countries due to cheaper substitutes, increased energy efficiency or slowing growth in coal consuming countries, so that investment has already started to shift away from coal prior to the agreement. Using ETFs for Event Studies can potentially be problematic, as stocks are not only selected into the ETF based on their industry grouping, but also based on their past stock performance (returns, volatility), which may induce some form of endogeneity. Abnormal returns on ETFs might therefore potentially not only arise because firms are active in renewable electricity markets, but also because they have been selected for example as a particularly well-balanced portfolio or as a portfolio of highly-promising renewable firms.

In this paper, we use novel data on the precise share of firms’ revenues from producing green goods and services. This allows us to show that investors value both the extensive and intensive margin of firms’ involvement in green technologies. Furthermore, we show that the effect is not only limited to renewable energy generation, but spreads across a broad category of sectors. Furthermore, we are able to show that emissions-intensity is a less clear-cut indicator for investors. On its own it appears not to be a strong determinant of investment decisions following international climate agreements. Emissions-intensive electricity generating firms seem to be a special case in the current policy environment. For electricity providers with mixed portfolios of both highly carbon intensive fossil fuels as well as emerging shares of renewable electricity, we show that the opportunities arising from the share of renewable electricity appears to be particularly valued by investors.

3.3 Methodological Approach

3.3.1 Event Study Methodology

Event studies mostly examine so-called "normal" and "abnormal returns", which are estimated from capital asset pricing models (CAPM). The most basic approach is the one-factor model based on the CAPM for a firm or stock *i* on day t (i=1,..., N; t=1,...,T) ((Brown and Warner, 1980; Campbell et al., 1997))

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it} \tag{3.1}$$

where r_{it} is the return for share *i*, and r_{mt} is the return of the market portfolio at the end of day t. The risk-free interest rate at the beginning of period t is expressed by r_{ft}, and ε_{it} is the error term with expectation $E(\varepsilon_{it}) = 0$ and variance $Var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$. The term $(r_{it} - r_{ft})$ on the left hand side is also referred to as the excess return r^e_{it} , and $r_{mt} - r_{ft}$ as the index excess return r^e_{mt} (with respect to the risk-free rate). All returns are defined as logarithmic returns. The parameters α_i, β_i are unknown and estimated by the model. The normal (excess) returns $E(r_{it} - r_{ft})$ are unknown and defined as the expectation of (excess) returns without conditioning on the event. Abnormal returns (AR) are defined as the difference between the observed and the normal (excess) returns (Oberndorfer et al., 2013):

$$AR_{it} = (r_{it} - r_{ft}) - E(r_{it} - r_{ft}) \tag{3.2}$$

While this one-factor market model for abnormal returns is the simplest approach, many studies show that the three-factor model developed by (Fama and French, 1993) has more explanatory power and also shows desirable characteristics for robust statistical inference (Fama and French, 1993, 1996; Hussain et al., 2002; Kolari and Pynnonen, 2010).[4] The three-factor model includes two additional terms SMB_t and HML_t. The former is called the small-minus-big market capitalisation factor return. The latter is referred to as the high-minus-low book-equity/market-equity factor return at day t. The rationale for the SMB factor is that stocks with small market capitalisations tend to outperform the market. The HML factor adjusts for the finding that so called value stocks, which are stocks with a low market valuation relative to its fundamentals (measured by Price-to-earnings or Price-to-book ratio among others), also tend to outperform the market. Including these two factors allows to control for this systematic

[4] By including the additional two factors the Fama French model reduces cross-sectional correlation between shares substantially (Kolari and Pynnonen, 2010), which is important for correct inference in particular in the context of event day clustering.

outperformance. Fama and French (1993) show that these additional terms are particularly well-suited to capture common variation in stock returns (for further details on these factors see Fama and French (1993)).[5] All of the models require the underlying assumptions that there is an element of surprise in the event and that there are no other confounding events occurring.

In the 3-factor model, the abnormal returns are estimated as the difference between the realised and predicted returns on day t in the event period.

$$\widehat{AR}_{it} = r^e_{it} - \left(\hat{\alpha}_i + \hat{\beta}_{i1} r^e_{mt} + \hat{\beta}_{i,2} SMB_t + \hat{\beta}_{i,3} HML_t\right) \tag{3.3}$$

The estimated abnormal returns can be aggregated cross-sectionally and over multiple event days. Estimated average abnormal returns (AAR) over the cross-section of N firms are defined as ((Khotari and Warner, 2006):

$$\widehat{AAR}_t = \frac{1}{N}\sum_{i=1}^{N}\widehat{AR}_{it} \tag{3.4}$$

Aggregating these estimated average abnormal returns over multiple event days (starting at time t_1 through time t_2) results in estimated cumulative average abnormal returns (CAAR)

$$\widehat{CAAR}_{t_1,t_2} = \sum_{t=t_1}^{t_2}\widehat{AAR}_t \tag{3.5}$$

Figure 3.1 illustrates the stylised time line of event studies. The "estimation period" is used to generate predictions of returns for the event period. These predictions capture the returns in the non-observed potential outcome that the event had not taken place. Abnormal returns are then estimated for each firm i in the "event window" by comparing the observed returns relative to the predicted counterfactual. If the estimation window is sufficiently large the estimated abnormal returns are approximately normally distributed with expectation zero and variance $\sigma^2_{\varepsilon_i}$. The event window is typically defined as beginning twenty days prior to the event, to reduce bias from anticipation. and

[5]The daily Fama-French factors, are constructed using 6 value-weight portfolios formed on size and the book-to-market ratio. The SMB factor is constructed by subtracting the average return of the three 'large portfolios' consisting of large firms according to their market equity, from the average return of the three portfolios containing small firms (according to their market equity). The HML factor is constructed by subtracting the average returns of the two growth portfolios from the two value portfolios. The growth and value portfolio is constructed based on the ratio of book equity to market equity (BE/ME). Firms in the top 30% of BE/ME are included in the growth portfolios. Firms with a BE/ME ratio in the bottom 70% are included in the value portfolio. The portfolios include all NYSE, AMEX and NASDAQ stocks (Information taken from Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.)

ending up to ten days after the event ($t_{-20,10}$). In line with the existing literature we define the estimation window to be the one hundred days prior to the event window ($t_{-121,-21}$). The event day t_0 is defined as the first trading-day at which the event becomes effective (MacKinlay, 1997). In our case this is Monday 14 December, the first trading day following the agreement (See timeline of negotiation process in Section 3.3.2).

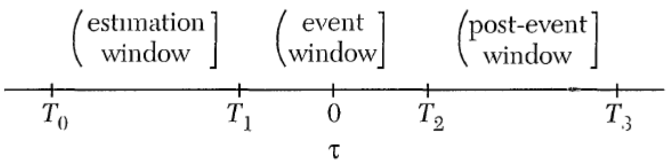


Figure 3.1: Time line for an Event Study (from MacKinlay (1997))

The null hypothesis of event studies is that the event has no effect on excess returns. To test this hypothesis we use the commonly used nonparametric Corrado (1989) rank test with the aggregation approach by Cowan (1992) for cumulative average abnormal returns (CAARs), which implicitly accounts for cross-sectional correlations across firms (Kolari and Pynnonen, 2010; Oberndorfer et al., 2013).[6] One advantage of nonparametric tests over parametric tests such as the Patell (1976) and Boehmer et al. (1991) (also known as the BMP test) is that they do not rely on distributional assumptions of abnormal returns. Since stock prices are typically not normally distributed, nonparametric tests have become the most commonly used test statistics (Kolari and Pynnonen, 2011). As a robustness check we also use parametric tests, in particular the commonly used BMP (Boehmer et al., 1991) test as well as the parametric KP test, developed by Kolari and Pynnonen (2010). One concern in event studies is that the cross-sectional variation in the true abnormal returns results in variance increases around the event (also called event-induced volatility). This may bias commonly used parametric tests towards rejecting the null hypothesis (such as the Patell (1976), or Brown and Warner (1985) tests). Harrington and Shrider (2007) show that among the parametric tests, the BMP test is robust to such an event induced increase in volatility.[7] Furthermore, we also use the KP test statistic, which further modifies the BMP-test statistic to account for cross-correlation in abnormal returns. We report results using the nonparametric Corrado test in the main part of the paper. Results using the BMP, and KP test statistics are reported in the Appendix in Figures C.8 & C.9, and C.10 & C.11.

Instead of using OLS to estimate the 3-factor Fama-French model, we use a more

[6]Using the Cowan (1992) adjustment for CAARs is important as these nonparametric tests were developed to examine single-day returns (Kolari and Pynnonen, 2011). The Cowan (1992) approach overcomes the potential problems with the Corrado test by cumulating daily ranks of abnormal returns within the CAR-period.

[7]In other words the test is robust to heteroskedasticity arising from unexplained variation in the true abnormal returns Harrington and Shrider (2007)

robust GARCH model (Bollerslev, 1986). GARCH stands for generalised autoregressive conditional heteroskedasticity model. One concern for correct inference in event studies is that the variances of the returns are time varying with some degree of autocorrelation, which is not accounted for in OLS models. Financial markets are prone to conditional heteroskedasticity, as upward or downward price spikes can trigger automated response orders, which are commonly used to manage risks among investors. Price spikes can therefore induce additional volatility, which is serially correlated, or in other words conditional on periods with elevated variance. GARCH models consider a varying conditional variance and are therefore able to deal with such serial heteroscedasticity by using past values of the variance. More specifically GARCH uses autoregressive lags and moving average lags of the variance to absorb the effects of conditional heteroskedasticity (Kolari and Pynnonen, 2010, 2011). The GARCH(p,q) model is a generalised model, in which p and q indicate the order of autoregressive terms in the model. The GARCH(1,1) model is a specific case commonly applied in financial time series. It considers one autoregressive lag and one moving average lag. We use GARCH(1,1) models throughout the analysis.

Similarly to Sen and von Schickfus (2019) we report our main results in 3-day 'rolling' cumulative average abnormal returns (CAARs), which cover the 3-day window centred around the respective median day (3-day windows are also used by Kogan et al. (2017) among others). This allows us to show further variation in the data compared to for example a 5-day analysis window (used among others in Oberndorfer et al. (2013)). We also report and discuss results on 5-day CAARs in particular to quantify the magnitude of the effects over the entire post-event period (Figures C.6 and C.7 in the Appendix). Inference based on CAARs reduces the possibility of incorrect rejection of a true null hypothesis (of no difference) (type I error). However, it increases the possibility of failing to reject a false null hypothesis (of no difference) (type II error) (Sen and von Schickfus, 2019).[8]

3.3.2 Event Studies with Partial Anticipation

One particularity of studying the effect of the Paris Agreement is that it was preceded by a two-week negotiation period. Information on the negotiation process was regularly made public and covered in liveblogs and newsfeeds. Hence, the two-week negotiation period provides us with interesting insight into the uncertainty in the market and varying expectations about the agreement as the negotiations progressed. One

[8]In other words, inference based on CAARs reduces the likelihood of observing significant effects, even though a true difference exists. It increases the likelihood of observing no significant effects, even though a true significant difference exists. The comparison is with respect to firm-specific cumulative abnormal returns and average abnormal returns

crucial requirement for event studies is that the event contained a surprise element. In the absence of surprise the outcome would already have been absorbed by the market. Hence, it is important to show that there was still considerable uncertainty on the last day prior to the agreement. The agreement was scheduled to be passed on Friday 11 December. The negotiations were however extended until Saturday, as an agreement could not be reached by Friday. Hence, on the last trading day prior to the signing there was still considerable uncertainty on whether the agreement would actually be passed, whether all countries would sign-up and how stringent it would be. In particular it was unclear if the more stringent 1.5°C warming target would be included instead of the more lenient 2°C. In particular the role of large emerging economies remained unclear until the very end of the negotiations. Brazil for example only joined the "coalition of high ambition" (also known as the "progressive alliance") at around 4:30pm (CET) on Friday 11 December. This was considered a potential game changer, as it was the first large emerging country to join this coalition. This raised expectations that it would become a bridge builder towards the other large emerging economies to increase their ambition (See for example the Guardian liveblog on 11 December 4:30pm (CET) from the Paris negotiations (Vaughan, 2015)). Furthermore, large oil producing states like Saudi Arabia risked an unanimous agreement. In overnight negotiation sessions towards the last officially planned day of the negotiations (Friday 11 December), Saudi Arabia stepped up its opposition against the 1.5°C target, arguing that the science is not entirely conclusive on the issue of whether 1.5°C warming is preferable compared to a 2°C scenario. This objection risked that the more ambitious 1.5°C target could be adopted unanimously. Lastly, on Friday 11 December at around 4pm (CET) the Indian Environment Minister gave a press conference saying that there would still be a "long road ahead" if there was not more effort from the developed nations and that the likelihood of passing the agreement hang in balance (ClimateHome, 2015). Hence, there was still considerable uncertainty on Friday 11 December 2015 on the ambition, the unanimity, and the final wording.

It is however important to note that the potentially surprising outcome of the agreement was accompanied by an ex-ante probability. Conceptually our approach is similar to Kogan et al. (2017) who examine the market's reaction to firms' being granted a patent after a period of uncertainty between the patent application date and the decision of the patent office. Similar to their theoretical framework we assume that the individual market value γ_i for firm i in the potential outcome that the Paris Agreement is accepted is known to investors. π_i denotes the market's ex ante probability assessment that the agreement is passed in the final, more ambitious wording. On Monday 14 December a firm's stock market reaction ΔV_j is then given by

$$\Delta V_i = (1-\pi_i)\gamma_i \tag{3.6}$$

It represents the change in the market value for firm i in a scenario where the agreement is passed compared to the counterfactual of it not being passed (Kogan et al., 2017). In particular, we observe the effect of the resolved uncertainty in the market following the agreement. The market's reaction to the agreement therefore understates the total impact on the firm value since the information about the probability is known prior to the agreement.

It is important to note that investors' responses to the Paris Agreement may be different from their response to more common events such as earnings announcements. The agreement contains a complex set of information that needed to be absorbed by the market. First, the ambition of countries' pledges had to be understood. Second, since emission reduction pledges are voluntary and non-enforceable, the political interpretation became essential to assess how serious countries were in implementing the agreement. Absorbing such a complex set of information might therefore be different from reacting to firms' earnings announcements, which occur frequently and in a standardised format. Hence, we might expect a gradual onset of effects, as investors had to digest a rich set of information.

3.4 Data

In this paper we test in particular whether groups of 'green' and 'dirty' firms have experienced abnormal returns in the week following the Paris Agreement. To test the hypotheses we mainly rely on two separate datasets: the share of firms' revenues generated by producing green goods and services ("green revenues"), and firms' emissions-intensity. Each dataset is outlined below in detail. For each sample, we divide firms into deciles based on the relative metric (green revenue share, emissions intensity).[9] Based on the deciles we construct portfolios of 'green' and 'dirty' firms. Descriptive statistics for each of the subsamples are reported in the Appendix in Table C.1. When grouping firms into particularly 'green' or 'dirty' portfolios it is important to take a sufficiently early cut-off date to avoid anticipation effects as much as possible. While the COP-21 took place at the end of 2015, in 2014, the US and China already made a joint announcement on climate change to work constructively together to mitigate climate change.[10] The announcement already included emission-reduction pledges from

[9] The Green Revenue and Trucost Emissions database provide information on a yearly basis.

[10] See for example this article in the Guardian (Taylor and Branigan, 2014): `https://www.theguardian.com/environment/2014/nov/12/china-and-us-make-carbon-pledge`,

both countries. It was considered to be a major milestone in increasing the likelihood that a global agreement could be passed at the next COP in Paris. Hence, we choose 2013 as the cut-off year to group firms into portfolios to prevent direct anticipation effects.[11] We outline the precise grouping in the following sections for each dataset separately. First, we discuss the financial data, which we use across all subsamples.

3.4.1 Financial Data

Throughout the analysis we only look at US firms. The crucial assumption required to obtain robust results from an event study is that the underlying "market" (counterfactual) is a good comparison to the portfolio of firms being analysed. We use the daily 3-factor data provided by Kenneth French on his website.[12] The US time series includes all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ, which gives a comprehensive counterfactual market. The Center for Research in Security Prices (CRSP) provides the most comprehensive coverage of US stock price data covering more than 32,000 securities with primary listings in any of the main US stock indices. More recently data on the SMB and HML factors has also been provided for other parts of the world e.g. for Europe or a global coverage. However, these are constructed by using regions' value-weighted portfolios. Hence, different country-weightings in our available green revenue and emissions data would make the results less reliable and may introduce bias. Early results have confirmed this concern. For European and global portfolios we observed significant abnormal returns across many pre-negotiation periods, which indicates that the market may not be a suitable counterfactual for the selected portfolio of firms. This prevents robust causal analysis, as any significant abnormal returns in a post-event period may also simply result from using a poor counterfactual. Hence, we have focused on US firms in this analysis.

3.4.2 Green Revenue Data

We use a novel dataset developed by the financial services company *FTSE Russell*, which captures the share of firms' revenues that is generated by 'producing' green

or the statement provided by the Obama Administration (The White House, 2014): `https://obamawhitehouse.archives.gov/the-press-office/2014/11/11/us-china-joint-announcement-climate-change`.

[11] We want to rule out as much as possible that firms anticipated that an ambitious climate agreement would be passed in 2015 and therefore invested in green technologies in anticipation of positive returns for their firm.

[12] The data is available from: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. (We downloaded the data on 18 March 2019).

goods and services (See Kruse et al. (2019) (Chapter 2) for a detailed discussion of the Green Revenues (GR) dataset). When referring to green firms, we refer to firms that produce a share of their revenue from selling green goods and services. *FTSE Russell* developed its own classification for green revenues. It covers a broad group of products and services, including traditionally green activities such as water-, and waste-management as well as more recent technologies such as electric vehicles and renewable electricity. The analysis is conducted in a centralised way within *FTSE Russell* to reduce potential bias from self-reported non-quantifiable environmental performance metrics provided by the firms themselves. In particular, analysts screen firms' annual reports to identify the share of revenue being generated in one of the segments classified as 'green'. The entire dataset covers approximately 16,500 global publicly listed firms, representing approximately 98% of global market capitalisation for the years 2008-2017.[13] The data is provided at a sub-firm level depicting the company segments, in which the revenue share is generated. This information is then aggregated at the company level. In case a firm does not report the precise share of green revenues generated within a firm-specific subsegment, the analyst provides a green revenue range. For this analysis we only use the minimum value of this range, which provides a certain and conservative lower bound in case of uncertainty on the precise green revenue share.[14]. As explained above we only include US firms. For our main specification we divide these firms into deciles according to their green revenue share in the year 2013. As a robustness check we also use firms' average green revenue share between 2009-13 to divide firms into deciles. For the analysis we focus in particular on the greenest deciles of firms. Our preferred specification is for the top 3 deciles of green firms (N=63 firms, GR=97-100%). Due to equal values (taking the value of 1) it is not possible to analyse the top 10 or 20% separately. The smallest feasible cut-off is the top 30%. In addition, we also construct a portfolio based on firms, which generate one hundred percent of their revenue from green activities (N=51). As robustness checks and to establish the intensive margin effects we also examine portfolios constructed as the top 40% (N=83, GR=70-100%), the median decile (N=22, GR=25-42%), and as the most conservative estimate, firms with any positive green revenue share between 2009-2013 (N=249).

[13]We omit the earliest year 2008 due to concerns about data quality for that year similar to Kruse et al. (2019) (Chapter 2).

[14]It can be argued that firms, which are actually generating green revenues, but are not included in our 'treated' dataset because they do not disclose their precise revenue share may violate the Stable Unit Treatment Value Assumption (SUTVA) assumption. In particular this may mean that the potential outcomes may not be well defined as some 'treated' firms are not identified as such. However, this would work against our estimated coefficients. Hence, our results are conservative estimates

3.4.3 Emissions Intensity Data

For emissions intensity, we use the *Trucost* Emissions dataset. It provides detailed emissions, and emissions-intensity information for firms representing approximately 93% of global market capitalisation.[15]. We use Scope 1 and Scope 2 emissions for our analysis. Scope 1 emissions are direct emissions from owned or controlled sources (typically power plants). Scope 2 emissions are emissions from purchased electricity, heat or steam. Scope 3 emissions are indirect emissions not captured by Scope 2 such as transport related activities in vehicles not owned or controlled by the entity, waste disposal or outsourced activities. Scope 3 emissions are notoriously difficult to measure and we are concerned about the data quality, which is why we omit them from the analysis. Emissions-intensity (EI) is defined as emissions (tons) of carbon dioxide equivalents (CO_2e) divided by revenue in million US dollars. To categorise firms into emissions-intensity deciles, we use firms' average carbon intensity for the period between 2009-13 to smooth potential outliers.

The sectoral composition of the most emissions intensive firms in Scope 1 and 2 emissions are very different. The most emissions intensive firms according to Scope 1 emissions are mostly electricity producers (see Figure 3.6 panel (b)). Scope 2 emissions are more dispersed across energy-intensive sectors such as chemical manufacturing or primary metal industries (see Figure 3.6 panel (d)). However, differences between scope 1 and scope 2 emissions might also simply result from the decision to either produce electricity on-site or to purchase from the grid. Therefore, we once treat scope 1 and 2 as two separate subsamples, and once group them together. For the latter we simply construct a portfolio of the most emissions intensive firms according to their sum of scope 1 and 2 emissions (See Figure 3.6 panel (f) for sectoral composition). Again, we use the top deciles of the most emissions intensive firms to construct our portfolios of emissions intensive firms (Scope 1: (N=102) mean (median) EI= 2601 (1468) (tCO_2e/USDm); Scope 2: (N=103), mean (median) EI = 170 (125) (tCO_2e/USDm); Scope 1&2: (N=101) mean (median) EI=1356 (909) (tCO_2e/USDm)).

3.4.4 Robustness Check using Clean Patent Data

We are concerned that any effect we see from the green revenue data might be an artefact of this particular dataset, which is still relatively new to the literature. Hence, as a robustness check and in addition to the Green Revenue data, we use clean patent data. We use the World Patent Statistical Database (PATSTAT), which is maintained by

[15]For the time period up to 2013, which we use in our empirical analysis, the Trucost data represents approximately 85% of global market capitalisation.

the European Patent Office (EPO)[16]. In particular we adopt the commonly used Y02 patent classification for our "clean" patent measure. The general patent data extends back until the late 1800s, whereas Y02 patents only start emerging in the later part of the 20th century. We construct a measure of clean patent intensity by taking the share of granted Y02-patents between 2000-13 and divide it by the total number of patents granted over the same period.[17] This measure captures the extent, to which firms are focused on clean patenting (and innovation) activity compared to their overall level of patenting (and innovation). We would expect to see at least qualitatively similar effects as for the green revenue data. Otherwise, we might be concerned that any effects on green revenues could reflect a particularity of the dataset. Thus, we examine the top decile (N=37) of firms with the highest clean patent intensity as a robustness check.[18] [19]

3.5 Results

We present most of our results in graphs showing the event path over three time windows: (a) the ten days (2-trading weeks) prior to the beginning of the negotiations of the Paris Agreement (pre-negotiation period). (b) the ten day negotiation period, and (c) the ten days following the agreement (post-negotiation period). To assess the robustness of event study results, it is important to show that the portfolios of firms are not systematically different from the market prior to the treatment (in particular in the pre-negotiation window). Across the different portfolios, we observe that the abnormal returns prior to the passing of the agreement are not significantly different from zero. The Paris Agreement provides a fairly unique case, since information on the negotiation progress was regularly released. This is mirrored in the event path, as we observe an increase in the volatility during the negotiation window and in particular in the last days prior to the passing of the agreement.

The uncertainty in the market matches anecdotal evidence from observers of the negotiation process. Heads of state were present in the first days and contributed to optimism that the agreement could be passed. The early optimism shifted towards un-

[16]For a detailed account of the data see Dechezleprêtre et al. (2017)

[17]We allow for a slightly larger time period compared to the green revenue and emissions intensity data since we are using a stock measure of clean patents and since patents might require some time to be reflected in firms' products, production processes or other tangible outputs. Also, many firms do not file a (clean) patent each year, which prevents us from using a single year to define the quantiles.

[18]This sample of firms with the highest clean patent intensity has an average share of clean to total patents granted of 0.67. Hence, on average more than half of their granted patents are green.

[19]Unfortunately, there is no good equivalent to the clean YO2 classification for dirty patents. Dechezleprêtre et al. (2017) started developing such a classification, which however only covers a narrow subset of sectors and firms. Due to ambiguity on the classification of dirty patents and the small number of listed firms with that classification, we decided against using it for our analysis.

certainty in the last three trading days (Wednesday to Friday). The negotiations had to be extended, which increased uncertainty (See Section 3.3 for details). The agreement was then eventually passed on Saturday 12 December. The first trading day after the agreement was Monday 14 December 2015, which is our first post-treatment day.

We present our results first for 'green' firms based on the green revenue variable. This is followed by the robustness check using clean patent data. Subsequently, we show our results based on emissions-intensity of firms. All main results are reported using the nonparametric Corrado (1989) rank test with the aggregation approach by Cowan (1992) for cumulative average abnormal returns (CAARs). As robustness checks and to quantify the overall magnitude of the effect, we also report the CAARs for the entire post event window (days 0-5) in Figures C.6 and C.7 in Appendix C.7. As further robustness checks we use the (Boehmer et al., 1991) BMP and (Kolari and Pynnonen, 2010) KP parametric test statistic (See Figures C.8 and C.9 in Appendix C.8 for results with BMP tests and Figures C.10 and C.11 in Appendix C.9 for results with KP tests). Average abnormal returns (AARs) are reported in Figures C.12 and C.13 in Appendix C.10.

3.5.1 Abnormal returns of green firms

As outlined above, we divide firms for each of our datasets into deciles. Our main specification is the top 30% of green firms (top 3 deciles). These firms have a green revenue share of between 97-100%. We also examine separately the effect on those firms, which have one hundred percent green revenue share. To further examine the intensive margin of the effect we examine the effect for different decile groupings individually.

For the greenest firms we observe 3-day 'rolling' cumulative average abnormal returns (CAARs) of around 6% in the days following the agreement (Figure 3.2). These capture the moving 3-day average returns around the respective median day.[20] The effect persist for approximately five days following the agreement. The confidence intervals show the higher volatility or variance in the returns in the days prior to passing the agreement. The uncertainty is then released on the first trading day, when the confidence intervals become much narrower. The abnormal returns then gradually level off again, so that they are not any more significantly different from zero in the second week following the agreement. The effect exists similarly for the subsample of firms with 100% green revenues (CAARs of 6-7%) (Figure 3.3a). When also including the

[20] An advantage of using 'rolling' 3-day average returns is that it allows us to incorporate partial anticipation into the effects, as suggested by Sen and von Schickfus (2019). It furthermore allows for more flexibility compared to the commonly used 5-day intervals.

top 4th decile to examine the top 40% of green firms, we observe significant returns of around 4-5% (Figure 3.3b). We can also examine just the median green firms (with a green revenue value between 25-42%) (Figure 3.3c). The effect remains significant with CAARs around 2-3%. Lastly, we also take a more conservative robustness check and examine the effect for all firms which have generated at least some positive green revenue share ($> 0\%$) between 2009-13. We observe significant CAARs of around 2% for this sample of 249 firms (Figure 3.3d). Across all models we observe that using the BMP test statistics instead of the Corrado test tends to result in smaller standard errors and more pronounced significance of effects (see Figure C.8 in the Appendix). Using the KP statistic instead, we observe that the standard errors increase relative to the main specification. We however still observe significant effects (at 5%) across the different portfolios (see Figure C.10 in the Appendix). Thus, overall we observe a clear effect, showing that green firms have significantly outperformed the market in the week following the Paris Agreement.

The significant abnormal returns imply a level change in firms market value following the Paris Agreement. To assess the quantity of the effect, we use the (non-rolling) cumulative average abnormal returns over the entire post event window [0,5] (in line with Oberndorfer et al., 2013). From the previous results we have seen that the effect persists for about five days following the agreement. Therefore, we use this window size to quantify the entire magnitude of the effect. Using this wider window also provides a more conservative robustness check in terms of significance of the coefficients. If for instance the true effect for a particular sub-sample only exists for the first two days, then the likelihood of a type 2 error increases, as we average over a wider time window.[21] In this entire post-event window following the Paris Agreement the greenest firms (top 3 deciles and firms with 100% GR) experienced nearly 10% significantly (at 5%) higher returns (Figures C.6a and C.6b). For the conservative sample of 249 firms with any green revenue, we still observe significantly (at 5%) higher average returns of nearly 3% over this entire post-event window C.6e. The effect is also significant for the top 40% of green firms, which observe 8% higher returns. For the median decile of green firms the effect is only marginally significant, showing nearly 2% higher returns. The decline in significance may partly arise because of the relatively small sample size of the median decile (N=22) in combination with the wider averaging compared to the main results.[22]

The effects imply that on average the market capitalisation[23] of the firms in the 3 greenest deciles increased by 10% following the Paris Agreement, relative to the over-

[21] The type 2 error captures the likelihood of failing to reject a false null hypothesis (of no difference).

[22] The effect is also significant (at 5%) for the sub-sample of the top 3 deciles excluding electricity generation with 7% higher returns C.6f, which is discussed in more detail in the section 3.5.2.1.

[23] Market capitalisation is measured as (share price * number of outstanding shares)

all market. On average these firms have a market capitalisation of 2 billion USD (Table C.1). Hence, the market capitalisation of the greenest firms increased on average by approximately 200 million USD following the Paris Agreement and compared to the overall market. This is equivalent to a relative increase in market capitalisation of approximately 12.6 billion USD across these firms. The larger sample of 249 firms with any positive green revenue share has an average market capitalisation of 6 billion USD. With a 3% higher return over the entire post-treatment period, the market capitalisation of such firms increased by approximately 180 million USD, compared to before the agreement, and relative to the overall market. Over the 249 firms this is equivalent to an increase in market capitalisation of approximately 45 billion USD compared to the overall market.[24] These effects are both statistically significant and economically meaningful.

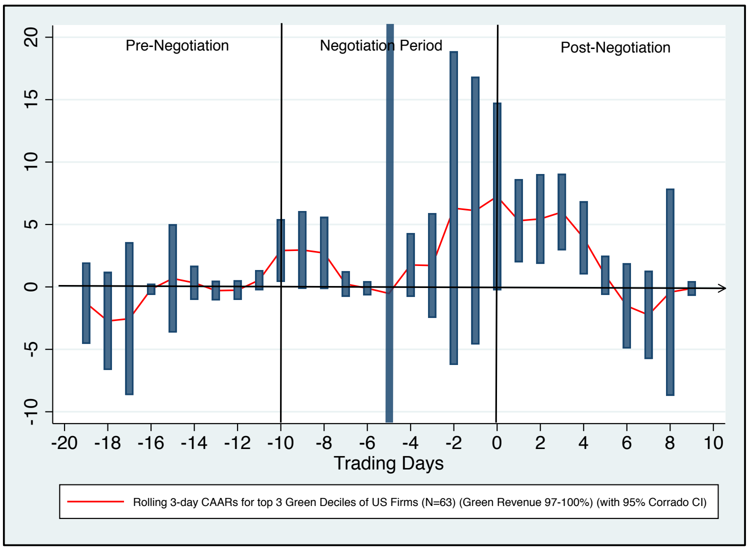


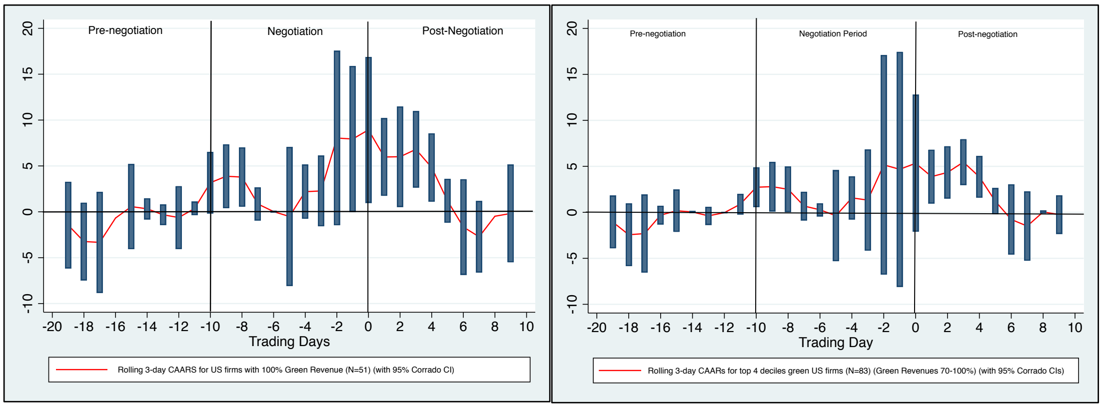
Figure 3.2: Event Path for top 30% green firms (top 3 deciles)

While from the above graphs, we can already observe that portfolios with a higher green revenue share observe larger abnormal returns, we can test whether the returns are significantly different from another. Table 3.1 shows the results of the t-tests comparing CAARs over the entire post-event window (days 0-5). In particular we compare the returns of the two greenest samples (portfolio of firms in the top 3 deciles, and firms with a 100% green revenue share) to the firms in the top 40%, to the median decile, and the conservative group of firms with any green revenue share. Across all six combinations we observe highly significant differences with the greenest firms experiencing significantly higher abnormal returns than the other three groups. Therefore, we conclude that we observe not only an extensive, but also an intensive margin effect. Firms

[24]For comparison, the overall market capitalisation of all domestic US companies was approximately 25 trillion USD over the same time period. The increase of 45 billion USD is therefore roughly equivalent to a 0.2% increase of the overall US market capitalisation (The World Bank, 2019). It is important to note that this provides a back-of-the-envelope calculation and denotes the relative increase in market capitalisation compared to the overall market.

(a) Event Path for firms with 100% Green Revenue in 2013)

(b) Top 40% green firms (top 4 deciles)



(c) Median (5th) decile of green firms

(d) Any green revenue (>0) between 2009-13

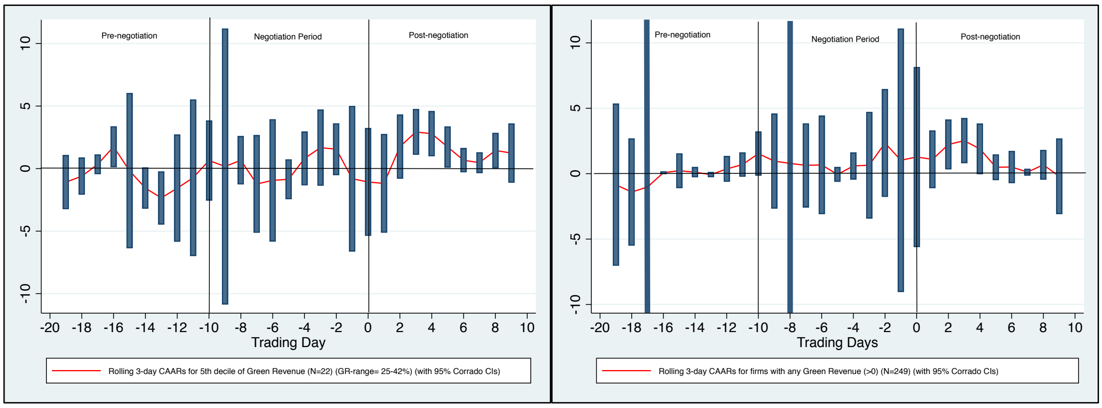


Figure 3.3: Event Paths for portfolios consisting of firms with different green revenue intensity (intensive margin)

with high green revenue shares have outperformed not only the overall market, but also firms with lower green revenue shares.

3.5.2 Robustness Checks for Green Firms

3.5.2.1 Excluding Electricity Generation

We are concerned that the effects might be driven by renewable energy generation, which may be a unique sector due to sector-specific subsidies and other support measures. Electricity generating firms (US SIC 491) also form the largest group of approximately 18% in our sample. (See Figure C.2)[25]. Hence, as a robustness check, we exclude electricity generating firms from the analysis. Figure 3.4 shows that the effect persists when excluding electricity generation and shows significant abnormal returns

[25]The sector distribution at the 2-digit SIC code level is shown in Figure C.1

Sample (a)	Mean (Std. Dev.) (CAAR [0;5]	Difference tested with respect to sample (b)	Mean (CAAR [0;5])	Two-sided t-test and (p-value)	One-sided t-test Sample(a) > Mean(b)
Sample with Green Revenue =100%	10.81 (2.34)	Any Green Revenue (>0)	2.98	3.34 *** (0.0016)	(0.008)***
	10.81 (2.34)	Deciles 5-7 of most Green firms (Green Revenue range (25-96%)	3.83	2.98 *** (0.004)	(0.002)***
	10.81 (2.34)	5th Decile (GR-range: 25-42%	1.60	3.93*** (0.0003)	(0.0001)***
Sample Top 30% green (deciles 8-10) (GR-range 97-100%)	9.22 (1.96)	Any Green Revenue (>0)	2.98	3.19*** (0.002)	(0.001)***
	9.22 (1.96)	Deciles 5-7 of most Green firms (Green Revenue range (25-96%)	3.83	2.75 *** (0.008)	(0.004)***
	9.22 (1.96)	5th Decile (GR-range: 25-42%	1.60	3.93*** (0.0003)	(0.0001)***

Table 3.1: T-test to test difference in intensive GR-margin for CAAR [0;5]

of around 4-5%.[26] The results are still also marginally significant when excluding all public utilities Electricity, Gas, and Sanitary Services (SIC 49), which however reduces the sample size substantially (see Figure C.3 in the Appendix).

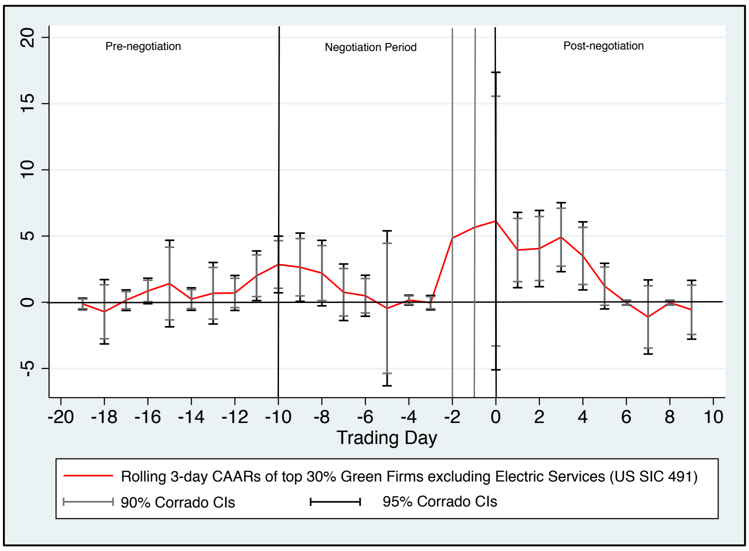


Figure 3.4: Event Path of top 30% green firms excluding Electricity Generation

[26]We report all robustness-checks, which cover only certain sectors with both 90% and 95% confidence intervals. This allows us to also report marginal significance in particular when the portfolio size becomes small.

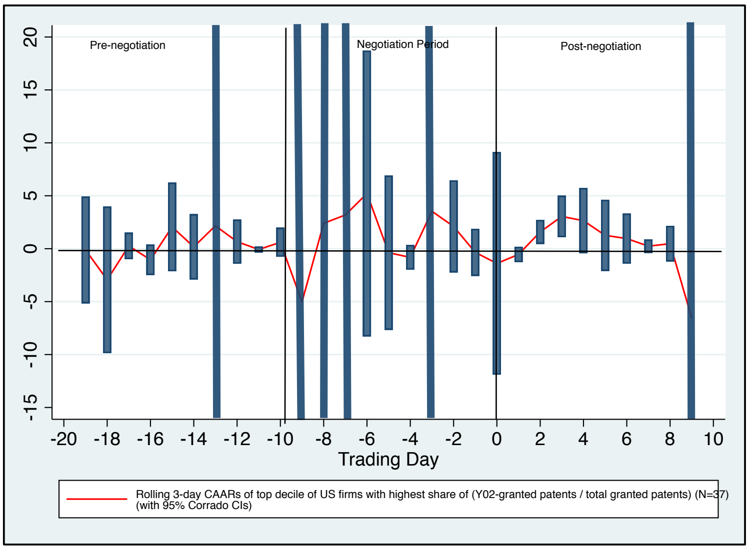


Figure 3.5: Abnormal Returns of top decile of firms with the highest clean patent intensity.

3.5.2.2 Clean Patent Data

We might be concerned that unobservable particularities of the data might be driving our results. As a robustness check we use use clean patent data, to verify that an effect exists for firms with a high share of clean innovation activity. Even though green revenues and clean patents capture different stages of firms' innovation in green technologies, we would expect at least the same sign on the effect for firms with a high intensity of clean patents. It is interesting to note that only 3 firms overlap the subsamples of the top green firms and the top clean patenting firms. Hence, any similar effect is not just an artefact of capturing the same firms. Figure 3.5 shows that a significant positive effect exists with CAARs of around 2-3% for the top decile of clean patenting firms. While clean patents are a different and potentially a less precise estimator of firms' involvement in the green economy, we see qualitatively similar results for the firms with the highest clean patent shares.

3.5.3 Abnormal returns of emissions-intensive firms

As a next step we examine whether the Paris Agreement also resulted in abnormal returns for portfolios of highly emissions-intensive firms. Ex-ante we might expect the opposite sign of an effect. With growing ambition on climate change mitigation emissions-intensive firms might experience declining market shares or even stranding of their assets. This might apply to both their physical assets such as fossil reserves as well as intangible assets such as knowledge stocks. However, we have also observed political measures to compensate emissions-intensive firms for example in Germany to dampen losses from a coal phase-out (e.g. Sen and von Schickfus, 2019). Abnormal returns for the most emissions-intensive firms might provide insight into investors' perception of the credibility that the Paris Agreement will result in drastic emission cuts from phasing out emissions-intensive fossil fuels.

On average, across the most-emissions intensive firms we do not observe significant abnormal returns following the agreement (Figure 3.6). Yet, interestingly the agreement seems to have introduced a substantial degree of variability in returns for highly emissions intensive firms, as seen by the large increase in the confidence intervals around the event date (Figures 3.6a, 3.6c, and 3.6e). This suggests that some firms might have experienced highly positive returns, while others suffered negative returns. We disentangle the effect by examining sector-specific returns. The distribution of firms across sectors is different for scope 1 and scope 2 emissions. Scope 1 is heavily dominated by electric, gas, and sanitary services, whereas Scope 2 shows a more diverse spread across sectors (Figure 3.6b and 3.6d).

In particular we disaggregate the effect for scope 1 emissions by the largest sectors. Scope 1 emissions are arguably easier to measure and more salient compared to scope 2 emissions. We do not observe any significant sector-specific effects for scope 2 emissions, which are therefore omitted from the results.[27] Within the portfolio of the scope 1 most emissions-intensive firms we begin by isolating the effect of electricity generating firms, as the largest sector. Interestingly, for this group of firms we observe small positive and marginally significant effects (Figure 3.7a). On the contrary, the effect for the most emissions-intensive firms in oil and gas extraction (the second largest sector) is negative and marginally significant (Figure 3.7b). Similarly, when excluding all public utilities (Electric, Gas, and Sanitary Services), the effect is negative and marginally significant (Figure 3.7c). Hence, electricity generating firms and public utilities appear to play a special role and behave significantly different to other emissions-intensive firms. Again, we observe smaller standard errors when using the BMP test statistic so that the effects for the sector-specific sub-samples become significant at 5% (Figure C.9 in the Appendix). We also observe significant abnormal returns for the aggregate sample of the top decile of emissions intensive firms (scope 2). Since this effect is however insignificant when using the Corrado or the KP test statistics, we do not consider it to be a robust finding. When using the KP test, the standard errors tend to increase across models. We still observe some marginal significance for the sub-sample of electric services firms and after excluding all utilities. The previously marginally significant results for the oil and gas firms are however not significant any

[27]It might be difficult for investors to assess the effect on firms that are highly reliant on electricity. However, it might also be the case that these firms will become automatically less carbon intensive, as the overall electricity grid shifts to renewables. It could be argued that firms, which purchase electricity from the grid might only be affected if the electricity price changes substantially as a result of a shift to renewables. Yet, the sharp decline in the costs of renewables that have in parts already made them competitive with fossil fuel electricity might mitigate such concerns for investors.

more (Figure C.11 in the Appendix). Since these findings are also only marginally significant in the main specification using the Corrado test, they should be interpreted with caution.

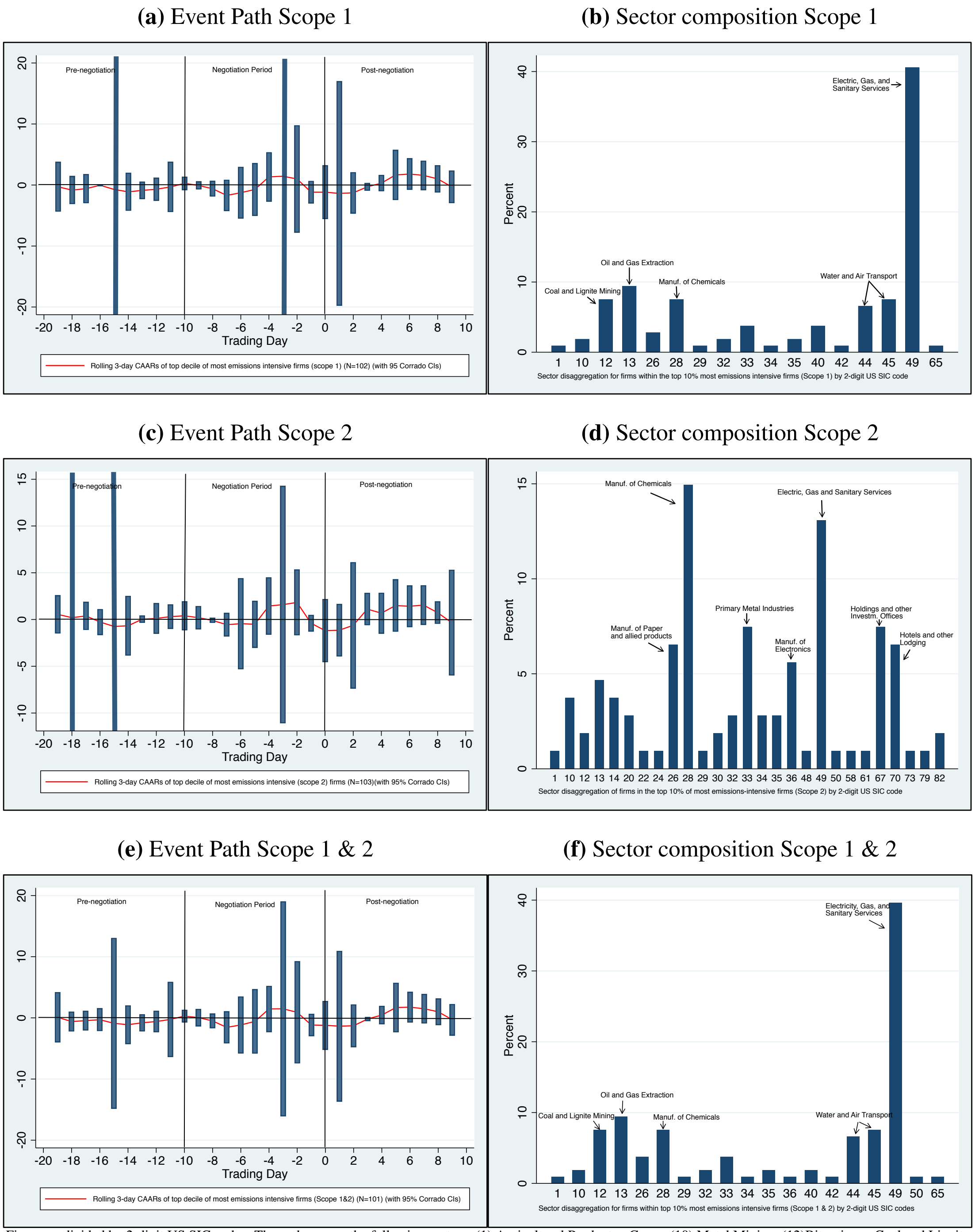
The results for the entire post-event window (days 0-5) show that the standard errors increase, as we are averaging over a longer time period (See Figure C.7 in the Appendix). This is particularly the case for the smaller industry-specific sub-samples. While, the signs of the coefficients remain the same, the effects are not statistically significant anymore. We therefore do not quantify the magnitude of the effects since they are not significantly different from zero for the entire post-event window.

Using the *FTSE Russell* Green Revenue database, we further investigate the electricity generating firms that are among the most emissions intensive firms, but experience positive abnormal returns after the Paris Agreement. We observe that all of these firms, even though they are highly emissions intensive, are also engaged in green technologies, largely in renewable electricity generations. Many firms even have substantial revenue shares from renewable energy generation. The subsample of the most emissions-intensive (scope 1) firms has a mean of 7% and maximum of 35% in the conservative minimum green revenue variable. All of the firms in this subsample, are active in at least one green subsegment as defined by *FTSE Russell*.[28] This finding suggests that for electricity generating firms with mixed portfolios of highly carbon intensive fuels as well as renewable shares, the latter appears to be particularly valued by investors. Investors might anticipate that it could be easier for electricity generating firms to shift from carbon-intensive to renewable electricity generation compared to other sectors in the economy.

3.6 Evidence in Support of Event Study Assumptions

A fundamental condition for event studies is the existence of surprise. If the event was perfectly anticipated we would not expect to see any abnormal returns, as the event would already be priced into the market. To establish surprise for the Paris Agreement being passed in its final form, we make use of data on future contracts from the S&P 500 and the S&P 500 Energy Futures. It is possible that the Paris Agreement introduced overall uncertainty in the market, leading to an increased demand for hedging through futures. Only if the final agreement (or its precise wording) came as a surprise, this would result in increased trading activity. We observe a substantial increase in the trading volume of the S&P 500 Futures (Figure 3.8) and the S&P 500 Energy Futures

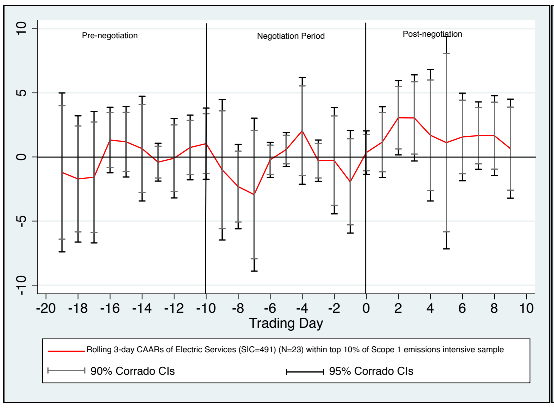
[28] Firms in this subsample might have a minimum green revenue share of 0 due to incomplete reporting of the precise revenue share from a particular green subsegment. Yet, for all firms in this subsample the analysts have identified a green subsegment, in which the firm is active.



