ABSTRACT

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The first chapter explores the effect of credit constraints on production-generated pollution emissions. I develop a theoretical model wherein polluting firms borrow externally to finance investment in various assets, subject to a credit constraint with lenders. The main insight of the model is that credit constraints distort the composition of assets towards over-investment in tangible assets, which can be pledged as collateral, thereby increasing the intensity of pollution emissions. The predictions of the model are tested using plant-level pollution emissions data for manufacturing plants from the EPA's Risk-Screening Environmental Indicators, and measures of creditworthiness from Dunn and Bradstreet. The empirical results indicate that credit constraints significantly increase pollution emissions (even after accounting for a countervailing scale effect) using both Pooled OLS and Fixed Effects, and the results withstand multiple robustness checks. Overall, I find that a one standard deviation in creditworthiness reduces pollution emissions by around 4.5 percent.

The second chapter focuses on the influence of household credit constraints in a general equilibrium framework on the composition of output in the "clean" and "dirty" industries and the pollution intensity of production, which in turn determines aggregate pollution emissions. I propose a simple two-sector model, where producer-consumers face credit constraints when young and, therefore, invest less in human capital. As a result, production is oriented towards more pollution-intensive industries and therefore entails more pollution. This prediction is supported for production-generated air pollutants SO_2 and lead using both reduced-form and two-stage regressions.

The third chapter explores the role of tax policy in shaping incentives for corporate executive effort (labor supply) and rent seeking. This chapter develops a theoretical model that distinguishes between effort and rent-seeking responses and provides a framework to empirically quantify the two responses. Using executive compensation and governance data, this paper empirically demonstrates that rent seeking constitutes a quantitatively significant response to changes in marginal income tax rates. Finally, this paper provides another piece of evidence suggesting that tax cuts may be one factor leading to the rise in top incomes over the last three decades.

ESSAYS ON FINANCIAL MARKET IMPERFECTIONS AND THE ENVIRONMENT

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Dedication

This dissertation is dedicated to my parents, Ted and Vicki, for their loving support. And to my love, Pinar, for her untellable warmth and companionship.

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Chapter 1: Do Credit Constraints Favor Dirty Production? Theory and Plant-Level Evidence

1 