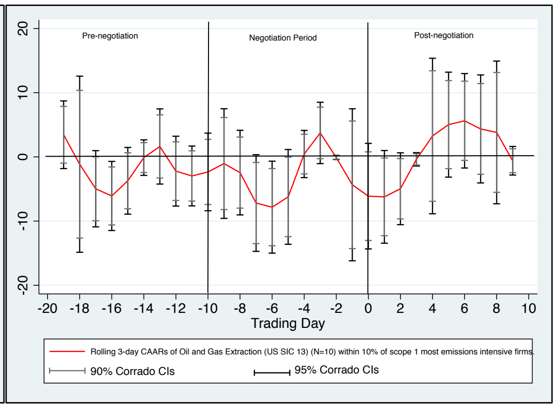
Firms are divided by 2-digit US SIC codes. The codes cover the following sectors. (1) Agricultural Products - Crops, (10) Metal Mining, (12)Bituminous Coal and Lignite Mining, (13) Oil and Gas Extraction, (14) Mining and Quarrying of Nonmet. Minerals, (20) Food and Kindred Products, (22) Textile Mill Products, (24) Lumber and Wood Products, (26) Paper and Allied Products, (28) Chemicals and Allied Products, (29) Petroleum Refining , (30) Rubber and Misc. Plastic Products, (32) Stone, clay, glass, concrete products, (33) Primary Metal Industry, (34) Fabricated Metal Products, (35) Indust. and Commercial Machinery, (36) Electronic and other Electrical Equipm., (40) Railroad Transport, (42) Motor Freight Transport and Warehousing, (44) Water Transport, (45) Transport by Air, (48) Communications, (49) Electric, Gas, Sanitary Services, (50) Wholesale Trade - durable goods, (58) Eating and Drinking Places, (61) Non-depos. credit inst., (65) Real Estate, (67) Holding and other Invest. Offices, (70) Hotels and other Lodging, (73) Business Services, (79) Amusement and Recreation Services, (82) Educational Services

Figure 3.6: Abnormal returns of 10% most emissions intensive firms (Panel (a), (c) & (e) and the respective sectoral distribution (Panel (b), (d) & (f))

(a) Electric Services



(b) Oil and Gas Extraction



(c) Excluding Electric, Gas, and Sanitary Services

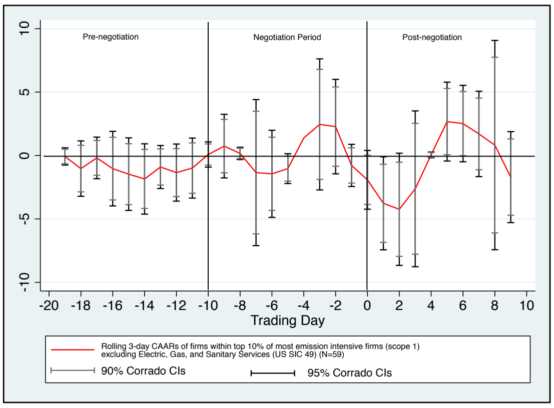


Figure 3.7: Event Paths for specific sectors (among the 10% most emissions intensive firms (Scope 1))

(Figure C.4 in the Appendix) on and around Monday 14 December 2015. This suggests that the final agreement surprised market participants. To show that the event was of importance and did not go unnoticed, we use Google Trends as an additional (albeit less robust) supporting evidence. Google Trends provides a measure of the relative frequency of searches for a specific keyword by week and region. It shows that the spike in searches for the term “Paris Agreement” occurred in the US in the week 13. - 19. December 2015, i.e. just after it was passed (See Figure C.5 in the Appendix). The Google Trend statistics show spikes on dates, for which we would expect increased searches for the term. We would be concerned if the line was flat or showed no spike during the event study period. This would suggest that the event might not actually have been of importance and was largely unnoticed. We have furthermore searched for odds ratios from betting agencies, which may indicate the ex-ante perceived likelihood of the agreement being passed. However, to the best of our knowledge odds ratios on the likelihood of the agreement being passed are not available.

A further concern is that the abnormal returns might have occurred simply due to increased media attention, which may have encouraged individuals to purchase ‘green’

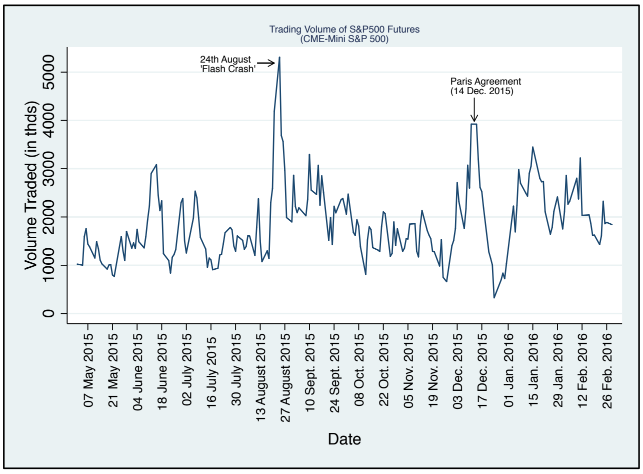


Figure 3.8: S&P 500 Futures Trading Volume

stocks. The effect might then not reflect a new 'informed' perception of the post-Paris policy framework. Yet, we want to emphasise that in the US the vast majority of stocks is owned by large scale investors rather than individuals. The latest available data from 2010 shows that 67% of all common shares were owned by large institutional investors (Gompers and Metrick, 2001; Blume and Keim, 2012) and has been increasing continuously since the 1950s[29]. This limits the ability for (potentially uninformed) individuals who purchase shares because of the increased media coverage to drive the substantial trends we observe across a number of relatively large portfolios. We argue that it is unlikely that the effect is entirely driven by 'uninformed' individual decision makers who simply purchased shares due to the increased media attention. To fully resolve this concern, we would however require data on the actual volume of individual stock market orders placed to buy or sell shares in the week following the agreement. We would need to identify whether orders were placed by professional investors or individuals. A significant change in the relative magnitude of shares purchased by individuals compared to professional investors in the week following the agreement could provide further insight. Yet, we are not aware of the availability of such highly sensitive data.

For the validity of event studies it is also important that there were no other potentially confounding events that might drive our results. We are particularly concerned about events that effect green or emissions-intensive firms differently from the overall market. Hence, we apply a news search using the Factiva database to investigate if other events happened in the week following the agreement that could potentially confound and drive the results we observe. We look in particular for events or policy announcements that would be beneficial to low-carbon technologies or impact emissions-intensive firms. We are relatively more concerned about any events that might effect

[29]Large institutional investors are defined as such when having more than 100 million USD under management.

firms in the same direction as the Paris Agreement, which would inflate our results. We search for events using the keywords "climate", "renewables", or "emissions". Similar to Mukanjari and Sterner (2018) we find no significant events in the week following the agreement that would affect our results.[30]

Lastly, we are concerned that more general policies or announcements might effect our results in ways that are not immediately obvious and that might not be detectable through keyword searches. Hence, we screen the most important general political and business news events in the week following the agreement. In particular, we want to mention two such events. First, in a widely expected move, the US Federal Reserve increased its interest rate by 0.25 percentage points on 16 December 2015. While this may be regarded as a positive signal, indicating that the US economy was growing stronger, it also increased the cost of borrowing for firms and households (Applebaum (2015), NYT). This event affected the entire market and hence is controlled for in our identification strategy, assuming that it had no differential effect across firms. Second, on the night from 15th to 16th December, the US Congress reached a deal to prevent a year-end government shutdown (Snell and DeBonis (2015) (The Washington Post)). This deal was reached as a compromise between the Obama White House and the Republican-controlled Congress. The deal included a $1.1 trillion USD appropriations package that would fund the federal government for the remainder of the 2016 fiscal year. It also included a tax break package, costing approximately $650 billion USD covering a large range of about 50 different credits for businesses and individuals. In addition, the bill also lifted a ban on crude oil exports. The effect of lifting the ban would, if anything, work in the opposite direction from what we observe for emissions-intensive firms in oil and gas extraction. The deal also included an extension of tax breaks for wind and solar energy producers for five years. The extension of the tax breaks for solar and wind industry could potentially inflate our results. However, these specific deductions were a relatively small part of the overall deal, which included among others state- and local sales tax deductions for businesses, which would have effected the overall market. The industry-specific extensions in tax breaks covered only a small set of renewable energy industries. Since our results also hold when excluding electricity generating firms, we are not concerned that this deal is driving our results.

[30] Mukanjari and Sterner (2018) state that on 16 December 2015, news articles on record highs of global temperature as well on solar energy were published. They conclude however that none of the news coverage on these topics was of a sufficient magnitude or direct importance. We come to the same conclusion from our key word search.

3.7 Discussion

The paper shows that international climate agreements, even if based on voluntary emission pledges, actually matter for financial markets. More specifically we show that financial markets reward the production of "green" goods and services following the Paris Agreement.

With this paper we contribute to the literature on the relationship between firms' environmental and economic performance. Previous studies have largely been limited to extensive margin effects using binary indicators (e.g. inclusion in a sustainability index, adoption of environmental certification) or have examined efficiency improvements in production processes. We are able to overcome some of the limitations by using a novel dataset capturing the share of firms' revenues being 'produced' from green goods and services. Few papers have analysed the so called "revenue channel". It suggests that firms' can improve their economic performance by shifting their business activities towards producing green goods and services (Ambec and Lanoie, 2008). Existing studies on the revenue channel have largely been limited to correlations using cross-sectional or panel regressions. This is to the best of our knowledge the first paper to identify a plausibly causal effect from firms' production of green goods and services on their market valuation. To identify this effect we use event study methodology and exploit the large, discrete and plausibly exogenous shift in reward for being green, following the Paris Agreement. We are able to show that both the extensive as well as the intensive margin of firms' green revenue share matter for investors.

In particular, we show that 'green' firms, which are defined as generating a share of their revenue from producing green goods and services, have significantly outperformed the market in the week following the Paris Agreement. The results are both statistically significant and economically meaningful. We identify a level shift in green firms' market capitalisation following the agreement. The sample of the greenest firms observed on average 10% higher returns for the post-event period (days 0-5) compared to the overall market. This is roughly equivalent to a relative increase of approximately 200 million USD in market capitalisation per firm, or a total relative increase of 12.6 billion USD in market capitalisation across the 63 greenest firms. The aggregate effect is even larger for the entire sample of 249 green firms (with any green revenue share $> 0\%$), which account together for an increase in market capitalisation of approximately 45 billion USD relative to the overall market, following the Paris Agreement. Our results hold both at the extensive and intensive margin of firms' 'green' revenue shares. Firms with high green revenue shares have significantly outperformed not only the overall market, but also firms with lower green revenue shares. Furthermore, we show that the overall results are not limited to electricity generation, the largest sector, which may be unique due to energy-specific subsidies. Investors seem to evaluate the post-Paris policy landscape as opening up further potential for firms producing green goods and services, and for the diffusion and adoption of green technologies.

In contrast to green revenues, firms' emissions-intensity is a less clear-cut predictor of investors' reaction to the Paris Agreement. On aggregate the most emissions intensive firms have not observed significant abnormal returns following the agreement. Yet, the sectoral disaggregation of the most emissions intensive firms (scope 1) reveals an interesting pattern. We observe negative (marginally significant) abnormal returns in particular for oil and gas extracting firms and for all sectors excluding utilities. Such negative returns may reflect the anticipated challenges for firms in these sectors to adjust their business model to the post-Paris policy landscape. It could also reflect an increasing risk of 'asset stranding', as firms' carbon-intensive physical or intellectual assets become less valuable. Interestingly, the most emissions-intensive electricity generating firms seem to be valued differently. They have experienced positive (marginally significant) abnormal returns following the agreement. Merging the green revenue and emissions-intensity databases we are able to see that all of the most-emissions intensive electricity generating firms are also active in 'green' sectors, with on average 7% (and a range up to a maximum of 35%) of their revenue being generated from such activities, mostly from renewable electricity generation. For such partially green and dirty firms, investors may face trade-offs regarding the relative valuation of the two components. The positive abnormal returns might suggest that investors anticipate the transition to low-carbon technologies to be easier for electricity generating firms relative to the overall market, and in particular relative to oil and gas firms.

Investors' responses to the Paris Agreement may be systematically different from their response to more common events such as earnings announcements, which occur frequently and in a standardised format. Investors had to absorb a large amount of information that was contained in the agreement. Moreover, the relative stringency of the agreement had to be understood by assessing the level of ambition of individual Nationally Determined Contributions (NDCs). Since the agreement relies on voluntary emission reductions, the political interpretation in the days following the agreement became important. Absorbing such a complex set of information might therefore be different from reacting to more common and standardised stock market events such as earnings announcements (e.g. MacKinlay, 1997). We observe a gradual onset of the effects in the week following the agreement. This is in line with findings showing that large and complex amounts of information may overwhelm investors and slow their reactions to a particular event because of limited cognitive attention (Hirshleifer et al., 2009)[31]. Our results show that abnormal returns existed for about a week following

[31] Hirshleifer et al. (2009) show that on days when a large number of announcements are made

the agreement. Thus, it appears that the market needed approximately this amount of time to fully price and absorb the effects of the agreement.

The positive abnormal returns for green firms suggest that the post-Paris policy landscape may be able to open up growing opportunities for green goods and services. This may allow for some optimism with respect to the increasing diffusion and adoption of low-carbon and green technologies. The non-existence of significantly negative results for the overall sample of emissions-intensive firms is however a more cautionary finding. The agreement in itself may not be sufficient to exert pressure on emissions-intensive firms and sectors. It may be due to the voluntary nature of the reduction pledges or potentially because of anticipated compensation measures for carbon-intensive firms. Given the drastic emission cuts that are required to limit global warming to well below 2°C, the results reinforce the urgency and importance of the gradual strengthening of the NDCs. The Paris Agreement could then potentially deliver the necessary policy framework to increase the diffusion and adoption of green and low-carbon technologies, while at the same time decarbonising existing technologies and industries.

by different firms investors tend to under-react to individual firms' earnings announcements. Hence investors can also be overwhelmed by a large amount of standardised events.

Chapter 4

Understanding Public Support for International Climate Adaptation Payments: Evidence from a Choice Experiment.

Abstract
Climate change adaptation is becoming increasingly important even if all nationally determined contributions of the Paris Agreement are implemented. However, funding for climate adaptation in developing countries remains scarce. Increasing and maintaining public support for such long-term projects is crucial to achieve acceptance, to ensure willingness-to-pay over a longer time horizon, and to avoid policy reversal. It is therefore important to understand perceptions of and preferences for international climate adaptation finance among individuals in donor countries. Previous research has shown that in particular distributional outcomes of policies determine their overall acceptability. Using a representative sample of the UK population this is to the best of our knowledge the first paper to provide comprehensive evidence of distributional preferences in the context of adaptation finance. We primarily elicit preferences with regards to two dimensions: (1) the burden-sharing principle among contributors, and (2) the distribution of financial resources across projects. We show that, contrary to mitigation policies, residents prefer an 'ability-to-pay' approach over the 'polluter-pays-principle' for climate adaptation policies. Hence, we would expect that using carbon pricing to collect revenues for a climate adaptation fund would receive less support compared to a progressive fee based on income. With respect to the second dimension, we show that UK residents have distributional preferences for funds to reach the poorest individuals. This finding supports the adoption of egalitarian policy mandates among international

climate adaptation funds. Lastly, our results suggest that adopting a communication strategy that focuses on future benefits to UK residents from contributing to international adaptation funds can increase support for such policies. Overall our findings also reveal that public support for global climate adaptation payments remains vastly insufficient in light of the overall financing requirements. Further research is required to identify policy characteristics and framings that can increase public support.

4.1 Introduction

Climate change adaptation is gaining traction and is becoming increasingly important. Even if the international community succeeds in limiting climate change to 1.5 or 2.0°C warming, climate change adaptation will be necessary, particularly in developing countries. Given the current gap between the required emission reductions and the submitted Nationally Determined Contributions (NDCs), climate change adaptation will likely become an enormous task. An estimated 100 billion US dollars will be required annually at least until 2050 to help developing countries adapt to the negative consequences of climate change (IBRD/The World Bank, 2010). The financial resources will need to be mobilised largely from developed countries. Ensuring public support for such long-term projects is important to obtain sustained acceptance, to ensure willingness-to-pay over a longer time horizon, and to avoid policy reversal. It is therefore essential to have a good understanding of public perceptions of and preferences for international climate adaptation finance among individuals in donor countries. Better knowledge of such preferences can advise policy design and help anticipate potential challenges (e.g. Hovi et al., 2009).

This paper draws upon the related literature on public acceptance for climate change *mitigation* policies, which has identified key policy characteristics that tend to increase public support. While the policy effectiveness and the overall costs are essential drivers, the distributional outcomes tend to play a fundamental role in determining if a policy receives sufficient public support (Drews and van den Bergh, 2016; Carattini et al., 2017a). Our knowledge of preferences for climate *adaptation* policies is however very limited.

In this paper we take a systematic approach to build upon the related *mitigation* literature to derive novel insight for climate *adaptation* policies. With respect to preferences for distributional outcomes of policies we examine two main elements. First, we examine the preferred burden-sharing between individuals in donor countries, which relates to questions of responsibility. Linking individual payments to emissions through a carbon tax for instance, suggests a more direct responsibility arising from one's own emissions in line with a 'polluter-pays-principle'. Alternative policy approaches could adopt an 'ability-to-pay' principle, in which individuals contribute proportional to their income or an 'equal-spares approach' that equally divides responsibility across all individuals.

Second, the allocation of scarce financial resources across projects will imply difficult moral judgements concerning the relative benefits of individual projects. Trade-offs between utilitarian approaches (protecting the largest group of people) and equity principles (protecting the most vulnerable) may arise (e.g. Le Grand, 1990, 1991). Such trade-offs may occur in particular when additional basic infrastructure or capacity building is necessary to allocate financial resources to the most marginalised communities. Knowledge about public preferences for the distribution of resources in situations where moral judgements are inevitable can be an important factor, in particular to avoid or respond to public discontent of project outcomes and to minimise concerns about wasteful use of public funds. While knowledge of such preferences is not meant to replace expert judgement, it can support and complement the decision-making. This is particularly important since existing (albeit scarce) evidence suggests that adaptation institutions tend to allocate financial resources not to the most vulnerable, but to projects with past experience, sufficient capacity to manage larger funds, and already established aid workers (Barrett, 2014; Stadelmann et al., 2014). Requirements to report tangible outcomes and fear of project failure may potentially encourage such decision-making. Knowing public preferences for the allocation of adaptation funds can help to manage such concerns. Since international contributions are likely going to be insufficient to support all communities threatened by climate change, it is important to develop decision-criteria, which allow an informed trade-off between projects in the context of scare resources. Having such transparent criteria may help to avoid misallocation and preferential treatment for political reasons.

Using a representative sample of the UK population, this paper provides the first comprehensive evidence of distributional preferences in the context of climate adaptation finance. We show that people prefer an 'ability-to-pay' approach to a 'polluter-pays-principle'. To the best of our knowledge this is the first time this has been demonstrated in the literature on climate adaptation. It may suggest that people do not see a strong link between individual emissions and a potential responsibility to contribute to climate adaptation payments. This is an important finding as it contrasts with results from the literature on public acceptance of climate *mitigation* policies, where 'polluter-pays-principles' typically increase public support (Atkinson et al., 2000; Dietz and Atkinson, 2010; Carattini et al., 2017a,b). We would therefore expect that using a carbon price to collect financial resources for an adaptation fund would receive relatively less public support compared to establishing a climate adaptation fee proportional to income levels. With respect to the allocation of scarce financial resources across projects we observe that individuals in the UK have distributional preferences with respect to allocating financial resources to the most vulnerable. We observe that purely utilitarian approaches are expected to be less popular compared to more egalitarian principles that allocate financial resources based on initial levels of vulnerability.

The remainder of the paper is structured as follows. Section 4.2 gives a detailed overview of the existing literature and the motivation for the study. In Section 4.3 we adopt a systematic approach for the choice experiment attribute selection and elaborate on our survey design. Section 4.4 describes the methodology of Multinomial Logit, Random Parameter Logit, and Latent Class Models, which we apply in the analysis. In Section 4.5 we present the results of the choice experiment and the accompanying survey. Section 4.6 discusses the findings and concludes.

4.2 Literature Review and Motivation

We divide the existing literature on this topic into three different sub-sections to give a detailed and systematic overview of the different research fields to which we contribute in this paper:

4.2.1 The Allocation of Climate Adaptation Resources

The International Bank for Reconstruction and Development (IBRD) and The World Bank estimate the global costs to help developing countries adapt to climate change at USD70-100 billion per year between 2010 and 2050 (IBRD/The World Bank, 2010). Similarly, the United Nations Framework Convention on Climate Change (UNFCCC, 2007b) estimates the required investment to be between USD 44-166 billion per year globally and USD27-67 billion in developing countries alone (see e.g. Barr et al., 2010; Fankhauser, 2010; Parry et al., 2009, for a detailed review). Building upon these estimates, the international community called for developed countries to allocate financial resources to help developing countries adapt to climate change, beginning with the Bali Action Plan in 2007 (UNFCCC, 2007a). Two years later in the Copenhagen Accord the international community first agreed upon the target to spend USD100 billion per year from 2020 onwards to address climate change related needs of developing countries. The target was further strengthened in the Cancun Agreements in 2010 where the Green Climate Fund (GCF) was established to act as a key delivery mechanism. It was subsequently incorporated into the Paris Agreement, in which countries pledged to provide USD100 billion per year by 2020 for both *adaptation* and *mitigation* support in developing countries (see e.g. Klöck et al., 2018). In the Paris Agreement the international community also agreed to raise the target after 2025 and decided that funding would come from a wide variety of sources including public, private, bilateral and multilateral sources (Westphal et al., 2015). Since the most recent international pledges from the Paris Agreement include both *adaptation* and *mitigation* support, they are considered a lower bar and are likely insufficient compared to the necessary financial support for climate change adaptation alone (Fankhauser, 2010; UNFCCC, 2014, 2015; Buchner et al., 2017).

The likely mismatch between financial pledges and the required financial support, as well as challenges in mobilising the pledged amounts (Buchner et al., 2017), emphasise that a shortage for international climate adaptation payments is likely to exist in the future. This raises normative questions of how international institutions such as the Green Climate Fund (GCF) or the Adaptation Fund (AF) are going to allocate scarce resources across projects. The current mandate of these funds is (a) to protect the most vulnerable from the detrimental impacts of climate change, (b) to help them adapt to climate impacts and (c) to increase their resilience to climate related events. It is however important to note that the adaptation funds do not have precise decision-criteria on how to make trade-offs in allocating scarce resources across projects that impact communities of different size and vulnerability (Horstmann, 2011). Thus, guidelines on dealing with equity-efficiency trade-offs and the underlying distributional preferences are not explicitly defined within existing mandates. Moreover, recipient countries can apply their own definitions to classify individuals or groups as 'vulnerable'. This leaves room for interpretation and can induce favouritism for political or other strategic reasons (e.g. Horstmann, 2011; Barrett, 2014; Stadelmann et al., 2014).

Fankhauser and Burton (2011) discuss the difficult trade-offs involved in adaptation projects, building upon Stern (2008, 2009) who defines 'good' adaptation to be (1) efficient in achieving results at lowest costs, (2) effective in reducing negative impacts of climate change, and (3) equitable in its distribution to target populations most worthy of assistance. While these criteria provide an important foundation, their operational implementation can be challenging in particular when trade-offs exist between the individual principles (Fankhauser and Burton, 2011). The existing evidence suggests that such equity-efficiency trade-offs[1] can arise in particular since additional technical assistance and additional capacity building tends to be required to manage projects among the poorest or most vulnerable communities. Additional financial resources may therefore be required to provide support for the management of large funds and projects. Similarly, basic infrastructure such as roads or electricity grids may need to be extended to such communities before adaptation infrastructure can be installed (Barr et al., 2010; Barrett, 2014). The poorest individuals are at the same time more exposed to climate induced events, are more vulnerable and have less formal or informal safety nets to prevent, prepare, and manage climate impacts and are therefore the most dependent on outside support (Hallegatte et al., 2016).

Preliminary evidence on decision-making within adaptation funds suggests that they tend to approve projects from communities with relatively higher incomes (Stadelmann et al., 2014). In a study on the distribution of subnational adaptation finance in Malawi,

[1]See also Le Grand (1990) and Le Grand (1991) for discussions on equity-efficiency trade-offs in public policy making

Barrett (2014, p.131) finds that the "poorest, most marginalised, and climate vulnerable districts receive the least adaptation finance". The author argues that the existing distribution of adaptation funds does not support the larger goal of climate justice. Instead donor utility and capacity to absorb the funds seem to drive the allocation. Adaptation assistance seems to arrive in districts with sufficient capacity to manage the assistance and where aid workers are already established. It does not seem to be invested to help the most marginalised improve their ability to manage such assistance in the future. Similarly, Stadelmann et al. (2014) analyse all 39 projects approved or endorsed by the Adaptation Fund Board in 2011 and find that all projects rank relatively low on equity metrics. They conclude that the fund approved projects from relatively high-income and less vulnerable countries with the potential for relatively high absolute economic gains, while not approving projects in the poorest and most vulnerable countries with high relative (but lower absolute) economic gains.

Fankhauser and Burton (2011) identify the challenges that arise due to the desire for 'additionality' of adaptation finance and a preference for tangible and visible projects, which can result in preferential project implementation in areas with sufficient capacity. One of the most fundamental risks for progress on adaptation in developing countries is "evidence, or even suspicion that the funds are being diverted or used wastefully" (Fankhauser and Burton, 2011, p.1038). Multilateral institution might therefore be overly risk-averse and prefer to implement 'safer' projects in communities with sufficient capacity. They may direct funds not to the most vulnerable communities, but to the safest projects. Perceived public preferences might play a relevant role in approval decisions for adaptation projects. Since the public acceptance in donor countries is an important determinant to ensure long-run support, understanding these preferences is an important first step to obtain such support. Knowing public preferences can help multilateral institutions in their decision-making process when faced with difficult moral judgements.

4.2.2 The Importance of Public Support for Policy Making and Lessons from the Mitigation Literature

The responsiveness of government policy to citizens' preferences is an important debate within economics, political sciences and political theory. Basic economic theory assumes a high degree of responsiveness of voters and politicians to questions of public concern. This high level of responsiveness is largely built on the assumption of perfect information among all agents in the public sphere. Building upon this stylised model, the political economy literature has incorporated frictions through information- and transaction costs, as well as through obstructions created by political interest groups

(Page and Shapiro, 1983). Nevertheless, a strong impact of public opinion on policy outcomes remains, even when the activities of political institutions and elites are accounted for. This impact is enhanced when the issue is particularly politically salient (Page and Shapiro, 1983; Burstein, 2003).

Knowledge about the public opinion helps to anticipate public responses in later stages of the policy-cycle, which can inform the design and facilitate the implementation of policies. This can help to improve long run public support for policies, and can prevent frequent policy reversals. This is particularly important for policies dealing with long-term issues such as climate change (Hovi et al., 2009; Drews and van den Bergh, 2016). Similarly, the lack of public support has been identified as a substantial barrier to implement ambitious carbon *mitigation* policies (Geels, 2013; Wiseman et al., 2013).[2]

A closely related field, on which we build in our attribute selection, is the literature on public acceptance for climate *mitigation* policies. The literature has identified five key attributes that drive public support: Perceived policy effectiveness, level of policy cost, policy fairness, use of revenues, coerciveness of policy, and trust in the institutional body implementing the policy (see e.g. Drews and van den Bergh, 2016; Carattini et al., 2017b). In particular the distributional impacts of climate policy, as well as the underlying burden sharing principles appear to be crucial drivers for public support. The public's willingness-to-pay for a GHG *mitigation* policy tends on average to increase if the payment mechanism is based on the 'polluter-pays principle' compared to other principles such as 'ability-to-pay' or an 'equal-shares principle'. This applies both at the international level (i.e. the payment distribution between countries) (Bechtel and Scheve, 2013) and at the national level (i.e. the payment distribution between individuals) (Atkinson et al., 2000; Hammar and Jagers, 2007; Lee and Cameron, 2008; Dietz and Atkinson, 2010). Policies are however also more likely to be accepted if poorer individuals bear relatively less of the overall burden or are exempt (e.g. Gevrek and Uyduranoglu, 2015; Carattini et al., 2017a). Preferences for a 'polluter-pays principle' and lower burdens for poorer individuals can therefore conflict at times (Atkinson et al., 2000; Dietz and Atkinson, 2010). Thus, to reduce the impact on low-income house-

[2]This paper is also linked to the political economy literature emphasising the impact of institutions and electoral systems for long-term policy making. A large body of literature highlights the importance of the institutional set up to be able to deal with long-term issues such as climate change (Hovi et al., 2009). One branch of that literature examines the importance of the number of veto players in a political system for policy reversal. Fewer veto players in the political system tend to allow easier policy reversal, making environmental policies potentially less credible (Lockwood et al., 2016). Furthermore, the literature on electoral competitiveness shows that a lack of political competition is significantly associated with higher taxes and lower capital spending. Hence, the overall competitiveness of an electoral system or even a particular election can affect the likelihood of implementing additional environmental taxes (Besley et al., 2010; Finnegan, 2018). These institutional factors are all likely to impact individuals' preferences. The implicit assumption of the literature on public support for climate policy is that these factors are constant at the point of preference elicitation.

holds, revenue-recycling mechanisms have been identified as popular policy characteristics. Overall support also tends to increase when emphasising how the majority of negative climate impacts will be borne by the world's poor (see e.g. Cai et al., 2010; Lee and Cameron, 2008). In general the literature on climate *mitigation* has shown that the distribution of financial resources and the burden sharing appear to be highly salient attributes.

We build upon this insight and examine in detail distributional dimensions within the context of global *adaptation* payments, which may differ systematically from preferred *mitigation* policy designs. In particular the perceived link between individuals' emissions and their responsibility to pay may be different. Moreover, revenues cannot be recycled nationally, which makes it more difficult to communicate and create tangible benefits to individuals contributing to the policy. Lastly, the resource transfer to other countries may systematically alter preferences for contributions. We explain our choice of distributional dimensions and attributes in detail in Section 4.3.

4.2.3 Insufficient Public Support for Climate Adaptation Transfers

This paper is in line with recent work by O'Garra and Mourato (2016) who use a contingent valuation survey to provide an assessment of public willingness-to-pay in the UK for international climate adaptation transfers. They estimate that a yearly payment of £70-100 per capita will be required to meet the UK's share of the global target of £70 billion (or roughly 100 billion USD in 2016). While this is a first back-of-the-envelope estimation it provides insight into the order-of-magnitude of payments that is required. They observe that current willingness-to-pay is vastly insufficient (mean of £27; median of £6), representing less than one third of what the authors estimate to be necessary. Moreover, they show that an emotive information treatment, which appealed to respondents' feelings and emphasised the scale and urgency of the challenge, did not have an effect on their WTP. It highlights the challenge to mobilise sufficient public support for global climate adaptation payments. The contingent valuation survey provides an important foundation and allows to establish an overall level of willingness-to-pay. Using a choice experiment, we are however able to go beyond the simple level of support and identify design features that may increase the public acceptance for a climate adaptation levy and show potential trade-offs that may exist between characteristics. We are also able to estimate the effects more robustly using more advanced choice modelling methodology.

The literature on public acceptance for climate adaptation policies is still relatively small. In particular, most of the papers focus on strategic interactions between countries rather than on individual or household characteristics. Gampfer et al. (2014) test the extent, to which individuals respond to fairness in the distribution of costs between countries. In line with expectations, they find that support increases with higher burdens being allocated to other countries. Moreover, they find that climate adaptation transfers receive more public support if they flow to more efficient governments, funding decisions are made jointly by donor and recipient countries and if the funding is used for joint mitigation and adaptation projects. They find however no effect on support for attributes that capture the level of income, climate change damage levels and the emissions of the recipient countries. This might however be a result of the somewhat unclear attribute levels for income, which state that the income level in the recipient country is 'somewhat' or 'much' lower than in the US, which might introduce ambiguity. Bechtel and Scheve (2013) find that respondents are indifferent between a polluter-pays-principle and an ability-to-pay approach at the country level, meaning that they are indifferent between a policy design in which countries pay according to their current emissions, their historic emissions or their income level. The most important driver for policy preferences is the overall policy cost. In line with expectations citizens are more likely to support costly policies if the burden is shared across a larger group of countries. In addition they find that sanctions for non-compliant countries increase policy support as well as compliance monitoring by an independent third party.

In addition to a systematic attribute selection, we also improve methodologically upon the existing papers. Gampfer et al. (2014) do not use an individual payment attribute and Bechtel and Scheve (2013) use the average cost to a household as their payment attribute. However, for contingent valuation studies, as well as choice experiments it is important that the payment mechanism is as credible as possible (Champ et al., 2017). To reduce hypothetical bias and warm-glow it is important that respondents take a decision with the knowledge of the direct costs to them as if the payment becomes effective immediately. By using a more direct payment we try to reduce such known biases. Furthermore, both studies use random designs for the choice experiment, instead of the preferred Bayesian efficient design, which we employ in this study.

4.3 Attribute Selection and Survey Design

4.3.1 Systematic Attribute Selection

Since the literature on public acceptance of climate adaptation policies is still in its infancy, the selection of policy attributes for choice experiments forms a major challenge and needs to be at least partly exploratory. Nevertheless, we tried to take a systematic approach in our attribute selection, informed by the findings from the closely related literature on climate *mitigation* policies. Since climate adaptation is a multi-dimensional and often less clearly defined concept, the precise selection of attributes can be less straightforward. Hence, for this choice experiment, we had to make relative judgements for each attribute between how realistic and important the attribute is within the context of climate adaptation and how easy it is for a respondent to understand an attribute's meaning. It is important to not leave much room for individual interpretation of an attribute's meaning as this may distort overall findings by subjective perceptions of the attribute (e.g. Champ et al., 2017). Such a trade-off can be illustrated for a policy effectiveness attribute: One of the most important tasks of international climate adaptation payments is to increase the overall resilience of communities. Being resilient may enable communities to deal with climate-induced shocks by themselves and may reduce the overall impact. Resilience is however a complex and multi-dimensional concept in itself. Using such an attribute in the choice experiment would increase the cognitive burden for respondents and might lead to biased responses depending on individual perceptions of the concept of resilience.

To select the relevant attributes for the choice experiment, we took a three-step approach, as illustrated in Figure 4.1. First, we list the attributes that have been identified as most relevant in the context of climate *mitigation* policies. Second, we transfer the meaning of these attributes to the context of climate adaptation policies. This step reveals the increased complexity of climate adaptation policies. For example, we now need to consider the distributional dimension among the individuals paying and among the individuals receiving transfers. In a third step we then conducted focus groups and piloted the survey to test and select different attribute framings. After analysing the results from two survey pilots and discussions in focus groups we decided on the final set of attributes and their precise wording. The final attributes and levels included in the choice experiment, as well as the underlying rationale for choosing these attributes are summarised in Table 4.1.

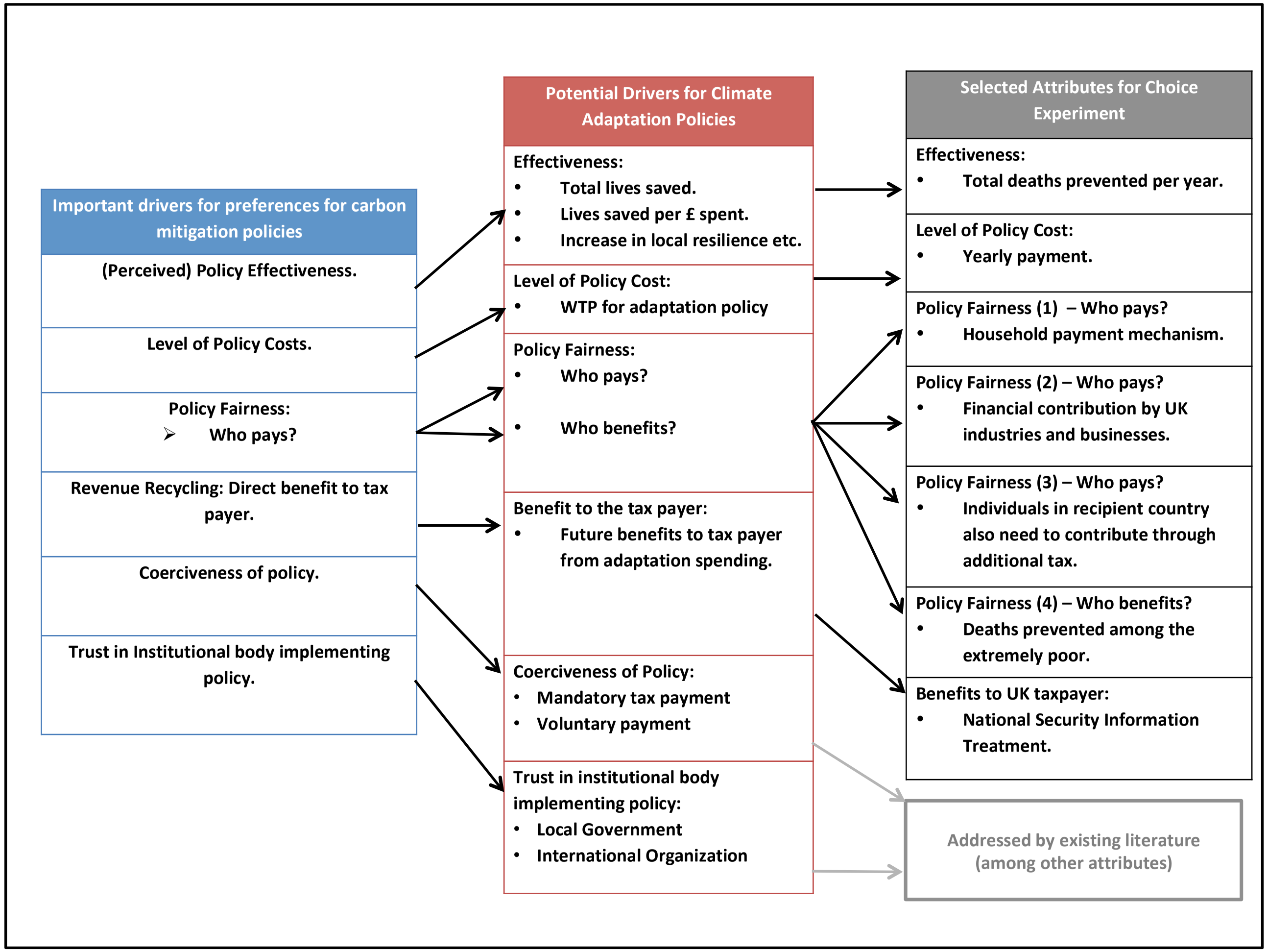


Figure 4.1: Systematic Attribute Selection Based on Knowledge from Climate Mitigation Literature

The two fundamental variables are the policy effectiveness and the policy cost, as these also allow us to conduct 'sanity' checks on whether individual responses are credible. We expect to see negative coefficients on the payment attribute and a positive coefficient on the effectiveness attribute. Choosing a suitable attribute to capture the effectiveness of an adaptation policy is however a challenging task. It is fundamentally different from a similar task in the context of climate mitigation policies, where typically emission reductions in absolute or relative terms are chosen. One possible option is to choose a deliberately vague term such as 'moderate increase in resilience'. However, this leaves too much room for individual interpretation and the concept of resilience might not mean the same to each respondent. Instead we build upon designs used commonly in other fields such as health economics (Dolan and Tsuchiya, 2009; Robson et al., 2017), transportation (Rheinberger, 2009; SWOF, 2012; Tsuge et al., 2005), terrorism research (Viscusi, 2009), or landmine clearance (Gibson et al., 2007) among others. These studies use the amount of 'prevented deaths' or actual 'lives lost' to assess preferences for different policy measures. It allows us to use a clearly quantifiable variable with as little ambiguity as possible on the precise meaning.

With respect to the distributional dimensions, we incorporate three different types of policy characteristics as illustrated in Table 4.1. The first distributional dimension refers directly to the distribution of benefits among eligible recipients and captures the share of deaths prevented among the extremely poor. It allows us to contrast purely utilitarian approaches which only value the total number of deaths prevented from more egalitarian preferences, which might be concerned about the type of individuals protected and their level of poverty. The second distributional dimension is informed by the literature on co-financing and potential crowding-in or crowding-out of individual payments (e.g. Andreoni et al., 2014; Zhang and Maruyama, 2001). It suggests that individuals' willingness-to-pay can differ according to the contributions made by others. *A priori* the effect of third party contributions on one's own payment is ambiguous. One side of the argument suggests that payments made by others can increase the credibility of projects and can impose moral pressure to also contribute. This could result in higher individual contributions compared to a case without third party inputs (crowding-in). The other side of the argument suggests that third party input can reduce one's own contributions, in particular when individuals think of a fixed total amount that is required to meet a project target. In this case it may reduce individual support (crowding-out). The relative strength of these effects may however be specific to the policy context (see e.g. Andreoni et al., 2014; Zhang and Maruyama, 2001). In particular we want to test the following two hypotheses: (1) Does an additional levy on UK industries and businesses have a significant impact on individuals' likelihood to contribute? (2) Does making the adaptation payment conditional on an additional tax levied by the recipient government to also contribute to the project impact individuals' support?

Our third distributional dimension captures the preferred payment principle for UK individuals. In line with the existing literature we distinguish between an 'ability-to-pay', a 'polluters-pay' and an 'equal-shares' principle (for a related application see for example (Dietz and Atkinson, 2010)). This allows us to identify the preferred policy design and to compare and contrast the results to findings in the related climate mitigation literature.

Attributes	Levels	Rationale for Attribute
Total deaths prevented per year.	10,000; 20,000; 40,000	**Distributional dimension 1:** How are the payments distributed among recipients?
Share of deaths prevented among the extremely poor.	20%, 50%, 80%	
The project is conditional on local government in the recipient country to also raise taxes to contribute to the project.	No (0), Yes (1),	**Distributional dimension 2:** Co-financing: Who contributes apart from UK households?
UK industries and businesses contribute as well through an additional levy.	No (0), Yes (1)	
UK household payment scheme.	(0) Every household pays the same amount. (Collected through an additional lump-sum household tax). (1) Households with higher carbon emissions from fuel consumption pay more. (Collected through and increase in fuel tax). (2) Households with higher income pay more. (Collected through a proportional increase in income tax).	**Distributional Dimension 3:** How should the burdens be shared among UK households?
Your yearly payment.	£5, £20, £50, £70, £120	/

Table 4.1: Attributes and Levels and Underlying Conceptual Meaning

4.3.2 Information Treatment

As part of the choice experiment, we want to test to what extent the framing of the issue can impact support for climate adaptation payments. From the literature on the acceptance of climate *mitigation* policies, we know that direct benefits to the taxpayer in the form of revenue recycling can significantly increase public support for a carbon price for instance (Carattini et al., 2017b; Drews and van den Bergh, 2016) [3]. Since the literature on preferences for climate adaptation support is still relatively young, choosing a particular framing perspective is exploratory in nature. Existing work has shown that emotive language, appealing to the urgency of the problem, does not seem to have an effect (O'Garra and Mourato, 2016). Informed by the climate mitigation literature we decided to focus on potential benefits to the UK, rather than altruistic motives.[4] In the case of climate adaptation payments, direct benefits to the UK taxpayer are not immediately obvious. Such benefits can take the form of larger and more prosperous markets to sell UK goods and services, more stable global food prices, as well as relatively improved global stability and economic growth (e.g. HM Government, 2017; UKCCC, 2017). Yet, in a choice experiment the researcher faces the trade-off between providing a realistic scenario and one that is easily understandable for respondents. The benefit therefore needs to be as tangible as possible.

We decided to use an assessment of the UK's Security Forces, which identified climate change as a potential threat to the UK's national security (HM Government, 2015). Much time was devoted to selecting the right phrasing of the information treatment. Climate change can be a highly polarising topic. While more than 90% of people in the UK believe that climate change is happening, only 36% believe that it is entirely or mainly due to human activities. More than 50% believe that natural processes and human activity cause it equally (Phillips et al., 2018). Hence, it is important to select an institution that is respected within the population and not believed to have a vested interest in commenting on climate change. Our decision was influenced by opinion polls suggesting that the UK's Security Forces enjoy a highly positive reputation and are highly trusted by British nationals (YouGov, 2014).

To test potential framing effects we randomly divided participants into a treatment and a control group. Individuals in the treated group saw an additional paragraph summarising the assessment of the UK's Security Forces. It states that climate change may pose an additional risk to the UK's national security and may exacerbate instability overseas through resource stresses, migration, impacts on trade, and global economic and food insecurity, which may result in violent conflict. The information treatment

[3] Revenue recycling typically takes the form of earmarking revenues to be re-paid to households either inversely proportional to their income or in a lump sum amount.

[4] Limited funding only allowed us to use one information treatment and not to test multiple framings.

furthermore states that international support to help countries adapt to the negative impacts of climate change can reduce such negative effects.

4.3.3 Survey Design and Implementation

Focus groups and an initial survey design testing took place in October and November 2017. We went through extensive testing among colleagues before piloting the choice experiment. We then conducted two separate (roughly representative) online pilots with 100 respondents each. Feedback on the first pilot revealed that the colour coding of the choice cards was potentially misleading (see Appendix D.1 for the final version of an example Choice Card). We were concerned that respondents might interpret the colour coding for the first two attributes incorrectly.[5] Following the first pilot, we also introduced a further comprehension question that tested whether respondents read the choice card correctly, in particular the colour coding of the first two attributes. Based on this improved design, a second online pilot was conducted in February 2018. It appeared however that the additional comprehension question drew too much attention to the first two attributes, which meant that other attributes were neglected. This observation illustrates that the researcher needs to make a relative judgement between (a) ensuring that respondents understand the choice cards correctly and (b) priming respondents to focus too much on a particular attribute which might not reflect their true preferences. For the full survey, we decided to keep the improved colour coding, which makes the distinction between the different household groups clearer. We decided however to drop the additional comprehension question to reduce priming-concerns.[6] The survey still contained two comprehension questions, which tested if respondents had read and understood the overall scenario (See Appendix D.2 for the Scenario).

Each respondent had to read the one-page scenario description, explaining the basic concept of climate change and adaptation support for developing countries as agreed by the Paris Agreement[7]. Each respondent was asked two comprehension questions,

[5]This involved mainly changing the colouring of the schematically illustrated icons to avoid misunderstandings potentially arising due to associations with ethnicities of individuals in the respective projects (see example Choice Card in Appendix D.1). This change was implemented after evaluating feedback from survey responses.

[6]The dropped comprehension question asked respondents to select the respective policy alternative, in which the larger number of deaths were prevented after showing them an example choice card, which was not used for the actual analysis.

[7]The scenario description was informed by WHO (2014) and Hallegatte et al. (2016), and IBRD/The World Bank (2010). The WHO (2014) estimates that climate change will induce an additional 250,000 deaths annually between 2030 and 2050. This is used as the baseline estimate for our scenario. The estimates for average annual incomes of the extremely poor are informed by The World Bank (2017)'s definition of extreme poverty (1.90 USD per day, which is roughly equal to 515 GBP per year (using 2017 exchange rates). The definition of the middle-income households is informed by The World Bank

which tested that they had actually read and understood the scenario. The questions were chosen to be fairly basic comprehension questions, which is important to obtain a representative sample.[8] Respondents had to answer both questions correctly. Otherwise, they were immediately redirected to the survey company and did not complete the survey. This test proved to be an important filter with nearly one thousand respondents being excluded from these testing questions. Respondents were also not able to attempt the survey more than once.[9]

The results of the second pilot were used to generate a Bayesian D-Efficient design for the full survey using the software *Ngene*.[10] For the Bayesian efficient design the coefficient and standard errors of the pilot were used to generate the new experimental design. Using both the standard error as well as the coefficient estimate is preferred relative to using an efficient design, which may be more prone to be affected by outliers in the pilot.[11] Each respondent had to complete 8 choice tasks, with 2 policy options each and one opt-out option of 'No additional Policy'. Respondents are randomly assigned to either a treatment or control group. We use two blocks, which allows us to have 16 different choice cards within each the treatment and control group.

(2017)'s classification of non-poor but vulnerable individuals who earn up to 13 USD per day, and the middle class which earns between 13 and 70 USD per day, which is equivalent to approximately 4000 to 20,000 GBP annually. IBRD/The World Bank (2010) estimate that 70-100 billion USD are required annually to help developing countries adapt to climate change. This is roughly equal to 50-80 billion GBP.

[8]The comprehension questions asked respondents in a multiple choice setting to select the correct answers. Question 1: "Based on the previous description: For what reason are additional financial resources required?"(Correct Answer: To help poor countries adapt to climate change.). Question 2: "According to the previous description: What is climate change expected to cause?" (Correct Answer: Rising average temperatures, rising sea-levels and more severe natural disasters).

[9]The "Qualtrics" survey setting 'prevent ballot box stuffing' prevented individuals from taking the survey multiple times.

[10]We used 29,760 iterations to generate the final design. The mean Bayesian MNL D-error is 0.101537.

[11]For the pilots we generated efficient designs using a combination of small and zero priors. When generating efficient designs, the researcher has to take a decision between 0 priors (in which case the design becomes an orthogonal design) and very small positive and negative priors, which allows the researcher to exclude dominant alternatives from the design. This is not generally possible within orthogonal designs, as it would result in a loss of orthogonality of the design. The researcher faces a trade-off in this case: Including dominant alternatives gives the researcher one additional tool to check that respondents answered 'rationally' and did not select clearly dominated alternatives, perhaps by selecting choices randomly. Yet, including such dominated options also bears the risk that respondents become irritated, which can lead to an increase in protest responses. We decided to use very small positive and negative priors where the researcher has good reason to believe that the relationship is either positive or negative and use zero priors for coefficients, where this is not the case. With small priors and a Bayesian efficient design, the risk of inserting bias into the design is minimised, while being able to exclude irritating dominant alternatives.

4.4 Methodology

4.4.1 MNL and RPL-EC Models

The Choice Experiment (CE) methodology is built upon the Random Utility Theory established by McFadden (1974). In this framework, utility (U) consists of two components: a deterministic or observable part V and a random or stochastic component ε. Thus, individual i chooses alternative j among n alternatives if $U_{ij} > U_{in} \forall n$. In the Random Utility Framework, the utility of individual i choosing alternative j can therefore be written as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{4.1}$$

The deterministic or observable component V_{ij} can written as:

$$V_{ij} = \sum_{k=1}^{K} \beta_{ikj} X'_{ikj} \tag{4.2}$$

The choice probability P at each choice occasion t is given by:

$$P_{ijt} = \frac{exp(\beta_k X'_{kjt})}{\sum_j exp(\beta_k X'_{kjt})} \tag{4.3}$$

where X' is a matrix of k attributes in levels, and β is a vector of utility parameters to be estimated. In the Multinomial Logit Model (MNL) the error terms are assumed to be independently and identically distributed (IID) with an extreme value type 1 distribution (also known as Gumbel distribution). This model implies independence of irrelevant alternatives (IIA). Furthermore, it assumes taste homogeneity across respondents, since the utility coefficient of an attribute k is the same for all individuals $\beta_{ik} = \beta_k$ (see e.g. Strazzerra et al., 2012). One alternative provides the Nested Logit (NL) model, which relaxes the IIA assumption, yet still relies on taste homogeneity (Ben Akiva and Lerman, 1985; Hensher et al., 2005; Contu et al., 2016). The restrictive taste homogeneity assumption is relaxed in the Random Parameter Logit Model (RPL), also known as Mixed Multinomial Logit (MMNL). The RPL model allows variation among individuals for the utility coefficients by assuming a continuous distribution of parameter vectors (Revelt and Train, 1998; Hensher and Greene, 2003). An alternative model also relaxing the taste homogeneity assumption is the Latent Class Model (LCM), which also allows for variation among individuals by assuming a discrete distribution with individual parameters clustered in classes (Boxall and Adamowicz, 2002; Greene and Hensher, 2003).

There is no clear decision-criteria to choose between the two models (RPL and LCM), and it remains for the analyst to make an informed decision (Hess, 2014). While in the RPL model the analyst needs to decide on the distribution of the random parameters, the analyst has to decide on the number of classes in the LCM. We begin by analysing the basic MNL and the RPL, as the latter allows us to incorporate an error-correction term, which is not possible in the LCM. The error-correction term allows adjustments for correlations between individual choice alternatives. We then estimate LCMs to be able to provide more specific estimates for heterogeneous socio-economic groups.

In the RPL model the utility function of individual i is characterised by an additional idiosyncratic random deviation η_{ik} from the mean value of β_k for each attribute k. The utility of individual i for alternative j at choice occasion t is (see e.g. Revelt and Train, 1998; Contu et al., 2016):

$$U_{ijt} = \beta_k X'_{kjt} + \eta_{ik} X'_{kjt} + \varepsilon_{ijt} \tag{4.4}$$

The distribution must be specified by the analyst. Normal and (negative) log-normal distributions are the most common in this context, depending on prior expectations on the sign of the coefficient. Without strong priors on the sign of a coefficient, using the normal distribution allows full flexibility on the sign and is the preferred option. In this context the choice probability is given by:

$$P_{ijt} = \int \frac{exp(\beta_{ik} X'_{kjt})}{\sum_j exp(\beta_{ik} X'_{kjt})} f(\beta_i|\Theta) d\beta_i \tag{4.5}$$

where $f(\beta_i|\Theta)$ represents the density function for the vector of taste coefficients β, which could allow for some fixed elements as well as correlation between individual random elements (Contu et al., 2016). This now allows the vector β to follow a random distribution with parameters Θ. Furthermore, by adding an error-correction term we can allow for inter-alternative correlations (Revelt and Train, 1998; Herriges and Phaneuf, 2002; Contu et al., 2016). All the random parameters were set to be distributed using a normal distribution, except for the monetary attribute and the interaction of the Information treatment with the monetary attribute, which are assumed to be fixed (i.e. non-random) (following Revelt and Train, 1998; Ruud, 1996; Contu et al., 2016) . The random parameters are estimated with a simulated maximum likelihood estimation using 100 inter-person Halton-draws.[12]

[12]For the estimation we use the R-package developed by the University of Leeds Choice Modelling

Once the parameters have been estimated in the respective models, we can compute the monetary valuations (MV). These are given by the absolute value of the ratio of the respective non-monetary coefficient (the marginal utility of each coefficient) over the coefficient of the monetary attribute (Contu et al., 2016):

$$MV = \left| \frac{\beta_{non-monetary}}{\beta_{monetary}} \right| \tag{4.6}$$

4.4.2 Latent Class Models (LCM)

While the RPL captures heterogeneity at the individual level, the Latent Class Model (LCM) accommodates taste heterogeneity at the group-level. It can be seen as a semi-parametric version of the RPL, as the analyst does not have to make assumptions about the distribution of the parameters, but instead has to restrict the number of classes and estimates a computationally simpler MNL (Greene and Hensher, 2003). The motivation for the LCM is the idea that the population can be divided into a discrete number of s segments and that preferences within these segments are relatively homogeneous, but differ across segments. In the LCM individuals are assigned probabilistically into the segments based on socio-economic variables and attitudes. Utility is then be modelled as: (Boxall and Adamowicz, 2002; Strazzerra et al., 2012).

$$U_{ij|s} = V_{ij|s} + \varepsilon_{ij|s} \tag{4.7}$$

The utility parameters β_k can now be divided into s segments. Hence, we now have $\beta_{k|s}$ which means that we have a parameter β_k for each segment s. The unconditional choice probability of individual i choosing alternative j becomes the weighted average of all $\beta_{k|s}$ (Strazzerra et al., 2012; Contu et al., 2016)[13]:

$$PR_{ij} = \sum_{s=1}^{S} h_s PR_{j|s} \tag{4.8}$$

where $PR_{j|s}$ is the probability of choosing alternative j conditional on being a member in class s. It is expressed as:

$$PR_{ij|s} = \frac{exp(\beta_{i1|s}X_{i1j} + \beta_{i2|s}X_{i2j} + \ldots + \beta_{ik|s}X_{ikj})}{\sum_{n=1}^{N} exp(\beta_{i1|s}X_{i1n} + \beta_{i2|s}X_{i2n} + \ldots + \beta_{ik|s}X_{ikn})} \tag{4.9}$$

Centre (Choice Modelling Centre (CMC), 2017)

[13]From here on we drop the subscript t for each choice occasion to improve readability

The segment membership probabilities $h_1,...,h_n$ are estimated using a multinomial logit model, assuming a logistic distribution. The classes can be characterised by conditioning h on socio-economic covariates, attitudes or perceptions collected alongside the choice experiment (Strazzerra et al., 2012). The segment membership probabilities are then expressed as:

$$h_s = \frac{exp(\delta_s W_c)}{\sum_{s=1}^{S} exp(\delta_s W_c)} \tag{4.10}$$

where W_c is a vector of c covariates, and δ_s is a vector of coefficients that is specific for class s. After estimating the model, it is possible to calculate within each class the marginal rates of substitution between the attributes. The monetary value (MV) for a change in attribute k in class s becomes:

$$MV_{k|s} = \left| \frac{\beta_{k|s}}{\beta_{m|s}} \right| \tag{4.11}$$

where β_m is the utility coefficient of the monetary attribute for individuals in class s and β_k is a non-monetary coefficient for individuals in class s (see e.g. Gevrek and Uyduranoglu, 2015; Strazzerra et al., 2012).

4.5 Results

4.5.1 Descriptive Results

We collect a sample of completed responses for 1,140 individuals representative of the UK in terms of gender, age, income, education and 12 UK regions (see Appendix D.1 for demographic summary statistics compared to the UK population). Each respondent answered 8 choice tasks, resulting in a total of 9,120 observations for the choice analysis. We slightly oversample individuals with lower levels of income (which is a common problem in online surveys), resulting in a slightly lower average sample household income (£36,732 vs. £38,291 in the population). We also have slightly more individuals with a university degree (29% vs. 27.2%), and fewer individuals with low levels of educational attainment (up to 4 GCSEs) (30.4% vs. 36%).

Overall, we observe an average willingness-to-pay of £27.5 (median £5), which supports the results obtained by O'Garra and Mourato (2016).[14] In our sample about 10%

[14] We observe a slightly higher mean WTP of £28.4 in the group receiving the information treatment compared to a mean WTP of £26.6 in the 'control' group which does not see the information treatment.

of the respondents always choose the option ‘No Additional Policy’, whereas 50% never chose that opt-out option (Figure 4.2). This provides a first indication of some support for additional policies.

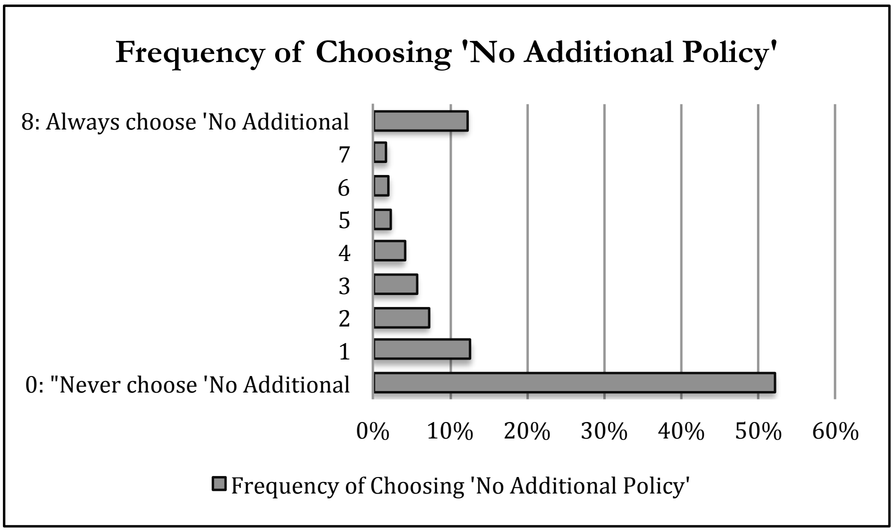


Table 4.2: Frequency of Choosing ‘No Additional Policy’

In addition to the choice experiment we asked for respondents’ opinions on topics such as climate change and social justice (see Appendix D.4 for descriptives on the opinion questions). In our sample 80% of respondents state that they think climate change is already happening, and 65% state that climate change is happening and GHGs such as CO_2 are its main cause. We have a little less than 10% of individuals not thinking that climate change is happening and 15% disagreeing with the statement that “Climate change is happening and mainly caused by CO_2” emissions. In our sample 60% disagree with the statement that climate change is largely caused by *nature*, while 20% agree with it and 17% don’t know (Figure D.2). The opinions are overall similar to what is reported by other UK surveys, although there seems to be a somewhat stronger belief in non-natural reasons for climate change compared to other UK surveys, although the different question phrasing might partially account for this difference (Phillips et al., 2018). Overall, 65% of our sample thinks that it is either extremely likely or somewhat likely that their children’s generation will be negatively impacted by climate change (Figure D.3).

Furthermore, we asked people what they thought is the main reason for why people live in poverty globally today. We find that slightly more than 20% of the sample thinks that “people are not doing enough to help themselves out of poverty”, while about 65% believes that “circumstances beyond people’s control” are the main cause (Figure D.4). We use the information from these opinion questions to inform our Latent Class Analysis.

4.5.2 MNL and RPL-EC Results

The results of the Multinomial Logit model (MNL) and Random Parameter Logit with Error Correction model (RPL-EC) are reported in Table 4.3.[15] In the interpretation we focus on the RPL-EC model (column 2), which provides the more reliable estimates. Most importantly the model does not rely on the assumption of homogeneity across individuals, but allows for variation among individuals in the utility coefficients. Firstly, we see as expected a negative coefficient on the payment attribute. Higher levies clearly imply lower acceptability. This emphasises again, similar to the climate mitigation literature, the public's sensitivity to costs from policies related to climate change. This is an important reminder to policy-makers to proceed in small steps, starting at moderate levels and increasing the rates gradually over time (in line with Baranzini and Carattini, 2014). Our results show that the public is willing to give up a small fraction of income to help poor countries adapt to climate change. We observe a mean annual WTP of £27 and a much lower median of £6.

Importantly, we see that respondents positively value the 'benefit' of projects, i.e. the number of people protected, but that they also value the share of extremely poor individuals protected. This provides first evidence that applying a strictly utilitarian framework when allocating adaptation support might not be the preferred strategy. As a robustness check and to identify potential non-linearities, we also estimate the model using factor variables for the first two attributes (See Appendix D.2). For the coefficients on the absolute number of individuals protected, we observe positive and significant coefficients for larger number of individuals protected. This suggests that individuals have strong preferences for protecting larger groups of people over smaller groups. Interestingly, for the share of individuals protected among the extremely poor, we observe a levelling-off effect. Individuals strongly prefer an equal share of extremely poor individuals protected to a distribution where only 20% of the protected individuals belong to the most vulnerable group. Yet, they do not significantly prefer the baseline outcome to a distribution, in which 80% of the individuals protected belong to the extremely poor group (see Appendix D.2). This suggests that individuals are concerned about the distribution of resources towards the poorest individuals but that there is a diminishing effect. Alternatively, the finding might also imply preferences for an equal allocation between individuals protected among the group of extremely poor and the lower-middle income households.

We observe that respondents' preferred payment mechanism is an ability-to-pay approach, meaning that individuals pay proportionally to their income levels. This is

[15] The choice models were estimated using the software R and the CMC (2017) choice modelling package as well as in Stata using lclogit for the Latent Class Analysis.

significantly preferred to a payment mechanism based on emissions (the baseline category). The least (marginally significant) preferred mechanism is to have a flat household levy. This reveals, that an 'ability-to-pay' approach is valued more relative to a 'polluter-pays-principle', which is in turn preferred to an 'equal-shares principle'. This is an important finding, which contrasts with the results obtained in the literature on mitigation policies. It suggests that respondents do not see such a strong link between individual emissions and their potential responsibility to contribute to adaptation payments. Hence, using carbon pricing to collect revenues to support a global adaptation fund would be expected to be less popular compared to a progressive fee based on income.

Dependent variable: Choice	(1) MNL	(2) PRL_EC	(3) RPL_EC	(4) MNL	(5) RPL_EC
Variable	Coeff (S.E.)	Coeff (S.E.)	S.D.	Monetary Valuation (£)	Monetary Valuation (£)
Total Deaths Prevented (thds.)	0.0314***	0.0470***	0.1001	2.07	1.92
	(0.0016)	(0.0036)	(0.0064)		
Share of Deaths Prevented among extremely poor	0.2718***	0.7840***	3.2345	17.93	31.97
	(0.0669)	(0.1383)	(0.2171)		
Payment Conditional	0.1736***	-0.0014	-0.6979	11.45	0.06
	(0.0339)	(0.0483)	(0.0966)		
Industry Co-Finance	0.1365***	0.0683*	-0.0571	9.00	2.78
	(0.0258)	(0.0370)	(0.1284)		
All HHs pay same	0.0103	-0.0984*	0.4508	0.68	4.01
	(0.0354)	(0.0531)	(0.1251)		
Richer HHs pay more	0.0311	0.1221**	0.0789	2.05	4.98
	(0.0377)	(0.0580)	(0.1279)		
Annual Payment (£)	-0.0152***	-0.0245***[b]	/	/	/
	(0.0008)	(0.0014)			
Information*Payment	0.0022**	0.0035**[b]	/	0.15	0.14
	(0.0011)	(0.0017)			
ASC 1 (Policy 1)	-0.0240	-0.0137	/	1.55	0.56
	(0.0252)	(0.0386)			
ASC 2 (Status-quo)	-0.0829	-1.3467***	/	5.47	54.92
	(0.0823)	(0.1115)			
Log-likelihood	-8888.761	-6957.890	/	/	/
Parameters	10	18	/	/	/
R-squared	0.11	0.31	/	/	/
Observations	9120	9120	/	/	/

Robust Standard errors reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%.
Omitted category: Payment based on households' emissions. b: Non-random fixed coefficients.

Table 4.3: MNL and RPL-EC Models

Lastly, it is interesting to note that our information treatment has a positive and significant (at 5%), impact on respondents' willingness-to-pay (WTP). Although the effect is small in terms of actual payment, this provides the first evidence of a successfully used information treatment within the context of public support for climate adaptation payments. It suggests that framing the issue in a way that also emphasises potential future benefits to the UK may be a promising strategy forward. Furthermore, this shows that using assessments from government institutions that are widely respected within the population and perceived to be impartial on the topic of climate change may help us to improve public acceptance. Nevertheless, this finding may also raise difficult moral concerns. Further work is required to better understand the underlying motivations, for why such a framing may positively impact individuals' contributions. The additional information may have convinced some people that urgent action is necessary, that climate change is a serious problem and that additional financial resources are required. It may however also be regarded as a relatively easy way to 'buy your way out' of any international responsibilities to deal with complex issues such as global food insecurities, conflicts or migration. Any communication strategy would therefore have to convey very clearly and carefully that financial support for climate adaptation is additional and not instead of other international responsibilities and commitments.

4.5.3 Latent Class Results

Finally, we consider how exploiting heterogeneity across individuals may provide additional information on their preferences for climate adaptation payments. Similarly to Gevrek and Uyduranoglu (2015) and Carattini et al. (2017a) in the climate mitigation literature we apply a Latent Class Model (LCM) to explain heterogeneous preferences. To construct our classes we use a combination of socio-economic variables and opinion-based questions on climate change and poverty (see Appendix D.6 for summary statistics of variables used to construct the latent classes).

Latent Class Models (LCM) require the researcher to make an informed decision on the number of classes to be chosen. The Bayesian Information Criterion (BIC) and the Aikaike Information Criterion (AIK) are the most commonly used. Both information criteria are designed for model selection and both incorporate a penalty for additional parameters. We choose a model with 5 classes as it has the lowest BIC and AIC values (Table 4.4).[16] Results from the LCM are reported in Table 4.5. Panel A in the table displays how preferences change across classes. Panel B shows the characteristics of respondents, which describe the composition of classes. The latent class model is

[16]Selecting LCMs with even more classes can become problematic, as the estimates become imprecise and potentially misleading. It is convention in the literature to not estimate models with more than 5 classes unless for studies with much larger sample sizes.

Number of Classes	BIC	AIC
2	13981.01	13839.92
3	13342.97	13111.19
4	13009.98	12687.51
5	12647.88	12234.70

Table 4.4: Criteria for selecting the preferred number of classes

estimated using a multinomial logit model (MNL). We summarise the results from this analysis for each class respectively below.[17]

Membership in class 1 is associated with being relatively less likely to believe that climate change will have a negative impact on future generations. Secondly, members of this class are more likely to believe that individuals hold the main responsibility for living in poverty.[18] They are also less likely to have an above average income. 10% of our sample falls into this group. Members of this class are more likely to support policies, which involve industry co-financing. They do not have strong distributional preferences, which is in line with their view on the underlying reasons for poverty.

Nearly one quarter of our sample falls into class 2. Membership in this class is characterised by a relatively lower income and educational level.[19] They are relatively less likely to choose the status-quo option of no additional policy (ASC_Status-quo). Hence, members in this class are more likely to support additional policy measures. Individuals in this class are relatively more likely to be a member of an environmental organisation. They are less likely to support a policy, which requires the recipient country to also issue additional measures to raise funds.

Approximately 15% of our sample belongs to class 3. Individuals in this class are relatively sceptic about the existence of climate change and do not have strong distributional concerns. More precisely, membership in this class is associated with a lower likelihood to believe that carbon emissions are the main reason for climate change and that climate change will have a negative impact on future generations. Members in this class are also more likely to believe that individuals hold the main responsibility for living in poverty. In line with their relative disbelief in climate change they are more

[17]We do not estimate the LCM with factor variables, as the estimates in LCMs can become unstable, meaning imprecise and potentially misleading, with too many parameters and classes. As we already estimate the model with 5 classes, we want to avoid adding further parameters through factor variables.

[18]This is equivalent to the following statement: Membership in class 1 is associated with being significantly less likely to believe that the main reasons why some people live in poverty lies in reasons beyond their control.

[19]Based on the exact variable specifications, it is expressed as: Membership in class two is associated with a lower likelihood of having above average income and a lower likelihood of having higher educational level.

likely to chose the status-quo option of no further policies. Furthermore, when choosing between additional policies they prefer a payment mechanism, in which individuals contribute based on their income levels and not proportional to their emissions.

Members of class 4 can be categorised as having relatively strong distributional and fairness concerns and by being concerned about the negative impacts of climate change. It consists of nearly 25% of our sample. Membership in this class is characterised by a higher likelihood of being a member in an environmental organisation, believing that climate change will have negative impacts on future generations and believing that the main reason for poverty lies beyond individuals control. In line with such believes they are more likely to support projects targeted towards a larger share of extremely poor individuals. Furthermore, they dislike if projects are conditional on financial contributions by the recipient country. But they support co-financing by UK industries and businesses. They are less likely to support a payment mechanism, in which every household pays the same. This may also reflect their views on the underlying reasons for unequal income distributions, which may require exemptions for lower income groups.

Individuals attributed to class 5 can be characterised as having strong preferences on the burden-sharing of additional policies. In particular they care about the distribution of the burden between donor and recipient countries as well as between households and industry in donor countries. Nearly 28% of our sample belongs to this class. Individuals in this class are more likely to support policies, which involve industry co-financing and are conditional on the recipient country also contributing. They also prefer a policy design in which richer households pay more. They are less likely to choose the status-quo option, which suggests that they are willing to contribute to additional policies.

One way to summarise the results from the Latent Class Analysis is by grouping the classes 1 and 3 together. Respondents in these groups are sceptical about the existence or the negative impacts of climate change. Furthermore, they appear to not have strong distributional preferences. They tend to support the view that individuals are largely responsible themselves for living in poverty. Approximately 25% of our sample belongs to this group. Convincing individuals from this group to contribute to climate adaptation payments is likely to be challenging. They appear to be opposed to the two main underlying ideas that may results in a willingness to support such policies: (1) believing in the existence of climate change, and (2) international solidarity to help individuals move out of poverty. Yet, reversely this also means that about 75% of our sample belongs to any of the other classes. This allows potentially for a more optimistic view that a substantial majority believes both in the negative impacts of climate change and acknowledges that poverty can be caused by reasons beyond individuals' control. The combination of these two factors appears to be somewhat necessary for being willing to contribute to climate adaptation in the long-run. In particular, since climate change is expected to affect poor people more severely and to increase and exacerbate existing poverty.

Variable	Class 1	Class2	Class 3	Class 4	Class 5
Panel A	Coeff. (S.e.)				
Total Deaths prevented (thds.)	0.032***	0.015***	0.008	0.220***	0.023***
	(0.009)	(0.003)	(0.017)	(0.024)	(0.005)
Share of deaths prevented among the extremely poor	-0.285	0.284	-0.663	3.300***	-0.194
	(0.465)	(0.205)	(0.830)	(0.646)	(0.410)
Payment Conditional	0.237	-0.188**	-0.017	-0.620**	0.348***
	(0.233)	(0.087)	(0.456)	(0.241)	(0.130)
Industry Co-finance	0.751***	0.087	-0.823	0.449***	0.154*
	(0.208)	(0.067)	(0.559)	(0.128)	(0.089)
All HHs pay same	0.368	-0.064	0.370	-0.458**	-0.127
	(0.230)	(0.097)	(0.570)	(0.190)	(0.123)
Richer HHs pay more	0.275	-0.027	1.046*	-0.109	0.337*
	(0.255)	(0.104)	(0.570)	(0.334)	(0.180)
Annual Payment	-0.086***	-0.001	-0.021**	-0.032***	-0.036***
	(0.007)	(0.001)	(0.009)	(0.006)	(0.003)
Information * Payment	-0.002	-0.000	-0.010	0.002	-0.036
	(0.010)	(0.001)	(0.013)	(0.003)	(0.003)
ASC_Status quo	-0.432	-0.414**	3.467***	-0.756	-3.965***
	(0.514)	(0.162)	(0.793)	(0.536)	(0.296)
ASC_option 2	0.386**	0.295***	0.112	-0.171	-0.164*
	(0.168)	(0.056)	(0.436)	(0.130)	(0.084)
Panel B					
Class Membership Function					
High Income	-0.755**	-0.517**	-0.414	0.248	0[a]
	(0.294)	(0.254)	(0.234)	(0.229)	
A-level & above	0.187	-1.108***	-0.294	0.120	0[a]
	(0.254)	(0.236)	(0.236)	(0.216)	
CO_2 main cause	0.004	-0.277	-0.980***	0.313	0[a]
	(0.274)	(0.236)	(0.247)	(0.255)	
CC negative impact	-0.710**	-0.069	-1.545***	0.549*	0[a]
	(0.275)	(0.250)	(0.254)	(0.296)	
Cause Poverty beyond control	-0.764***	-0.228	-0.882***	0.873***	0[a]
	(0.260)	(0.232)	(0.234)	(0.278)	
Member in Env. Org.	0.480	1.699***	-1.004	0.995*	0[a]
	(0.725)	(0.516)	(1.113)	(0.527)	
Car ownership (2 or more)	0.451	0.319	0.314	0.062	0[a]
	(0.281)	(0.248)	(0.261)	(0.247)	
Constant	-0.057	0.574**	1.289***	-1.745***	0[a]
	(0.307)	(0.278)	(0.252)	(0.394)	
Average Class Probability	0.104	0.234	0.145	0.239	0.278
Log-likelihood	-6035.35	/	/	/	/
Observations	9120	/	/	/	/

Table 4.5: MNL and RPL-EC Models

Robust Standard errors reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%. Omitted category: Payment based on household emissions. a: constrained values.

4.6 Discussion and Conclusion

Global climate change adaptation is becoming increasingly important. This holds in particular since global emission levels are still rising and current emission-reduction commitments from the Paris Agreement are expected to lead to 3°C of global warming, rather than the planned 1.5-2.0°C (UNEP, 2017; Met Office, 2019). Even if a gradual strengthening of emission reduction pledges can still limit warming to well below 2°C, large-scale financing to help developing countries adapt to climate change will be necessary. The estimated (lower-bound) of 100 billion USD that are required annually, at least until 2050, for global climate adaptation will need to be mobilised largely from developed countries (IBRD/The World Bank, 2010). Ensuring public support for such long-term projects is crucial to obtain sustained acceptance and to avoid policy reversal. It is therefore essential to better understand public perceptions of and preferences for international climate adaptation finance. Improved knowledge about public preferences for such policies can inform policy design and help anticipate potential challenges.

In this paper we examine such preferences based on a representative sample of the UK population, an important donor country. We systematically draw from previous work in the related literature on preferences for climate change *mitigation* policies, which has shown that distributional policy outcomes are particularly salient and can drive public perception. Specifically, we elicit (1) preferences with respect to burden-sharing principles among contributors and (2) distributional preferences with respect to the allocation of financial resources across projects.

To the best of our knowledge this is the first paper to show that payment mechanisms based on 'ability-to-pay' are preferred over a 'polluter-pays-principle' in the context of climate adaptation. This is a key result as it contrasts with findings from the *mitigation* literature where public support for policies is typically higher if the payment mechanism is linked to individual emissions. It suggests that respondents do not make a strong link between individuals' emissions and their potential responsibility to contribute to adaptation payments. We would therefore expect that using carbon pricing to collect revenues for a global adaptation fund would be less popular compared to using a progressive fee based on income.

With respect to the second distributional dimension, we argue that the allocation of scarce financial resources across projects can contain difficult moral judgements with respect to the relative benefits of individual projects. These may involve trade-offs between efficiency considerations (protecting the largest amount of people) and equity principles (protecting the most vulnerable) (e.g. Le Grand, 1990, 1991). Such trade-offs may arise as for instance additional infrastructure or capacity building is necessary when allocating funds to the poorest or most vulnerable groups. Existing (suggestive) evidence states that some adaptation institutions have allocated financial resources not to the most marginalised, but to projects with sufficient capacity and past experience, which tend to have relatively higher incomes (Stadelmann et al., 2014; Barrett, 2014). Fear of project failure or a need to report tangible outcomes may potentially drive such decision-making. Knowledge about public preferences for the allocation of scarce public financial resources in the context of moral judgements can be an important factor. This is particularly relevant to avoid or respond to potential public discontent or concerns about wasteful use of public funds. It is however important to note that this is not to replace expert judgement, but rather to inform or complement it.

We show that individuals have preferences for distributing resources to the most vulnerable individuals. On average, projects supporting the most marginalised receive larger public support in our representative sample of the UK population. Respondents do not only care about the absolute number of people protected. This finding implies that purely utilitarian approaches, which focus exclusively on the number of people protected would not be the most popular policies. We however also observe that the concern for the poorest individuals levels-off at high levels. Exploring such diminishing effects provides an interesting avenue for future research. Our findings imply the presence of egalitarian principles, which support adaptation funds in making trade-offs in favour of the most marginalised communities, instead of adopting purely utilitarian approaches.

In addition, we also test the effectiveness of a novel policy framing in this field that emphasises potential benefits to the UK from helping developing countries adapt to climate change, using a randomised information treatment. We show that such a policy framing can lead to a statistically significant increase in public support, even though the magnitude of the effect is marginal. This finding provides an interesting avenue for future research to test similar framings that focus on donor country benefits from adopting climate policies. Such effects may also be observable beyond this specific context and could be tested further for climate mitigation or development policies.

Lastly, our latent class analysis has shown that there is a high degree of heterogeneity in preferences and perceptions of climate change adaptation among individuals in the UK. We observe that 25% of our sample is either sceptic about the existence of climate change or sceptic about concepts of solidarity towards people living in poverty. It appears particularly difficult to mobilise support from this group of individuals. On the flip side this implies that a large majority of 75% shows the basic requirements to be willing to contribute to international climate adaptation funds. Overall we however find that public support for international climate adaptation projects remains vastly insufficient to meet international commitments. Further research in this field is necessary to test additional policy framings and to identify policy attributes that can help to increase public support for climate adaptation finance.

Chapter 5

Oil Price Shocks and Income Inequality: An Analysis of Resource Dependent Countries and US States.

Abstract

This paper contributes to the literature on socio-economic impacts of natural resource wealth. In particular we examine the impact of the shift from a low- to a high oil price regime post 1998 on income inequality in resource rich countries and US states. The theoretical framework developed by Corden and Neary (1982) and further applied by Goderis and Malone (2011) predicts that resource booms can reduce income inequality, particularly in developing countries through additional spending in domestic low-skill sectors. We empirically examine the relationship between resource wealth and inequality using a time period that is characterised by particularly high levels of inequality, for which outcomes may systematically differ from earlier low-inequality periods. By adopting panel regression techniques, as well as the quasi-experimental synthetic control method, we are able to show average effects across all resource rich units, as well as identify unit-specific effects, which allow for a more detailed insight. Overall we do not find strong support for an effect of the post-1998 oil price boom on income inequality within resource dependent countries or US states. Our analysis discusses challenges in empirically identifying effects on income inequality indices such as the Gini coefficient.

5.1 Introduction

The empirical literature on the natural resource wealth of countries and the potential existence of a "resource curse" was started by the seminal papers by Sachs and Warner (1995, 1997, 1999b,a, 2001). These studies and the majority of studies that followed in the literature have examined the effect of resource dependence on aggregate outcomes such as GDP or the averaged effect of per capita GDP, remaining largely silent on distributional questions. Little attention has been given to the impacts of resource dependence on inequality.

Rents from natural resource extraction provide a unique type of income arising partly by chance due to the location of the resource. It has been argued that these rents take the form of "unearned income" (Segal, 2011, p.1) that belong to all citizens of a country equally and should therefore be distributed equally. Depending on the inequality aversion of the social planner, resource booms might therefore require additional policy measures to achieve desirable outcomes from resource wealth. Inequality has received increasing attention in academic- and policy-circles as well as within the general public. There is a relatively large body of literature arising mostly out of sociology that illustrates the negative social consequences of rising inequality (see e.g. Wilkinson and Pickett, 2009). Similarly, there is an increasing concern within the economics profession that high levels of inequality might have negative effects on productivity and can increase transaction costs through lower levels of trust and social cohesion (Stiglitz, 2009; Jayadev and Bowles, 2006; Bowles, 2012).

This paper contributes to the literature in two ways: First, it applies a quasi-experimental methodology to study distributional outcomes of the oil price shock post 1998, which to the best of our knowledge has not been done before. Earlier empirical studies (e.g. Goderis and Malone, 2011) focused on the time horizon up to the 1990s, which were characterised by relatively low levels of inequality (Fig. 5.1), or only applied panel regression methods (such as OLS, random- or fixed-effect estimations) (e.g. Parcero and Papyrakis, 2016). We examine a time period that is characterised by particularly high levels of inequality, for which outcomes may systematically differ from earlier low-inequality periods. Second, to the best of our knowledge we are the first paper to provide evidence of the impact of a resource price boom on income inequality for resource rich US states. The institutional set-up of US states is different to the set-up of (resource rich) countries. Hence, we might expect that results may be systematically different for US states compared to resource rich countries. By adopting panel regression techniques, as well as a quasi-experimental approach we are able to show average effects across all resource rich units, as well as the individual effects of each unit compared to a synthetic counterfactual.

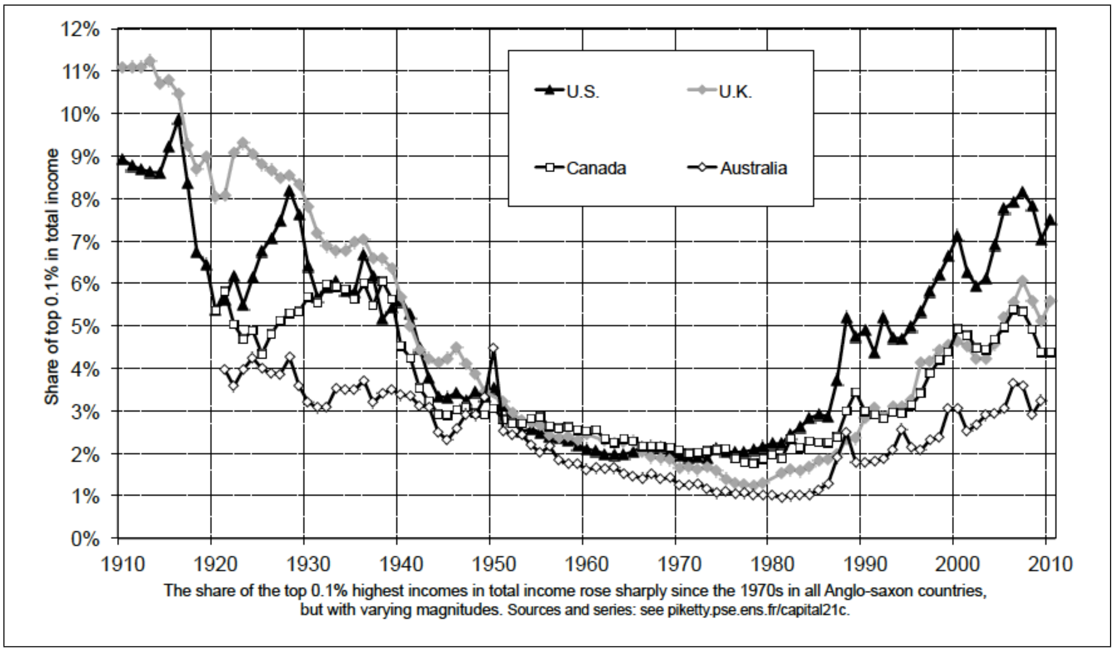


Figure 5.1: Long-run income inequality trends in the US, UK, Canada and Australia measured as the share of top 0.1% highest income in total income (Source: Piketty (2013))

The rest of the paper is structured as follows: Section 5.2 provides an overview of the literature on the resource curse. Section 5.3 outlines challenges of data availability and the selection of a suitable treatment period and treated units. In section 5.4 we describe the theoretical channels between resource wealth and income inequality. Section 5.5 illustrates the synthetic control methodology and section 5.6 describes the empirical specification. We present the results in section 5.7 and discuss the results and conclusions in section 5.8.

5.2 Literature

The extensive literature on the 'resource curse' was started by the seminal papers by Sachs and Warner (1995, 1997, 1999b,a, 2001). This literature focussed predominantly on the effect of resource wealth on economic growth at the country-level. The early papers found support for the existence of a negative relationship between countries' resource wealth and their economic growth. They sparked an entire research area in this field (see for example Anderson and Aslaksen, 2008; Arezki and van der Ploeg, 2010; Baggio and Papyrakis, 2010; Caselli and Cunnigham, 2009; Gylfason and Zoega, 2006; Kolstad, 2009; Murshed and Serino, 2011; Papyrakis and Gerlagh, 2004, 2007; Papyrakis, 2011, 2014). While the earlier papers found support for the resource curse, the more recent papers have typically provided a more sceptical view on such a generalised relationship. These more recent papers largely focussed on improving the econometric approach to identify a causal relationship. They applied instrumental variable approaches to address problems with endogenous variables and moved from cross-sectional to panel data analysis to reduce omitted variable bias. Some of the initial findings of the resource curse literature do not hold anymore when applying such additional scrutiny by, for example, accounting for country-specific variables (such as institutional settings, trade-openness etc.) (see for example Arezki and van der Ploeg, 2010, for a discussion). It has therefore become relatively clear that the earlier results do not hold anymore in a generalisable way. Building upon this initial branch of the literature, the research field expanded to examine a broader set of outcome variables beyond economic growth or GDP levels. Natural resource wealth has subsequently been linked to conflict and civil war (Collier and Hoeffler, 1998; Brunnschweiler and Bulte, 2008; Dixon, 2009; Lujala, 2010; Lei and Michaels, 2014), to lower values on the Human Development Index (HDI) (Bulte et al., 2005; Daniele, 2011), higher gender inequality (Ross, 2008), lower rates of poverty alleviation (Pegg, 2006), low levels of human capital accumulation (Bravo-Ortega and De Gregorio, 2005), and lower health outcomes (Cotet and Tsui, 2013).

Most of these studies find undesirable outcomes for countries with natural resource wealth. However, some contrary findings were established more recently showing that resource discoveries can have predominantly positive effects on per capita GDP, with strongest effects for non-OECD countries (Smith, 2015). A further branch of the literature has looked at institutional factors around resource booms with varying conclusions (for example Ross, 2001; Leite and Weidmann, 2002; Brueckner et al., 2012; Caselli and Tesei, 2011, 2016; Haber and Menaldo, 2011; Caselli and Michaels, 2013). Haber and Menaldo (2011) examine the relationship between resource wealth and regime type. Contrary to theoretical predictions (for example from Mahdavy (1970) and Ross (2001)), they find no evidence that natural resource wealth fuels authoritarianism. Similar findings are obtained for example by Herb (2005). They even observe a tendency in the opposite direction towards more democratic political regimes. In the case of Brazil, Caselli and Michaels (2013) find that oil-rich municipalities have higher revenues and increased spending on public goods, however survey data do not show a substantial increase in a number of public services and little benefit to the wider population, potentially indicating corruption by government officials. Overall, the evidence on whether resource wealth is a blessing or a curse remains inconclusive, context specific and conditional on the type of outcome variable being analysed.

Studies which applied quasi-experimental techniques to study impacts of natural resource shocks have largely assessed aggregate outcome variables, but have remained relatively silent on distributional outcomes. Liou and Musgrave (2014) study the impact of the 1973 oil embargo on per capita GDP and political regimes of resource-dependent countries. The authors conclude that their evidence does not support the existence of a resource curse, for neither outcome variable. Mideksa (2013) examines the case of petroleum discovery in Norway in the mid 1970s. The author finds that the oil discovery accounts for about a 20% increase in annual GDP per capita. Smith (2015) combines evidence from developing and developed countries and concludes that a significantly positive impact on per capita GDP is only detectable for developing countries with no effect for developed countries. Overall, there are relatively few papers employing quasi-experimental methods within this literature.

Since the late 1990s, there has been increasing interest in studying the effect of natural resource wealth on inequality. Using cross-sectional data, Leamer et al. (1999) examine why Latin American countries have substantially higher levels of inequality compared to East Asian countries. They draw upon trade theory to demonstrate that natural resource intensive sectors absorb capital, which would in the absence of the natural resource flow into manufacturing sectors. This delays industrialisation and reduces workers' incentives to accumulate skills. The reduced incentive among workers to gain skills may therefore result in higher levels of inequality. Sokoloff and Engerman (2000) elaborate on natural resource wealth endowments and their management across European colonies in the Americas to explain historic differences in inequality over the past centuries. Gylfason and Zoega (2003) develop a theoretical model to link resource wealth with lower economic growth and higher inequality. They also provide some simple regression results to support their theoretical predictions. Ross (2007) provides a conceptual overview of the impacts of resource wealth on inequality across socio-economic groups, as well as across regions in resource rich countries. It focuses in particular on the (dis-) advantages of decentralising resource revenues across regions. Subsequently, Goderis and Malone (2011) develop a theoretical framework in the context of a two-sector growth model to explain income inequality following a resource boom. Using variations in resource prices, they provide some support for their theory for the time period 1965 to 1999 using panel data techniques. Parcero and Papyrakis (2016) apply panel regressions and find that oil rich countries have significantly lower levels of inequality, with the exception of few very oil dependent countries, which experience higher levels of inequality. Nevertheless, this remains a field, in which relatively little empirical work has been conducted.

The literature on comprehensive (or inclusive) wealth accounting is closely related, but looks at natural resource wealth from a different angle. Instead of being interested in the immediate effect on economic outcome variables it is primarily interested in the sustainability of a country's growth path. It regards natural resources as a form of natural capital that is part of a country's total wealth. The literature is concerned about the use of the natural resources and the way, in which these forms of natural capital are invested into other forms of capital. Sustainability is thereby defined such that the total value of all capital assets of a country (i.e. including natural capital) has to be non-declining over time (Pearce and Atkinson, 1993; Hamilton and Clemens, 1999; Pezzey, 2004). This literature finds that countries with large natural resource endowments have difficulties in managing their resource revenues sustainably. They tend to have low or even negative Genuine Savings, which suggests that the country might be on an unsustainable development path, consuming its overall asset base (Atkinson and Hamilton, 2003; Dietz and Neumayer, 2007). Until lately, this literature has also focused predominantly on the aggregate wealth accumulation, irrespective of its distribution. Only over the past years new frameworks were developed that highlight he implications from unequal distributions of comprehensive wealth for sustainable development (Fenichel et al., 2016; Baumgärtner et al., 2017; Drupp et al., 2018). These studies show that inequality can be an important driver for societies' valuation of public goods, and that more equal societies tend to express higher valuations specifically for non-market environmental goods.

5.3 Data Availability

A key challenge in studying distributional outcomes is the lack of reliable data on income inequality for a sufficiently large panel of countries. The data on income shares provided by the World Bank (The World Bank, 2016) has many missing observations as well as often insufficient data coverage. Similar limitations apply to the Deininger and Squire (1996, 2013) data sets, as well as other sources, such as the Luxembourg Income Study (LIS, 2016). The fundamental problem when studying the effect of natural resource wealth on the income distribution is that most resource wealth exists in developing or emerging countries, for which income distribution data is hardly available in a standardised format. On the flip side, countries with reliable income distribution data (mainly OECD countries) are often not resource dependent. In order to establish a causal relationship between natural resource discovery and inequality one requires inequality data for a sufficiently long time period for countries with and without natural resources to construct a control group. Ideally, one would study the effect of a natural resource discovery on a country's change in the inequality level. Resource discoveries contain a degree of exogeneity, as they cannot be perfectly timed. Countries may increase their efforts to discover resources, which in turn increases the likelihood of discovery, but the precise timing of discovery may not be possible to plan. Hence, some exogenous variation can be exploited around natural resource discoveries.

However, to apply quasi-experimental techniques, we require data of more than 10 years prior to the treatment to establish credible control groups (following Abadie and

Gardeazabal, 2003; Abadie et al., 2010, 2015). Most oil-dependent countries discovered the resource at the latest in the 1960s or early 1970s, if not much earlier. Reliable inequality data for a sufficiently large group of oil-dependent countries and for suitable control group countries only exists from the 1970s onwards. Therefore, to the best of our knowledge, it is currently not possible to systematically examine the effect of oil-discoveries on within country income inequality for a group of resource-dependent countries.

5.3.1 Time Period Selection

Most of the past studies in this literature have used the discovery of natural resources as an exogenous treatment that allowed countries to reap resource rents. Yet, even when examining the resource discovery, it is not always easy to pick the precise beginning of the 'treatment' year. Mideksa (2013) argued that although Norway discovered oil in 1971, the impact on GDP per capita did not begin until 1974, which is when Norway expanded its extraction and generated larger shares of oil revenues. The advantage of using the moment of the resource discovery is the potential exogeneity of the treatment. Even resource discoveries might however not be entirely exogenous and uncorrelated with outcome variables due to policy pressures to increase exploration activities. The potential endogeneity applies even more to expansions in extractions, as these might be driven by political concerns to increase economic growth.

Since all countries in our sample had already discovered the resource by the mid-1970s when reliable income inequality data is becoming available, it is not possible for us to examine the effect of resource discoveries. Instead, we rely on a second-best identification strategy by examining the effect of an oil price shock. The global oil price trend reveals two periods of substantially higher oil prices: The first between 1973 and 1986, which was driven by the oil embargo established by OPEC, the Iranian Revolution and the Iran/Iraq war (Fig. 5.2). A second period of high oil prices started after 1998 and went until 2008, when the financial crisis started. This period of high oil prices was driven by stringent OPEC export limits established in 1999 after the Asian financial crisis, the events of 9/11 and the subsequent wars in Afghanistan and Iraq (Alhajji and Huettner, 2000; Reuters, 2017). These two time periods of markedly high oil prices provide the opportunity to study the effect of an increased inflow of oil revenue for resource-rich countries. Since revenue consists of the product of quantity and price, it is not necessarily the discovery of the resource per se that has an impact on the country's economy, but the combination of resource availability together with the resource price.

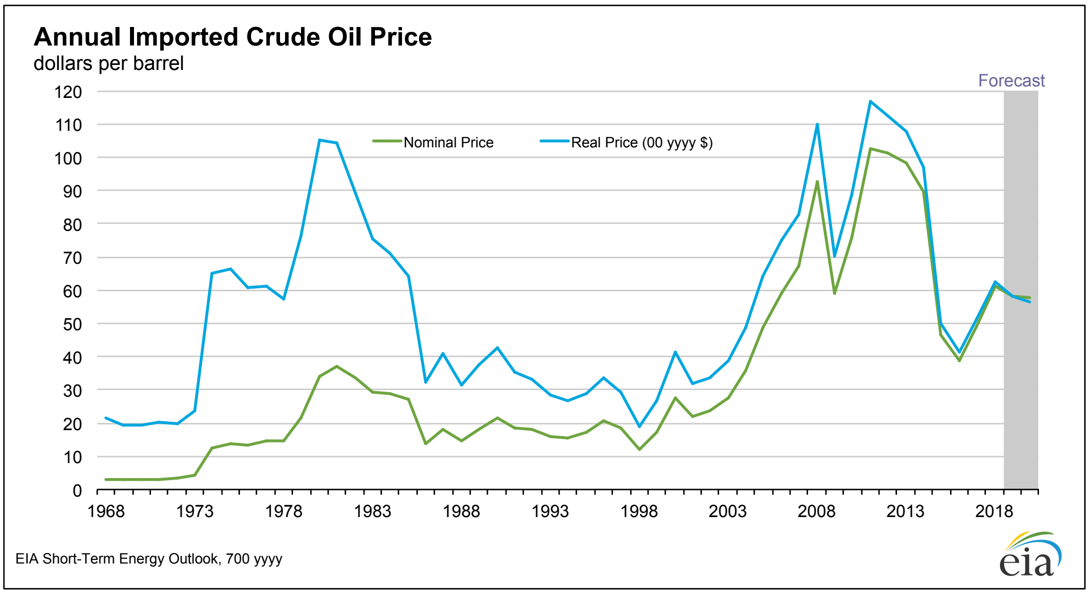


Figure 5.2: Annual imported crude oil price (nominal and real) (Source EIA (2019))

It is important to note that the second price rise post 1998 has been attributed largely to Saudi Arabia's cut in production. During the late 1990s and early 2000s Saudi Arabia was the only 'swing producer' and dominated OPEC. It has indeed been argued that OPEC did not actually operate as a commodity cartel, but was rather fully dominated by Saudi Arabia's decision-making in 1999. It was the only OPEC member country (with marginal support from Kuwait and the United Arab Emirates (UAE)), which actively and voluntarily decided to reduce production (Alhajji and Huettner, 2000; Reuters, 2017). Venezuela, Iran, Ecuador and Indonesia (which are included in our sample) are members of OPEC during the treatment period. They however did not voluntarily reduce production in 1999. The oil production levels of these countries were entirely driven by technical and natural factors and some third-party political factors due to for example sanctions in the case of Iran and Libya (Alhajji and Huettner, 2000; Reuters, 2017). Therefore, we argue that the treatment is sufficiently exogenous for our set of countries. Our main endogeneity concern is that the decision to reduce oil production is correlated with our outcome variable, income inequality. This would results in reverse causality or simultaneity bias. We believe this concern is sufficiently alleviated by the observation that the countries included in our analysis did not voluntarily reduce oil production in 1999, but that the production cut was entirely driven by Saudi Arabia, which is not included in our sample.

For our analysis we use a 'price shock' to assess the impact of resource wealth on within unit (country or US state) inequality. We examine the effect on treated (resource-rich) units compared to the effect on non-treated counterfactual units with otherwise similar characteristics. In our analysis we focus on the second of these price shocks due to the availability of income inequality data, i.e. the period from 1999 until 2007. To select our treatment year, we argue that the year 1998 marks the end of a low oil price regime, with a treatment commencing from 1999 onwards. In 1998 the oil prices reached its lowest level since the mid-1970s at US$ 12.28 per barrel. After 1998 the oil price increases and has never reached that same low level again. From 1999 onwards there are multiple exogenous shocks leading to high oil price levels. It is not easy to pin this shift to a single date, as it is possible with similar analysis of the 1973 oil crisis and the Iranian Revolution. However, tensions in the Middle East, the events of 9/11 and the Iraq war were contributing factors for a steep rise in the oil price after 1999.

We face a trade-off between accidentally either picking a treatment year too early or a year too late. When choosing a year after the actual treatment it might be difficult to establish a good synthetic control group in the years just before the treatment and we might capture other effects that are not due to the treatment. When selecting a treatment year that is too early, we might observe no treatment effect for the first couple of years and observe a gradual onset of the treatment. Moreover, the further away from the actual treatment the observations are, the less reliable becomes the comparison to the synthetic control unit, as other effects might play a role. The interpretation of effects becomes less reliable the further away from the selected treatment period. We prefer selecting a rather early year, to capture all elements of the gradual treatment. This allows us to observe a gradual onset of the treatment effect similar to other synthetic control studies (e.g. Abadie and Gardeazabal, 2003). Based on these characteristics we decided that 1999 would be the preferred treatment year for this analysis. We can use 1986 until 1998 as the pre-treatment period during which oil prices were relatively stable and low compared to the two high-price periods. This gives us 13 pre-treatment periods to create the synthetic control groups for the treated countries.

5.3.2 Selection of 'Treated' Units

In our setting, we define 'treated' units, as those countries or states that are relatively dependent on oil revenues. In other words these units generate a relatively large share of their income from oil revenues. In our selection of resource rich countries, we follow Haber and Menaldo (2011) who characterise countries based on their fiscal reliance on oil revenues as being 'resource dependent' (the approach is also used by Liou and Musgrave (2014) among others). They define countries as being fiscally reliant if on average their share of national income from oil revenues was 5% or larger for the time period 1972-1999. They identify 16 countries as being reliant on these revenues.[1] For us the main constraining factor is the availability of inequality data for the respective countries. In particular for developing countries, obtaining a sufficiently long time series of income inequality is challenging. We are left with 6 resource rich countries, which have sufficient income inequality data. These are Ecuador, Indonesia, Iran, Mexico, Norway, and Venezuela (Table 5.1).

In addition to the country-level analysis, we also examine resource-rich US states. The institutional setting and the relative dependence on natural resources is clearly very different for states within the US compared to natural resource rich countries. Therefore, we keep the two samples entirely separately for the econometric analysis. We mimic the approach from Haber and Menaldo (2011) at the country level and apply it to US states. We use the share of state-income from oil and gas extraction and related support activities to classify states as relatively resource dependent. We use the last pre-treatment year 1998 to classify states. The fiscal reliance of US states is comparatively much lower relatively to resource-dependent countries. We select states generating more than 1% of their state-level income from oil and gas activities in 1998 as being relatively resource dependent (Figure 5.3) [2]. This leaves us with Louisiana, Alaska, Wyoming, Texas, Oklahoma, and New Mexico (Table 5.1) as our 'treated' US states. It is important to note that the list of states is selected based on information before the recent expansion of hydraulic fracking in the US. Alaska had to be dropped from the synthetic control analysis. It has much higher levels of income inequality and is an outliner across all the US states. The synthetic control method was therefore not able to create a synthetic counterpart to this outlier. This is unfortunate, since Alaska is a very oil rich state. Yet, Alaska is in many ways different from the other states due to its extremely low population density and its geographic detachment.

[1] The 16 countries identified by Haber and Menaldo (2011) as being fiscally reliant on oil and gas revenues are: Mexico, Venezuela, Ecuador, Trinidad and Tobago, Nigeria, Angola, Indonesia, Iran, Algeria, Bahrain, Equatorial Guinea, Gabon, Yemen, Oman, Kuwait, and Norway.

[2] The classification is based on the NAICS sectors "Oil and gas extraction" and "Support activities for mining", which also includes the support activities for oil and gas extraction. See Bureau of Economic Analysis Regional Economic Accounts (BEA, 2016) for further details on the sector definitions: `https://apps.bea.gov/iTable/iTable.cfm?acrdn=6&isuri=1&reqid=70&step=1#reqid=70&step=1&isuri=1`.

Number	Resource Dependent Countries	'Treated' US States
1	Ecuador	Alaska
2	Indonesia	Louisiana
3	Iran	New Mexico
4	Mexico	Oklahoma
5	Norway	Texas
6	Venezuela	Wyoming

Source: Authors' calculations based on data from the Bureau of Economic Analysis (BEA, 2016). Oil and gas dependence is defined as the share of total income coming from the sum of the sectors "Oil and gas extraction" and "Support activities for mining", which also covers the support activities for oil and gas extraction.

Table 5.1: List of resource dependent countries and 'treated' US states

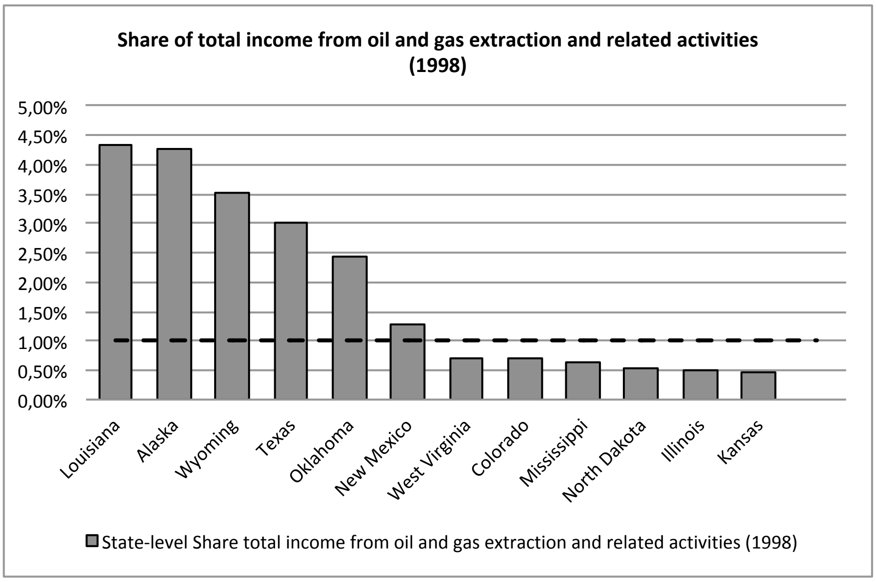


Figure 5.3: US state-level dependence on oil and gas activities (1998)

5.3.3 Inequality Data

In order to analyse how resource benefits are distributed within countries and states we would ideally analyse the effect of the shock separately for each income quantile. Unfortunately, the quantile-level income data provided by the World Bank (The World Bank, 2016)[3] and the Luxembourg Income Study (LIS, 2016)[4] do not cover a suffi-

[3] World Development Indicators: Distribution of income or consumption, The World Bank, 2016, accessible from: `http://wdi.worldbank.org/table/2.9#` The World Bank (2016).

[4] Luxembourg Income Study Database (LIS), Cross-National Data Center in Luxembourg, accessible from: `http://www.lisdatacenter.org/our-data/` (LIS, 2016).

ciently large amount of countries and years. The World Wealth and Income Database (WID) (WID, 2016) (previously known as the World Top Income Database)[5] is the first approach to develop a large panel of top income shares (top 10, 5 or 1 percent). Yet, the current coverage is not yet comprehensive enough for the treated countries and non-OECD control countries. Due to these data limitations we are not able to examine the effect of the oil price shock on separate income quintiles. Instead, we use the Gini coefficient from the Standardised World Income Database (SWID) (Solt, 2016) for the country analysis and the Gini coefficient from Frank (2014) for US states, as a measure of income inequality.[6] To the best of our knowledge, these provide the most comprehensive income inequality data for countries and states respectively.

5.4 Oil and Income Inequality: Theoretical Channels

A number of theories have been developed to assess the effect of natural resource booms on corruption and rent seeking within developing countries (for example Leite and Weidmann, 2002; Caselli and Michaels, 2013). These theories suggest that resource booms increase corruption and thereby lead to increased inequality, as elites obtain larger shares of the rents. In parallel, a second branch of literature has been developed that looks more directly on the effect of income inequality through wages. This theory was developed by Corden and Neary (1982) and further extended by Goderis and Malone (2011). We use their theoretical framework as a motivation for our paper.

The economic model developed by Corden and Neary (1982) and Goderis and Malone (2011) consist of three sectors: Non-traded (N), Non-Resource Traded (T), and the Resource Sector (R). Labour is divided into unskilled (L) and skilled (S) labour, with wages v of skilled worker and w the wage of unskilled worker (with $v > w$). Output is generated according to the Cobb-Douglas production functions:

$$X_N = A_N S_N^{\Theta_{SN}} L_N^{\Theta_{LN}} \tag{5.1}$$

$$X_T = A_T S_T^{\Theta_{ST}} L_T^{\Theta_{LT}} \tag{5.2}$$

[5] The World Wealth And Income Database, 2016, accessible from: `http://www.wid.world/`. (WID, 2016).

[6] The Gini coefficient is a statistical measure for distributions. It ranges from 0 (or 0%) to (1 or 100%). An income Gini coefficient of 0 represents a situation in which every individual has the same income (also called perfect equality). A value of 1 represent a situation of perfect inequality, in which one individual earns all the income while everyone else earns zero. It can graphically be illustrated through the Lorenz Curve, which is obtained by plotting the population percentile by income on the horizontal axis and the cumulative income on the vertical axis. The Gini coefficient is double the area between the Lorenz curve and the line of perfect equality.

where output X and productivity A are sector-specific. Perfect factor mobility is assumed, as well as constant returns to scale, so that: $\Theta_{SN} + \Theta_{LN} = 1$ and $\Theta_{ST} + \Theta_{LT} = 1$.[7] Aggregate income is denoted as:

$$Y = p_N X_N + X_T + A_T R \tag{5.3}$$

where p_N is the relative price of non-traded goods in terms of traded goods. A resource boom is defined as an increase in R. Following Torvik (2001) they measure resource income in the productivity units of the traded sector (A_T).[8]

Goderis and Malone (2011) distinguish between two relevant sources of inequality following a resource boom: (1) the unequal distribution of resource income, and (2) the shift of production factors to the non-traded sector, because at least some parts of the resource income are spent domestically, whereas the traded sector is not directly affected by the increase in R. It might even be influenced negatively due to 'Dutch-disease' effects such as an appreciation of the currency. Thus, total inequality (I_T) consists of non-resource inequality (I_{NR}) and resource inequality (I_R), i.e.

$$I_T = I_{NR} + I_R \tag{5.4}$$

The literature focuses on non-resource inequality, as it is argued that this inequality dominates overall inequality. The non-resource effect dominates in particular the direct effect from the unequal distribution of resource income. The implicit assumption is that compared to the total economy the wage payments and the resulting inequality arising directly from these wage payments within the resource sector are negligible. (Goderis and Malone, 2011). Non-resource inequality is then defined as:

$$I = \frac{vS}{wL} \tag{5.5}$$

It is the inequality that arises in the overall economy as a result of the resource extraction, but does not explicitly include the potentially unequal distribution of resource income. It measures the value share of unskilled labour relative to the value share of skilled labour.

[7] They furthermore assume that unskilled and skilled labor earn their marginal products, and with perfect factor mobility, the marginal product of each factor is equal across sectors. Agents have identical preferences with Constant Elasticity of Substitution (CES) utility. Agents maximise their utility with respect to N and T consumption goods. The model is closed and the markets for traded and non-traded goods must clear.

[8] They state that measuring resource income in the productivity units of the traded sector is irrelevant in the short-run since productivity is assumed to be constant. For further details on long-run implications see Goderis and Malone (2011).

In short, a resource boom leads to an increase in R. This additional influx into the economy leads to a relative increase in spending in the non-traded sector compared to the traded sector since at least part of the revenues are spent domestically. The traded sector is not directly impacted by the increase in R, or declines relatively to the non-traded sector due to 'Dutch Disease' effects.

The effect of the natural resource extraction on the above defined non-resource inequality is defined by the relative skill intensity of the traded versus the non-traded sector. Thus, if the non-traded sector is relatively intensive in its use of unskilled labour, i.e. if $\Theta_{LN} > \Theta_{LT}$, then inequality will decline with the resource boom. This is because the total wages of unskilled labour will increase more than the total wages of the skilled workers, which reduces inequality, since $v > w$. If however the traded sector is relatively intensive in its use of unskilled labour, which means that the non-traded sector is relatively intensive in it is use of skilled labour, then inequality will increase. In this case skilled worker will benefit more than unskilled worker from the increase in R. Goderis and Malone (2011) argue that in developing countries the non-traded sector tends to be relatively intensive in unskilled labour (e.g. taxi drivers, shop and restaurant owners, hair dressers, etc.). The traded sector needs to compete with international standards and tends to require higher skill levels. One would therefore expect a relative decline in inequality in resource-rich developing countries after a natural resource boom. For developed countries, the authors argue that the effect is more likely to be reversed, although differences in skill-level between traded and non-traded sectors tend to be less strong[9]. The anticipated effect might therefore be more ambiguous or less pronounced in developed countries. These theoretical predictions provide the background for our analysis and may help us interpret any empirical findings.

5.5 Methodology: Synthetic Control

The Synthetic Control method is developed and described in the landmark papers by Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015). In our paper we use two different samples, namely resource-dependent countries and US states, and within each sample we also have multiple treated units. The method is applied to each sample separately and within each sample it is also applied separately for each treated unit at a time. Thus, for each sample (and for each treated unit) we observe the units $j = 1, \ldots, J+1$, which are countries or US states respectively in the analysis[10]. We

[9] Goderis and Malone (2011) argue that non-traded sectors which require high skill levels such as banking, healthcare and other high value-added services tend to dominate the non-traded sectors in developed countries and are at least as intensive in high-skill labour as the traded sectors.

[10] Treated units are never used as potential control units for other treated units.

observe these for the time periods $t = 1, \dots, T$ in a balanced panel, in which the units are observed at the same time periods. The first unit is the respectively treated unit (i.e. $j = 1$ is the "treated unit", which is exposed to the shock). So, we are left with J control units in our "donor pool" that can form the synthetic control unit. The "treatment" or "shock" occurs in period $T_0 + 1$. Hence, the time periods $1, 2, \dots, T_0$ are a positive number of pre-intervention periods, and $T_0 + 1, T_0 + 2, \dots, T$ are a positive number of post-intervention periods.

We have two potential outcomes: Y_{jt}^N is the outcome variable (here the Gini coefficient) for the untreated unit j at time t. Y_{jt}^I is the Gini coefficient of unit j at time t when treated. Formally we want to find the effect $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$, which is the difference in the two potential outcomes. It captures the effect of the treatment on the outcome for the treated unit $j = 1$ in the post-intervention period. However, Y_{jt}^N cannot be observed in the post-intervention period for the treated unit $j = 1$. Thus, we do not know what the treated unit would have looked like post-treatment if it had not been treated. This is the motivation for constructing a synthetic control group, which allows us to estimate this missing potential outcome as closely as possible given the observations in the donor pool.

Instead of taking a single untreated unit, as it is done in a typical difference-in-difference setting the synthetic control method takes a weighted average of untreated units and constructs a synthetic untreated unit. Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015) show that this is often more accurate than relying on a single untreated unit. The synthetic version of the treated country or state is constructed as a weighted average from the country or states from the donor pool, i.e. units $j = 2, \dots, J + 1$. We have a $(J \text{ x } 1)$ vector of weights $W = (w_2, \dots, w_{J+1})'$, for which $0 \leq w_j \leq 1$ and $w_2 + \cdots + w_{J+1} = 1$. We then want to choose the weights W so that the synthetic control resembles most closely the treated unit pre-treatment. We therefore have a $(k \text{ x } 1)$ vector X_1, which contains the pre-treatment values of the treated unit of both the key predictors as well as the outcome variable itself. We want to match these values as closely as possible with the values in the donor pool. We therefore have a $(k \text{ x } J)$ matrix X_0, which contains the values for the same variables for the non-treated units (see also Andersson, 2015).

The method aims to find the optimal weights $W^* = w_2^* + \cdots + w_{J+1}^*$ so that the synthetic version of the treated unit best resembles the actually treated unit with respect to covariates Z_j and pre-treatment outcomes, so that

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, \sum_{j=2}^{J+1} w_j^* Y_{j2} = Y_{12}, \dots, \sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0}, \text{and} \sum_{j=2}^{J+1} w_j^* Z_j = Z_1 \qquad (5.6)$$

For the post-treatment period $T_0+1, T_0+2, \ldots, T$ we obtain an estimator α_{1t}:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{5.7}$$

To implement the synthetic control method, we need to define a measurable distance of pre-treatment values of the predictors and of the outcome variables, which we can then minimise. This will give us the most appropriate synthetic counterpart to the treated unit based on the available observations. Hence, we choose W^* to minimise the distance $||X_1 - X_0 W||$ subject to the weight constraints. More explicitly the synthetic control method solves for a W^* that minimises (see also Abadie et al., 2010; Andersson, 2015)

$$||X_1 - X_0 W||_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{5.8}$$

where V is a symmetric and positive semidefinite $(k \text{ x } k)$ matrix, which assigns weights to minimise the mean square prediction error of the synthetic control estimator. The term V allows us to weight the predictors and assign larger weights to more important predictors. We choose the data-driven approach to select V, which is recommended by Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2011, 2015). Thus, we select V so that the mean square prediction error of the outcome variable is minimised over the entire pre-treatment period[11].

Instead of result tables that are typically the standard output of regression analysis, the synthetic control analysis provides graphical illustration of the effects. It compares the trend of the weighted untreated unit to the treated unit over the pre- and post-treatment periods. Robustness checks are obtained through placebo-tests. These can be conducted either as placebo-in-space or placebo-in-time tests. The placebo-in-space test applies a placebo-treatment to the control states and compares the effect of the treatment on the treated unit with the placebo-treatment effect on the control units. The placebo-in-time test assumes a hypothetical treatment at an earlier year than the actual treatment. Comparing the outcomes of these placebo tests to the main results allows the researcher to make an assessment of the robustness of the results. This is particularly important since the synthetic control method does not provide standard errors that can be used to assess the statistical significance of effects.

[11] For non-data driven approaches the researcher could for instance manually assign weights based on findings from prior studies. This would however require the existence of a large and consolidated literature, which is not the case in our context.

5.6 Empirical Specifications

We begin our empirical analysis with simple panel regression estimations to obtain average effects across multiple treated units. In a second step we will use the quasi-experimental synthetic control technique to probe a more robust identification of the effect and to illustrate the effect for each treated unit (country or US state) separately. Goderis and Malone (2011) observe only short-run effects with the strongest effects for the first year after a resource boom. Their effects level off over a 5-year period post the resource boom.[12] This provides part of the motivation to apply a quasi-experimental technique, which is particularly well suited to examine short-term effects using a potential outcomes framework. While we start with simple panel regression techniques to motivate our study, the emphasis lies on the synthetic control analysis.

For each sample we begin by running pooled OLS, random effects, and fixed effects regressions. Our regressions set-up is similar to the potential outcome framework with quasi-experimental techniques. Similarly to the synthetic control method, we define a pre- and post-treatment period, as well as treated and control units. We prefer to use the potential outcome framework in this context as it can be regarded as a conservative estimation strategy. A caveat of this approach is that it uses relatively little variation, coming only from the binary classification into treated and control units and differences between the pre- and post-treatment periods. Hence, it does not make use of yearly variations in oil prices to estimate an effect. An alternative approach would be to use a panel regression framework that exploits yearly variation in oil prices to estimate the effect on inequality. However, since inequality moves rather slowly and since the time lags on the relationship are unclear, we preferred the quasi-experimental approach.

Our preferred fixed-effect regression is specified as follows[13]

$$GINI_{jt} = \beta_1 NatRes_j + \beta_2 Shock_t + \beta_3 NatRes_j \cdot Shock_t + \beta_4 X_{jt} + \alpha_j + \gamma_t + \varepsilon_{jt} \quad (5.9)$$

Gini is the respective inequality variable for the unit (country or US state) j at time t. The variable *NatRes* is a dummy variable that indicates whether unit j is considered resource rich. This variable is fixed over time in our analysis. The variable *Shock* indicates the treatment at a particular time t, which in our case are the years 1999 onwards. Hence, it takes the value of 0 for observations in years prior to 1999 and the

[12] Their coefficients on long-term effects are insignificant.

[13] The pooled OLS and Random Effects models are specified similarly without the unit fixed effects. The pooled OLS does not take into account the panel structure of the data. It is run using Stata's 'reg' command. Random and Fixed Effects estimations are run using Stata's 'xtreg' commands.

value of 1 from the years 1999 onwards. Our panel starts in 1986 for the country-level analysis and in 1987 for US states due to missing values in the inequality data for 1986. The variable of interest is the interaction term of the time-treatment variable with the dummy variable characterising a natural resource endowment. The estimated coefficient tells us whether there was a heterogeneous change in inequality after 1998 for countries with natural resource endowments compared to countries without such endowments. We include a vector X_{jt} of control variables, which is different for the country- and US state analysis and explained in more detail separately below. In the respective samples we use the same control variables for the regressions and the synthetic control analysis. α_j are country-or state dummies, γ_t are year fixed effects, and ε_{jt} is the error term.

Since inequality is a complex phenomenon, there is no consensus on the set of control variables. A few key variables have been recognised: Per capita income was already identified as a determinant of inequality by Kuznets (1955). As an economy develops, workers move from low-income jobs in agriculture to higher income jobs in the industrial sector, which increases inequality initially. As more people move into the industrial sector inequality declines subsequently again, giving rise to an inverted U-shape (Goderis and Malone, 2011). Education has also been identified as a key determinant of income inequality. With higher levels of education there is more skilled labour, which lowers their relative wages and wage inequality (Tinbergen, 1975). Saint-Paul and Verdier (1993) draw upon the median voter model to explain the link between inequality and education. In their theoretical framework with high inequality the median voter is poor and votes for redistribution through public education, resulting in gradually increasing levels of human capital, which in turn influence wages and inequality. A third key determinant of inequality has been attributed to the political economy of a society and its form of governance. Acemoglu and Robinson (2002) develop a theory to explain the Kuznets curve using political stability and the institutional set-up of society.

5.6.1 Country-level specification

In our country-level analysis we include the following variables in line with the existing literature (see Table 5.2 for the summary statistics of the variables). Following empirical work by Barro (2000) we include GDP per capita in constant 2005 dollars ($GDPpcconstant2005$), the level of human capital ($HumCapPc$) based on the average years of schooling[14], and the $PolityScore$, which is a measure of the type of governance

[14] This variable is based on data from Barro and Lee (2013) and assumed rates of return to education based on Mincer equation estimates around the world from Psacharopoulos (1994).

in place in the respective country (CSP, 2014). It has a point scale and ranges from -10 (hereditary monarchy) to +10 (consolidated democracy). Furthermore we add to these variables: Number of people engaged in the labour market as a proportion of the population (*NoEngagedPop*) as a characteristic of the labour market, Gross Capital Formation (*GrossCapForm*) to capture investment, and GDP growth (*GDPgrowthpercent*) to control for different trends in economic development. Apart from the Polity Score all variables are taken from the Penn World Tables (Feenstra et al., 2015). The dependent variable (*GINI*) is taken from the Standardised World Income Inequality Database (SWIID) (Solt, 2016), which provides the most comprehensive country-year coverage for inequality data.[15][16]

Variable	Mean	Std. Dev.	Min	Max
Gini	45.97	6.60	20.25	69.36
Nat. Res. Dep.	0.11	0.31	0	1
Oil Price Shock	0.48	0.50	0	1
NatResDep*Shock	0.05	0.22	0	1
Share of population engaged in labour market	0.41	0.08	0.20	0.72
Education level (human capital per capita)	3.35	5.00	1.29	49.40
Gross Capital Formation (% of GDP)	0.23	0.07	0.03	0.59
GDP per capita (constant 2005 USD)	15924.66	16954.81	136.65	87772.69
GDP growth (%)	3.76	4.17	-50.25	35.22
Polity Score	6.18	5.45	-9	10

Table 5.2: Descriptive statistics for country-level variables.

5.6.2 State-level Specification

For the US state-level analysis the variable selection differs from the cross-country analysis (see Table 5.3 for descriptive statistics of the variables used in the state-level analysis). While states differ to some degree in their institutional set-up they are nevertheless constrained within the US federal system and thus institutional differences do not have the same relevance as in the cross-country analysis. Furthermore, the United States is a single labour market, in which individuals can move relatively freely between states. Compared to the cross-country analysis differences in educational attainment across US states are less pronounced. Moreover, to the best of our knowledge

[15] We use the market inequality variable, which is the inequality arising from the market before redistribution, as it captures more closely the concept of the non-resource sector inequality in the theoretical model developed by Goderis and Malone (2011).

[16] For the Synthetic control method we also use three pre-treatment Gini values as special predictors, which is in line with Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015).

there is no comprehensive data on annual state-level educational attainment reaching back until the 1980s.[17] Furthermore, we are constrained by the available data for a sufficiently long panel within the Regional Economic Accounts of the Bureau of Economic Analysis (BEA) (BEA, 2016). We selected GDP per capita ($GDPpc$) and GDP growth ($GDPgrowth$) to control for different levels of development and different trends. We also included the employment rate ($EmploymentPop$), which is similar to the proportion of individuals engaged in the labour force in the cross-country analysis. We include government transfers received per capita ($TransferPop$) to allow for redistributive policies within the states and include average dividend incomes ($DividendsPop$) to control for non-wage incomes. For the US state-level analysis the inequality data is taken from Frank (2014), which is to our knowledge the only available source of long-run annual inequality data at the state-level.[18][19]

Variable	Mean	Std. Dev.	Min	Max
Gini	58.07	3.64	48.94	71.14
Nat. Res. Depend.	0.12	0.32	0	1
Price shock	0.54	0.50	0	1
NatRes*Shock	0.06	0.24	0	1
GDP per cap. (USD)	38825.74	17786	15468	172917
GDP growth (%)	2.61	2.88	-10.3	19.5
Transfers Received per capita (thds. USD)	4.12	1.83	1.23	9.29
Share of population in employment	0.59	0.11	0.40	1.38
Dividend payments per capita (thds. USD)	5.52	1.94	1.91	15.40

Table 5.3: Descriptive statistics for US state-level variables

[17]The US Census bureau provides yearly estimates based on its 5-yearly census collection back until 2009 (`https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_15_5YR_S1501`)

[18]Again, in the synthetic control analysis, we also use three pre-treatment GINI values as special predictors, as recommended by Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015).

[19]To the best of our knowledge there is no equivalent variable to the gross fixed capital formation at the US state level available from the BEA. We believe that any differences in these investment levels, which are much smaller between US states than between countries, are controlled for by the state- and year- fixed effects. Furthermore, the variable is not significant in any of the robust regression models at the country-level, suggesting that it may not be an important determinant of income inequality.

5.7 Results

As a starting point and to motivate our further analysis using quasi-experimental methods, we begin with simple panel data estimation techniques. We run separate regressions with the Gini coefficient as the dependent variable starting with pooled OLS, followed by random- and fixed effects.[20]

Our main variable of interest is the interaction of natural resource dependence and the post 1998 price shock ($NatRes \cdot Shock$). It captures the average effect of the price rise on resource dependent units relative to non resource-dependent units. Across the two samples and the different models we observe a negative sign for the coefficient. We run the random and fixed effect models initially without any further controls (Models 3 and 6). We run all models once with standard errors clustered at the unit-level (country or state respectively) (Models 2, 5, 8) and once without clustering (Models 1, 4, 7).

Without clustering the effects of the coefficient of interest (the interaction $NatRes \cdot Shock$) are significant particularly in the US analysis. However, the coefficients become insignificant across all models once we cluster the standard errors at the unit level. Without clustering the standard errors are likely to be too small as they rely on the assumption that the error term is independently and identically distributed and that there is no correlation between observations in the same unit. Yet, observations within the same state- or country are likely to be correlated. Clustering standard errors at the unit level allows for such serial correlation within units. The sharp drop in significance after clustering the standard errors at the unit level is a problem that is similarly discussed in Parcero and Papyrakis (2016) and also may arise in part due to the use of variables with relatively little variation over time.[21]

Overall we observe negative coefficients on the interaction variable across all models. Yet, we do not observe significance after clustering the standard errors at the unit-level. We discuss the panel regression results in more detail separately for the country- and the state-level analysis below:

5.7.1 Panel Results - Country Level

The country-level regression results are presented in Table 5.4. Across all models we observe that the post-1998 time period is characterised by significantly (at 1%) higher levels of inequality. This is in line with findings by Piketty (2013) who showed that for

[20]Since the country-status on natural resource ownership is not time-variant, the coefficient gets dropped from the fixed effects estimation.

[21]Furthermore, we have relatively few units at which we cluster the standard errors (51 states; 52 countries), which may become problematic for fixed-effect estimations.

developed countries inequality levels have been rising since the 1980s. The interaction term ($NatRes \cdot Shock$) is negative but not significant in the robustly estimated models. Furthermore, the coefficients on the interaction are smaller than the coefficients of the post-1998 dummy variable (*Shock*). This suggests that inequality levels also increased for resource rich countries, but relatively less so compared to non-resource rich ones (although the difference is not significant). For the control variables, we see that the employment share is negatively and significantly associated with income inequality, which is as expected. In the random- and fixed-effects models we see that the polity score is negatively associated (although not significantly so in the robustly estimated models). This would suggest that higher scores, meaning more democratic forms of government, are associated with lower levels of inequality. Interestingly, we observe that per capita income and the level of schooling seem to be positively associated with income inequality. This suggests that on average for the countries in our panel higher levels of income and schooling are associated with higher levels of income inequality.

5.7.2 Panel Results - US States

The results of the regression analysis at the state-level are presented in Table 5.5. From the OLS and random effects models, we see that relatively resource dependent US states have significantly higher levels of income inequality.[22] We also see that post-1998 inequality levels seem to have increased in US States. Yet the significance disappears when clustering standard errors at the state level. The interaction between resource wealth and the time-dummy is negative, but the size of the coefficient is smaller than the coefficient of the time dummy. Hence, income inequality increased post 1998 on average also for resource dependent states, but slightly less so than for non-resource dependent ones. Again, the coefficients on the interaction term become insignificant after clustering the standard errors at the state-level. For the control variables, we see that per capita income is significantly (at 5%) negatively associated with income inequality, which is different from the country-level analysis, but might reflect the overall higher level of income in the US compared to some of the countries covered in the country-analysis. The employment share appears to be negatively associated with inequality, although the coefficient is only significant in the fixed effect framework without clustered standard errors. Transfer payments per capita are positively associated with income inequality. This might seem counter-intuitive. Yet, these do not show causal estimates. This coefficient might just reflect the need for larger transfer payments in states with higher levels of income inequality. The other control variable coefficients show no significant associations across models.

[22] The natural resource dummy is automatically dropped from the fixed-effects specifications, as it does not vary over time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	Gini	Gini	Gini	Gini	Gini	Gini	Gini	Gini
NatRes (dummy)	-0.631	-0.631	-1.088	-1.909	-1.909	/	/	/
(Yes = 1)	(0.772)	(2.056)	(2.541)	(2.515)	(0.2499)			
Price Shock	3.980***	3.975***	3.883***	3.778***	3.778***	3.883***	3.444***	3.444**
(dummy)	(1.243)	(1.318)	(0.594)	(0.644)	(1.349)	(0.594)	(0.654)	(1.472)
(Yes = 1)								
NatRes*Shock	-1.633	-1.644	-1.238**	-0.533	-0.533	-1.238**	-0.473	-0.473
	(1.091)	(1.360)	(0.532)	(0.531)	(1.105)	(0.532)	(0.528)	(1.108)
Employment Share	-9.857***	-9.857	/	-16.781***	-16.781*	/	-17.834***	-17.834*
	(2.837)	(15.294)		(3.970)	(10.109)		(4.141)	(10.268)
Human Capital per capita (schooling)	-0.152***	-0.152***	/	0.204**	0.204**	/	0.348***	0.348***
	(0.035)	(0.052)		(0.084)	(0.092)		(0.097)	(0.126)
Gross Cap. Formation	-11.512***	-11.512	/	-1.611	-1.611	/	-0.656	-0.656
	(2.674)	(9.994)		(2.213)	(7.620)		(2.271)	(7.748)
GDP per capita (USD 1000s).	0.036**	-0.036	/	0.115***	0.115**	/	0.151***	0.151**
	(0.015)	(0.058)		(0.028)	(0.047)		(0.032)	(0.068)
GDP growth (%)	-0.018	-0.018	/	0.010	0.010	/	0.011	0.011
	(0.046)	(0.087)		(0.024)	(0.044)		(0.234)	(0.044)
Polity Score	0.305***	0.305	/	-0.125***	-0.125	/	-0.133***	-0.133
	(0.0378)	(0.126)		(0.034)	(0.150)		(0.035)	(0.153)
Constant	49.665***	49.665***	43.623***	49.150***	49.150***	43.502***	48.325***	48.325***
	(1.388)	(5.861)	(0.937)	(1.710)	(3.944)	(0.418)	(1.527)	(3.857)
Observations	1300	1300	1350	1300	1300	1350	1300	1300
R-squared	0.1371	0.1371	0.041	0.0021	0.0021	0.0383	0.0006	0.0006
Model Type	OLS	OLS	RE – no controls	RE – with controls	RE – with controls	FE – no controls	FE – with controls	FE – with controls
Country FE	NO	NO	NO	NO	NO	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Std. Err.	Not robust	Clustered (52 countries)	Not robust	Not robust	Clustered (52 countries)	Not robust	Not robust	Clustered (52 countries

Standard Errors in parentheses: *** denotes significance at 1%, ** at 5%, and * at 10%.

Table 5.4: Panel Regression Results: Country-analysis

Dep. Var.	(1) Gini	(2) Gini	(3) Gini	(4) Gini	(5) Gini	(6) Gini	(7) Gini	(8) Gini
Nat Res (dummy) (Yes = 1)	4.148*** (0.365)	4.148*** (1.192)	3.891*** (0.971)	3.990*** (0.914)	3.990*** (1.295)	/	/	/
Price Shock (dummy) (Yes = 1)	0.960 (0.935)	0.960 (3.37)	8.740*** (0.004)	2.263* (1.252)	2.263 (2.494)	8.740*** (0.354)	3.174** (1.345)	3.174 (2.325)
NatRes*Shock	-2.122*** (0.474)	-2.122 (1.804)	-2.035*** (0.304)	-1.922*** (0.312)	-1.922 (1.816)	-2.035*** (0.304)	-1.831*** (0.309)	-1.831 (1.882)
GDP per capita (in 100,000s)	0.499 (1.150)	0.499 (4.250)	/	-2.802** (1.269)	-2.802** (1.420)	/	-3.337** (1.301)	-3.337** (1.488)
GDP growth	-0.008 (0.033)	-0.008 (0.057)	/	-0.043* (0.023)	-0.043 (0.056)	/	-0.022 (0.024)	-0.022 (0.064)
Transfer payments per capita	0.544*** (0.132)	0.544 (0.560)	/	0.901*** (0.187)	0.901** (0.431)	/	0.854*** (0.200)	0.854** (0.405)
Employment Share	-1.711 (1.406)	-1.711 (5.632)	/	-1.083 (2.456)	-1.083 (4.955)	/	-9.475*** (3.497)	-9.475 (7.230)
Dividend payments per capita	0.598*** (0.073)	0.598* (0.303)	/	0.062 (0.102)	0.062 (0.193)	/	0.031 (0.109)	0.031 (0.200)
Constant	52.366*** (0.831)	52.366*** (2.707)	52.794*** (0.410)	54.217*** (1.378)	54.217*** (0.026)	53.251*** (0.002)	59.639*** (0.019)	59.639*** (0.036)
Observations	1275	1275	1326	1275	1275	1326	1275	1275
R-squared	0.4333	0.4333	0.4220	0.3503	0.3503	0.3025	0.1472	0.1472
Model Type	OLS	OLS	RE – no controls	RE – with controls	RE – with controls	FE – no controls	FE – with controls	FE – with controls
Country FE	NO	NO	NO	NO	NO	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Std. Err.	Not robust	Clustered (51 States)	Not robust	Not robust	Clustered (51 States)	Not robust	Not robust	Clustered (51 States)

Standard Errors in parentheses: *** denotes significance at 1%, ** at 5%, and * at 10%.

Table 5.5: Panel Regression Results: US State-level

5.7.3 Results - Synthetic Control

In this section we present the results from the quasi-experimental Synthetic Control method. While the above regression gave us average effects across the group of countries or states, this approach allows us to explore in detail the paths of individual units.[23] An advantage of the synthetic control method is that it allows for more robust inference by creating a synthetic counterfactual. The synthetic counterfactual is created by a data-driven approach that minimises the distance between the respectively treated unit and synthetic counterfactual. Results are shown graphically. Figures 5.4 and 5.5 contain the main effects for the country- and state-level analysis respectively. The solid blue line indicates the trend of the respectively 'treated' unit and the grey dashed line shows the trend of the respective synthetic counterpart. The red line indicates the last year of the pre-treatment period (i.e. 1998). To the left of the red line we try to match the treated and synthetic counterpart as closely as possible. If the synthetic counterpart is sufficiently well matched before the treatment, the difference between the blue and the dashed grey line on the right side indicates a treatment effect.

5.7.3.1 Synthetic Control: Country-level Analysis

In the country-level analysis we see the challenge in obtaining sufficiently close counterfactuals for country-level variables. Countries differ across many characteristics and hence it can be quite difficult to get a close match. In addition, inequality appears to be a variable that is difficult to predict across countries through other macro-variables.

Overall, we tend to see that post-1998 the respectively treated units observe lower levels of income inequality, as the blue lines tend to be below the dash lines. This can be interpreted as being in line with the panel regression results. Yet, as in the regression results we remain doubtful whether this indicates a significant relationship. Overall, the pre-treatment match is not very close in particular for Indonesia, Mexico and Venezuela. This raises concerns on whether the synthetic counterfactuals are sufficiently precise and show a true treatment effect. To verify the results we conduct placebo-in-time (Figure E.1 in Appendix E.2) and the placebo-in-space (Figure E.3 in Appendix E.3) tests. The placebo-in-time test assumes a hypothetical treatment at an earlier year than the actual treatment. We set the year to be 1993, as it lies in the

[23] Regression-specifications with country dummy-variables, would also allow us to offer further insights at the country-by-country level. However, we decided instead to apply the synthetic control method, as it allows for more robust inference due to a more flexible and thereby arguably better control group. The method allows for more flexibility compared to other panel regression specifications (e.g. difference-in-difference). It is a data-driven approach to create a synthetic counterfactual consisting of shares of individual counterfactual units. Thereby, the researcher does not have to choose the counterfactual itself, but only the variables based on which the counterfactual is generated.

middle of the pre-treatment time period. Changing the year for the placebo test does not change the results. We would like to observe two lines that follow each other very closely. This would indicate that there is no placebo treatment in 1993 and that the treated and control units behave similarly. However, for the cross-country data we observe for some countries large differences between the two lines. The countries in the sample appear to differ on unobserved characteristics, making it difficult to create good synthetic counterparts. Furthermore, by setting an earlier placebo treatment we now only have seven pre-treatment observations to create the synthetic counterpart. With fewer observations the algorithm has less data to draw from to create the synthetic counterparts, making the match less precise.

The placebo-in-space test (Figure E.3 in Appendix E.3) applies a placebo treatment to the control units and compares the effect of the treatment for the treated unit with the placebo effect on the control units. The grey lines show the difference in the Gini coefficient between each country in the donor pool and its synthetic counterfactual. What we would ideally like to observe is that units with a good pre-treatment fit, i.e. units which are grouped closely around zero pre-treatment, observe less extreme values post-treatment relative to the solid black line (the treated unit). This would increase our confidence that the lower levels of inequality for the treated units do not just occur due to chance. With our sample we are not able to observe such clear-cut placebo-in-space tests. Yet, these challenges in obtaining precise placebo tests with macro-level variables are not uncommon in similar studies (see for example Liou and Musgrave, 2014).

Our country-level results do not allow us to draw strong conclusions on the relationship between resource dependence and income inequality. The negative interaction and the relative decline of the respectively treated units compared to the synthetic counterparts could suggest supporting evidence for the theoretical framework developed by Goderis and Malone (2011). However, our data does not allow us to conclude that the effect is statistically significant.

5.7.3.2 Synthetic Control: US-State Analysis

For the US we observe that the pre-treatment fit is better compared to the cross-country analysis. This indicates that US states are more similar to each other than countries, and that for US states it is easier to predict income inequality based on other macro-variables. Texas has the most notable post-treatment trend, for which we observe lower levels of income inequality relative to the synthetic counterfactual. For Oklahoma, Louisiana, Wyoming and New Mexico we observe no strong treatment effects. The treated and counterfactual lines follow each other relatively closely post treatment.

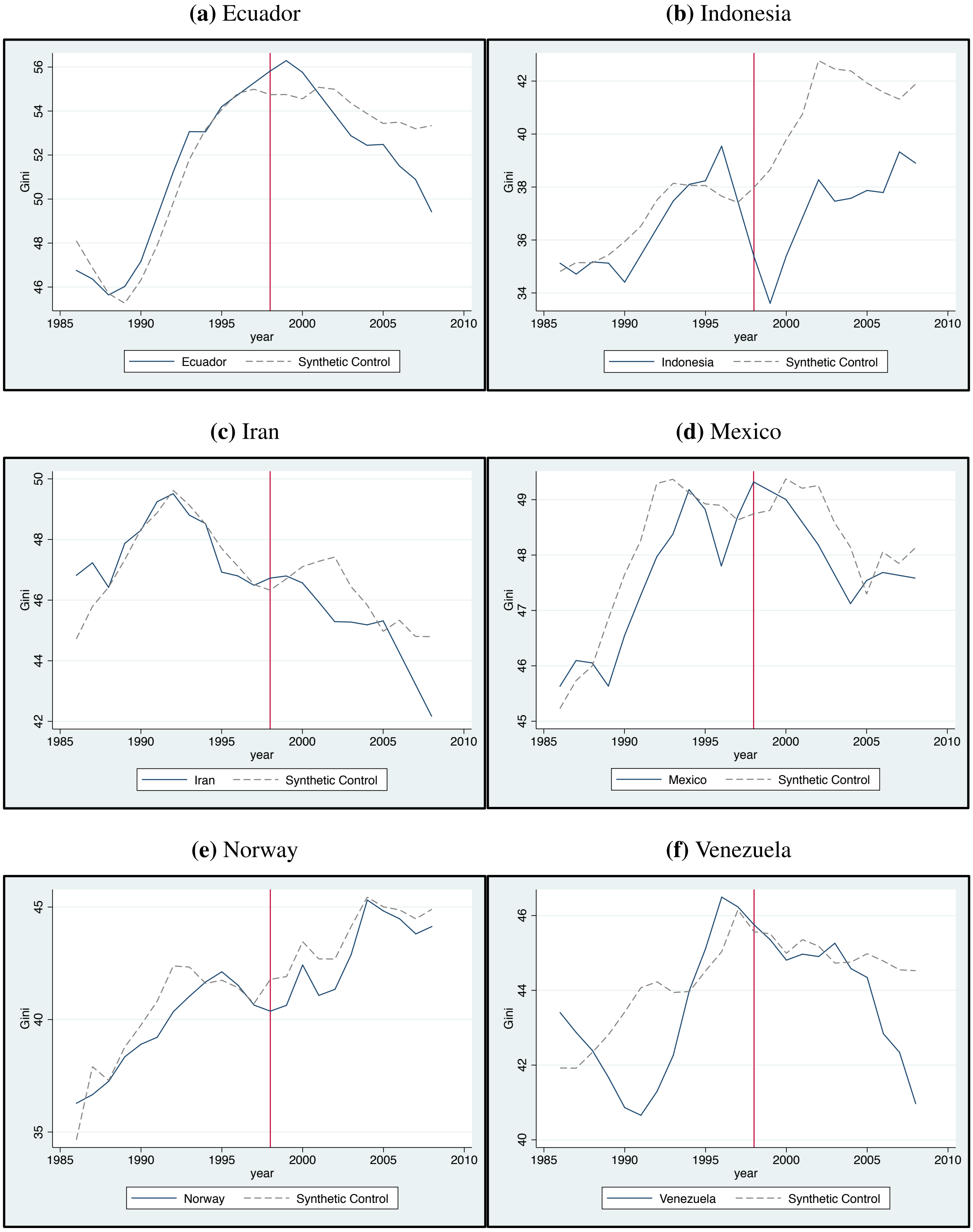
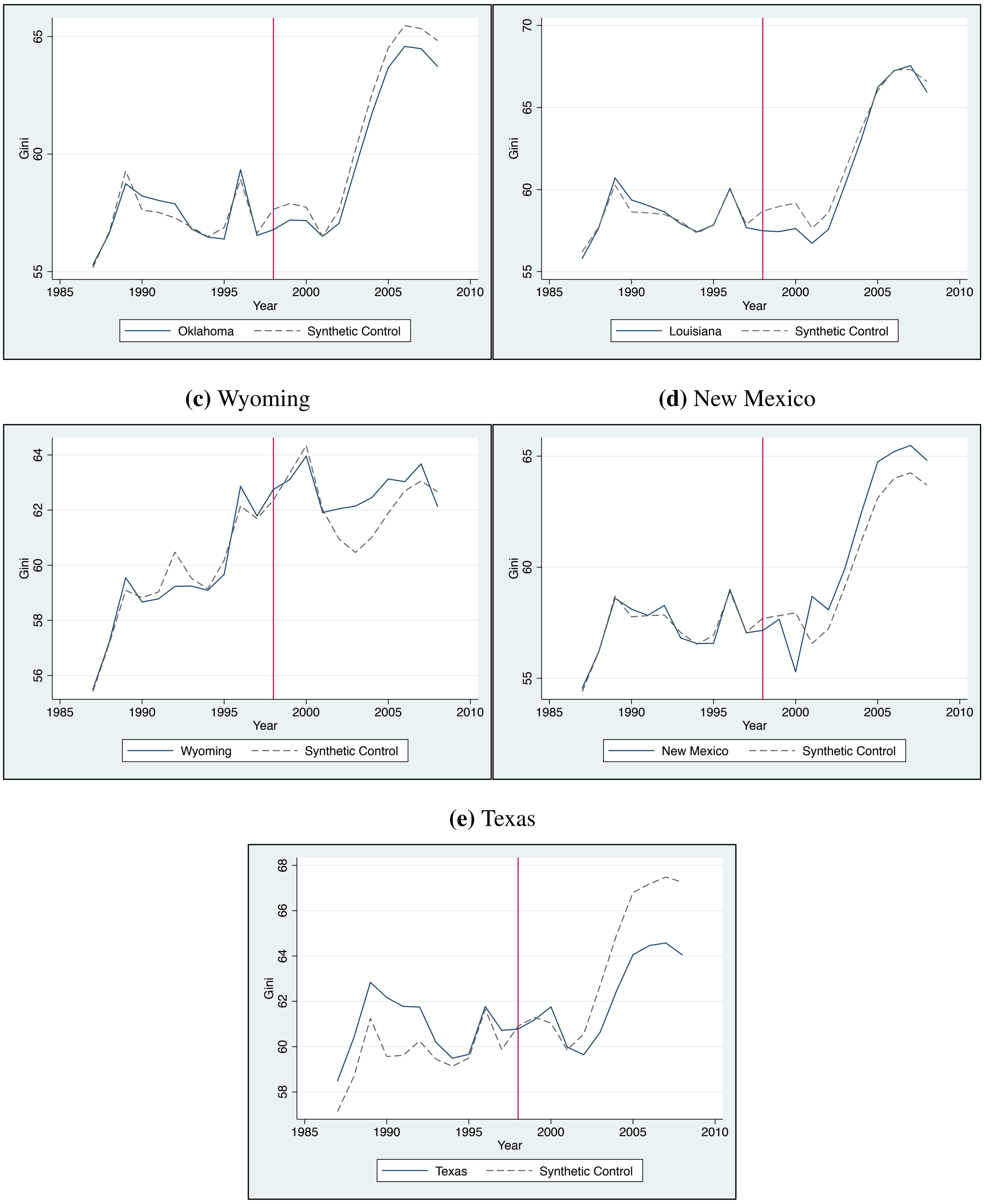


Figure 5.4: Synthetic Control Results Country-level

This holds particularly for the first two. In the case of Wyoming and New Mexico the results could be interpreted as having slightly higher levels of inequality compared to their counterfactuals. The effects tend to emerge a few years after the treatment.

The placebo-in-time tests (Figure E.2 in Appendix E.2) look relatively good for New Mexico and Oklahoma. The solid and the dashed lines follow each other fairly closely throughout. Regarding the placebo-in-space tests, we can again not rule out that the



(a) Oklahoma **(b)** Louisiana **(c)** Wyoming **(d)** New Mexico **(e)** Texas

Figure 5.5: Synthetic Control Results for US States

effects emerge due to chance. None of the black lines show the most pronounced treatment effect relative to the placebo treatments for the control states (grey lines) (Figure E.4 in Appendix E.3). We observe placebo treatments among control states with a good pre-treatment fit and more extreme post-treatment values. Therefore, we cannot rule out that our effects occurred due to chance. As stated above this is not an uncommon problem in synthetic control studies on macro variables (e.g. Liou and Musgrave, 2014). Overall we are more confident in the US-state level results than in the country-level findings, since the pre-treatment fit is better than in the case of the cross-country analysis. The results however suggest no significant treatment effect of the post-1998 oil price boom on within state income inequality.

5.8 Discussion and Conclusion

This paper contributes to the literature on the relationship between natural resource booms and socio-economic outcome variables at the country- and US state-level. Most of the existing literature on the resource curse looks at aggregate outcome variables such as GDP, or human development indicators, but not explicitly at distributional variables. While the early literature on natural resource wealth has found support for a resource curse largely from cross-sectional data, many of the more recent findings using panel data have attenuated the earlier results. Country-specific characteristics, such as institutional systems and institutional quality, matter for the management of natural resource wealth. Hence, the use of panel data (with unit fixed effects) and the construction of suitable counterfactuals are important in this context. Inequality has become an increasingly important outcome variable as high levels of inequality tend to be associated with lower levels of social cohesion, productivity and may increase transaction costs in society due to lower levels of trust. If high levels of inequality lead to social unrest, they can also have negative impacts on economic growth and overall welfare (see e.g. Jayadev and Bowles, 2006; Wilkinson and Pickett, 2009; Stiglitz, 2009).

Natural resources provide a unique type of income arising partly by chance due to the location of the resource and can be considered a form of "unearned income" (Segal, 2011, p.1). The overall distribution of benefits arising from natural resources can therefore be particularly contentious. Studying the effect of natural resource booms on inequality is therefore important. It can help in anticipating distributional implications and help design policies that can counteract such effects.

In this paper we examine the impact of the shift from a low- to a high oil price regime post 1998 on income inequality for resource dependent countries and US states using panel data. We specifically contribute to the literature in two ways. First, we apply a quasi-experimental methodology to study distributional outcomes of the oil price shock post 1998, which to the best of our knowledge has not been done before. Second, to the best of our knowledge this is the first paper to provide evidence of the effect of resource booms on income inequality (as measured by the Gini coefficient) within US states. We analyse the relationship for a time period that is characterised by particularly high levels of inequality, for which outcomes may systematically differ from earlier low-inequality periods.

Our empirical approach is motivated by the theoretical framework of Corden and Neary (1982) and Goderis and Malone (2011). The framework predicts a relative decline in inequality following a resource boom, in particular for developing, resource rich countries. By adopting panel regression techniques, as well as the quasi-experimental synthetic control method, we are able to show average effects across all resource rich units, as well as identify unit-specific effects, which allows for a more detailed insight. Overall we do not find strong support for an effect of the post-1998 oil price boom on income inequality within resource dependent countries or US states.

While we observe negative coefficients on inequality for resource rich units in the post-treatment period, the results are not robustly significant. Similar results are obtained from the synthetic control analysis. While we tend to see a relative decline in income inequality for the resource rich units, the effect is not well identified due to difficulties in creating sufficiently good control groups. The placebo tests cannot rule out that we observe any of the effects due to chance. It shows the difficulty in creating close counterfactuals for inequality levels for resource dependent countries and US states. Furthermore, the measurement of income inequality data may provide a challenge for empirical analysis. Since the data is typically collected from household surveys, the data may be imprecise or imperfectly measured. Limited yearly variation in inequality data also provides a challenge for statistical inference. Overall, the main constraint for our analysis arises from the availability of comprehensive and sufficiently detailed time series inequality data for resource dependent countries.

We conclude that further work in this field is necessary to better understand the relationship between resource discoveries, -prices and distributional outcomes. With more granular data becoming available on income deciles (such as for example the top income shares), disaggregating effects by decile will become possible. This could identify individual income groups that benefit and those that lose out from resource booms. This is important for policy-making to anticipate and manage the distributional impacts of resource wealth.

Concluding remarks

This thesis makes contributions to two broader literatures within environmental economics. In the first part, it helps to improve our understanding of the relationship between firm-level environmental and economic performance variables. In the second part it examines distributional questions within environmental economics.

The first part begins with a review of the extensive literature on the relationship between environmental and economic performance variables at the firm level. The literature has generally found positive associations between firms' environmental and their economic performance, although reverse effects also exist. Most of these studies have focused on environmental performance measures capturing emissions of pollutants and the adoption of international standards. One main reason for such effects appears to be that firms, which reduce material or energy costs are able to improve their economic performance, while reducing their environmental impact. A limitation of the existing literature is that it has largely relied on cross-sectional data, binary environmental performance indicators, or limited sector coverage. Moreover, the evidence on the relationship between environmental or 'green' product differentiation and firms' economic performance is very scarce. Examining whether diversifying into such goods and services is financially rewarded is however important as it can inform policy design to harness market forces to stimulate innovation that addresses environmental problems.

In chapter 2 we contribute to this literature by using a novel measure capturing firms' share of revenues from producing 'green' goods and services. We investigate in particular the 'revenue channel', through which firms may improve their economic performance by (green) product differentiation or improved access to new markets. The data allows us to examine the relationship using a continuous variable in a multi-year panel across a broad group of sectors for listed firms covering approximately 98% of global market capitalisation. We draw on the financial accounting literature and use a comprehensive set of accounting- and market based economic indicators and offer insight into the relationship between these indicators. We show that producing green goods and services is associated with higher operative profitability margins, across a broad group of sectors. These higher operative margins may however not translate into higher overall profitability. Producing green goods and services tends to require additional investments, which impose a downward drag on firms' overall profitability. With respect to investor valuation, higher green revenues are neither punished nor rewarded by investors, except for utilities, which tend to be sheltered from market forces and face unique regulatory settings. We show that relevant heterogeneities exist across sectors and economic performance metrics. Our empirical findings suggest that public policies can support and potentially accelerate the transition towards low-carbon technologies by facilitating cheaper access to capital for investments into green technologies. R&D support may also be necessary to reduce the costs of low-carbon technologies in sectors, in which the costs of such technologies are still relatively high. Helping to create and expand clearly distinguished markets for green goods and services (e.g. through labelling or additional information) may also help firms to move into such markets and invest in green technologies. While this chapter overcomes some important shortcomings of the prior literature and provides novel insights, an important limitation of this chapter, and the broader literature, remains that we are not able to establish causality. We address this limitation partly in chapter 3.

In chapter 3 we use event study methodology to examine whether financial markets reward environmental activities of firms. In particular we use the Paris Agreement, as it potentially created a shift in rewards for such environmental activities. We show that firms generating revenues from producing green goods and services have significantly outperformed the market in the week following the agreement, with the greenest firms experiencing 10% higher returns relative to the overall market. The effect exists both at the extensive and intensive margin of firms' green revenue share. This finding suggests that investors perceive the Paris Agreement to provide a credible mechanism to increase the diffusion and adoption of green technologies. We however observe that emissions intensity is a less clear-cut predictor for firms' stock performance following the agreement. Overall, the most emissions-intensive firms have not experienced different returns compared to the overall market. We observe important sectoral heterogeneities, and show that emissions-intensive electricity providers have marginally outperformed the market. Despite being emissions-intensive, these firms are also active in green technologies, largely by producing electricity from renewable sources. Investors might anticipate that the transition towards low-carbon technologies will be easier for these firms relative to firms in other sectors.

The second part of the thesis examines distributional questions within environmental economics. In chapter 4 I analyse distributional preferences within the context of global climate adaptation finance. I use primary data collected through a discrete choice experiment from a representative sample of the UK population, a large donor country. Understanding public preferences for climate policies is crucial to ensure and increase public support for such policies. I elicit preferences with respect to two distributional dimensions. First, the preferred burden sharing principle among UK individuals. Second the preferred distribution of financial resources across heterogeneous groups of individuals. The results show that, contrary to climate mitigation policies, individuals tend to prefer an 'ability-to-pay' approach over a 'polluter pays' mechanism in the context of climate adaptation finance. This suggests that using carbon pricing to collect financial resources for a climate adaptation fund is likely to be less popular compared to payment mechanisms based on income levels. This finding may imply that individuals do not see a strong link between their individual carbon emissions and their potential responsibility to contribute to global climate adaptation funds. This might suggest that generating support for climate adaptation policies may be even more challenging than in the case of climate mitigation. With regard to the second distributional dimension, we show that individuals have distributional preferences and prefer relatively egalitarian allocation decisions over purely utilitarian ones. Since financial support for global climate adaptation is likely to be scarce, difficult moral judgements will need to be made with respect to the resource allocation. While expert knowledge will be key in deciding how to allocate such resources, having broad public support for the allocation decisions will be important to ensure public support in the long run. While the results provide a first indication of such distributional preferences, further work is required to quantify such equity-efficiency trade offs more precisely. Overall, the results reveal vastly insufficient support for climate adaptation policies. Further work is also required to test alternative policy framings and -attributes, which could help to increase public support.

In Chapter 5 this thesis contributes to the literature on socio-economic outcomes of natural resource wealth. Most of the prior literature has focused on aggregate outcomes such as GDP or human development indicators. Relatively little work has examined the distributional impacts of resource booms. The distribution of income arising from natural resources may however be particularly contentious and require a unique management. Natural resource income arises partly due to chance because of the resource location. It has therefore been argued that such income should be distributed equally across the population. Since high levels of inequality can be detrimental to societies by diminishing societal cohesion and willingness to pursue public goods, it is particularly important for policy makers to manage any distributional implications of resource wealth. This chapter examines the impact on income inequality arising due to a shift from a low- to a high oil price regime for resource rich countries and US states. Using panel regressions as well as quasi-experimental methodology, it shows average impacts, as well as country- or state-specific effects. Overall, it does not find strong support for an effect of the post-1998 oil price boom on income inequality. The availability of inequality data provides a major limitation for this analysis. Furthermore, limited variation in the variables at the country- or state-level may make it difficult to identify an effect, in particular when using quasi-experimental methods. As more granular data on individual income quantiles becomes available, this offers an interesting avenue for further research. It would be valuable to know impacts on individual income groups, rather than analysing the effect on aggregate inequality metrics, which may hide quantile-level effects.

Lastly, I would like to emphasise two main concluding remarks from this thesis. First, climate change requires drastic and fast measures to reduce emissions across a broad group of industries and technologies in the economy. Setting the right policy frameworks and incentives will be fundamental to achieving the transition towards a low-carbon economy within the remaining time window and with manageable costs. Second, considering and managing the distributional consequences of climate and environmental policies will be essential for building and ensuring long run public support for such measures.

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Appendix A

Appendix to Chapter 1

A.1 Summary Table of Empirical Literature (continued over multiple pages)

Authors, Year	Environmental Performance Variable	Economic Performance Variable	Sample Size and Data Source	Data Structure (panel/ cross section)	Interpretation (correlation/ causation)	Results
Papers reviewed in section 2.1: Environmental performance and economic performance: Friends or foes?						
Al-Tuwaijri et al., 2014	Ratio of toxic waste recycled to total toxic waste generated.	Industry-adjusted annual return (expressing the firm's current-period economic performance relative to other firms in the same industry).	198 US firms. IRRC Environmental Profiles database provided by the US EPA (accessed through Freedom of Information Act requests), Compustat for financial data, LexisNexis for annual reports (commercial).	Cross-section (year 1994).	Correlation	Better environmental performance is significantly associated with better economic performance (significant only at the 10% level).
Ayerbe and Gorriz, 2001	Firm-specific costs of executing individual environmental project (i.e. firm-specific pollution abatement cost).	Work productivity (measured as value-added per worker).	53 large Spanish companies, quoted on the stock market. Data on participation in the PITMA programme is publicly available through the Official State Gazette from the Department of Industry and Energy (MINER) (public). Balance Sheet and Income Statement information are obtained from the National Securities Market Commission (CNMV), which is available for publicly listed companies (licence).	Panel (1990-1995).	Correlation	The authors study the effect of participation in the Spanish Industrial and Technological Programme for the Environment (PITMA), a subsidized pollution abatement programme. They find a small negative association between work productivity and pollution abatement investment dedicated to compliance with the pollution standard. They argue that this result is specific to the command-and-control regulation studied and may not be generalized to more flexible types of regulation.

Broberg et al. 2013	Environmental protection investment.	Technical efficiency.	Five Swedish industries: wood and wood products (279 obs.), pulp and paper (304 obs.), chemicals (289 obs.), rubber and plastics (223 obs.), basic metals (199 obs.). Two data sources from Statistics Sweden: 1) Industrial Economic Statistics (licence), 2) Industries' environmental protection expenditure (licence).	Panel (1999-2004).	Correlation	They use unique data on environmental protection investments in the Swedish manufacturing industry as a proxy for environmental stringency. This allows them to separate investments into pollution prevention and pollution control. They use a stochastic production frontier model to estimate if environmental regulation affects firms' production efficiency. They do not find support for the Porter Hypothesis as they observe a weak negative relationship between environmental investments and technical efficiency.
Darnall, 2009	Natural Resource Use, Solid Waste, Waste-water effluent, Air pollution, Greenhouse Gases, Overall environmental impact.	Self-reported profits.	The number of observations varies across models due to different response rates for each environmental performance variable: Natural resource use (2609), Solid Waste (2642), Waste Water (2386), Air pollution (2123), GHGs (1723), Overall environmental impact (1517). Survey conducted by the OECD's Environment Directorate.	Cross-section (survey was conducted in 2003).	Correlation	The authors use an OECD survey across seven countries to test the effect of regulatory stringency on firms' profits. They find that more stringent environmental policy regimes are negatively correlated with facilities' profits. This result holds for each of the individual environmental performance variables.
Fujii et al., 2013	CO_2 emissions, chemical emissions relative to sales.	Return on Assets (ROA), Return on Sales (ROS), Capital Turnover (CT).	758 Japanese manufacturing firms for CO_2 emissions; 2498 Japanese manufacturing firms for toxic chemicals emissions.	Panel; for CO_2 emissions (2006-2008); for toxic chemicals (2001-2008).	Correlation	The relationship between environmental performance and financial performance differs across pollutants: For toxic chemical substances

			GHG emissions from the mandatory GHG Accounting and Reporting System of the Japanese Ministry of Environment, Pollutant Release and Transfer Register (PRTR) from Ministry of Environment (licence), financial data from Nikkei Economic Electronic database system (licence).			they find a significant inverted U-shape relationship between ROA and environmental performance. For CO_2 Emissions they find a significant positive relationship between ROA, ROS and environmental performance. They find no significant relationship with CT.
Gray and Shadbegian, 2003	Abatement costs.	Productivity.	116 US pulp and paper plants. Longitudinal Research Database (LRD) containing data from the Annual Survey of Manufacturers and the Census of Manufacturers linked together, PACE survey for annual abatement cost data (licence).	Panel (1979-1990).	Correlation	They test whether the impact of environmental regulation on productivity differs by plant vintage and technology. Plants with higher pollution abatement costs have significantly lower productivity levels. The effect depends strongly on plants' technology. The negative relationship between higher abatement costs and lower productivity levels is largely driven by mills, which incorporate a pulping process. They show a strong negative impact of abatement cost on productivity. For mills without such technology the impact is negligible.
Hibiki et al., 2003	ISO14001 certification.	Stock returns; Tobin's Q (market value of the firm).	573 publicly-held firms in the manufacturing industry listed at the Tokyo Stock Exchange.	Cross-section (year 2002).	Correlation	The authors find that the voluntary introduction of the ISO 14001 certification contributes to a statistically significant increase in the market value of the firm by 11% to 14%. The authors

						explain this finding with two possible effects: the expected reduction in the potential risk of environmental liabilities, and the lower adjustment cost if environmental policy is tightened in the future.
Horvathova, 2012	Composite indicator on 93 pollutants (air, water, land, off-site transfers of waste, pollutants in waste water from industrial facilities).	Return on Assets (ROA), Return on Equity (ROE).	136 Czech firms. Environmental performance data from integrated register of pollutant emissions, which is part of the European Pollutant Release and Transfer register (EPRT) (publicly available), data on environmental managerial systems are collected using publicly available database (www.iso.cz) and double-checking the websites of companies, financial data are obtained from a commercial firm database CreditInfo (commercial).	Panel (2004-2008).	Correlation	Better environmental performance decreases financial performance in the following year, but increases financial performance after two years.
Jacobs et al., 2010	Corporate Environment Initiatives (CEI) announcements, which are self-reported corporate efforts to avoid, mitigate or offset the firm's environmental impact. Environmental Awards and Certification (EAC) announcements, which are awards granted by third parties. EAC announcements include ISO 14001 and LEED	Abnormal returns on stock prices.	340 firms across 63 three-digit NAICS codes, with a total of 780 announcements; 417 Corporate Environment Initiatives (CEI), 363 Environmental Awards and Certification (EAC). Dataset created by authors through monitoring business announcements in newspapers.	Panel; event study over a 200-day period, which is specific for each firm's announcement.	Correlation	The authors examine the stock market reaction associated with announcements of environmental performance. They find no significant effect for the aggregated sample of CEI and EAC announcements. Yet, they observe significant effects for sub-groups of the announcements. Announcements of philanthropic gifts for environmental causes and ISO 14001 are associated with a

	certification, as well as federal, state or local environmental awards.					significant positive market reaction. Voluntary emissions reductions are associated with significant negative market reactions.
Khanna and Damon, 1999	Toxic releases of 17 high priority toxic chemicals regulated under the voluntary US EPA 33/50 Programme.	Return on Investment (ROI), Excess value per unit sales (EVS).	123 US chemical firms. S&P's Compustat database (commercial), CD corporate database (commercial), Toxic Release Inventory (public).	Panel (1991-1993).	Correlation	Participation in the voluntary US EPA 33/50 programme led to a significant decline in toxic releases relative to non-participants, after controlling for sample selection through firm-specific factors. Programme participation had a significant negative effect on current returns on investment (ROI) relative to non-participants. Yet, it had a significant positive effect on the Excess Value per unit Sales (EVS). This indicates that investors anticipate that in the long run the current efforts to reduce pollution improve the expected profitability of firms participating in the programme.
King and Lenox, 2001	Total Emissions: Total facility emissions of toxic chemicals; Relative Emissions: Emissions relative to other facilities of similar sector, and size. Industry Emissions: Emissions per employee for the sectors in which the firm operates.	Tobin's Q financial performance measure (market valuation of a firm relative to the replacement costs of tangible assets).	652 US manufacturing firms. Toxic Release inventory (TRI) , facility data from Dun and Bradstreet (D&B), corporate data from Standard & Poor's Compustat database (commercial).	Panel (1987-1996).	Correlation	The authors identify three key results: 1) Higher total emissions are associated with lower financial performance. 2) Firms with higher relative emissions compared to firms of similar sector and size have lower financial performance. 3) No effect for Industry Emissions: Operating in a cleaner industry does not have an effect per se on financial performance.

Konar and Cohen, 2001	The aggregate pounds of toxic chemicals emitted per dollar revenue; The number of environmental lawsuits pending against the firm in 1989.	Intangible-asset value (market value).	321 mostly manufacturing firms in the S&P 500; Financial performance data taken from Compustat (commercial), market share and concentration data from Ward's Business Directory (commercial), R&D expenditures using data from the Disclosure database, advertising expenditures (ADVAL89) were taken from data published by the Arbitron Company, the number of environmental law suits pending and toxic emissions data from Investor Responsibility Research Center (commercial).	Cross-section (year 1989).	Correlation	The authors observe that bad environmental performance is negatively correlated with the intangible asset value of firms. They find that a 10% reduction in emissions of toxic chemicals results in a US$34 million increase in market value. Their evidence suggests that firms are rewarded in the marketplace for over-complying with environmental regulation and for externally portraying an image of being environmentally concerned.
Rassier and Earnhart, 2010b	Permitted wastewater discharge limits for BOD (biochemical oxygen demand) and TSS (total suspended solids).	Profitability as measured by returns on sales (ROS).	Publicly held chemical manufacturing firms. The sample of annual data contains 337 observations, consisting of 73 chemical manufacturing firms. The sample panel of quarterly data contains 926 observations, consisting of 59 chemical manufacturing firms. US EPA's Permit Compliance System (PCS) database for permitted discharge limits (public), S&P Compustat for financial data, PCS database for facility level environmental data (commercial).	Panel (1995-2001) yearly data.	Correlation	The authors obtain consistent results across both of their samples. A 10% reduction in the average relative permitted discharge limit causes the return on sales to decrease by as little as 0.8% and as much as 2.7% according to the 90% confidence interval of the estimated coefficient on the discharge limit

Rassier and Earnhart, 2010a	Permitted wastewater discharge limits for BOD (biochemical oxygen demand) and TSS (total suspended solids).	Tobin's Q financial performance measure.	229 observations covering 54 public owned chemical manufacturing firms. Environmental Protection Agency's (EPA's) Permit Compliance System (PCS) for permitted limits of wastewater discharge (public), Standard & Poor's Compustat Research Insight for financial data (commercial).	Panel (1995-2000).	Correlation	They find a negative relationship between clean water regulations and expected future financial performance. The more stringent clean water regulation induces investors to revise downward their expectations of future profits. A 50% decrease in the average firm's permitted discharge limit generates a decrease of 1.3% or approximately $310.4 million in the average firm's market value.
Rassier and Earnhart, 2011	Permitted wastewater discharge limits for BOD (biochemical oxygen demand) and TSS (total suspended solids).	Returns on Sales.	53 US firms belonging to the chemical manufacturing industry. EPA Permit Compliance System database on permitted discharge limits (public), S&P Compustat for financial data (commercial).	Panel (quarterly; 1st quarter of 1995 to 2nd quarter of 2001; maximum of 26 observations per firm).	Correlation	Lower emissions improve firm financial performance both in the short and long run, with a stronger effect in the long run.
Rassier and Earnhart, 2015	Permitted wastewater discharge limits for BOD (biochemical oxygen demand) and TSS (total suspended solids).	Actual Profitability (return on sales), Investors expectations of future profitability measured by Tobin's q.	740 observations from 47 firms. EPA's Permit Compliance System (PCS) database (public), S&P Compustat for financial data (commercial).	Panel (1995-2001) quarterly.	Correlation	Their results on actual profitability are consistent with the Porter Hypothesis indicating that tighter clean water regulation is positively associated with profitability. However, their results on expected profitability suggest that investors appear to expect a negative relationship between clean water regulation and profitability.

Sanchez-Vargas et al. (2013)	Environmental regulation (as measured by plant's pollution abatement expenditures).	Productivity	903 observations of Mexican firms. Data from the national industrial survey in Mexico by the Mexican Statistics agency (licence).	Cross-section (2002).	Correlation	They find a non-linear relationship between environmental regulation and productivity. They find a non-linear relationship between environmental regulation and productivity, and find that a decreasing trade-off between productivity and environmental regulation exists. Moreover, the relationship depends on the plant size and the trade-off is more important for small firms and a nearly negligible one for larger ones.
Shadbegian and Gray, 2003	Air pollution (Particulate Matter, Sulphur Dioxide) per unit of output.	Productivity	68 US pulp and paper mills. Longitudinal Research Database (LRD) (licence), PACE for pollution abatement costs (licence).	Cross-section (year 1985).	Correlation	The authors analyse the link between firm productivity and pollution abatement. They find that plants with a 10 percent higher productivity have 2.5 percent lower emissions, suggesting that productive efficiency and pollution abatement efficiency are complements. Better managers are better at both production and abatement, rather than concentrating on productive efficiency at the expense of abatement performance.
Telle, 2006	Plant-level pollution intensity calculated from an aggregate pollution index consisting of GHGs, acids, particles and ozone precursors (nmvoc-equivalents).	Return-on-Sales (ROS) (calculated as Sales minus variable production costs divided by sales).	1012 plant-years from manufacturing plants. Pollution data from the Norwegian Pollution Control Agency (NPCA) (licence), Economic performance data	Panel (1990-2001).	Correlation	In the pooled regression, which just controls for observable plant characteristics, the author finds that environmental performance is positively and significantly associated with

			(production, production costs, employees, gross investment) from Statistics Norway (licence)			economic performance. However, when controlling for unobservable plant heterogeneity using plant fixed effects, the effects are no longer significant.
Trumpp and Guenther, 2017	Carbon performance (negative GHG emissions divided by sales), Waste intensity (negative amount of waste produced by a firm divided by sales).	Profitability (Return over assets), stock market performance (annual change in stock prices plus dividends).	2361 firm-years. GHG emissions from Carbon Disclosure Project (public), waste intensity and financial data from Thomson Reuter's ASSET4 database (commercial).	Panel (2008-2012).	correlation	They find a non-linear U-shaped relationship between carbon performance and profitability, as well as between waste intensity and profitability. Thus, within their sample firms with a low corporate environmental performance (CEP) tend to have a negative relationship with corporate financial performance (CFP), whereas firms at high levels of CEP have a positive relationship with CFP.
Wagner and Blom, 2011	Environmental Management Systems (EMS).	Firms' financial performance (Return on Sales).	497 firms from Germany and the UK. Survey conducted by authors on EMS system, financial data from AMADEUS database (commercial).	Cross-section (survey conducted in 2001).	Correlation	The authors use the implementation of an Environmental Management System (EMS) for firms' level of sustainability. They find a positive association between the implementation of an EMS and financial performance for already well-performing firms only. For less well-performing firms they find a negative relationship between EMS implementation and financial performance. They find no effect for their pooled dataset.

Papers reviewed in section 2.2: Understanding the drivers: why environmental performance can go hand in hand with economic performance

2.2.2 Better economic performance through increased revenues

Antweiler and Harrison, 2003	192 toxic air, water, land, and subsoil pollutants covered in Canada's National Pollutant Release Inventory (NPRI).	Consumer market exposure.	2500 Canadian facilities, which report emissions under Canada's NPRI. Canada's National Pollutant Release Inventory (NPRI) (publicly accessible through website), Canadian Census for facility location (public), Statistics Canada (public).	Panel (1993-1999).	Correlation	Companies that are relatively more exposed to final consumers and that have a greater diversity of emissions across products (i.e. are more "environmentally-leveraged") reduce their releases to air and transfers of wastes off site most strongly. Yet, they also increase more the less visible releases of subsoil emissions. They argue that this indicates the existence of a "green consumerism", although its overall environmental impact is small.
Horbach, 2010	Environmental product innovations.	Employment at the firm level.	900 German firms operating in environmental sectors; 12.400 German firms operating in non-environmental fields. Establishment panel of the Institute for Employment Research Nuremberg (licence).	Panel (2002-2005).	Correlation	Firms in the environmental sector that developed new or modified products from 2002 to 2003 increased their employment from 2003 to 2005. The employment impact of innovation is larger than for firms in non-environmental sectors.
Palmer and Truong, 2017	Technological green product introductions (NPI).	Firm profitability measured by turnover and return on capital.	79 global firms (1020 technological green product introductions. Authors constructed the	Panel (2007-2012).	Correlation	They find a significant positive correlation between technology-based green new product introductions (NPI) and short term profitability

			dataset of NPIs based on press releases.			measured by turnover or return on capital. They also find a weakly significant relationship when using the ratio of technological green NPIs to the total number of NPIs. This finding might suggest that a higher share of green products is associated with extra profitability.
Rennings and Zwick, 2002	Introduction of new environmental products; environmental innovations.	Employment at the firm level.	1594 interviews of environmentally innovative industry and services firms from Germany, Italy, Switzerland, UK, and Netherlands. The firms span across 8 NACE sectors (D-K). Firms were only included if they self-reported to have done at least one environmental innovation in the past three years. Survey conducted by authors.	Cross-section (interviews were carried out in 2000).	Correlation	Environmental innovations have a small but positive effect on employment at the firm level. Product and service innovation generate more jobs than process innovations. Employment impacts differ according to the intended goals of the innovations: If they are motivated by cost reductions, they tend to reduce employment. If they are motivated by goals to increase the market share, the effect can be positive or negative.
Rennings et al., 2004	Environmental Innovations.	Employment at the firm level.	1594 interviews of environmentally innovative industry and services firms from Germany, Italy, Switzerland, UK, and Netherlands. The firms span across 8 NACE sectors (D-K). Firms were only included if they self-reported to have done at least one environmental innovation in the past three years. Survey conducted by authors.	Cross-section (interviews were carried out in 2000).	Correlation	Environmental product and service innovations increase the likelihood that the firm increases its employment base. Yet environmental end-of-pipe innovations increase the likelihood that the firm decreases its employment base.

2.2.3 Improved economic performance through reduced cost of inputs						
Energy and materials						
Bloom et al., 2010	Energy Intensity.	Total factor productivity, Quality of management.	300 manufacturing firms in the UK. UK establishment-level Census of Production data from the UK ONS (license), survey collected by Center for Economic Performance (CEP).	Cross-section (Management Survey Data from 2006).	Correlation	They find a robust negative relationship between management practices and energy intensity. Improving management practices from the 25th to the 75th percentile is associated with a 17.4% reduction in energy intensity and with a 3.7% increase in total-factor productivity. They also find that better economic performance as measured by TFP is associated with lower energy intensity. The results suggest that management practices that are associated with improved productivity are not linked to worse environmental performance.
Gosnell et al., 2017	Airplane fuel consumption, CO_2 emissions.	Airplane fuel cost. (Experimental treatments: Monitoring, performance information, personal targets, pro-social incentives).	335 Virgin Atlantic airline captains, 110.000 captain-level observations over 40.000 unique flights. Data provided by Virgin Atlantic to the authors.	Panel (eight-month experimental study period in 2014).	Causation	The experiment in partnership with Virgin Atlantic Airlines finds that low-cost behavioural treatments (monitoring, performance information, personal targets, and prosocial incentives) reduced captain's fuel consumption pre-flight (aircraft fuel load), in-flight, and post-flight (taxi) significantly. Simply informing pilots that they are

						being monitored already reduces their fuel consumption significantly. The behavioural changes generated more than 7700 tons of fuel saved for the airline over the eight-month experimental period ($6.1 million in 2014 prices), which translates to about 24.500 tons of CO_2 abated. They estimate a marginal abatement cost per ton of CO_2 at negative $250 (i.e. $250 savings per ton abated) from implementing the low-cost behavioural interventions, which is the lowest marginal abatement cost so far calculated in the literature.
Horbach and Rennings, 2013	Cleaner Production innovations, Environmental end-of-pipe innovations.	Employment at the firm level.	Between 3700 and 4500 German firms from the Community Innovation Survey (CIS), covering mining and quarrying, manufacturing, energy and water supply, large number of service sectors (licence). 2009 wave of the German Community Innovation Survey (CIS) (licence).	Cross-section (Community Innovation Survey 2009).	Correlation	The realization of environmental process innovations leads to a higher employment within the firm. Furthermore, material and energy savings are positively correlated to employment because they help to increase the profitability and competitiveness of the firm. Yet, end-of-pipe technologies (in particular air and water process innovations) have a negative impact on employment.

Kumar and Managi, 2010	SO_2 emissions price.	Innovation activity.	50 electricity generating plants. Federal Energy Regulatory Commission (FERC) for electricity production at the plant level, employees and capital stock (licence), US EPA Aerometric Information Retrieval System (AIRS) database for SO_2 emissions and emissions prices (public).	Panel (1995-2007).	Correlation	The authors have tested whether an increase in SO_2 emissions prices leads to a reduction in pollution emissions. They observe that electricity generating plants experience positive induced technological change. Electricity-generating plants are able to increase electricity output and reduce emissions of SO_2 and NOx from 1995 to 2007 due to the introduction of the allowance trading system.
Martin et al., 2012	Energy intensity (energy expenditure / gross output) and (energy intensity / variable cost); Composite Index on management practices related to climate change collected through interviews.	Productivity	190 UK manufacturing plants. ORBIS database for random selection of UK manufacturing plants (commercial). Survey data collected by authors.	Cross-section (interview data collected in 2009).	Correlation	Climate friendly management practices, as measured by an index constructed from survey responses are associated with lower energy intensity and higher productivity at the establishment level. They suggest that there might be a win-win scenario from improving environmental management, which could also raise firm productivity.
Pfeiffer and Rennings, 2001	Environmental Innovations.	Employment at the firm level.	419 German environmentally innovative manufacturing firms (a company was defined as such if it carried out at least one environmental innovation between 1993 and 1995). Survey of the Mannheim Innovation Panel (licence).	Cross-section (1996 wave of the Mannheim Innovation Panel).	Correlation	Cleaner production processes are more likely to increase employment compared to end-of-pipe technologies. The authors conclude that the transition from end-of-pipe technologies to cleaner production can lead to a net creation of jobs.
Shadbegian and Gray, 2005	Pollution abatement expenditure.	Productivity	68 US pulp and paper mills, 55 oil refineries, and 27 steel mills.	Panel (1979-1990).	Correlation	The authors analyse the impact of traditional environmental regulation on

			Longitudinal Research Database (LRD) for economic outcomes (licence), PACE for pollution abatement costs (licence).			productivity in U.S. paper mills, oil refineries, and steel mills. They find that pollution abatement contributes little or nothing to firms' productivity.
Shadbegian and Gray, 2006	Air pollution (Particulate Matter, Sulphur Dioxide), water pollution (biological oxygen demand, total suspended solids), toxic releases; all in per unit of plant output.	Production efficiency (measured through stochastic frontier production models).	plants in 327 pulp and paper mills, 121 oil refineries, and 83 steel mills; Longitudinal Research Database (LRD) (licence), Census Bureau's Boston Research Data Center (licence), Firm financial data from Compustat, PACE survey for abatement costs, environmental performance measures come from several EPA databases (licence): National Emissions Inventory (NEI), Permit Compliance System (PCS), Toxic Release Inventory (TRI), and Compliance Data System (CDS) (public).	Panel (1990-2000).	Correlation	There is a positive correlation between the environmental and economic performance at the plant level. The finding suggests the importance of unmeasured characteristics that improve both the plant's environmental performance and its economic performance.
van Leeuwen and Mohnen, 2017	Eco-innovations (process-, and end-of-pipe).	Total factor productivity.	Approximately 2000 Dutch manufacturing firms. Environmental Cost of Firms (ECF) survey for eco-innovations, Community Innovation Survey (CIS) for existence or anticipation of environmental regulation and for environmental innovation targets (licence), Production Statistics Survey for production and financial firm data (licence).	Panel (2003-2008) yearly, but with imputation.	Correlation	There is a significantly positive correlation between existing or anticipated environmental regulation and eco-innovations. Moreover, they observe that production process eco-innovations are positively correlated with firms' productivity, whereas end-of-pipe innovations are negatively correlated with firms' productivity.

Labour costs						
Delmas and Pekovic, 2013	Adoption of environmental standards (ISO14001, organic labelling, fair trade labelling, other types of environmental-related standards).	Labour productivity.	10.663 employees from 5220 firms. French Organizational Changes and Computerization (COI) 2006 survey, Annual Enterprise Survey (EAE), Annual Statement of Social Data (DADS) (licence).	Cross-section (2006).	Correlation	Firms that have adopted environmental standards enjoy a one standard deviation higher labour productivity compared to firms that have not adopted such standards. Furthermore, the adoption of such standards is associated with increased employee training and interpersonal contacts, which can in turn contribute to improved labour productivity.
Grolleau et al., 2012	Adoption of environmental standards (ISO14001, organic labelling, fair trade labelling, other types of environmental-related standards).	Self-reported difficulties in recruiting professional and non-professional staff.	10.840 French firms. French Organizational Changes and Computerization's (COI) 2006 survey, Annual Statement of Social Data (DADS) and the Annual Enterprise Survey (EAE) for information on wages and export respectively (licence).	Cross-section (2006).	Correlation	The adoption of voluntary environmental standards is associated with reduced self-reported difficulties in the recruitment of professional and non-professional employees.
Lanfranchi and Pekovic, 2012	Firm registration with at least one environmental standard (ISO14001, organic labelling or fair trade labelling).	Self-reported employee attitudes (usefulness to others, equitable recognition for work, employee's involvement, absence of compensation for supplementary work hours).	11600 employees at 7700 French firms from a representative French employer-employee dataset of firms with more than 20 employees. French Organizational Change and ICT's (COI) 2006 survey, French Organizational Change and ICT's (COI) 2006 survey for employee compensation,	Cross-section (2006 survey).	Correlation	Employees of firms that have adopted voluntary environmental standards report a significantly higher feeling of usefulness at work. Firms' registration for environmental-related standards is associated with higher feelings of usefulness to others and feelings of being equitably recognized among the employees. While the

			Annual Enterprise Survey (EAE) for firm export levels (licence).			employees do not claim to be more involved in their jobs, they are more likely to work uncompensated for supplementary work hours compared to workers in non-green firms.
Nyborg and Zhang, 2013	Corporate Social Responsibility (CSR) reputation rating collected through a survey. Respondents stated whether they associate a given firm with CSR activities. This response was combined with the respondent's opinion on whether they consider the firm an "ideal employer" to obtain a relative CSR reputation score.	Employee wages.	100.000 Norwegian employees. Young Professionals Survey and Graduate Student survey conducted by Universum (commercial), official Norwegian employee-employer register for wages (licence).	Cross-section (2007).	Correlation	Firms with higher CSR ratings pay substantially and significantly lower wages. The authors therefore conclude that even if CSR is associated with higher costs (e.g. higher emission abatement expenses), responsible firms are still able to compete in the market even in the absence of ethical consumers or investors.
Cost of capital						
Attig et al., 2013	Corporate Social Responsibility (CSR) score provided by a third party research company.	Firm credit ratings (compiled by S&P).	1585 US firms. S&P credit ratings, Compustat, Center for Research in Security Prices database (CRSP), Thompson's Institutional Brokers Estimate System, MSCI ESG Stats (commercial).	Panel (1991-2010).	Correlation	The authors find a significant positive impact of CSR on firm credit ratings. They suggest that by investing in CSR, firms' financing costs are likely to decrease due to the better credit rating, which all else equal should enhance firm value and shareholders' value.
Cheng et al., 2013	Corporate Social Responsibility (CSR) score provided by a third party.	Capital constraints expressed through five accounting ratios: 1) cash flow to total capital, 2)	2439 publicly listed firms across 49 countries. Thompson Reuters ASSET4 database (commercial).	Panel (2002-2009).	Correlation	Firms with better CSR performance face lower capital constraints.

		market to book ratio, 3) debt to total capital, 4) dividends to total capital, 5) cash holdings to total capital.				
El Ghoul et al., 2011	Corporate Social Responsibility (CSR) ratings provided by a third party research company.	Ex-ante cost of equity capital implied in stock prices and analysts' earnings forecasts.	2809 US firms; Thompson Institutional Brokers Earnings Services for analyst forecast data, Compustat North America for industry affiliation and financial data, KLD STATS for CSR data, CRSP monthly return files for stock returns (commercial).	Panel (1992-2007).	Correlation	Firms with higher CSR scores enjoy significantly lower cost of equity capital. The authors conclude that improved CSR can enhance firm value by reducing the firm's cost of equity capital. They argue that CSR activities can enhance the company's investor base by attracting socially responsible investors.
Goss and Roberts, 2011	Corporate Social Responsibility (CSR) ratings provided by a third party.	Spread basis points (the amount the borrower pays over LIBOR for each loan dollar).	3996 loans to US firms. KLD Research and Analytics Inc. for measure of social responsibility, Compustat for financial information, Thompson CDA spectrum for institutional ownership, Dealscan for loan pricing data (commercial).	Panel (1991-2006).	Correlation	Firms with social responsibility concerns pay between 7 und 18 basis points more than firms that are more responsible. Lenders demand higher yield spreads from borrowers with the worst records in social responsibility. Yet, they recognize greenwashing activities and punish CSR activities that are unlikely to add value.

Papers reviewed in section 3: The impact of green growth policies on environmental and economic performance						
3.1. The impact of green growth policies on economic outcomes						
Albrizio et al., 2017	Environmental Policy Stringency Index	Productivity Growth	191,597 firms across 22 manufacturing sectors in 11 OECD countries. Firm MFP is constructed using Orbis (commercial), Industry productivity growth is constructed from OECD STAN and PDBi database, Environmental Policy Stringency Index from the OECD (public).	Panel(2000-2009)	Correlation	A more stringent environmental policy is associated with a productivity increase for the most productive firms and a productivity slowdown for the less productive ones. The average firm experiences no effect.
Dlugosch and Kozluk, 2017	Energy price inflation as a proxy for environmental policy stringency,	Firm-level investment (measured as capital expenditure relative to capital stock).	70,479 observations (firm-years) from publicly listed firms from 30 OECD countries across 10 manufacturing industries. Financial data from Worldscope (commercial) and OECD STAN database, Energy Price index from Sato et al. (2015) (public)	Panel (1995-2011)	Correlation	Higher energy prices are associated with a small but significant decrease in total investment across firms. However, total investment increases in the most energy intensive sectors. Higher energy prices are associated with a negative effect on domestic investment independent of the energy intensity, which the authors interpret as an indicator for increased offshoring.

Garsous and Kozluk, 2017	Energy prices as a proxy for environmental policy stringency	Foreign Direct Investment (FDI) (measured as the international-to-total assets ratio)	6806 publicly listed firms from 23 OECD countries and 9 industries Financial variables from Worldscope (commercial), Energy Price index from Sato et al. (2015) (public)	Panel (1995-2011)	Correlation	The effect of higher domestic energy prices is positively associated with firms outward stock of FDI, but small in magnitude. The effect is driven by more permanent shocks to energy prices.
3.2. The empirical evidence on the environmental effectiveness of green growth policies						
Ahmadi, 2017	Plant-level GHG emissions, emissions intensity	Plant-level production output	24,200 plant-years for triple difference, 35,227 plant-years for DiD. Canadian Annual Survey of Manufacturing (licence) for plant level data (fuel purchases, shipment destinations, sales, final products, plant location, plant total production costs). Fuel prices collected for cities and provinces to estimate plant-level fuel quantities. Embodied GHG emissions by fuel-type to estimate GHG emissions. Fuel prices are from Natural Resources Canada and Statistics Canada (public).	Panel (2004-2012)	Causation	Using a DiD approach the author finds a significant 8% reduction in CO_2 emissions from the British Columbia carbon tax. Yet, the triple difference method results in non-significant 2% reduction. The author concludes that the BC carbon tax had zero to little negative effect on plants' GHG emissions in British Columbia. Yet, they find that plants' output levels increased and the emissions intensity declined by about 7%. They attribute this finding to the unique design and the revenue neutrality of the tax.

Walker, 2011	Plant-level Clean Air Act regulatory status (proxy for plant-level environmental performance)	Employment levels and employment growth.	470,958 plants in Manufacturing and Utility sectors Census Bureau Longitudinal Business Database (LBD) (licence) for employment, payroll, firm age, entry/exit at the establishment level. Air Facility Subsystem for plant regulatory and permit data (licence)	Panel (1985-2005)	Correlation	Plant-level non-attainment designation is associated with a decline in plant-level employment growth.
3.3 The joint impact of environmental regulations on environmental and economic performance						
3.3.1 The joint impact of the EU ETS on carbon emissions and firm performance						
List et al., 2003	Air pollution (Nitrogen oxide and volatile organic compounds as the primary chemical precursors to ozone).	Plant location (openings, closing, expansions, contractions).	280 pollution-intensive plants across the 62 counties in New York State. Industrial Migration File that was maintained by the New York State Department of Economic Development (licence).	Panel (1980-1990).	Causation	Pollution-intensive plants respond adversely to more stringent environmental regulation.

France						
Wagner et al., 2014	Greenhouse Gas Emissions, Carbon Intensity.	Employment.	9500 French manufacturing firms (approximately 12.000 establishments) with more than 20 employees. EACEI (Annual survey of energy consumptions in the industry) for energy consumption, French annual business survey (Enquete Annuelle des Entreprise) (licence) for balance sheet data, ETS transaction log for emissions allowances (public).	Panel (1999-2010).	Causation	French manufacturing plants regulated under the EU ETS reduced carbon emissions by 15% during Phase II (2008-2013) compared to unregulated plants. No effect has been found during Phase I (2005-2007). They do not find significant impacts on employment or on emission reallocation. Reductions in emissions appear to be largely driven by reductions in the carbon-intensity of production.

Germany						
Petrick and Wagner, 2014	Carbon emissions and carbon intensity.	Employment, turnover, exports.	1658 German manufacturing facilities with more than 20 employees. AFiD-Betriebspanel from German Research Data Centre (licence), CITL for list of treated plants, AMADEUS (commercial).	Panel (2007-2010).	Causation	The EU ETS caused treated firms (firms that were regulated by the EU ETS) to reduce their emissions by 25 to 28 percentage points more than non-treated firms (non-regulated firms which were otherwise similar). The carbon intensity of treated firms declined between 18 and 30 percentage points faster for EU ETS firms relative to control firms. Firms largely reduced their carbon emissions by switching from high-carbon fuels to low-carbon fuels. The authors find no evidence that being regulated under the EU ETS had a negative impact on employment. The authors estimate that the EU ETS increased gross output between 4 and 7 percent for regulated firms compared to non-regulated firms. The evidence suggests that firms responded to the EU ETS regulation by reducing their carbon intensity and not by reducing the scale of their production.

Norway						
Klemetsen et al., 2016	Air pollutants (CO_2, N_2O, PFCs) all measured in CO_2 equivalents, Emissions Intensity (emissions divided by man hours), Emissions Level.	Value added at factor prices, labour productivity.	152 Norwegian plants, of which 72 plants are regulated by the EU ETS. Annual emissions of Norwegian plants from the Norwegian Environment Agency (licence), Statistics Norway for plant level data on employment, value added, energy use and prices (licence).	Panel (2001-2013).	Causation (yet there remain differences in treatment and control group after matching).	Plants regulated under the EU ETS reduced emissions by 30% in Phase II of the EU ETS, but not in the other phases. Plants did not reduce their emissions intensity in any phase. The authors find positive effects on value added and labour productivity for plants regulated under the EU ETS compared to the control group.
Lithuania						
Jaraite and Di Maria, 2016	CO_2 emissions, CO_2 intensity.	Profitability, Investment.	353 Lithuanian firms (41 ETS firms, 312 non-ETS firms). Sample survey of non-financial enterprises (F-01) from Statistics Lithuania for main financial indicators (licence). EU CITL for emissions data (public).	Panel (2005-2010).	Causation	During Phase I the EU ETS did not cause a reduction in CO_2 emissions. Yet, CO_2 intensity decreased slightly between 2006 and 2007. They find no significant effect on firm profitability from the EU ETS. Yet, the authors suggest that the EU ETS might have induced the retirement of old and less efficient capital stock during Phase I, and led to some additional investments into new capital equipment from 2010.

Pan-European studies						
Abrell et al., 2011	CO_2 emissions.	Profits, employment, value added.	2101 European firms. Community Independent Transaction Log (CITL) collected by the European Commission for emission allowances (public), AMADEUS for firm production data (commercial).	Panel (2005-2008).	Causation	Emission reductions were 3.6% higher between 2007 and 2008 than between 2005 and 2006, which the authors attribute to the increased stringency of the regulation of the EU ETS. They argue that the shift from Phase I to Phase II of the EU ETS had a significant impact on firms' emission reductions. They find that the EU ETS did at most modestly affect profits, employment and value added of regulated firms. This study finds a causal effect, yet they take control firms only from non-regulated sectors, which likely introduce a selection bias at the sector level).
Dechezleprêtre et al. (2018)	CO_2 emissions	Revenues, assets, profits and employment.	240 matched pairs of EU ETS and similar non-EU ETS installations across France, Netherlands, Norway, and the UK. Carbon emissions data at the installation level are from the national Pollutant Release and Transfer Registers (PRTR) from France, Netherlands, Norway and the UK. These are complemented with	Panel (2005-2012)	Causation	The authors use a matching procedure in combination with a difference-in-difference estimation to identify the causal effect of the EU ETS on firms' economic performance. They find that between 2005 and 2012 the EU ETS has led to carbon emission reductions of around 10% while not having any adverse impacts on firms' economic performance.

			data from the European PRTR. Economic performance data are from the BvD Orbis database.			The regulation seems to have even led to an increase in revenues and fixed assets of regulated firms compared to the matched counterfactuals.
3.3.2: The joint impact of the UK Climate Change Levy on carbon emissions and firm performance						
Martin et al., 2014a	Energy intensity, electricity use.	Employment, Revenue, Total factor productivity, plant exit.	6886 UK plants. Annual respondents database (ARD) which is maintained by the Office for National Statistics (licence), Quarterly Fuels Inquiry (QFI) for energy use information, information on CCA participation from both DEFRA and HM Revenue and Customs (HMRC) websites, European Pollution Emissions Register (EPER) (public).	Panel (2001-2004).	Causation	The UK Climate Change Levy had a strong negative impact on energy intensity (-18%) and electricity use (-22.6%). No statistically significant impacts are found for employment, revenue, total factor productivity or plant exit. The results suggest that firms substituted labour for energy and increased output prices in response to the energy price increase.
3.3.3: The joint impact of energy prices on economic and environmental performance						
Marin and Vona, 2017	CO_2 emissions, energy consumption.	Employment, wages, productivity.	French manufacturing establishments with 61153 establishment-year observations. Datasets provided by the French Statistical Office (INSEE) (licence): EACEI survey on energy purchase and consumption, DADS for employment and wage data, FARES-FICUS on firms'	Panel (2000-2010).	Correlation	The authors find that a 10 percent increase in energy prices leads to a 6 percent reduction in energy consumption and to an 11 reduction in CO_2 emissions. They find a modestly negative impact on employment of negative 2.6 percent and small negative effects on wages and productivity. The negative employment effects are

			balance sheets (licence).			mostly concentrated in energy-intensive and trade-exposed sectors.
3.3.4 The joint impact of environmental regulation on environmental and economic performance through innovation						
Lanoie et al., 2011	Environmental performance (self-reported survey answer), Environmental R&D (self-reported survey answer).	Business performance (self-reported survey answer).	4144 facilities across 7 OECD countries covering facilities with more than 50 employees across all manufacturing sectors. OECD survey.	Cross-section (survey conducted in 2003).	Correlation	Using a survey across 7 OECD countries, the authors obtain self-reported data on environmental and business performance to test different versions of the Porter Hypothesis and its causality chains. The authors find support for the "weak" version of the Porter Hypothesis, showing that environmental regulation induces innovation. Furthermore, they also find that more flexible "performance standards" are more likely to induce innovation than more prescriptive "technology-based standards". Yet, they find no support for the "strong" version of the Porter Hypothesis. They find a negative direct effect of policy stringency on business performance, which exceeds the indirect positive effect, mediated through R&D.
Rexhauser and Rammer, 2014	Environmental Innovation (Defined as a new or significantly new product introduced between 2006 and 2008 in the firm that creates environmental benefits compared to alternatives; self-reported).	Firm profitability.	3618 German firms. German part of the Community Innovation survey (Mannheim innovation panel) (licence).	Cross-section (Survey conducted in 2009).	Correlation	The authors provide evidence that environmental innovation, which improves firms' resource efficiency, can provide positive profitability effects. Yet, for any other environmental innovation, which does not improve resource efficiency, they find some weak evidence for adverse profitability effects.

Table A.1: Summary Table of Empirical Literature (continued)

Appendix B

Appendix to Chapter 2

B.1 FTSE Russell Low Carbon Economy Sector Classification

ENERGY GENERATION — EG
- **Bio Fuels**
  - Bio Gas
  - Bio Mass (Grown)
  - Bio Mass (Waste)
- **Cogeneration**
  - Cogeneration (Biomass)
  - Cogeneration (Renewable)
  - Cogeneration (Gas)
- **Fossil Fuels**
  - Clean Fossil Fuels
- **Geothermal**
- **Hydro (General)**
  - Large Hydro
  - Small Hydro
- **Nuclear**
- **Ocean & Tidal**
- **Solar (General)**
- **Waste to Energy**
- **Wind (General)**

ENERGY EQUIPMENT — EQ
- **Bio Fuels**
  - Bio Fuel (1st & 2nd Gen)
  - Bio Fuel (3rd Generation)
  - Bio Gas
  - Bio Mass (grown)
  - Bio Mass (waste)
- **Cogeneration Equipment**
  - Cogeneration (Biomass)
  - Cogeneration (Renewable)
  - Cogeneration (Gas)
- **Fossil Fuels (Integrated)**
  - Carbon Capture & Storage
  - Fuel Cells
- **Geothermal**
- **Hydro (General)**
  - Large Hydro
  - Small Hydro
- **Nuclear**
- **Ocean & Tidal**
- **Solar (General)**
- **Waste to Energy**
- **Wind (General)**

ENERGY MANAGEMENT AND EFFICIENCY — EM
- **Buildings & Ppty (Integrated)**
- **Controls**
- **Energy Mgmt Log & Support**
- **Industrial Processes**
- **IT Processes**
  - Cloud Computing
  - Efficient IT
- **Lighting**
- **Power Storage**
  - Power Storage (Battery)
  - Power Storage (Pumped Hydro)
- **Smart & Efficient Grids**
- **Sustainable Ppty Operator**

ENVIRONMENTAL RESOURCES — ER
- **Advanced & Light Materials**
- **Key Raw Minerals & Metals**
  - Cobalt
  - Lithium
  - Platinum & Platinum-Group
  - Rare Earths
  - Silica
  - Uranium
- **Recyclable Prods & Matls**
  - Recyclable Materials
  - Recyclable & Resusable

ENVIRONMENTAL SUPPORT SERVICES — ES
- **Environmental Consultancies**
- **Finance & Investment**
  - Carbon Credits trading
  - Sustainable Investment Funds
- **Smart City Des & Engineering**

FOOD & AGRICULTURE — FA
- **Agriculture**
  - GM Agriculture
  - Machinery
  - Meat & Dairy Alternatives
  - Non GM Advanced Seeds
  - Organic & Low-Impact Farming
- **Aquaculture**
  - Aquaculture (General)
  - Aquaculture (Sustainable)
- **Land Erosion**
- **Logistics**
- **Food Safe, Process & Pack'g**
  - FSP&P - no single use plas
  - FSP&P - with single use plas
- **Sustainable Planations**
  - Sustainable Forestry
  - Sustainable Palm Oil

TRANSPORT EQUIPMENT — TE
- **Aviation**
- **Railways**
  - Railway (Infrastructure)
  - Trains (Electric / Magnetic)
  - Trains (General)
- **Road Vehicles**
  - Advanced Vehicle Batteries
  - Bikes and Bicycles
  - Bus and Coach Manufacturers
  - Electrified Vehicles & Devices
  - Energy Use Reduction Devices
- **Shipping**

TRANSPORT SOLUTIONS — TS
- **Railways Operator**
  - General Railways
  - Electrified Railways
- **Road Vehicles**
  - Bike Sharing
  - Bus and Coach operators
  - Car Clubs
  - Ride Hailing
- **Video Conferencing**

WATER INFRASTRUCTURE & TECHNOLOGY — WI
- **Adv Irrigation Sys & Devices**
- **Desalination**
- **Flood Control**
- **Meteorological Solutions**
- **Natural Disaster Response**
- **Water Infrastructure**
- **Water Treatment**
  - Water Treatment Chemicals
  - Water Treatment Equipment
- **Water Utilities**

WASTE & POLLUTION CONTROL — WP
- **Cleaner Power**
- **Decontam Services & Devices**
  - Air Decontamination
  - Land & Soil Decontamination
  - Sea & Water Decontamination
- **Environ. Test. & Gas Sens.**
- **Particles & Emiss. Reduc. Dev.**
  - Industrial Pollution Reduction
  - Transport Pollution Reduction
- **Recycling Equipment**
- **Recycling Services**
- **Waste Management (General)**
  - Hazardous Waste Management
  - Organic Waste Process
  - General Waste Management

Table B.1: FTSE Russell Low carbon Economy Sectors and Sub-sectors

B.2 Measuring Green Revenue

We illustrate the green revenue imputation with an example company (see Figure B.1). For this particular company, we do not know the share of hybrid- and electric vehicles that are being sold in a particular year. However, we know that the sector Road vehicles generates 60% of the company's revenues. Since the company's primary industry code (US SIC) is manufacture of transportation equipment, we take the year-specific average of that primary SIC code and multiply it by the firm-specific segment revenue share (here 60%) and use that result as the imputed value. We did this imputation once at the 2- and once at the 4-digit SIC averages and generated separate augmented green revenue values for each. Furthermore, we also generate the industry averages for (1) the entire sample of approximately 16,500 companies (full sample) and (2) the 3,500 companies which generate some green revenue (restricted 'green candidate' sample). Focusing on the potential green firms restricts the sample to more similar firms. In this specific case, the industry averages at the 2-digit SIC level are 2% for the full sample and 5% for the restricted sample. Hence, in this example for Manufacture and Sale of hybrid and electric vehicles, we would impute a green revenue share of 1.2% $(0.02 \cdot 0.6)$ and 3% $(0.05 \cdot 0.6)$ for cases (1) and (2) respectively. The respective value at the sub-segment level is then added to the conservative FTSE minimum green revenue value at the company level (here 8%). The same approach applies at the 4-digit level.[1]

Segment – Name	Segment- Revenue (%)	Sub-Segment Name	Sub-Segment Revenue (%)
Road vehicles	60%	Non-green conventional cars	95%
		Manufacture and Sale of hybrid- and electric vehicles	N.A.
Energy Storage Solutions	5%	Sale of energy storage solutions for PV energy	100%
Machinery Manufacturing	5%	Non-green machinery manufacturing	100%
Industrial Processes	30%	Non-green industrial process products	20%
		Sale of energy-efficiency improving technologies	10%
Overall Green Revenue Share (%)			**8.00 – 32.00%**

Figure B.1: Example of Database and Missing Values

After extensive verification and manual checking, we chose the version, which used 2-digit SIC codes from the "green candidate" sample as our preferred augmented mea-

[1]Note that if for instance the revenue share on green Industrial processes had been missing, we would still use the primary SIC code average green revenue share to impute the missing share. The sub-sector industry averages cannot be used for imputation, as these values are more strongly impacted by missing values.

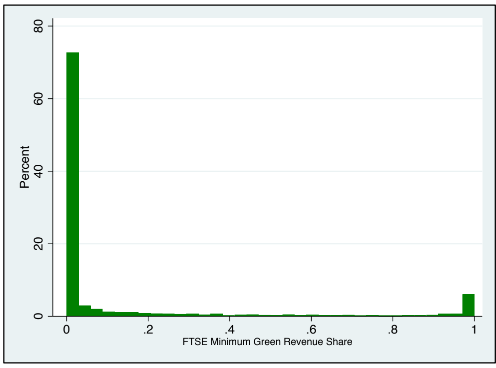


Figure B.2: Raw FTSE Minimum Green Revenue

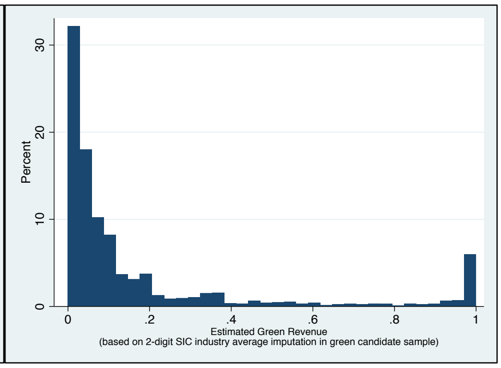


Figure B.3: Augmented Green Revenue based on imputation

sure. Figures B.2 and B.3 show how the imputation procedure changed the distribution in particular in the lower range between 0 and 20%. This augmented measure is our main variable for the analysis as well as in the descriptive statistics. We also refer to it as 'Green Revenue'. When using the 'raw' FTSE Russell minimum green revenue value, we refer to it as FTSE Minimum Green Revenue.

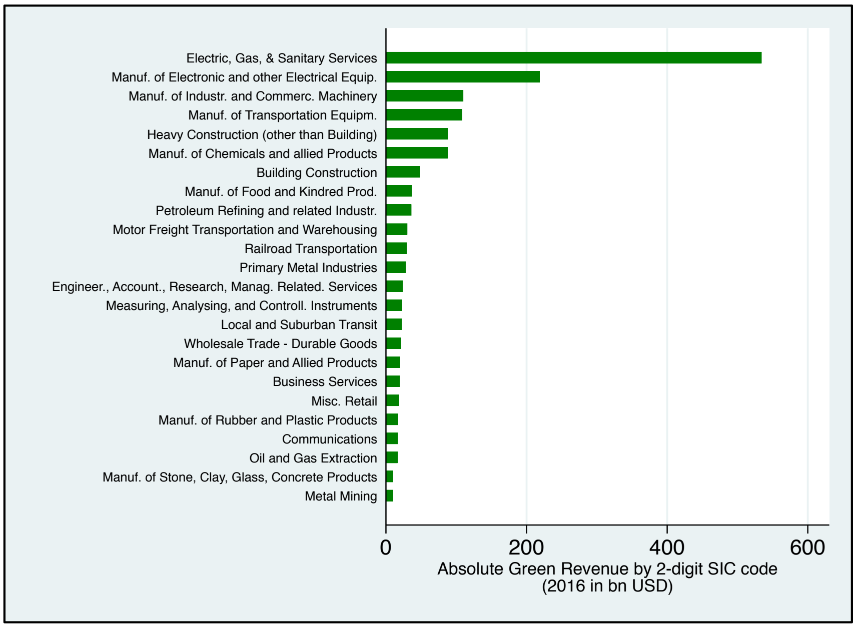


Figure B.4: Decomposition of Green Revenue (in billion USD) by 2-digit SIC code

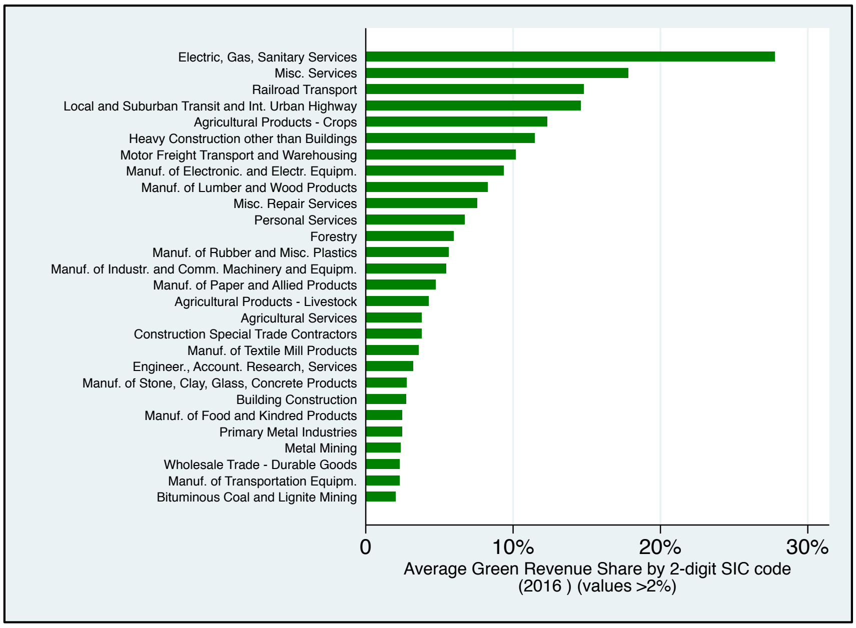


Figure B.5: Average Green Revenue Share by 2-digit SIC code

B.3 Green Revenue Decomposition by 3-digit SIC code

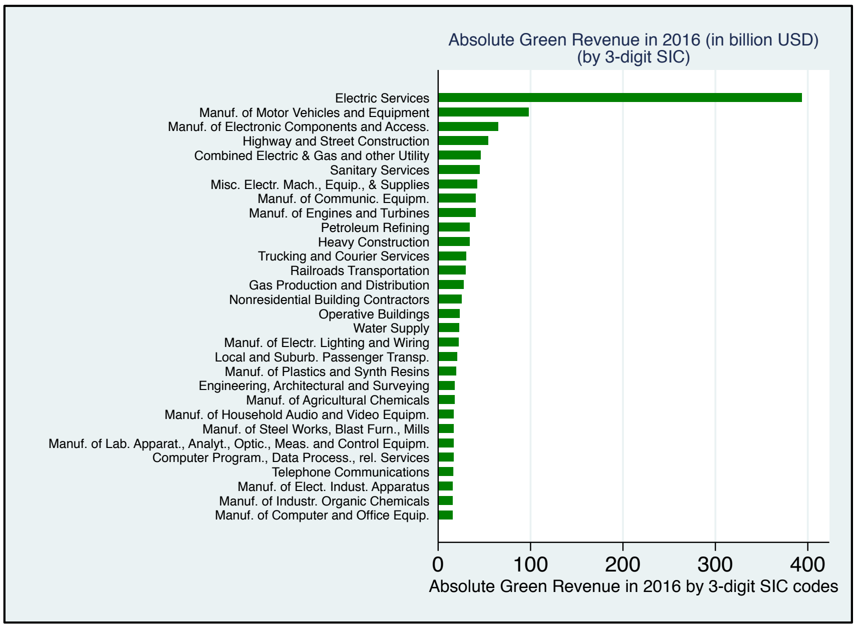


Figure B.6: Decomposition of Green Revenue (in billion USD) by 3-digit SIC code

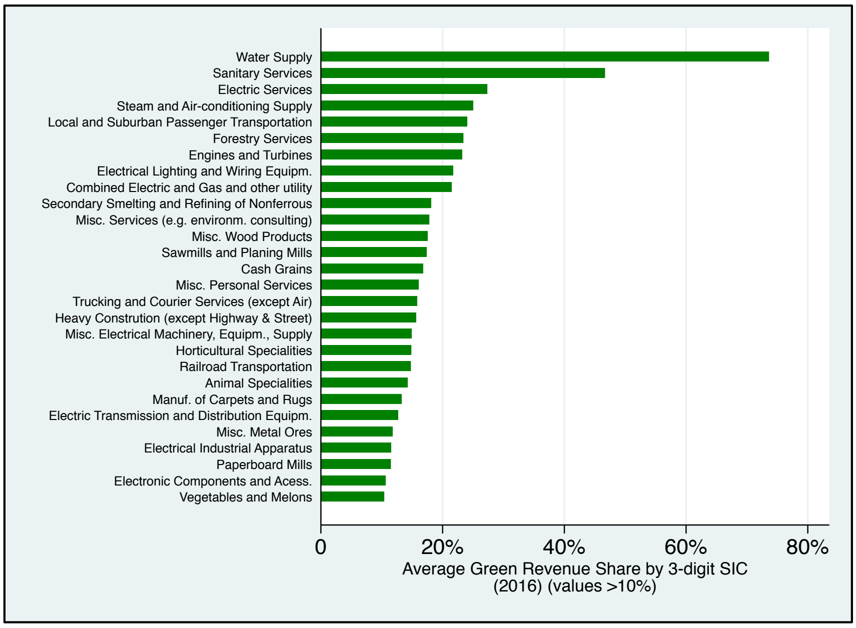


Figure B.7: Average Green Revenue Share by 3-digit SIC code

B.4 Correlation Table for Explanatory Variables

Table B.2: Pairwise Correlations of Explanatory Variables

	Minimum GR	Estimated GR	Employees (log)	Assets/Sales (log)	R&D>0	Dividends per Share	Leverage (log)	Sales Growth
Minimum GR	1							
Estimated GR	0.96	1						
Employees(log)	-0.01	0.02	1					
Assets/Sales (log)	0.09	0.09	-0.28	1				
R&D>0	0.06	0.08	0.04	-0.06	1			
Dividends per Share	-0.00	0.02	0.23	-0.08	0.04	1		
Leverage (log)	0.04	0.04	0.08	0.11	-0.20	0.08	1	
Sales Growth	0.02	0.01	-0.11	0.02	-0.01	-0.07	0.02	1

B.5 Descriptive Statistics for Green- and Non-Green Firms

Table B.3: Descriptive Statistics of Green- and Non-Green Firms

Variable	Green Median (Mean)	Non-Green Median (Mean)
Employees	5,000	2,084
	(16,417)	(9,013)
Total Assets (thds USD)	2,101,094	604,726
	(8,340,089)	(3,284,654)
Market Capitalisation (thds USD)	1,540,340	682,350
	(5,449,818)	(3,008,581)
Return-on-Equity	0.09	0.08
	(0.08)	(0.04)
Return-on-Assets	0.05	0.05
	(0.04)	(0.03)
Return-on-Sales	0.08	0.08
	(0.05)	(-0.11)
Leverage	0.04	0.03
	(0.13)	(0.11)
Tobin's Q	1.24	1.44
	(1.57)	(1.98)

'Green Firms' are defined as generating at least some positive green revenue share over the sample period (2009-2016) (based on the augmented green revenue share).

B.6 Additional Descriptive Statistics: Matching

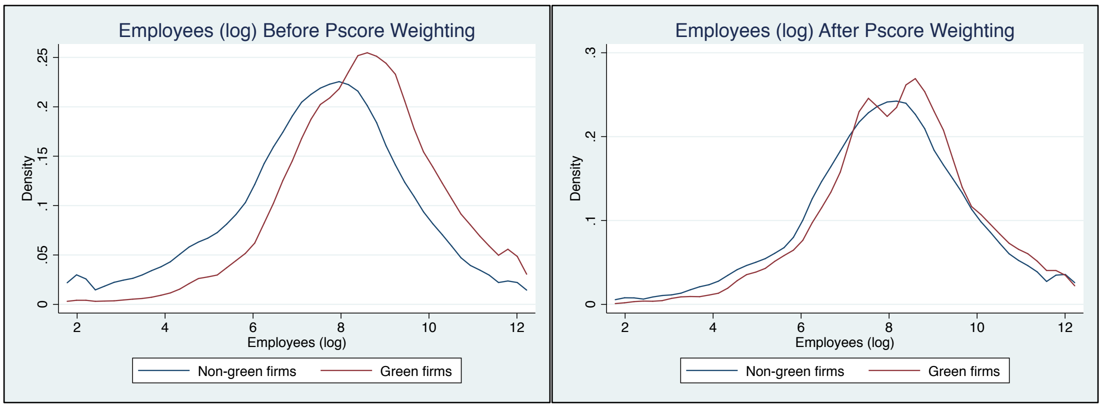


Figure B.8: Number of employees

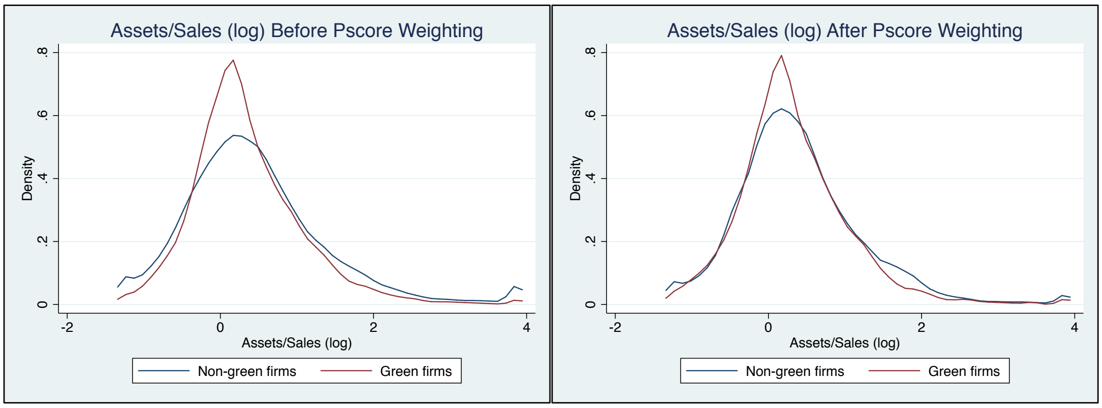


Figure B.9: Assets/Sales

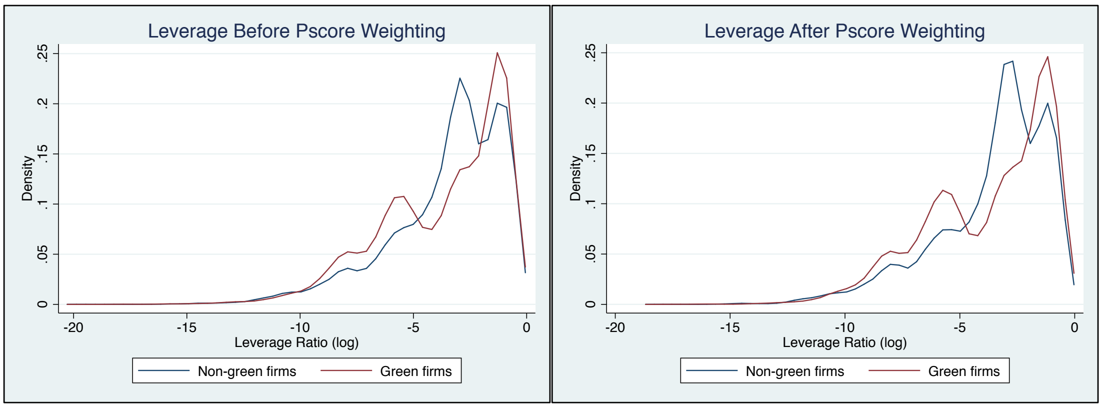


Figure B.10: Leverage

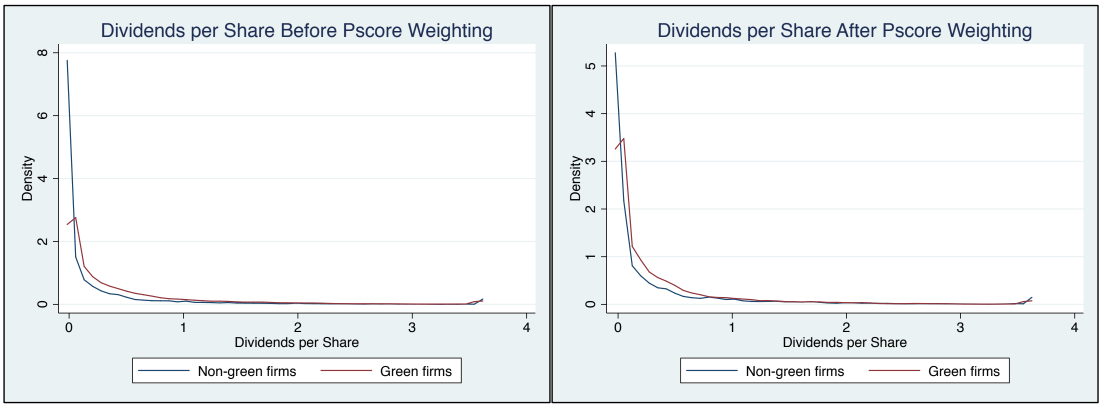


Figure B.11: Dividends per Share

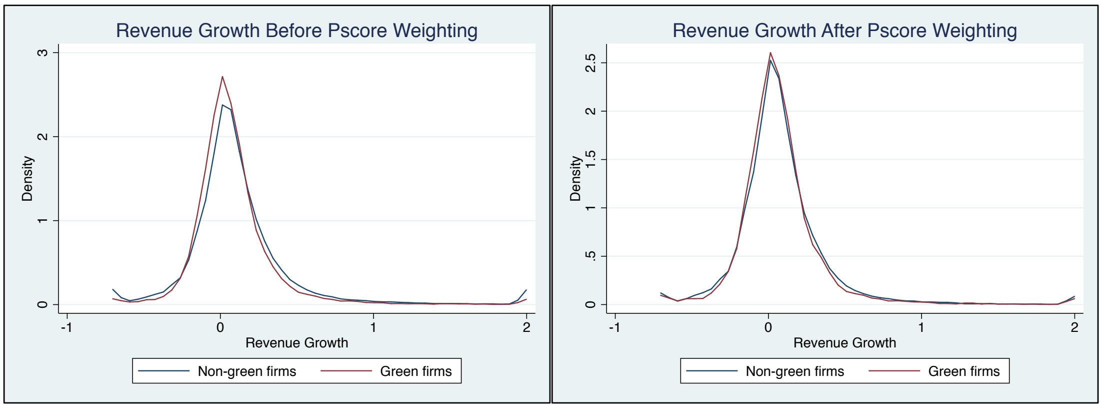


Figure B.12: Revenue Growth

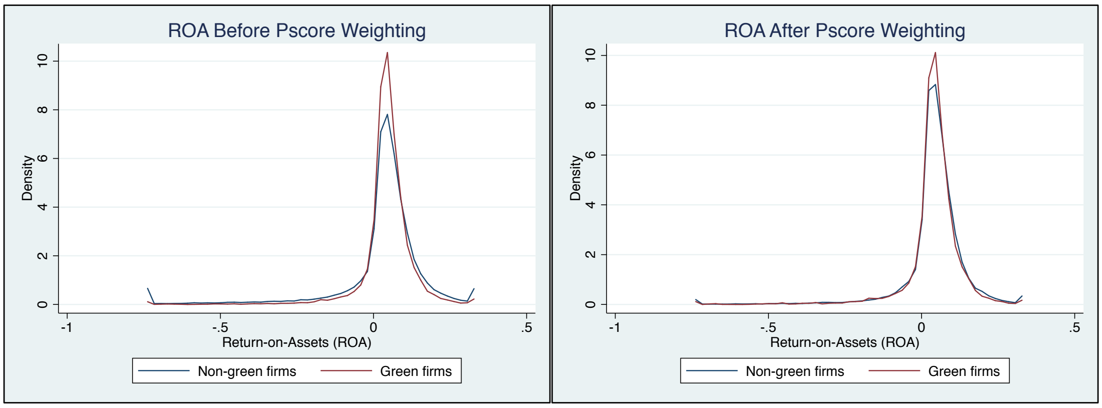


Figure B.13: Return-on-Assets (ROA)

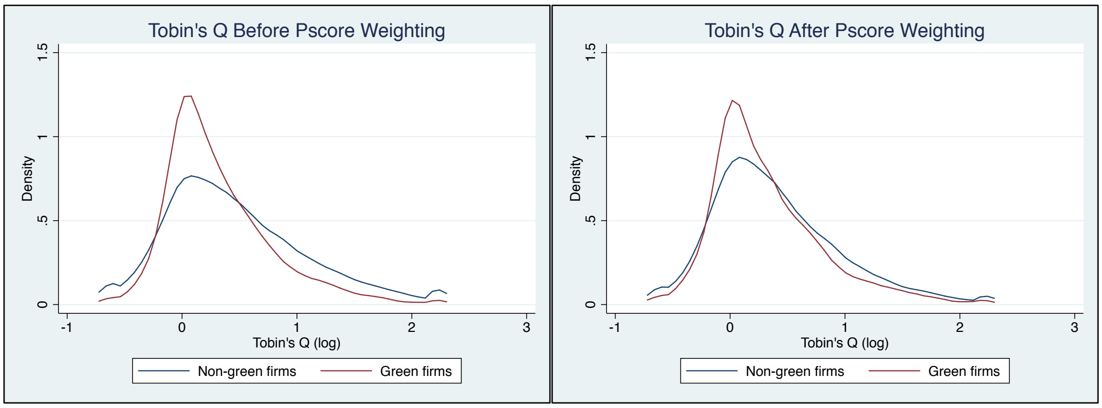


Figure B.14: Tobin's Q

B.7 Additional Results

B.7.1 Green Revenues and Sales/Assets (from next page onwards).

Table B.4: Green Revenues (lead) and Sales/Assets

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$
Green Revenue (current period)	-0.82***					
	(0.31)					
Green Revenue (1-year lead)		-0.30***				
		(0.11)				
Green Revenue (2-year lead)			-0.07			
			(0.08)			
Green Revenue (3-year lead)				0.06		
				(0.13)		
Green Revenue (4-year lead)					-0.24	
					(0.26)	
Green Revenue (5-year lead)						-0.05
						(0.14)
Constant	-0.33***	-0.34***	-0.34***	-0.34***	-0.32***	-0.33***
	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
R^2	0.868	0.880	0.894	0.908	0.922	0.947
Nb. of obs.	48,754	42,820	36,780	30,704	24,586	18,418
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Sales over Assets is measured in logs.

Table B.5: Green Revenues (lag) and Sales/Assets

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$
Green Revenue (current period)	-0.82***					
	(0.31)					
Green Revenue (1-year lag)		-0.08				
		(0.16)				
Green Revenue (2-year lag)			0.28			
			(0.23)			
Green Revenue (3-year lag)				0.11		
				(0.23)		
Green Revenue (4-year lag)					-0.83	
					(0.77)	
Green Revenue (5-year lag)						0.03
						(0.08)
Constant	-0.33***	-0.37***	-0.40***	-0.41***	-0.37***	-0.43***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)	(0.00)
R^2	0.868	0.879	0.895	0.908	0.920	0.940
Nb. of obs.	48,754	42,460	36,360	30,266	24,100	17,931
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Sales over Assets is measured in logs.

Table B.6: Green Revenues (lead) and Sales/Assets (Non-utilities Only)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$
Green Revenue (current period)	-0.85**					
	(0.35)					
Green Revenue (1-year lead)		-0.29**				
		(0.12)				
Green Revenue (2-year lead)			-0.05			
			(0.08)			
Green Revenue (3-year lead)				0.09		
				(0.15)		
Green Revenue (4-year lead)					-0.26	
					(0.29)	
Green Revenue (5-year lead)						-0.05
						(0.15)
Constant	-0.29***	-0.30***	-0.30***	-0.30***	-0.27***	-0.28***
	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
R^2	0.860	0.873	0.887	0.901	0.916	0.943
Nb. of obs.	46,029	40,427	34,729	28,993	23,218	17,388
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Sales over Assets is measured in logs.

Table B.7: Green Revenues (lead) and Sales/Assets (Utilities Only)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$	$\frac{Sales}{Assets}$
Green Revenue (current period)	-0.63**					
	(0.31)					
Green Revenue (1-year lead)		-0.36				
		(0.26)				
Green Revenue (2-year lead)			-0.22			
			(0.22)			
Green Revenue (3-year lead)				-0.18		
				(0.16)		
Green Revenue (4-year lead)					-0.04	
					(0.15)	
Green Revenue (5-year lead)						-0.03
						(0.09)
Constant	-0.99***	-1.01***	-1.02***	-1.02***	-1.04***	-1.04***
	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)
R^2	0.865	0.874	0.900	0.934	0.953	0.963
Nb. of obs.	2,725	2,393	2,051	1,711	1,368	1,030
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Sales over Assets is measured in logs.

B.7.2 Green Revenues and Assets/Equity (from next page onwards).

Table B.8: Green Revenues (lead) and Assets/Equity (equity multiplier)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$
Green Revenue (current period)	-0.08					
	(0.07)					
Green Revenue (1-year lead)		-0.08				
		(0.06)				
Green Revenue (2-year lead)			-0.10			
			(0.06)			
Green Revenue (3-year lead)				-0.10**		
				(0.05)		
Green Revenue (4-year lead)					-0.07	
					(0.06)	
Green Revenue (5-year lead)						-0.08
						(0.06)
Constant	-0.84***	-0.84***	-0.84***	-0.84***	-0.83***	-0.83***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.805	0.826	0.850	0.872	0.895	0.922
Nb. of obs.	48,940	42,982	36,918	30,814	24,676	18,486
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Assets over equity is measured in logs.

Table B.9: Green Revenues (lag) and Assets/Equity (equity multiplier)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$	$\frac{Assets}{Equity}$
Green Revenue (current period)	-0.08					
	(0.07)					
Green Revenue (1-year lag)		-0.05				
		(0.07)				
Green Revenue (2-year lag)			0.01			
			(0.07)			
Green Revenue (3-year lag)				-0.02		
				(0.06)		
Green Revenue (4-year lag)					-0.01	
					(0.06)	
Green Revenue (5-year lag)						0.01
						(0.05)
Constant	-0.84***	-0.84***	-0.84***	-0.84***	-0.84***	-0.84***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.805	0.830	0.851	0.872	0.895	0.925
Nb. of obs.	48,940	42,631	36,512	30,398	24,216	18,021
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	yes	yes	yes	yes	yes	yes
Weighting Sample	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Assets over equity is measured in logs.

B.8 Robustness Checks

B.8.1 Controlling for negative ROS (from next page onwards).

Table B.10: Regressions of operating profit margins with negative ROS-dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.41**	0.35**	0.30**	0.33*	0.34*	0.20	0.34**	0.33**	0.28**
	(0.17)	(0.15)	(0.12)	(0.20)	(0.19)	(0.14)	(0.16)	(0.15)	(0.12)
Employees	0.03**	0.03*	0.03*	0.05***	0.05***	0.03**	0.06***	0.05***	0.04***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.51***	-0.41***	-0.63***	-0.35***	-0.28***	-0.48***	-0.36***	-0.29***	-0.49***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
D(R&D>0)	0.03**	0.03***	0.02**	0.03**	0.03***	0.02**	0.03**	0.03**	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Leverage	-0.01	-0.01	0.00	-0.02***	-0.02***	0.00	-0.01	-0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D($ROS < 0$)	-0.19***	-0.16***	-0.16***	-0.19***	-0.16***	-0.15***	-0.17***	-0.15***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Constant	-0.09	-0.01	0.05	-0.34**	-0.26*	-0.06	-0.33***	-0.26*	-0.09
	(0.13)	(0.12)	(0.13)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
R^2	0.774	0.769	0.831	0.757	0.748	0.827	0.721	0.712	0.780
Nb. of obs.	51,498	51,444	52,653	35,233	35,212	35,721	35,233	35,212	35,721
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.11: Regressions of Return on Assets and Equity with negative ROS-dummy

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.03**	0.04	0.03**	0.05*	0.02*	0.05
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Employees	-0.00***	-0.01*	0.00	0.00	0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Assets/Sales	-0.03***	-0.04***	-0.02***	-0.02**	-0.01	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
D(R&D>0)	0.00	0.00	0.00**	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Leverage	-0.01***	-0.02***	-0.01***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D($ROS < 0$)	-0.08***	-0.23***	-0.08***	-0.22***	-0.08***	-0.22***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.07***	0.11***	0.02	0.01	-0.00	-0.05
	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.05)
R^2	0.756	0.684	0.723	0.649	0.698	0.633
Nb. of obs.	51,814	51,617	35,549	35,506	35,549	35,506
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.12: Regressions of Tobin's Q with negative ROS-dummy

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.06	0.10**	0.12**	0.05	0.10**	0.08*
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Employees	-0.06***	-0.06***	-0.07***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets/Sales	-0.12***	-0.13***	-0.13***	-0.11***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D(R&D>0)	-0.06***	-0.07***	-0.08***	-0.02***	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends per Share	0.11***	0.11***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D($ROS < 0$)	-0.06***	-0.05***	-0.05***	-0.04***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sales-Growth	/	/	/	0.07***	0.07***	0.07***
				(0.01)	(0.01)	(0.01)
Constant	0.87***	0.82***	0.84***	0.83***	0.76***	0.79***
	(0.06)	(0.07)	(0.08)	(0.06)	(0.08)	(0.09)
R^2	0.844	0.839	0.837	0.862	0.860	0.858
Nb. of obs.	57,354	40,141	40, 141	50,582	34,819	34,819
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.8.2 FTSE Minimum Green Revenue Measure (from next page onwards).

Table B.13: FTSE minimum green revenue share impacts on operating profit margins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
FTSE Min Green Revenue	0.41**	0.34**	0.28**	0.33*	0.33*	0.21	0.22**	0.22**	0.17**
	(0.16)	(0.15)	(0.12)	(0.18)	(0.18)	(0.13)	(0.11)	(0.10)	(0.08)
Employees	0.04**	0.03**	0.03**	0.07***	0.06***	0.04**	0.06***	0.06***	0.05***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.54***	-0.44***	-0.66***	-0.41***	-0.32***	-0.54***	-0.36***	-0.28***	-0.50***
	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
D(R&D>0)	0.02**	0.02**	0.02*	0.02*	0.02**	0.02	0.04**	0.03**	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Leverage	-0.01*	-0.01*	0.00	-0.02**	-0.01**	0.00	-0.02*	-0.01*	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.15	-0.05	-0.00	-0.41**	-0.31**	-0.13	-0.43***	-0.33**	-0.19
	(0.13)	(0.12)	(0.13)	(0.17)	(0.15)	(0.16)	(0.15)	(0.14)	(0.14)
R^2	0.722	0.767	0.829	0.749	0.741	0.822	0.722	0.715	0.786
Nb. of obs.	51,498	51,444	52,653	32,696	32,676	33,131	32,696	32,676	33,131
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the FTSE Minimum green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.14: FTSE minimum green revenue share impacts on Return on Assets and Equity

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
FTSE Min Green Revenue	0.03***	0.06**	0.03***	0.07**	0.02**	0.05*
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Employees	-0.00	0.00	0.00	0.01**	0.00***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Assets/Sales	-0.04***	-0.08***	-0.03***	-0.06***	-0.02*	-0.05**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
D(R&D>0)	-0.00	0.00	0.00*	0.01	0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Leverage	-0.01***	-0.02***	-0.01***	-0.02***	-0.01***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.04***	0.04	-0.01	-0.09**	-0.03*	-0.13***
	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.05)
R^2	0.729	0.650	0.676	0.594	0.666	0.595
Nb. of obs.	51,814	51,617	32,973	32,931	32,973	32,931
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the FTSE Minimum green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.15: FTSE minimum green revenue share impacts on Tobin's Q

	(1)	(2)	(3)	(4)	(5)	(6)
	log (Tobin's Q)					
FTSE Min Green Revenue	0.09**	0.10**	0.15***	0.09**	0.11**	0.11*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Employees	-0.06***	-0.07***	-0.07***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets/Sales	-0.13***	-0.13***	-0.14***	-0.12***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D(R&D>0)	-0.06***	-0.07***	-0.07***	-0.02***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends per Share	0.11***	0.11***	0.11***	0.11***	0.10***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Sales-Growth	/	/	/	0.08***	0.07***	0.08***
				(0.01)	(0.01)	(0.01)
Constant	0.86***	0.84***	0.83***	0.81***	0.77***	0.71***
	(0.06)	(0.07)	(0.09)	(0.06)	(0.08)	(0.10)
R^2	0.843	0.836	0.833	0.862	0.857	0.857
Nb. of obs.	57,354	37,058	37,058	50,582	32,140	32,140
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the FTSE Minimum green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.8.3 Excluding Electricity Generation (from next page onwards).

Table B.16: Regressions of operating profit margins excluding Electricity Generation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.41**	0.34*	0.26*	0.31	0.32	0.15	0.33**	0.32**	0.26**
	(0.19)	(0.17)	(0.14)	(0.23)	(0.23)	(0.16)	(0.17)	(0.16)	(0.13)
Employees	0.04***	0.03**	0.03**	0.06***	0.06***	0.04**	0.06***	0.06***	0.04***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.54***	-0.44***	-0.65***	-0.37***	-0.30***	-0.49***	-0.37***	-0.30***	-0.49***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
D(R&D>0)	0.02**	0.02**	0.02*	0.02*	0.02**	0.02	0.03*	0.03*	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Leverage	-0.01*	-0.01*	-0.00	-0.02***	-0.02***	0.00	-0.01	-0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.18	-0.07	-0.03	-0.44***	-0.34**	-0.15	-0.42***	-0.34*	-0.17
	(0.14)	(0.13)	(0.14)	(0.16)	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)
R^2	0.776	0.771	0.835	0.761	0.751	0.836	0.729	0.720	0.797
Nb. of obs.	49,878	49,826	51,022	33,831	33,810	34,313	33,831	33,810	34,313
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.17: Regressions of Return on Assets and Equity excluding Electricity Generation

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.03**	0.06*	0.03**	0.07*	0.03*	0.06*
	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)
Employees	-0.00	0.00	0.00*	0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Assets/Sales	-0.04***	-0.08***	-0.03***	-0.06***	-0.02**	-0.05***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
D(R&D>0)	-0.00	0.00	0.00	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Leverage	-0.01***	-0.02***	-0.01***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.04***	0.03	-0.01	-0.09**	-0.04**	-0.16***
	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.06)
R^2	0.729	0.653	0.690	0.609	0.661	0.593
Nb. of obs.	50,202	50,007	34,148	34,105	34,148	34,105
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.18: Regressions of Tobin's Q excluding Electricity Generation

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.07	0.11**	0.13**	0.05	0.09*	0.08
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Employees	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets/Sales	-0.14***	-0.14***	-0.14***	-0.12***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D(R&D>0)	-0.07***	-0.08***	-0.08***	-0.02***	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends per Share	0.12***	0.11***	0.11***	0.11***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sales-Growth	/	/	/	0.08***	0.07***	0.07***
				(0.01)	(0.01)	(0.01)
Constant	0.87***	0.82***	0.82***	0.82***	0.76***	0.77***
	(0.06)	(0.07)	(0.08)	(0.07)	(0.08)	(0.09)
R^2	0.842	0.838	0.836	0.861	0.858	0.857
Nb. of obs.	55,569	38,574	38,574	49,007	33,452	33,452
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.8.4 Excluding all Utilities (from next page onwards).

Table B.19: Regressions of operating profit margins excluding Utilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.28**	0.19*	0.25**	0.08	0.08	0.12	0.22*	0.20*	0.26**
	(0.14)	(0.11)	(0.11)	(0.09)	(0.09)	(0.08)	(0.13)	(0.12)	(0.12)
Employees	0.04**	0.03**	0.03*	0.06***	0.06***	0.04**	0.06***	0.06***	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.54***	-0.44***	-0.65***	-0.37***	-0.30***	-0.50***	-0.37***	-0.30***	-0.49***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
D(R&D>0)	0.02**	0.02**	0.02*	0.02*	0.02**	0.02*	0.03*	0.03*	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Leverage	-0.01*	-0.01	0.00	-0.02***	-0.01***	0.00	-0.01	-0.01	0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.18	-0.07	-0.03	-0.43***	-0.33**	-0.13	-0.43***	-0.35*	-0.17
	(0.14)	(0.13)	(0.14)	(0.16)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)
R^2	0.778	0.773	0.836	0.764	0.754	0.839	0.731	0.721	0.798
Nb. of obs.	48,943	48,891	50,081	33,097	33,076	33,573	33,097	33,076	33,573
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses.The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.20: Regressions of Return on Assets and Equity excluding Utilities

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.03*	0.05	0.02	0.05	0.02	0.05
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)
Employees	-0.00	0.00	0.00*	0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Assets/Sales	-0.04***	-0.08***	-0.03***	-0.06***	-0.02**	-0.05***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
D(R&D>0)	-0.00	0.00	0.00	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Leverage	-0.01***	-0.02***	-0.01***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.04***	0.03	-0.01	-0.09**	-0.05**	-0.17***
	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.06)
R^2	0.729	0.654	0.690	0.609	0.661	0.593
Nb. of obs.	49,277	49,083	33,416	33,372	33,416	33,372
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.21: Regressions of Tobin's Q excluding Utilities

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.05	0.09	0.12**	0.03	0.07	0.07
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Employees	-0.06***	-0.06***	-0.07***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets/Sales	-0.14***	-0.14***	-0.14***	-0.12***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D(R&D>0)	-0.06***	-0.08***	-0.08***	-0.02***	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends per Share	0.12***	0.11***	0.11***	0.11***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sales-Growth	/	/	/	0.08***	0.07***	0.07***
				(0.01)	(0.01)	(0.01)
Constant	0.87***	0.83***	0.84***	0.83***	0.78***	0.79***
	(0.06)	(0.07)	(0.09)	(0.07)	(0.08)	(0.10)
R^2	0.842	0.838	0.836	0.861	0.859	0.858
Nb. of obs.	54,541	37,730	37,730	48,098	32,720	32,720
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.9 Sector-specific Effects

B.9.1 Only Utilities (4900-4999) (from next page onwards).

Table B.22: Regressions of operating profit margins for Utilities only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.89*	0.91*	0.50	1.23*	1.25*	0.58	1.40*	1.42*	0.63
	(0.52)	(0.52)	(0.39)	(0.66)	(0.66)	(0.53)	(0.73)	(0.73)	(0.60)
Employees	0.02	0.03	0.02	0.04	0.04	0.04	0.05	0.05	0.05
	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.06)
Assets/Sales	-0.51**	-0.39*	-0.74***	-0.60*	-0.49	-0.78**	-0.81	-0.68	-1.05*
	(0.25)	(0.23)	(0.26)	(0.34)	(0.31)	(0.37)	(0.55)	(0.50)	(0.62)
D(R&D>0)	0.04	0.02	0.00	0.06	0.05	0.02	0.05	0.04	-0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
Leverage	-0.05	-0.05	0.05	-0.08	-0.07	-0.01	-0.01	-0.00	0.05
	(0.07)	(0.06)	(0.08)	(0.10)	(0.09)	(0.11)	(0.09)	(0.08)	(0.12)
Constant	0.19	0.11	0.77	-0.07	-0.07	0.47	0.33	0.30	0.86
	(0.47)	(0.44)	(0.57)	(0.68)	(0.63)	(0.85)	(0.83)	(0.77)	(1.02)
R^2	0.641	0.626	0.686	0.630	0.635	0.677	0.620	0.625	0.652
Nb. of obs.	2,555	2,553	2,572	2,136	2,136	2,148	2,136	2,136	2,148
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.23: Regressions of Return on Assets and Equity for Utilities only

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.05*	0.09	0.07**	0.13	0.09**	0.15
	(0.03)	(0.09)	(0.04)	(0.11)	(0.04)	(0.11)
Employees	-0.00	-0.00	0.00	0.01	0.00	0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Assets/Sales	-0.01	-0.03	-0.00	-0.02	-0.01	-0.02
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
D(R&D>0)	0.00	0.00	0.00	-0.00	0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.01**	-0.02**	-0.02***	-0.04***	-0.01***	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.02	0.03	-0.04	-0.10	-0.01	-0.04
	(0.03)	(0.10)	(0.04)	(0.12)	(0.03)	(0.10)
R^2	0.731	0.545	0.744	0.548	0.709	0.516
Nb. of obs.	2,537	2,534	2,133	2,134	2,133	2,134
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.24: Regressions of Tobin's Q for Utilities only

	(1)	(2)	(3)	(4)	(5)	(6)
	log (Tobin's Q)					
Green Revenue	0.13*	0.15**	0.15*	0.17**	0.19**	0.19**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Employees	-0.04**	-0.04**	-0.05**	-0.03*	-0.03	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.06***	-0.08***	-0.10***	-0.04	-0.05	-0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
D(R&D>0)	-0.05	-0.06*	-0.10*	-0.04	-0.06*	-0.10*
	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.06)
Dividends per Share	0.07***	0.08***	0.06***	0.06***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.06***	-0.04***	-0.04*	-0.05***	-0.04***	-0.05*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Sales-Growth	/	/	/	0.09***	0.08***	0.09***
				(0.02)	(0.02)	(0.02)
Constant	0.41***	0.46***	0.60***	0.32**	0.28*	0.44**
	(0.14)	(0.16)	(0.18)	(0.14)	(0.17)	(0.19)
R^2	0.820	0.817	0.822	0.848	0.839	0.844
Nb. of obs.	2,813	2,411	2,411	2,484	2,099	2,099
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.9.2 Only Electricity Generation (491 & 493) (from next page onwards).

Table B.25: Regressions of operating profit margins (Only Electricity Generation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.48**	0.48**	0.71***	0.65**	0.64**	0.70**	0.91*	0.88**	0.93*
	(0.22)	(0.20)	(0.24)	(0.28)	(0.26)	(0.28)	(0.48)	(0.44)	(0.48)
Employees	-0.02	0.00	-0.03	-0.00	0.01	-0.02	0.05	0.06	0.04
	(0.04)	(0.04)	(0.07)	(0.06)	(0.05)	(0.09)	(0.10)	(0.09)	(0.13)
Assets/Sales	-0.51	-0.38	-0.92**	-0.60	-0.48	-0.93*	-0.94	-0.78	-1.10
	(0.36)	(0.33)	(0.38)	(0.45)	(0.41)	(0.50)	(0.72)	(0.66)	(0.80)
D(R&D>0)	0.06	0.04	0.03	0.07	0.06	0.05	0.03	0.02	-0.03
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.09)
Leverage	0.05	0.02	0.17**	0.03	0.03	0.12	0.09	0.08	0.18
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.10)	(0.09)	(0.09)	(0.14)
Constant	0.89	0.62	1.70**	0.77	0.61	1.44	0.83	0.68	1.48
	(0.67)	(0.60)	(0.82)	(0.85)	(0.77)	(1.09)	(1.11)	(1.02)	(1.41)
R^2	0.604	0.569	0.655	0.540	0.556	0.620	0.574	0.581	0.619
Nb. of obs.	1,620	1,618	1,631	1,402	1,402	1,408	1,402	1,402	1,408
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.26: Regressions of Return on Assets and Equity (Only Electricity Generation)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.05*	0.04	0.05*	0.05	0.07*	0.09
	(0.03)	(0.07)	(0.03)	(0.08)	(0.04)	(0.10)
Employees	-0.00	-0.02	0.00	-0.00	0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
Assets/Sales	-0.00	0.01	0.01	0.02	-0.00	0.00
	(0.01)	(0.04)	(0.01)	(0.04)	(0.02)	(0.04)
D(R&D>0)	0.01	0.01	0.00	0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Leverage	-0.01	-0.01	-0.02***	-0.04***	-0.01***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.04	0.14	-0.03	-0.02	-0.03	-0.03
	(0.04)	(0.12)	(0.04)	(0.12)	(0.04)	(0.14)
R^2	0.765	0.536	0.784	0.514	0.730	0.470
Nb. of obs.	1,612	1,610	1,401	1,401	1,401	1,401
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.27: Regressions of Tobin's Q (Only Electricity Generation)

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.02	0.06	0.08	0.05	0.09	0.12**
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Employees	-0.03	-0.04	-0.07**	-0.03	-0.03	-0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Assets/Sales	-0.03	-0.08**	-0.12***	-0.01	-0.04	-0.08*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
D(R&D>0)	-0.02	-0.03	-0.06	-0.03	-0.04	-0.09
	(0.04)	(0.04)	(0.07)	(0.04)	(0.05)	(0.08)
Dividends per Share	0.07***	0.07***	0.06***	0.06***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.06**	-0.03	-0.04	-0.05**	-0.03	-0.05
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
Sales-Growth	/	/	/	0.08***	0.06***	0.07***
				(0.02)	(0.02)	(0.03)
Constant	0.29	0.47**	0.79***	0.23	0.33	0.67**
	(0.22)	(0.22)	(0.29)	(0.23)	(0.25)	(0.30)
R^2	0.786	0.794	0.804	0.818	0.825	0.831
Nb. of obs.	1,785	1,567	1,567	1,574	1,367	1,367
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.9.3 Energy versus Non-energy related Utilities (from next page onwards).

Table B.28: Regressions of operating profit margins for non-energy utilities only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	1.30	1.35	0.26	2.10	2.18	0.47	2.30	2.40	0.39
	(0.95)	(0.94)	(0.73)	(1.37)	(1.36)	(1.23)	(1.60)	(1.57)	(1.35)
Employees	0.21	0.20	0.37*	0.25	0.23	0.43	0.19	0.18	0.34
	(0.14)	(0.13)	(0.21)	(0.15)	(0.15)	(0.24)	(0.13)	(0.14)	(0.21)
Assets/Sales	-1.05***	-0.98**	-0.45***	-1.14***	-1.07**	-0.47***	-0.83**	-0.74**	-0.43***
	(0.39)	(0.40)	(0.11)	(0.40)	(0.41)	(0.14)	(0.35)	(0.35)	(0.13)
D(R&D>0)	-0.03	-0.03	-0.07	0.17	0.16	-0.00	0.10	0.08	0.02
	(0.12)	(0.12)	(0.08)	(0.17)	(0.17)	(0.11)	(0.14)	(0.13)	(0.11)
Leverage	-0.25	-0.22	-0.29	-0.44	-0.40	-0.46	-0.19	-0.17	-0.26
	(0.24)	(0.22)	(0.25)	(0.39)	(0.35)	(0.39)	(0.25)	(0.22)	(0.25)
Constant	-1.57	-1.41	-3.00	-2.80	-2.56	-4.00	-1.60	-1.47	-2.64
	(1.39)	(1.34)	(2.08)	(1.71)	(1.65)	(2.74)	(1.27)	(1.27)	(2.10)
R^2	0.731	0.722	0.786	0.763	0.756	0.794	0.744	0.738	0.787
Nb. of obs.	425	425	431	346	346	352	346	346	352
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.29: Regressions of Return on Assets and Equity for non-energy utilities only

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.06	0.13	0.10	0.20	0.11	0.22
	(0.05)	(0.15)	(0.07)	(0.21)	(0.07)	(0.22)
Employees	0.00	0.02	0.01	0.05	0.00	0.02
	(0.02)	(0.05)	(0.02)	(0.05)	(0.01)	(0.05)
Assets/Sales	-0.06***	-0.26***	-0.05***	-0.16**	-0.05***	-0.14**
	(0.01)	(0.08)	(0.01)	(0.07)	(0.01)	(0.06)
D(R&D>0)	0.00	-0.01	0.01	-0.00	0.00	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Leverage	-0.02**	-0.05	-0.03**	-0.07*	-0.01	-0.02
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.03)
Constant	0.03	0.08	-0.07	-0.40	0.02	-0.07
	(0.15)	(0.50)	(0.19)	(0.57)	(0.14)	(0.46)
R^2	0.669	0.589	0.643	0.652	0.651	0.657
Nb. of obs.	424	422	350	350	350	350
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.30: Regressions of Tobin's Q for non-energy utilities only

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.28***	0.28*	0.25	0.32**	0.37**	0.35*
	(0.12)	(0.14)	(0.16)	(0.13)	(0.15)	(0.18)
Employees	-0.10**	-0.09	-0.05	-0.12**	-0.09	-0.05
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Assets/Sales	-0.26***	-0.16**	-0.11	-0.19**	-0.08	-0.01
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
D(R&D>0)	-0.13*	-0.18**	-0.29***	-0.07	-0.12*	-0.20***
	(0.07)	(0.08)	(0.11)	(0.05)	(0.06)	(0.07)
Dividends per Share	0.39***	0.39***	0.42***	0.40***	0.39***	0.46***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.10)
Leverage	-0.03*	-0.03*	-0.02	-0.03*	-0.04*	-0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Sales-Growth	/	/	/	0.12**	0.11**	0.12**
				(0.05)	(0.05)	(0.06)
Constant	1.23***	0.88*	0.76*	1.14**	0.68	0.47
	(0.44)	(0.46)	(0.43)	(0.51)	(0.53)	(0.52)
R^2	0.868	0.859	0.862	0.882	0.869	0.873
Nb. of obs.	473	406	406	415	351	351
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.31: Regressions of Tobin's Q for energy-related utilities (SIC 491-493)

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.03	0.06	0.07	0.06	0.09	0.10*
	(0.06)	(0.06)	(0.07)	(0.06)	(0.05)	(0.05)
Employees	-0.03*	-0.03*	-0.05**	-0.02	-0.01	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Assets/Sales	-0.03	-0.07**	-0.09***	-0.01	-0.04	-0.06
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
D(R&D>0)	-0.03	-0.04	-0.06	-0.03	-0.04	-0.08
	(0.03)	(0.04)	(0.06)	(0.04)	(0.04)	(0.07)
Dividends per Share	0.06***	0.07***	0.06***	0.05***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.06***	-0.04*	-0.05	-0.05***	-0.04*	-0.05
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Sales-Growth	/	/	/	0.08***	0.07***	0.07***
				(0.02)	(0.02)	(0.03)
Constant	0.26*	0.34**	0.54***	0.20	0.18	0.39*
	(0.14)	(0.15)	(0.19)	(0.14)	(0.16)	(0.20)
R^2	0.787	0.789	0.797	0.820	0.817	0.822
Nb. of obs.	2,340	2,005	2,005	2,069	1,748	1,748
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.32: Regressions of operating profit margins for energy-related utilities (SIC 491-493)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.43**	0.44**	0.64***	0.58**	0.58**	0.62**	0.80*	0.77**	0.81*
	(0.19)	(0.18)	(0.22)	(0.25)	(0.23)	(0.25)	(0.42)	(0.39)	(0.41)
Employees	-0.00	0.01	-0.02	0.00	0.01	-0.02	0.03	0.03	0.01
	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)	(0.05)	(0.04)	(0.06)
Assets/Sales	-0.42	-0.30	-0.77***	-0.50	-0.38	-0.83**	-0.79	-0.64	-1.14
	(0.27)	(0.25)	(0.29)	(0.38)	(0.35)	(0.42)	(0.62)	(0.57)	(0.69)
D(R&D>0)	0.06	0.04	0.01	0.07	0.06	0.02	0.06	0.05	-0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)
Leverage	0.03	0.01	0.14**	0.02	0.02	0.12	0.07	0.07	0.17
	(0.05)	(0.04)	(0.06)	(0.07)	(0.06)	(0.09)	(0.09)	(0.08)	(0.12)
Constant	0.62	0.50	1.39***	0.59	0.54	1.34*	0.78	0.72	1.51
	(0.43)	(0.39)	(0.51)	(0.61)	(0.56)	(0.76)	(0.81)	(0.75)	(0.99)
R^2	0.591	0.567	0.645	0.535	0.559	0.614	0.562	0.576	0.609
Nb. of obs.	2,130	2,128	2,141	1,790	1,790	1,796	1,790	1,790	1,796
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.33: Regressions of Return on Assets and Equity for energy-related utilities (491-493)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.05*	0.05	0.05*	0.06	0.07*	0.09
	(0.03)	(0.07)	(0.03)	(0.08)	(0.04)	(0.10)
Employees	-0.00	0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Assets/Sales	-0.01	0.01	0.01	0.02	-0.00	-0.00
	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)
D(R&D>0)	0.00	0.00	0.00	0.00	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Leverage	-0.01*	-0.01	-0.02***	-0.04***	-0.01***	-0.03**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.03	0.06	-0.02	-0.02	-0.01	-0.01
	(0.03)	(0.07)	(0.03)	(0.08)	(0.03)	(0.08)
R^2	0.750	0.540	0.772	0.511	0.722	0.469
Nb. of obs.	2,113	2,112	1,783	1,784	1,783	1,784
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.9.4 Manufacturing of Motor Vehicles and Equipment (SIC 371) (from next page onwards).

Table B.34: Regressions of operating profit margins for Manufacturing of Motor Vehicles and Equipment (SIC 371)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	-0.06	-0.11	-0.13	-0.09	-0.14**	-0.16*	-0.10**	-0.18***	-0.21***
	(0.08)	(0.09)	(0.11)	(0.05)	(0.07)	(0.09)	(0.05)	(0.06)	(0.07)
Employees	0.01	0.01	-0.01	0.03	0.03	0.03	0.07	0.08	0.08
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.07)	(0.08)	(0.07)
Assets/Sales	-0.41	-0.35	-0.36*	-0.18	-0.15	-0.18***	-0.40	-0.37	-0.30***
	(0.27)	(0.24)	(0.21)	(0.12)	(0.12)	(0.06)	(0.26)	(0.26)	(0.12)
D(R&D>0)	0.06	0.06	0.04	0.01	0.01	-0.00	0.03	0.03	0.01
	(0.05)	(0.05)	(0.04)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)
Leverage	-0.01	-0.01	-0.02	-0.00	0.00	-0.00	0.01	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.07	-0.06	-0.00	-0.23	-0.19	-0.21	-0.58	-0.57	-0.64
	(0.33)	(0.31)	(0.28)	(0.33)	(0.34)	(0.31)	(0.71)	(0.73)	(0.68)
R^2	0.578	0.548	0.628	0.744	0.737	0.798	0.791	0.782	0.838
Nb. of obs.	1,385	1,385	1,394	1,083	1,083	1,087	1,083	1,083	1,087
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.35: Regressions of Return on Assets and Equity for Manufacturing of Motor Vehicles and Equipment (SIC 371)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.07	0.18	0.07	0.20	0.03	0.14
	(0.09)	(0.23)	(0.10)	(0.24)	(0.07)	(0.17)
Employees	0.01	0.01	0.02	0.03	0.04*	0.03
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)
Assets/Sales	-0.05***	-0.14***	-0.06***	-0.15***	-0.05***	-0.12**
	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.05)
D(R&D>0)	-0.01	-0.01	-0.01	-0.02	-0.01	-0.03
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.03)
Leverage	-0.01	-0.02*	-0.01	-0.01	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.07	0.01	-0.18	-0.22	-0.34	-0.17
	(0.09)	(0.19)	(0.13)	(0.27)	(0.22)	(0.26)
R^2	0.750	0.650	0.736	0.626	0.816	0.746
Nb. of obs.	1,373	1,370	1,082	1,082	1,082	1,082
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.36: Regressions of Tobin's Q for Manufacturing of Motor Vehicles and Equipment (SIC 371)

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.01	0.01	0.00	0.06	0.07	0.05
	(0.19)	(0.18)	(0.16)	(0.18)	(0.16)	(0.15)
Employees	-0.01	-0.03	-0.04	-0.02	-0.08**	-0.08**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Assets/Sales	-0.24***	-0.22**	-0.22***	-0.20***	-0.14*	-0.12
	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)
D(R&D>0)	-0.10**	-0.10**	-0.11***	-0.03	-0.05	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Dividends per Share	0.05**	0.05*	0.04*	0.05**	0.04	0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Leverage	-0.04	-0.03	-0.01	-0.04*	-0.03*	-0.00
	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
Sales-Growth	/	/	/	0.05	0.04	0.02
				(0.04)	(0.05)	(0.07)
Constant	0.32	0.53	0.73**	0.38	0.93**	1.06***
	(0.31)	(0.35)	(0.36)	(0.37)	(0.39)	(0.35)
R^2	0.770	0.770	0.767	0.791	0.804	0.808
Nb. of obs.	1,510	1,231	1,231	1,339	1,069	1,069
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

B.9.5 Manufacturing of Electronic and other Electrical Equipment (SIC 367 & 36) (from next page onwards).

Table B.37: Regressions of operating profit margins for Manufacturing of Electronic Components and Accessories (SIC 367)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	-0.06	-0.03	0.05	-0.04	-0.01	0.07	0.01	0.04	0.11
	(0.28)	(0.25)	(0.12)	(0.36)	(0.32)	(0.16)	(0.33)	(0.29)	(0.21)
Employees	-0.09	-0.10	-0.03	-0.12	-0.14	-0.03	-0.21	-0.22	-0.13
	(0.09)	(0.08)	(0.09)	(0.12)	(0.11)	(0.12)	(0.18)	(0.17)	(0.18)
Assets/Sales	-0.42**	-0.29	-0.54**	-0.53**	-0.38	-0.66**	-0.75*	-0.59	-0.87**
	(0.20)	(0.18)	(0.21)	(0.25)	(0.23)	(0.27)	(0.41)	(0.38)	(0.43)
D(R&D>0)	0.03	0.01	0.01	0.04	0.03	0.01	0.07	0.06	0.05
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)
Leverage	0.02	0.02	0.02	0.03	0.04	0.03	0.07	0.07	0.06
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)	(0.05)	(0.06)
Constant	0.93	1.11	0.55	1.24	1.49	0.60	2.19	2.34	1.58
	(0.81)	(0.74)	(0.82)	(1.14)	(1.06)	(1.16)	(1.78)	(1.65)	(1.79)
R^2	0.744	0.719	0.814	0.678	0.657	0.765	0.688	0.666	0.756
Nb. of obs.	1,721	1,717	1,806	1,351	1,347	1,381	1,351	1,347	1,381
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.38: Regressions of Return on Assets and Equity for Manufacturing of Electronic Components and Accessories (SIC 367)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.01	0.01	0.00	0.01	0.02	0.03
	(0.07)	(0.14)	(0.08)	(0.16)	(0.08)	(0.16)
Employees	-0.00	0.00	-0.00	-0.00	-0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
Assets/Sales	-0.06***	-0.11***	-0.06***	-0.11**	-0.06***	-0.12***
	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
D(R&D>0)	0.00	0.03	0.00	0.04	0.01	0.04
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
Leverage	-0.01**	-0.01**	-0.01*	-0.01*	-0.01	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.05	-0.03	0.05	-0.00	0.05	-0.04
	(0.07)	(0.17)	(0.09)	(0.21)	(0.10)	(0.22)
R^2	0.735	0.606	0.683	0.555	0.680	0.553
Nb. of obs.	1,778	1,774	1,377	1,377	1,377	1,377
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.39: Regressions of Tobin's Q for Manufacturing of Electronic Components and Accessories (SIC 367)

	(1)	(2)	(3)	(4)	(5)	(6)
	log (Tobin's Q)					
Green Revenue	0.45**	0.50**	0.49**	0.22	0.28	0.28
	(0.19)	(0.20)	(0.20)	(0.19)	(0.20)	(0.19)
Employees	-0.18***	-0.17***	-0.16***	-0.17***	-0.15***	-0.14***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Assets/Sales	-0.16***	-0.16***	-0.13***	-0.10**	-0.11**	-0.08*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
D(R&D>0)	-0.08*	-0.13**	-0.11**	-0.03	-0.08	-0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Dividends per Share	0.29***	0.28***	0.28***	0.29***	0.28***	0.31***
	(0.07)	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)
Leverage	-0.00	-0.01	-0.01	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sales-Growth	/	/	/	0.10***	0.11***	0.11***
				(0.03)	(0.04)	(0.04)
Constant	1.96***	1.83***	1.69***	1.89***	1.71*****	1.51***
	(0.26)	(0.28)	(0.27)	(0.31)	(0.33)	(0.32)
R^2	0.831	0.822	0.827	0.849	0.842	0.850
Nb. of obs.	1,956	1,560	1,560	1,736	1,350	1,350
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.40: Regressions of operating profit margins for (2-digit) Manufacturing of Electronic and other Electrical Equipment and Components except Computer Equipment (SIC 36)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS	Ebit	Ebitda	ROS
Green Revenue	0.17	0.16	0.25	0.25	0.26	0.33	0.28	0.29	0.36
	(0.26)	(0.24)	(0.22)	(0.38)	(0.35)	(0.33)	(0.36)	(0.33)	(0.31)
Employees	-0.02	-0.03	0.03	-0.03	-0.05	0.03	-0.09	-0.09	-0.03
	(0.05)	(0.04)	(0.04)	(0.07)	(0.07)	(0.07)	(0.10)	(0.09)	(0.10)
Assets/Sales	-0.52**	-0.41**	-0.57***	-0.61**	-0.49**	-0.71**	-0.62**	-0.50**	-0.73***
	(0.20)	(0.18)	(0.20)	(0.25)	(0.23)	(0.26)	(0.27)	(0.24)	(0.28)
D(R&D>0)	0.02	0.02	0.01	0.03	0.02	0.02	0.04	0.03	0.04
	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Leverage	0.00	0.01	0.00	0.02	0.02	0.02	0.04	0.04	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	0.30	0.44	-0.09	0.51	0.67	-0.04	1.02	1.12	0.55
	(0.40)	(0.37)	(0.38)	(0.61)	(0.58)	(0.58)	(0.95)	(0.87)	(0.94)
R^2	0.738	0.723	0.802	0.682	0.664	0.747	0.681	0.662	0.737
Nb. of obs.	4,047	4,070	4,249	3,138	3,134	3,212	3,138	3,134	3,212
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	no	no	yes	yes	yes
Weighting Sample	no	no	no	yes	yes	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are Ebit-margin in columns 1, 4, and 7, Ebitda-margin in columns 2, 5 and 8 and Return-on-sales (ROS) in columns 3, 6, and 9. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.41: Regressions of Return on Assets and Equity for (2-digit) Manufacturing of Electronic and other Electrical Equipment and Components except Computer Equipment (SIC 36)

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROE	ROA	ROE	ROA	ROE
Green Revenue	0.01	-0.01	0.02	0.02	0.03	0.02
	(0.04)	(0.08)	(0.05)	(0.10)	(0.05)	(0.10)
Employees	-0.00	0.00	0.00	0.01	0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Assets/Sales	-0.04***	-0.08***	-0.03**	-0.05*	-0.04***	-0.06**
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
D(R&D>0)	0.00	0.01	-0.00	0.01	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Leverage	-0.01***	-0.01***	-0.01***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.03	-0.02	-0.02	-0.14	-0.01	-0.22
	(0.05)	(0.12)	(0.06)	(0.15)	(0.06)	(0.15)
R^2	0.731	0.622	0.700	0.593	0.694	0.583
Nb. of obs.	4,183	4,169	3,202	3,202	3,202	3,202
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	no	no	yes	yes
Weighting Sample	no	no	yes	yes	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variables are ROA in columns 1, 3, and 5, and ROE in columns 2, 4, and 6. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Table B.42: Regressions of Tobin's Q for (2-digit) Manufacturing of Electronic and other Electrical Equipment and Components except Computer Equipment (SIC 36)

	(1)	(2)	(3)	(4)	(5)	(6)
			log (Tobin's Q)			
Green Revenue	0.20	0.30*	0.33*	0.11	0.21	0.26*
	(0.14)	(0.16)	(0.16)	(0.12)	(0.14)	(0.13)
Employees	-0.13***	-0.12***	-0.13***	-0.13***	-0.11***	-0.11***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Assets/Sales	-0.15***	-0.14**	-0.12***	-0.11***	-0.10***	-0.09**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
D(R&D>0)	-0.08***	-0.13***	-0.12***	-0.03	-0.08***	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Dividends per Share	0.21***	0.21***	0.21***	0.20***	0.19***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Leverage	-0.01	-0.02**	-0.02**	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sales-Growth	/	/	/	0.11***	0.11***	0.10***
				(0.02)	(0.03)	(0.03)
Constant	1.54***	1.45***	1.44***	1.54***	1.34***	1.30***
	(0.22)	(0.23)	(0.20)	(0.24)	(0.25)	(0.22)
R^2	0.826	0.816	0.823	0.844	0.835	0.843
Nb. of obs.	4,592	3,639	3,639	4,081	3,159	3,159
Firm FE	yes	yes	yes	yes	yes	yes
Industry-by-year dummies	yes	yes	yes	yes	yes	yes
Pscore-weight	no	no	yes	no	no	yes
Weighting Sample	no	yes	yes	no	yes	yes

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Estimates stem from an ordinary least square estimation with robust standard errors, clustered at the level of the firms, reported in the parentheses. The dependent variable is the log of Tobin's Q. Green revenue is measured as a continuous variable based on the augmented green revenue variable. Number of employees, assets over sales and leverage are all measured in logs.

Appendix C

Appendix to Chapter 3

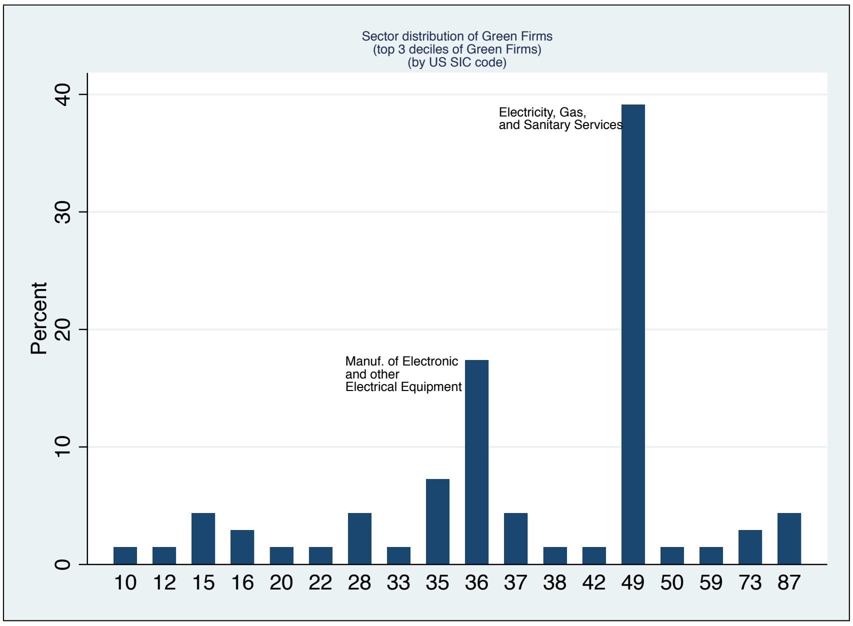
C.1 Descriptive Statistics by Subsamples

	Mean	Median	Std. Dev.	1st perct.	5th perct.	95th perct.	99th perct.	Min	Max
Daily Returns (in %)									
Top Green Firms (top 3 deciles)	-0.16	0	5.87	-12.82	-6.49	6.02	13.35	-163.14	268.17
Most Emissions Intensive firms (Scope 1) (top decile)	-0.21	0	3.46	-9.20	-4.41	3.44	7.92	-98.40	45.87
Most Emissions Intensive firms (Scope 2) (top decile)	-0.14	0	2.81	-7.35	-4.05	3.49	7.38	-98.40	28.04
Firms in top decile of clean Patent Intensity	-0.17	0	10.31	-13.28	-4.30	3.40	15.42	-230.26	230.26
Market Capitalization (in million USD)									
Top Green Firms (top 3 deciles)	2,147.29	362,16	4286,54	14.06	21.83	11,965.28	20,834.07	14.061	20,834.07
Most Emissions Intensive firms (Scope 1) (top decile)	12,092.59	7060.63	13880.84	281.48	927.91	37244.7	75698.73	231.733	76608.17
Most Emissions Intensive firms (Scope 2) (top decile)	13,759.27	8792.16	13,373.65	784.762	927.91	39,373.53	60,226.28	784.76	75,698.73
Firms in top decile of clean Patent Intensity	6,867.26	1,236.98	10,962.36	33.71	66.47	37,584.89	39,9953.48	33.707	39,9953.48
Average Market Capitalization of all listed domestic companies in the US (2013)	5,750.00	/	/	/	/	/	/	/	/
3-factor parameters									
r_{mt} (in %)	-0.04	-0.02	1.11	-2.95	-2.03	1.81	2.52	-3.9	3.68
r_{ft} (in %)	0	0	0	0	0	0	0	0	0
SMB (in %)	-0.05	-0.07	0.54	-1.35	-0.88	0.85	1.41	-1.66	1.82
HML (in %)	-0.03	-0.07	0.60	-1.23	-0.88	1.17	1.87	-1.49	1.99

Note: Daily values are for the period covered in the event study Event days [-121; +10]. Subsample market capitalisation is for 2013, the last pre-treatment year. The average market capitalisation of all listed domestic US firms is calculated by using World Bank Data and dividing the 2013 market capitalisation of listed domestic companies in the US by the total number of listed domestic companies in the US (The World Bank, 2019).

Table C.1: Descriptive Statistics

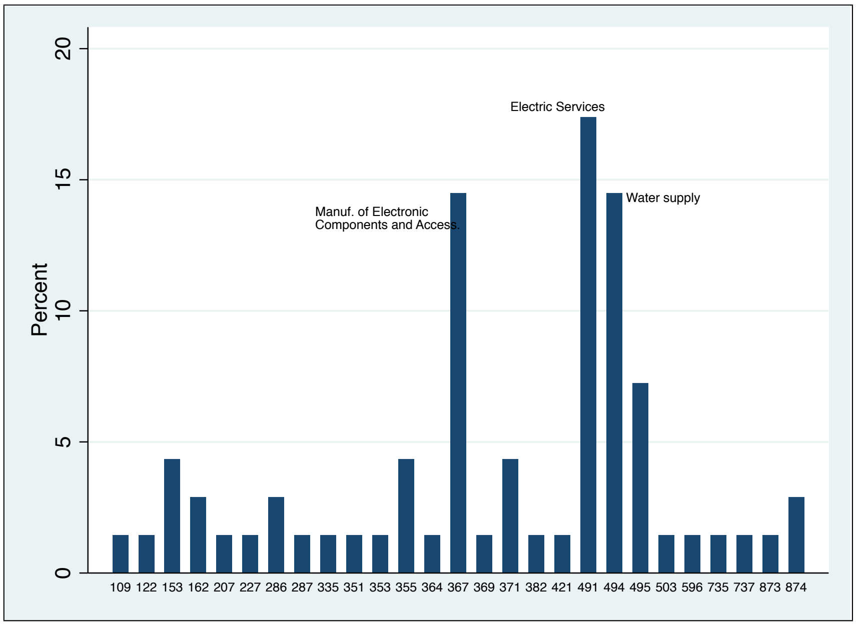
C.2 Sector Distribution of Green Firms (top 3 deciles of Green firms) by 2-digit US SIC codes



The horizontal axis denotes 2-digit US SIC codes. The codes correspond to the following sectors. (10) Metal Mining, (12) Bituminous Coal and Lignite Mining, (15) Building Construction General Contractors and Operative Builders, (16) Heavy Construction other than Building Construction Contractors, (20) Manuf. of Food and Kindred Products, (22) Manuf. of Textile Mill Products, (28) Manuf. of Chemicals and Allied Products, (33) Primary Metal Industries, (35) Manuf. of Industrial and Commercial Machinery and Computer Equipment, (36) Manuf. of Electronic and other Electrical Equipment and Components, except Computer Equipment, (37) Manuf. of Transportation Equipment, (38) Manuf. of Measuring, Analysing and Controlling Instruments, (42) Motor Freight Transportation and Warehousing, (49) Electric, Gas, and Sanitary Services, (50) Wholesale Trade - Durable Goods, (59) Misc. Retail, (73) Business Services, (87) Engineering, Accounting, Research, Management, and rel. serv..

Figure C.1: Sector Distribution of Green Firms (top 3 deciles of Green firms) by 2-digit US SIC code

C.3 Sector Distribution of Green Firms (top 3 deciles of Green firms) by 3-digit US SIC codes



The horizontal axis denotes 3-digit US SIC codes. The codes correspond to the following sectors. (109) Misc. Metal Ores, (122) Bituminous Coal and Lignite Mining, (153) Operative Builders, (162) Heavy Construction, exc. Highway and Streets, (207) Manuf. of Fats and Oils, (227) Carpets and Rugs, (286) Industrial Organic Chemicals, (287) Agricultural Chemicals, (335) Rolling, Drawing, and Extruding of Nonferrous Primary Metals, (351) Engines and Turbines, (353) Construction, Mining, and Materials Handling, (355) Spec. Industry Mach., exc. Metalworking, (364) Elect. Lighting and Wiring Equipm., (367) Electronic Components and Accessories, (369) Misc. Electr. Mach., Equipm., Supplies, (371) Motor Vehicles and Motor Vehicle Equipm., (382) Laboratory App. and Analytical, Optical, Measuring and Controlling Instr., (421) Trucking and Courier Services, exc. Air, (491) Electric Services, (494) Water Supply, (495) Sanitary Services, (503) Lumber and other Construction Materials, (596) Nonstore Retailers, (735) Misc. Equipm. Rental and Leasing, (737) Computer Program., Data Processsing, and other Computer Related Services, (873) Research, Development, and Testing Services, (874) Management and Public Relations Services.

Figure C.2: Sector Distribution of Green Firms (top 3 deciles of Green firms) by 3-digit US SIC code

C.4 Event Path for Green firms (top 3 deciles) excluding public utilities: Electricity, Gas, and Sanitary Services (SIC 49)

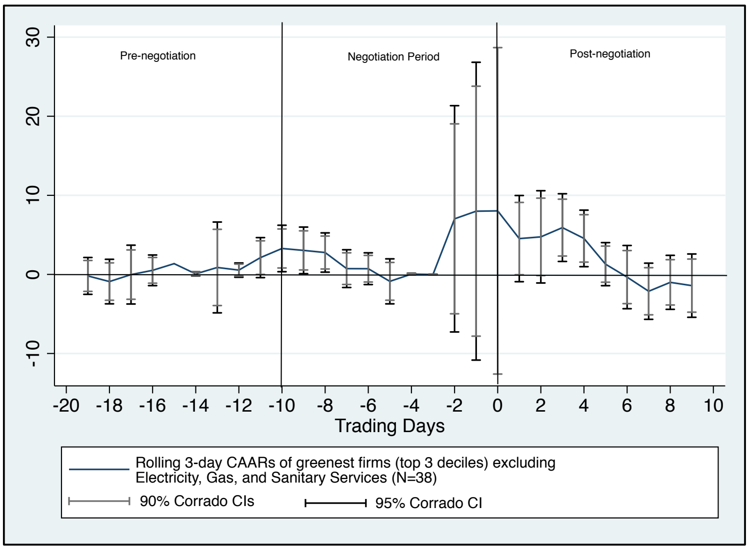
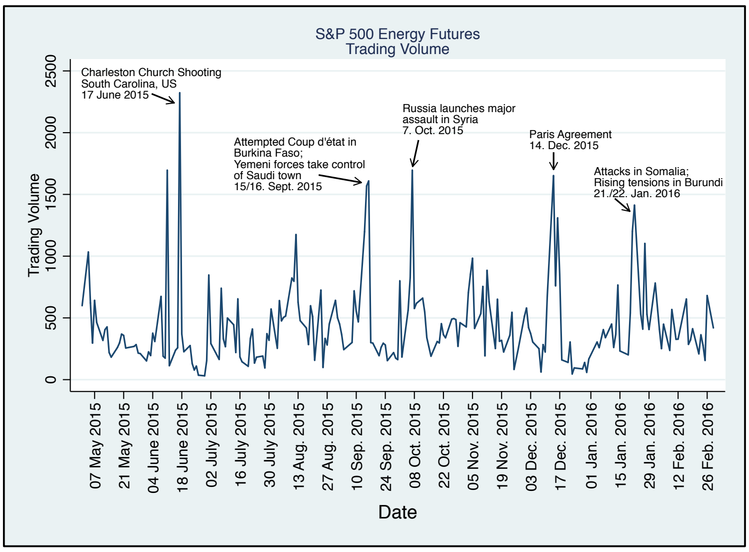


Figure C.3: Event Paths for Green firms (top 3 deciles) excluding public utilities: Electricity, Gas, and Sanitary Services (SIC 49)

C.5 S&P 500 Energy Futures Trading Volume



Note: After a careful news search, the authors decided that the indicated events appeared to be the most significant and likely drivers of the trading volume. This does however not imply that the spikes were caused by the respective events.

Figure C.4: S&P 500 Energy Futures Trading Volume

C.6 Google Trend Statistics

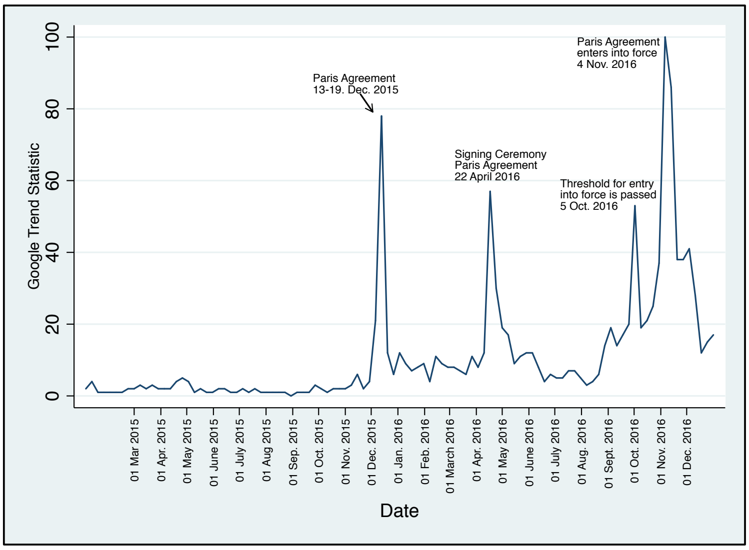
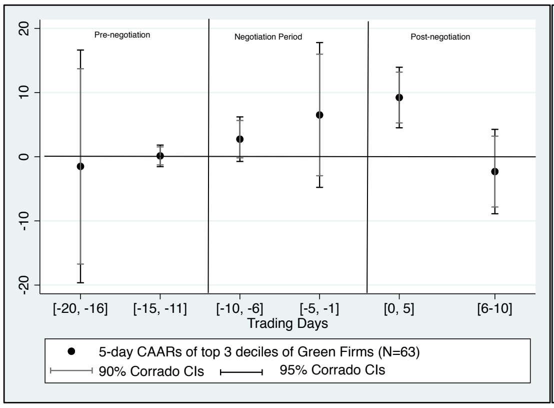


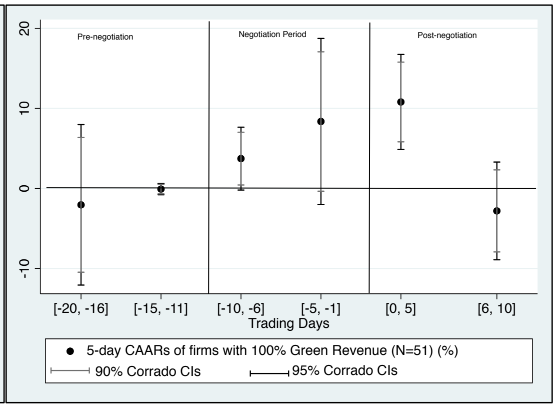
Figure C.5: Google Trend Statistics for the term 'Paris Agreement' (searched for in the US between March 2015 and December 2016).

C.7 Results with 5-day CAARs

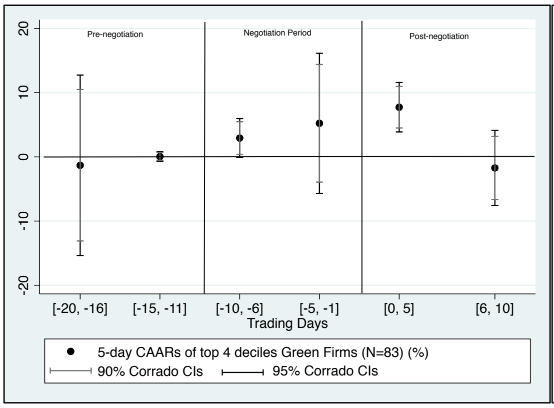
(**a**) Top 30% green firms



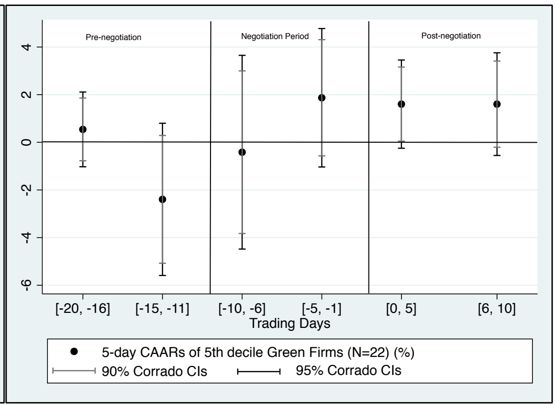
(**b**) Firm with 100% GR



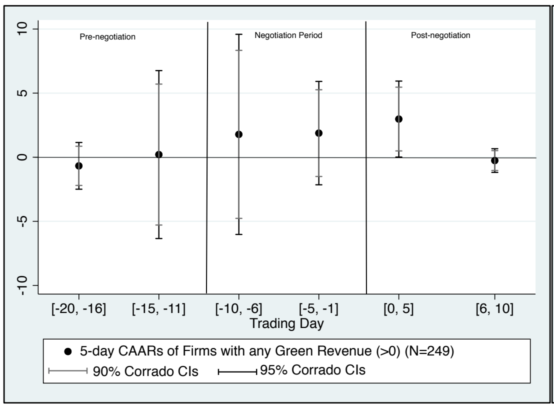
(**c**) Top 40% green firms



(**d**) Median (5th) decile of green firms



(**e**) Any green revenue (>0) between 2009-13



(**f**) Top 30% of green firms excluding electricity generation (SIC 491)

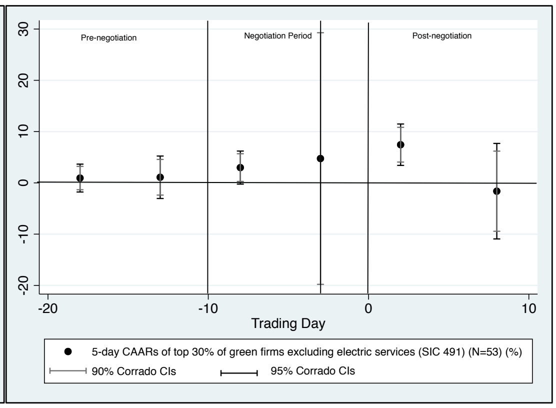
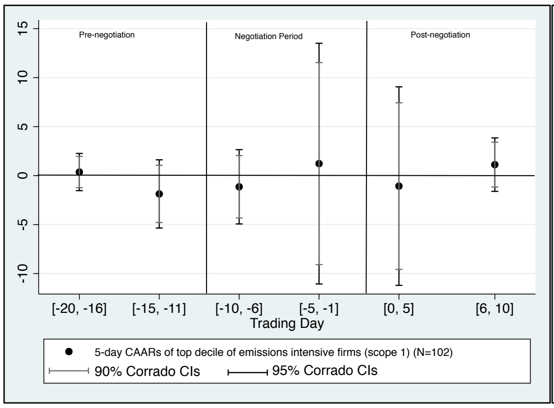
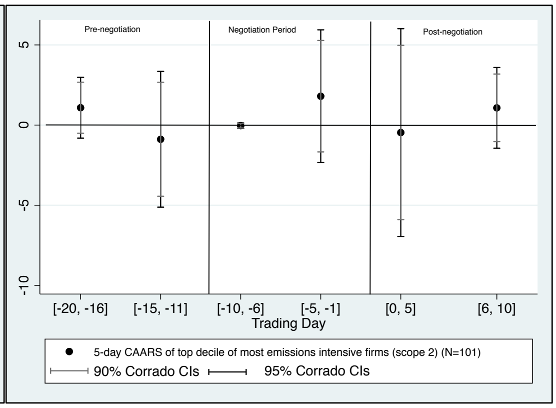


Figure C.6: Results with 5-day Cumulative Average Abnormal Returns (part 1)

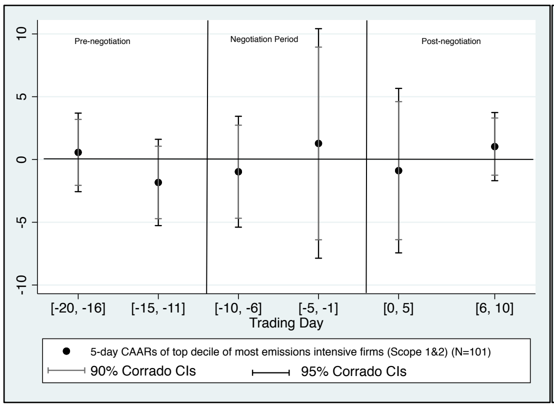
(a) Top 10% of most emissions intensive firms (Scope 1)



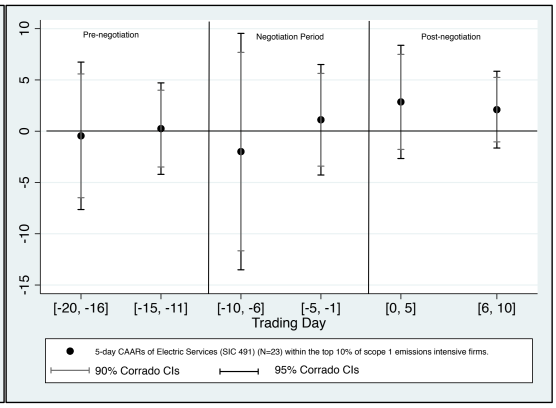
(b) Top 10% of most emissions intensive firms (Scope 2)



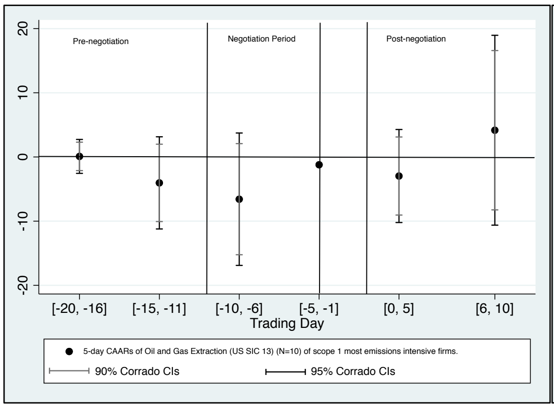
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction (SIC 13) firms among top 10% of most emissions intensive firms (scope 1)



(f) Excluding Electric, gas and sanitary services (SIC 49) firms among top 10% of most emissions intensive firms (scope 1)

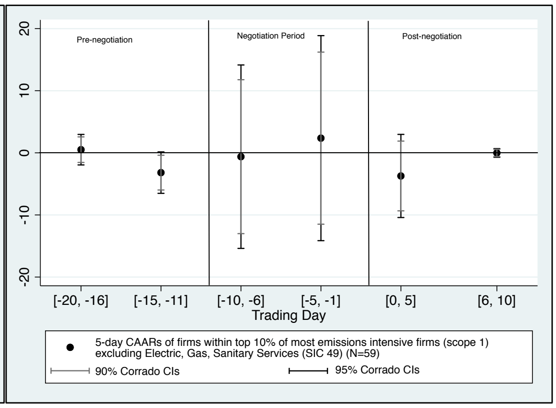
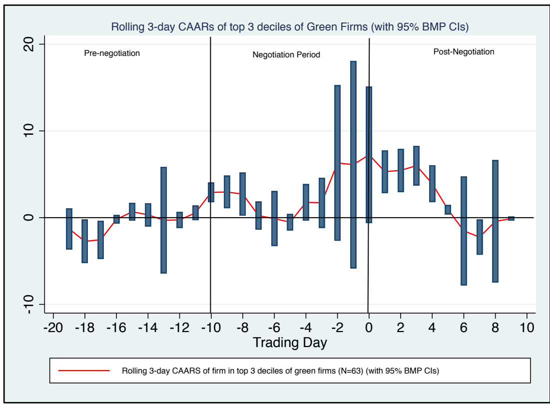


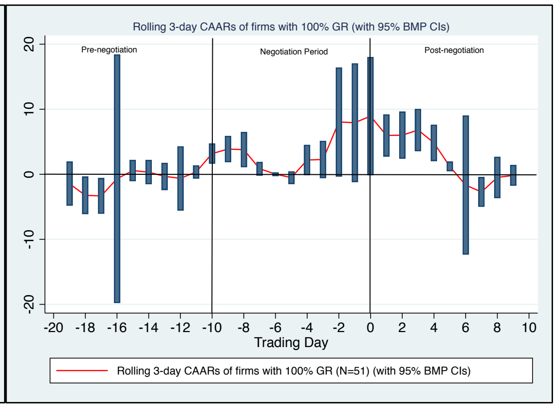
Figure C.7: Results with 5-day Cumulative Average Abnormal Returns (part 2)

C.8 Robustness Check using the BMP test statistic (developed by (Boehmer et al., 1991))

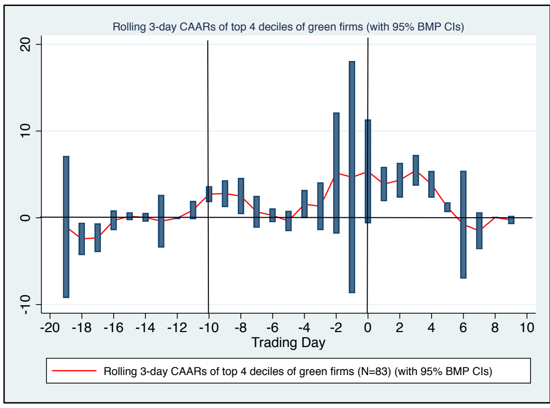
(a) Top 30% green firms



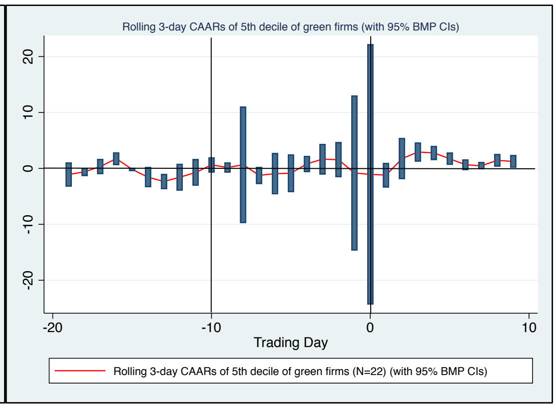
(b) Firm with 100% GR



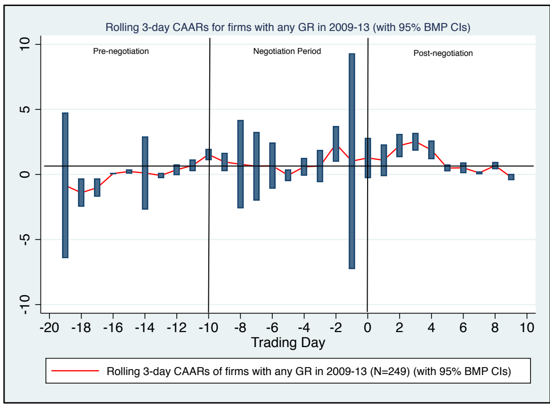
(c) Top 40% green firms



(d) Median (5th) decile of green firms



(e) Any green revenue (>0) between 2009-13



(f) Top 30% of green firms excluding electricity generation (SIC 491)

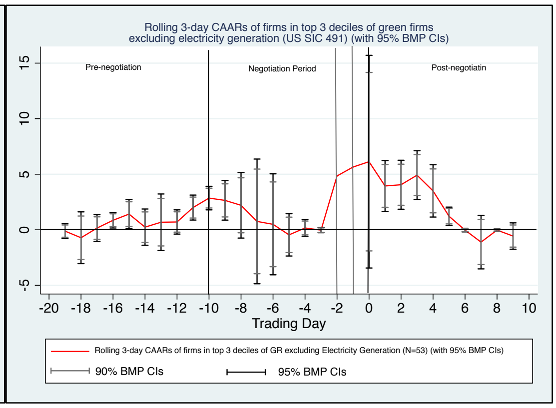
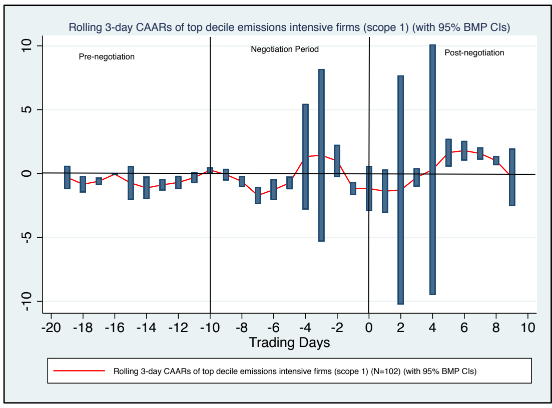
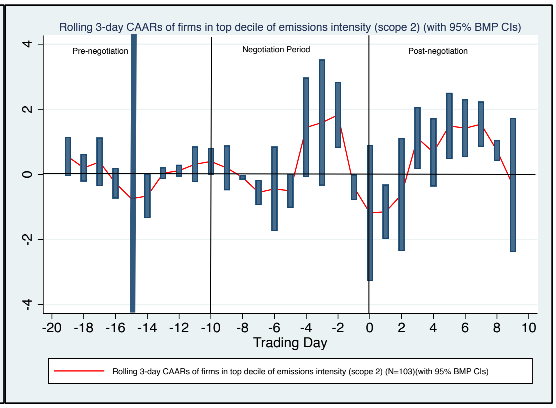


Figure C.8: Robustness checks using BMP test statistic (developed by (Boehmer et al., 1991)) (part 1)

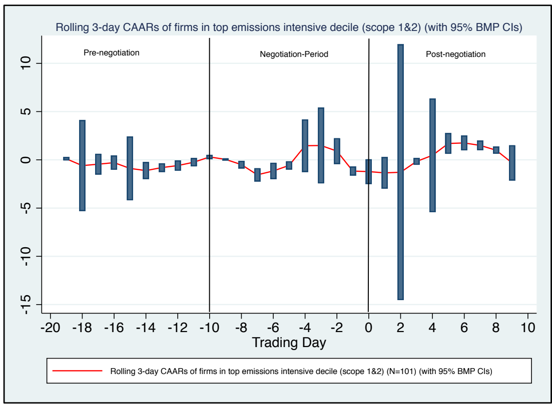
(a) Top 10% of most emissions intensive firms (Scope 1)



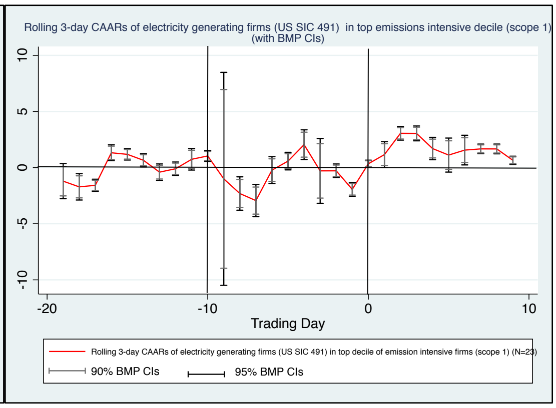
(b) Top 10% of most emissions intensive firms (Scope 2)



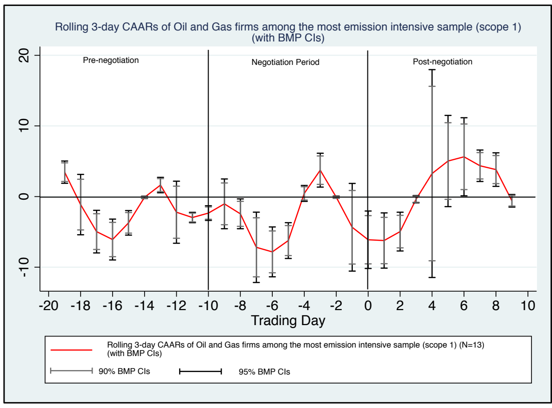
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)



(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

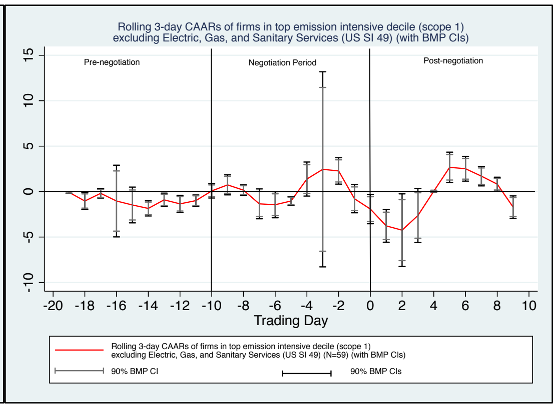
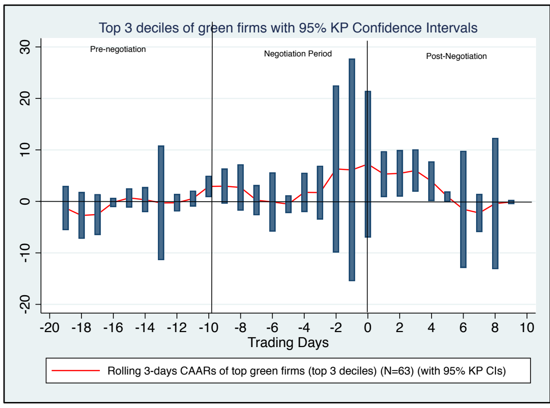


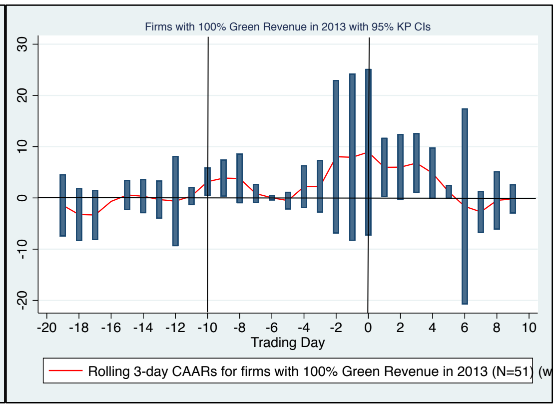
Figure C.9: Robustness checks using BMP test statistic (developed by (Boehmer et al., 1991)) (part 2)

C.9 Robustness Check using the KP test statistic (developed by (Kolari and Pynnonen, 2010))

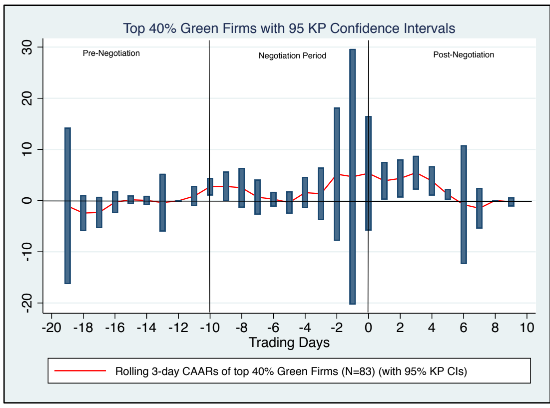
(a) Top 30% green firms



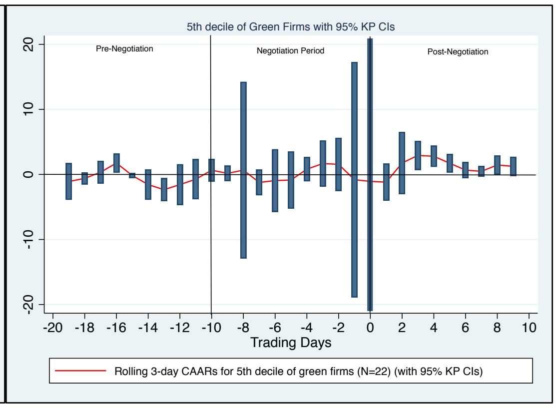
(b) Firm with 100% GR



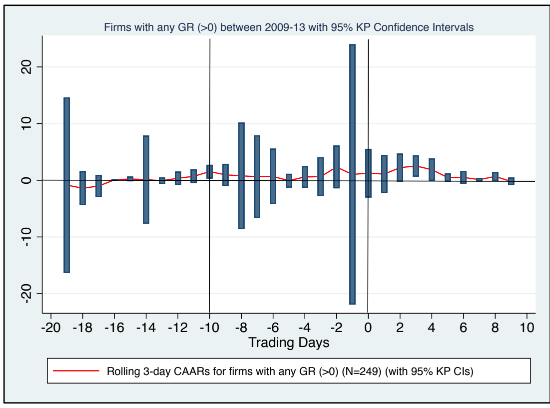
(c) Top 40% green firms



(d) Median (5th) decile of green firms



(e) Any green revenue (>0) between 2009-13



(f) Top 30% of green firms excluding electricity generation (SIC 491)

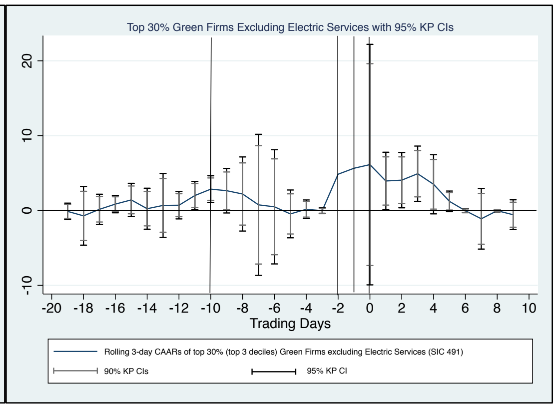
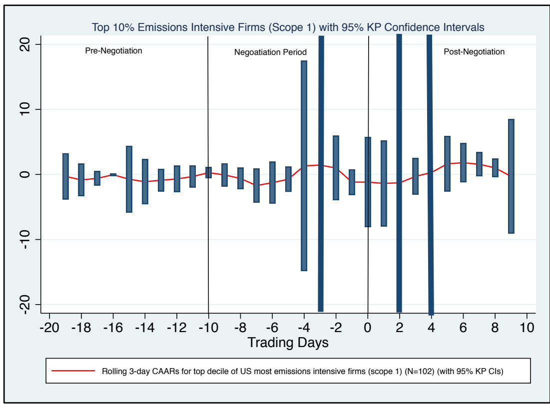
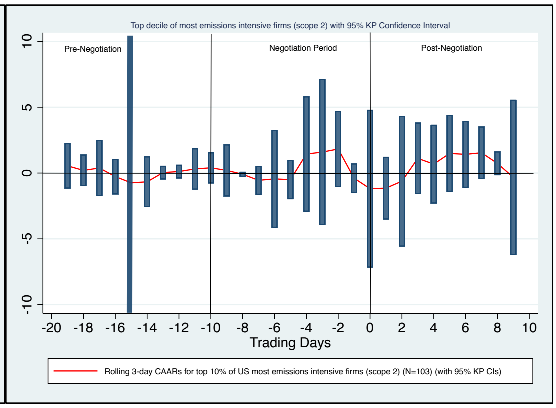


Figure C.10: Robustness checks using KP test statistic (developed by (Kolari and Pynnonen, 2010)) (part 1)

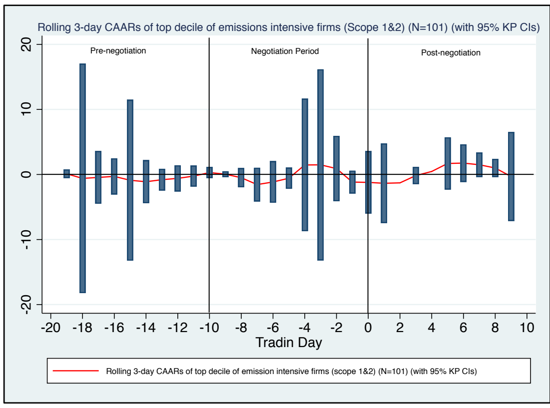
(a) Top 10% of most emissions intensive firms (Scope 1)



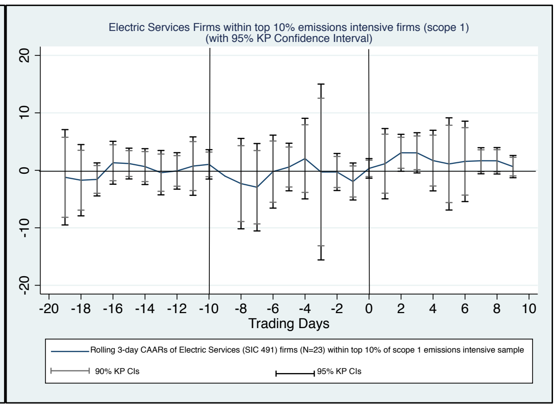
(b) Top 10% of most emissions intensive firms (Scope 2)



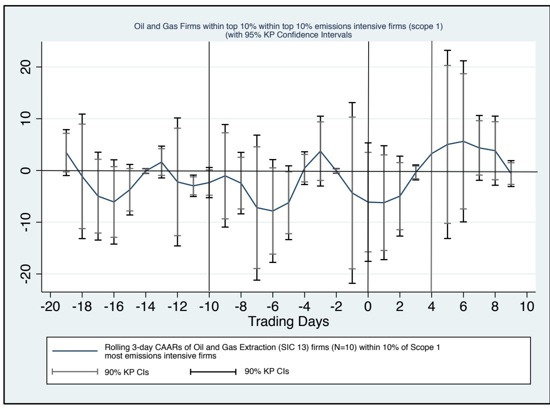
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)



(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

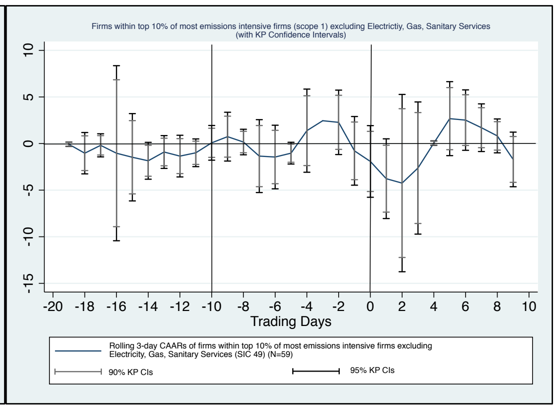
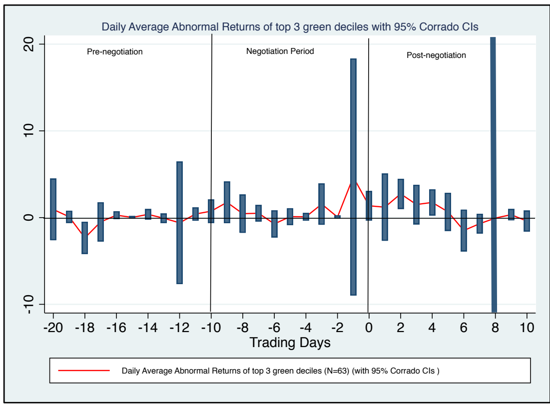


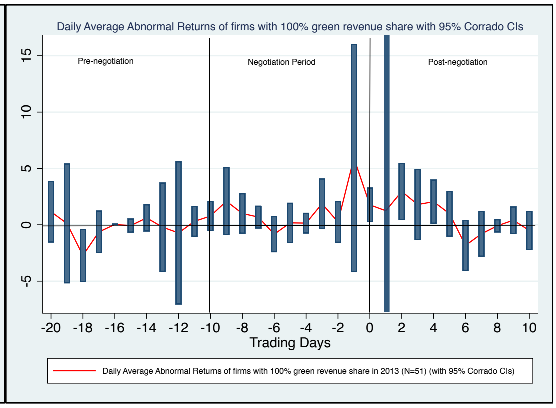
Figure C.11: Robustness checks using KP test statistic (developed by (Kolari and Pynnonen, 2010)) (part 2)

C.10 Average Abnormal Returns (AARs)

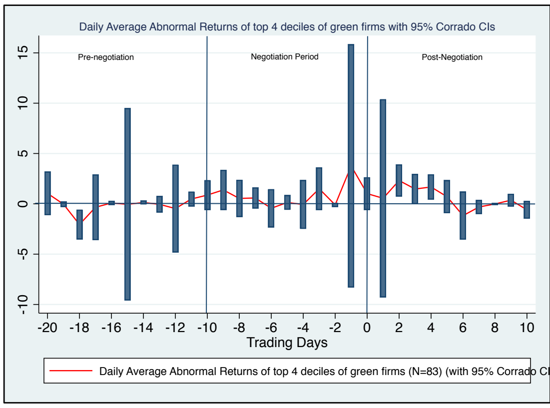
(a) Top 30% green firms



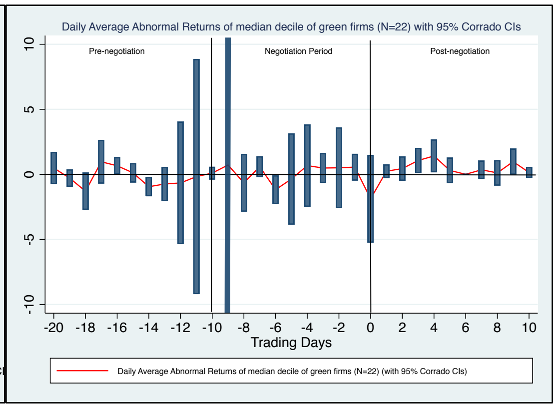
(b) Firm with 100% GR



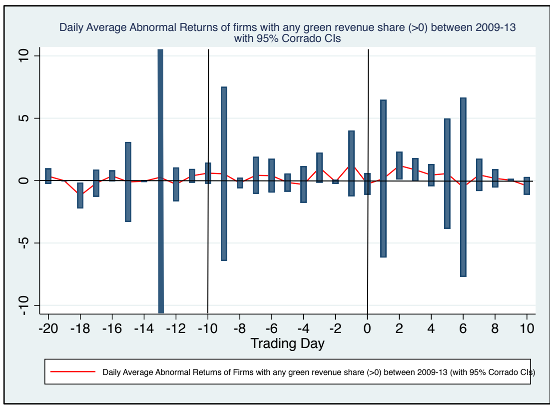
(c) Top 40% green firms



(d) Median (5th) decile of green firms



(e) Any green revenue (>0) between 2009-13



(f) Top 30% of green firms excluding electricity generation (SIC 491)

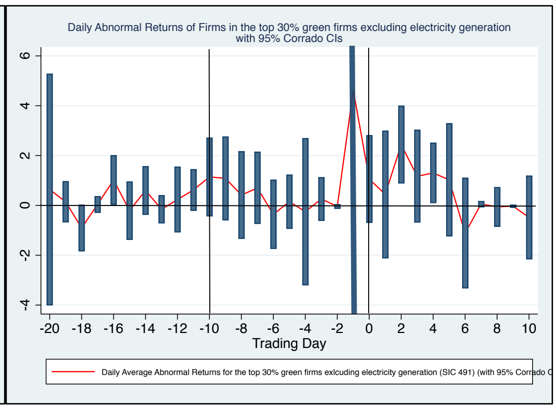
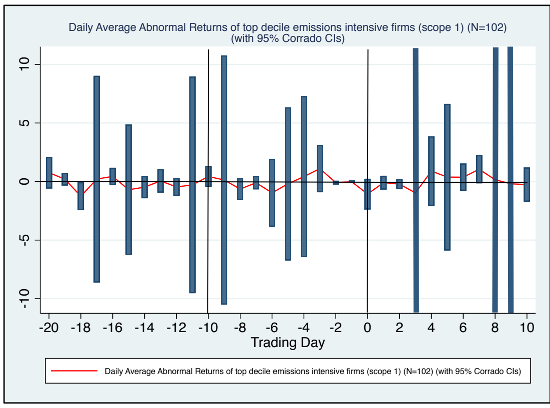
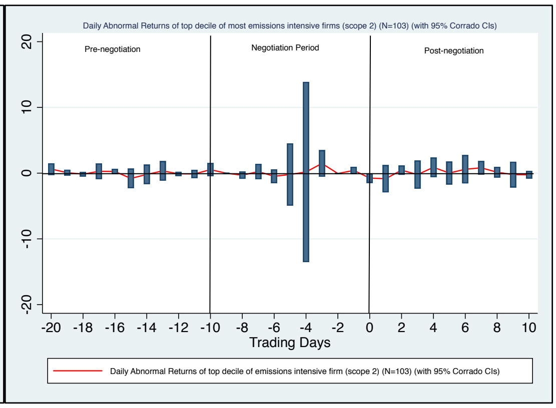


Figure C.12: Average Abnormal Returns (AARs) (part 1)

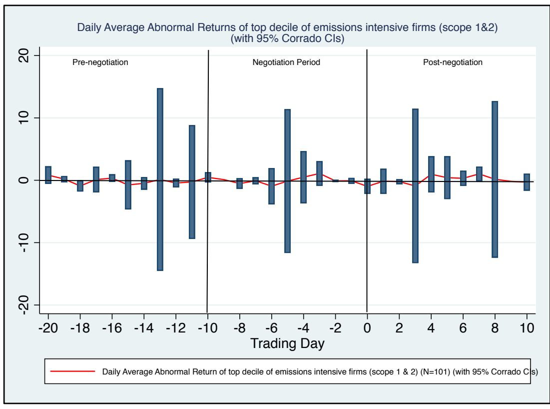
(a) Top 10% of most emissions intensive firms (Scope 1)



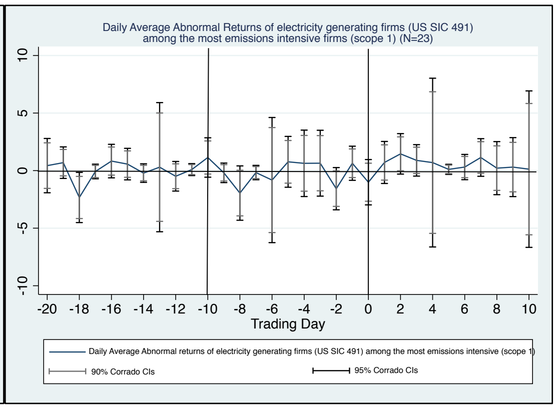
(b) Top 10% of most emissions intensive firms (Scope 2)



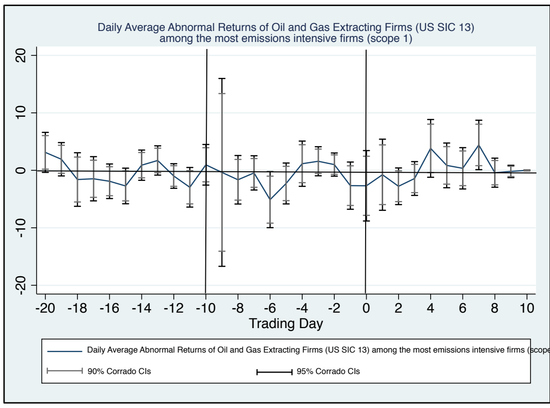
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)



(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

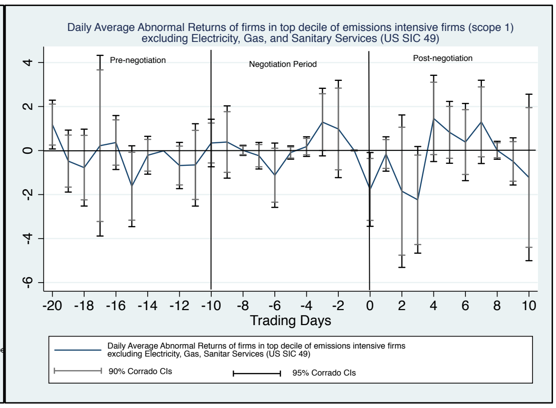


Figure C.13: Average Abnormal Returns (AARs) (part 2)

Appendix D

Appendix to Chapter 4

D.1 Example Choice Card

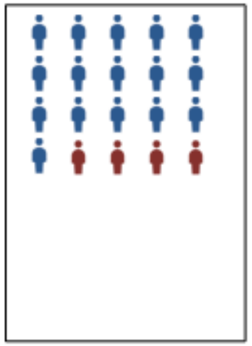
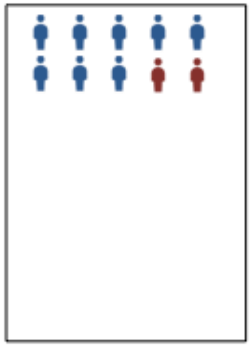
	Climate Adaptation Project 1	Climate Adaptation Project 2	No Additional Policy
Total **deaths prevented** per year – Blue: Deaths prevented among the **middle-income households** Red: Deaths prevented among the **extremely poor.**	 Total **deaths prevented** (blue & red): 20,000 **Deaths prevented** among **the extremely poor** (red): 4,000 (20%)	 Total **deaths prevented** (blue & red) 10,000 **Deaths prevented** among the **extremely poor** (red): 2,000 (20%)	Zero deaths prevented Zero deaths prevented among the extremely poor.
UK's financial contribution is **conditional** on people in recipient country also paying an additional adaptation tax.	No	Yes	
UK industries and businesses contribute through an additional levy	Yes	Yes	
UK household payment scheme	Households with higher income pay more. (Collected through a proportional increase in income tax).	Every household pays the same amount (Collected through an additional lump-sum household tax).	
Your yearly payment	£20	£5	£0

Figure D.1: Example Choice Card

D.2 Scenario Description

Developed countries, including the UK, are responsible for most of the historic greenhouse gas (GHG) emissions such as carbon dioxide (CO_2) that cause climate change. Global climate change is a serious environmental problem faced by humankind. It is caused by greenhouse gas emissions such as CO_2 that originate from burning of fossil fuels like coal, oil or natural gas. Climate change is expected to cause rising average temperatures, rising sea-levels and more severe natural disasters. The World Health Organization estimates that climate change will cause additional 250,000 annual deaths across the world by 2030. To prevent any of these deaths, financial resources are required from now on to gradually improve the resilience of affected people.

The developed countries have committed themselves to help poor countries adapt to the impacts of climate change. Globally, approximately £75 billion per year will be required to help poor countries adapt. Contributions for these climate adaptation programmes will come from all advanced economies, based on GDP and population size.

The UK Department for International Development (DFID) requires additional financial resources to implement such climate change adaptation projects. These projects focus on preventing deaths from droughts, floods, and heatwaves for example by building flood barriers, and distributing drought-resistant crops and air-conditioning units.

Project Characteristics: Projects available to DFID differ along a set of characteristics. One such characteristic is the distribution of resources within the recipient country. Two groups are eligible to receive funding:

1. The extremely poor: These people live in shanty towns on less than £515 per year. These groups are particularly vulnerable to any natural disasters and climatic changes. (For comparison, the median annual household income in the UK is £26,000).

2. Middle-income households: These people live in basic but solid housing on approximately £5000 per year. These people do not live in poverty but are still vulnerable to climate change events (for comparison, the median annual household income in the UK is £26,000).

Yet, without support climate change induced deaths will occur in both groups. Depending on the distribution of the resources across these groups the total cost may differ. However, the surviving members of the extremely poor face greater difficulties in managing the impact of a death on their household compared to middle-income households. Extremely poor families experiencing such a climate change induced death are expected to receive less support from the community and friends, as they are also poor. The extremely poor also have less access to social safety nets and formal financial tools (e.g. savings, credit, insurance) to help them manage these negative impacts resulting from the death of a family member compared to middle-income households.

You will be asked to give your preferred choice on a sequence of policy alternatives. Each set of policy alternatives is completely independent of any preceding or following alternative. The policies differ in their characteristics and you can only choose one of them. You can also choose the "no additional policy" scenario, in which case no additional costs would be incurred and zero deaths would be prevented.

I'd like you to think how much each of these programmes are worth to you. Then please consider whether you would be willing to pay a surcharge, to support either of these programmes.

You will now be asked two comprehension questions on the above description.

D.3 Demographic Summary Statistics

Variable	Statistic	Overall Sample	UK Population Statistics
Gender	% Male	47.0	49.3
Mean Age	Mean	47.7	46.9
Household Income (£)	Mean	36,732	38,291
Education	% University Degree	29	27.2
	% 2 or more A-levels or equiv.	13.4	12.3
	% 5 or more GCSEs or equiv.	16.7	15.3
	% Up to 4 GCSEs	30.4	36
	% Apprenticeship	3.9	3.6
	% Other	6.1	5.7
Region	%South East	15.2	13.7
	% London	12.0	13.4
	% North West	10.7	11.0
	% East	10	9.3
	% West Midlands	8.7	8.8
	% South West	8.3	8.4
	% Yorkshire and the Humberlands	9.1	8.3
	% East Midlands	7.6	7.2
	% North East	4.5	4.0
	% Wales	4.7	4.7
	% Scotland	7.2	8.2
	% Northern Ireland	1.9	2.8

Table D.1: Demographic Summary Statistics [1]

[1] Note on Sources for the UK Population Statistics:
Geographic Statistics: (For England (ONS, 2017b): https://www.statista.com/statistics/294681/population-england-united-kingdom-uk-regional/ ;
For Wales and Northern Ireland (ONS, 2017d,c): https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates#timeseries.
Gender Statistics (ONS, 2014a): https://www.ons.gov.uk/visualisations/nesscontent/dvc219/pyramids/index.html (Based on predictions for 2017 based on last Census).
Age Statistics (ONS, 2014a): https://www.ons.gov.uk/visualisations/nesscontent/dvc219/pyramids/index.html (based on predictions for 2017 based on last Census).
Education Statistics (ONS, 2014b) (only available for England and Wales): http://webarchive.nationalarchives.gov.uk/20160105191238/http://www.ons.gov.uk/ons/rel/census/2011-census-analysis/local-area-analysis-of-qualifications-across-england-and-wales/rpt---local-area-analysis-of-qualifications-across-england-and-wales.html#tab-Overview-of-Qualifications-in-England-and-Wales.
Income Statistics (ONS, 2017a):
https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/adhocs/006770grosshouseholdincomebyincomedecilegroupukfinancialyearending2016

D.4 Summary of Survey Results of Respondents' Opinions on Climate Change and Distributional Questions

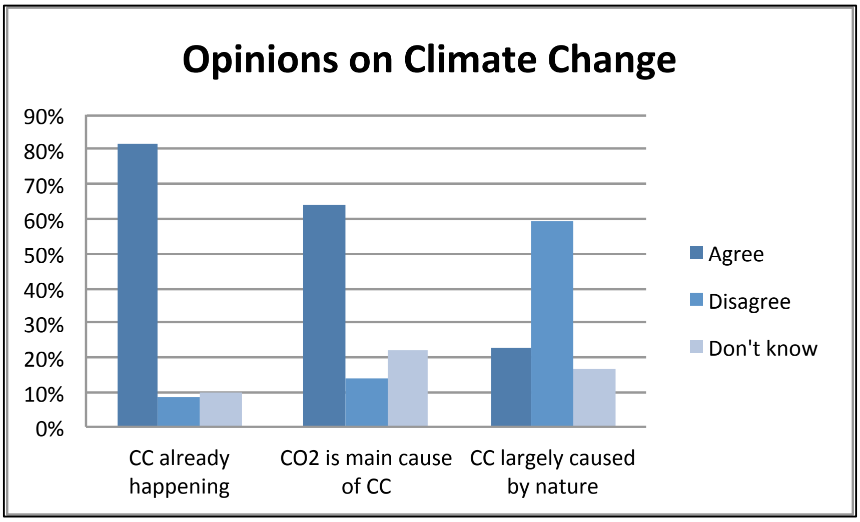


Figure D.2: Opinions on Climate Change

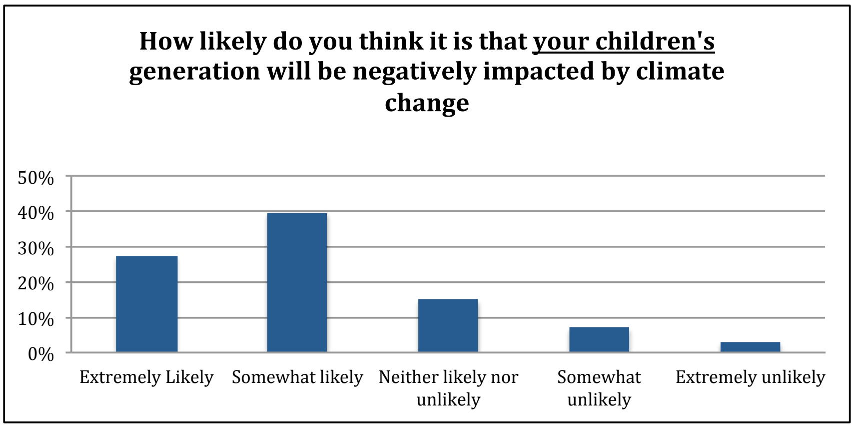


Figure D.3: Opinions on Future Impacts of Climate Change

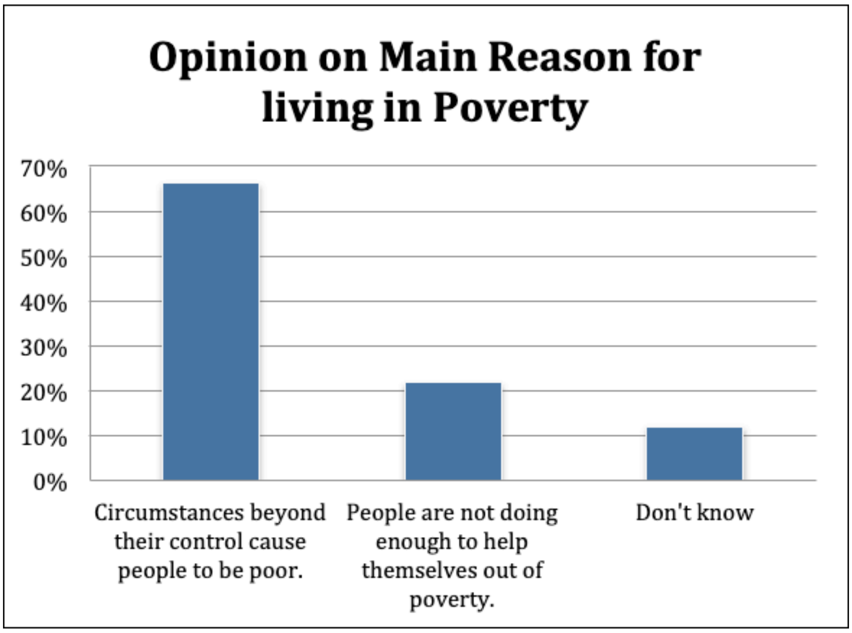


Figure D.4: Opinions on Main Underlying Reasons for why People Live in Poverty

D.5 MNL and RPL-EC Models with Factor Variables (next page)

Dependent Variable: Choice	(1) MNL	(2) RPL_EC	(3) RPL_EC	(4) MNL	(5) RPL_EC
Variable	Coeff. (S.E.)	Coeff. (S.E.)	S.D.	Monetary Valuation (£)	Monetary Valuation (£)
Total Deaths prevented: 20k	0.0207*** (0.0324)	0.7430*** (0.0643)	-0.7813*** (0.1568)	12.55	31.00
Total Deaths prevented: 40k	0.0765** (0.0362)	1.3262*** (0.0898)	-2.1500*** (0.1199)	4.63	55.33
Share of deaths prevented among extremely poor: 50%	0.3356*** (0.0434)	0.6440*** (0.0801)	1.2257*** (0.1756)	20.31	26.87
Share of deaths prevented among extremely poor: 80%	0.1836*** (0.0398)	0.0067 (0.0723)	-0.4741 (0.4431)	11.11	0.28
Payment Conditional	-0.0942*** (0.0380)	0.0877 (0.0600)	-1.6822*** (0.1030)	5.70	3.66
Industry Co-Finance	-0.0958*** (0.0275)	0.0333 (0.0441)	0.9074*** (0.0931)	5.80	1.39
Payment mech.: All HHs pay the same	0.2533*** (0.0363)	-0.0434 (0.0586)	-0.6154*** (0.2168)	15.33	1.81
Payment mech.: Richer HHs pay more	-0.0499 (0.0404)	0.2423*** (0.0757)	0.9321*** (0.1637)	3.02	10.11
Annual Payment (£)	-0.0165*** (0.0008)	-0.0240*** b (0.0013)	/	/	/
Information*Payment	0.0022** (0.0011)	0.0033** b (0.0015)	/	0.14	0.14
ASC 1 (Policy opt. 1)	-0.0413* (0.0242)	-0.0568 (0.0418)	/	2.50	2.37
ASC 2 (Status-quo)	-0.9706*** (0.0676)	-0.6661*** (0.0977)	/	58.73	27.79
Log-likelihood	-9122.15	-7804.38	/	/	/
Parameters	12	22	/	/	/
R-squared	0.09	0.22	/	/	/
Observations	9120	9120	/	/	/

Robust Standard errors reported in parentheses. *** denotes significance at 1%, ** at 5%, and * at 10%. Omitted category: Total Deaths prevented: 10k, Share of deaths prevented among the extremely poor: 20%, Payment mechanism: Payment based on HHs emissions, implemented through an increase in fuel tax. b: Non-random fixed coefficients.

Table D.2: MNL and RPL-EC Models with Factor Variables

D.6 Descriptive Statistics of Class Membership Functions in LCM

Variable	Mean	Std. Dev.	Min	Max	Observations
Income above average (yes=1)	0.3368	0.4727	0	1	9120
A-level or above (yes=1)	0.4289	0.4950	0	1	9120
GHGs are the main cause of climate change (yes=1)	0.6412	0.4797	0	1	9120
Climate Change is likely to have negative impacts on future generations (yes=1)	0.6702	0.4702	0	1	9120
Biggest reason for poverty lies in reasons beyond individuals' own control (yes=1)	0.6632	0.4727	0	1	9120

Table D.3: Descriptive Statistics of Variables to Characterise Class Membership Functions in LCM

Appendix E

Appendix to Chapter 5

E.1 List of Potential Control Units

Number	List of Potential Control Countries	Number	List of Potential Control Countries (cont.)
1	Argentina	29	Netherlands
2	Australia	30	New Zealand
3	Austria	31	Pakistan
4	Bangladesh	32	Panama
5	Belgium	33	Peru
6	Bolivia	34	Philippines
7	Brazil	35	Portugal
8	Bulgaria	36	Rwanda
9	Canada	37	Singapore
10	Chile	38	South Africa
11	China	39	Spain
12	Colombia	40	Sri Lanka
13	Costa Rica	41	Sweden
14	Denmark	42	Thailand
15	Finland	43	Tunisia
16	France	44	Turkey
17	Germany	45	Uganda
18	Greece	46	United Kingdom
19	Hong Kong	47	United States
20	India	48	Uruguay
21	Ireland		
22	Italy		
23	Japan		
24	Jordan		
25	South Korea		
26	Luxembourg		
27	Malawi		
28	Malaysia		

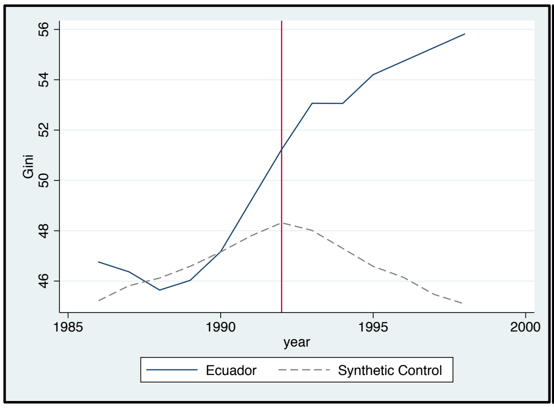
Table E.1: List of Potential Control Countries

Number	List of Potential Control States	Number	List of Potential Control States (cont.)
1	Alabama	26	Nebraska
2	Arizona	27	Nevada
3	Arkansas	28	New Hampshire
4	California	29	New Jersey
5	Colorado	30	New York
6	Connecticut	31	North Carolina
7	Delaware	32	North Dakota
8	District of Columbia	33	Ohio
9	Florida	34	Oregon
10	Georgia	35	Pennsylvania
11	Hawaii	36	Rhode Island
12	Idaho	37	South Carolina
13	Illinois	38	South Dakota
14	Indiana	39	Tennessee
15	Iowa	40	Utah
16	Kansas	41	Vermont
17	Kentucky	42	Virginia
18	Maine	43	Washington
19	Maryland	44	West Virginia
20	Massachusetts	45	Wisconsin
21	Michigan		
22	Minnesota		
23	Mississippi		
24	Missouri		
25	Montana		

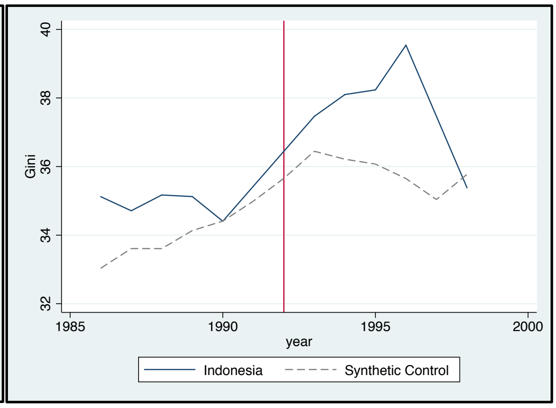
Table E.2: List of Potential Control States

E.2 Placebo-in-Time Tests

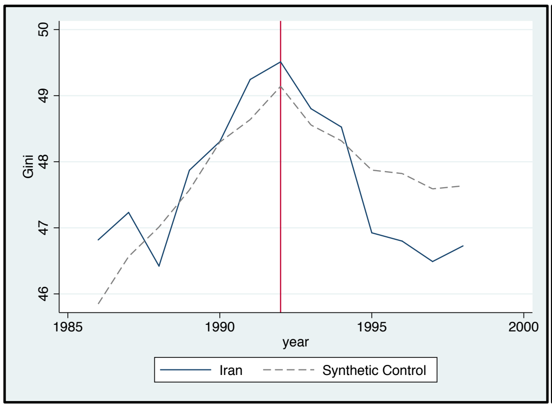
(a) Ecuador



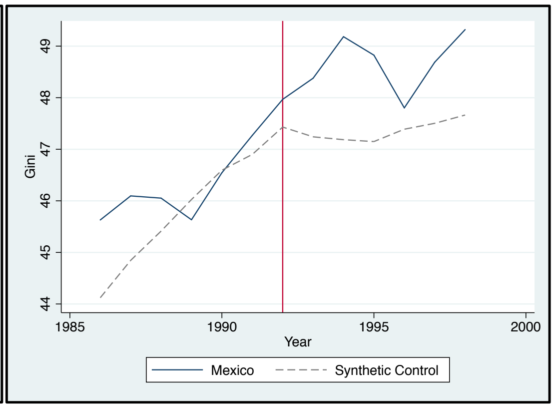
(b) Indonesia



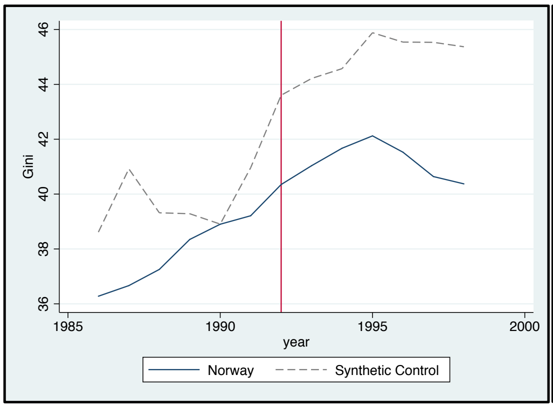
(c) Iran



(d) Mexico



(e) Norway



(f) Venezuela

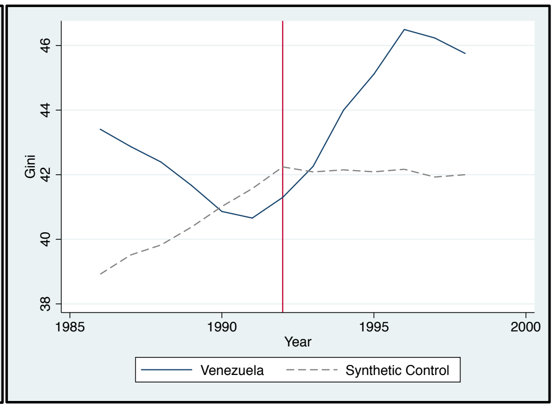
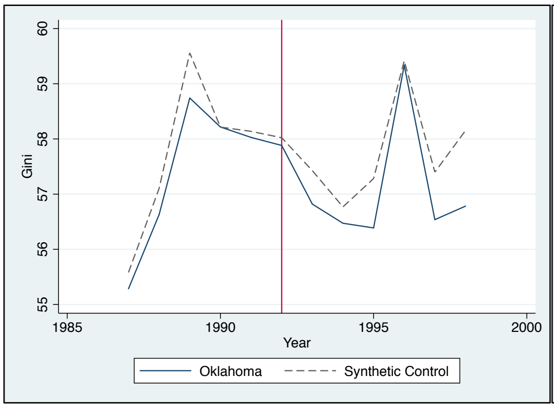
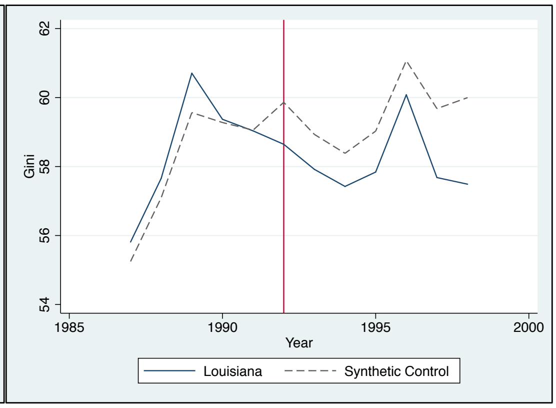


Figure E.1: Placebo-in-Time Tests Country-level

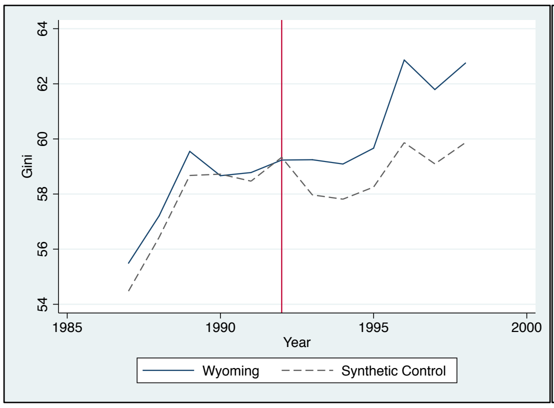
(a) Oklahoma



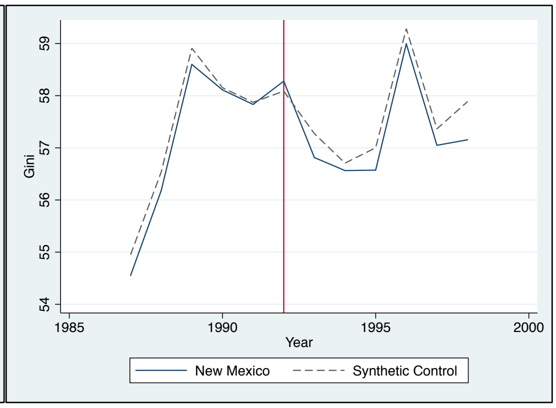
(b) Louisiana



(c) Wyoming



(d) New Mexico



(e) Texas

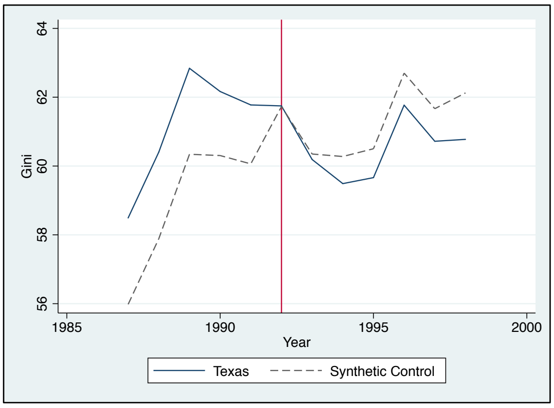


Figure E.2: Placebo-in-Time Tests US States

E.3 Placebo-in-Space Tests

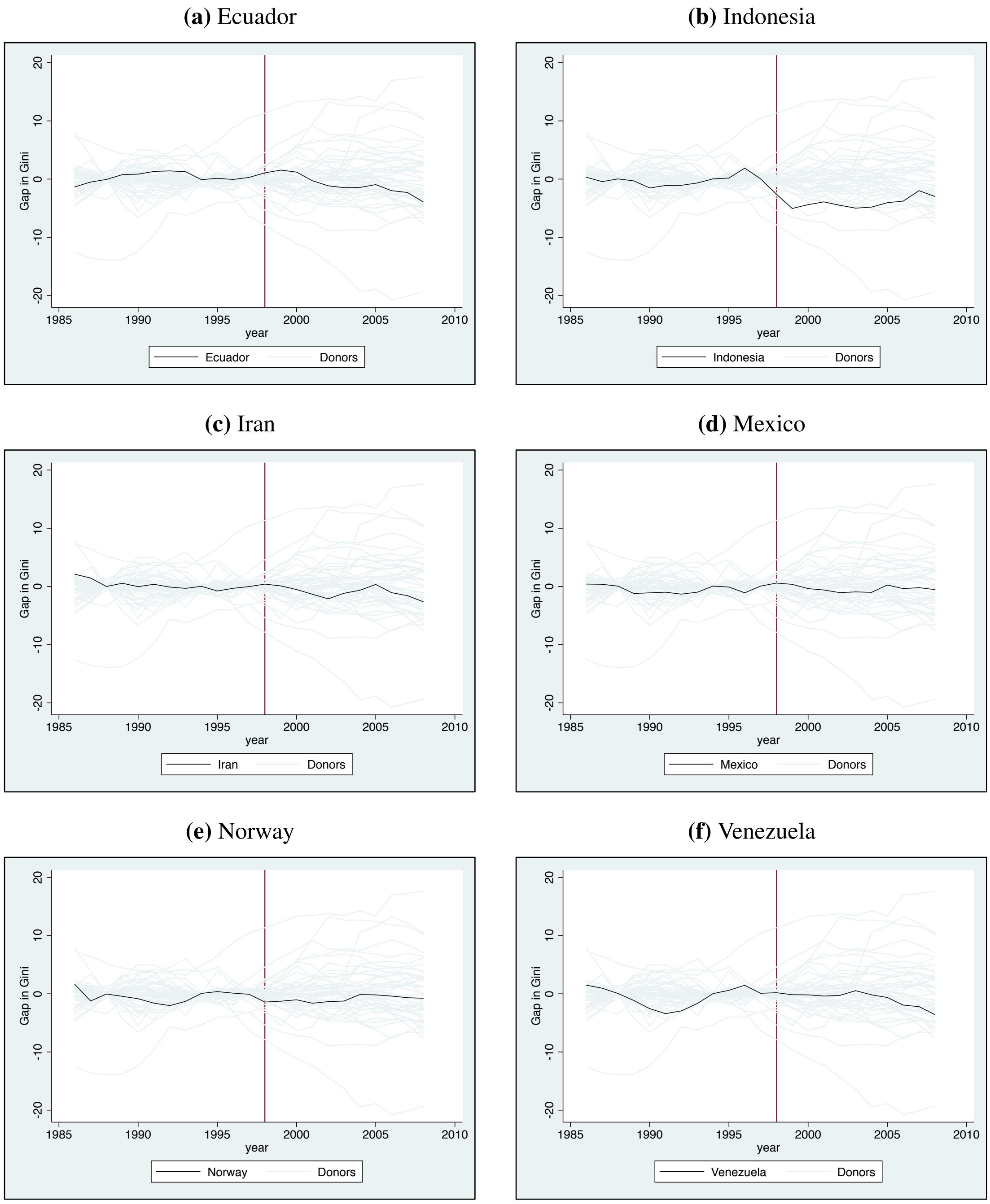
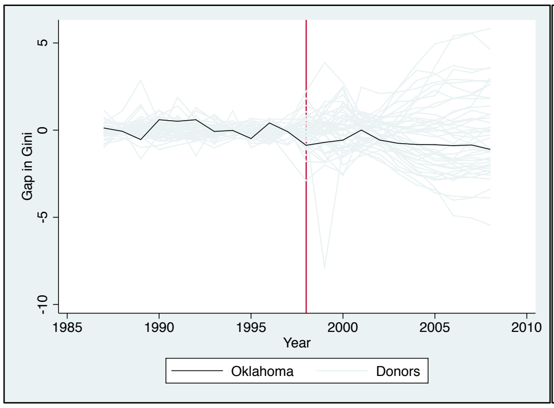
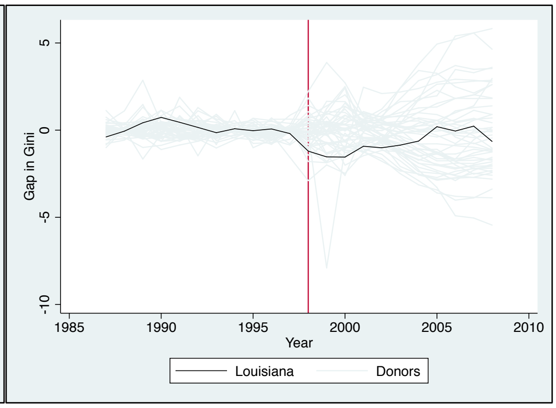


Figure E.3: Placebo-in-Space Tests Country-level

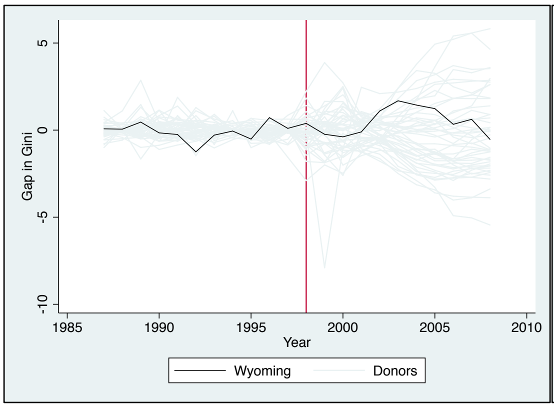
(a) Oklahoma



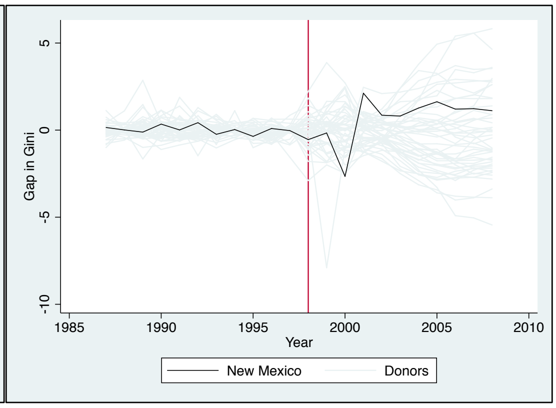
(b) Louisiana



(c) Wyoming



(d) New Mexico



(e) Texas

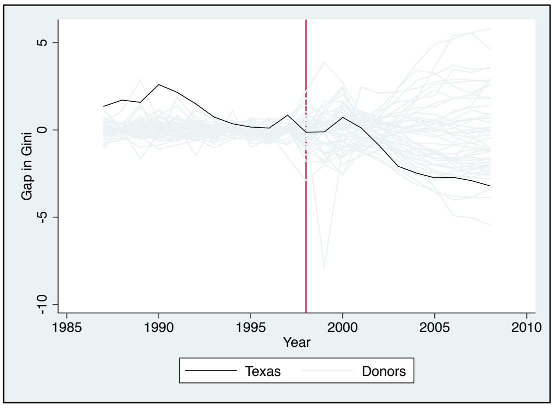


Figure E.4: Placebo-in-Space Tests US States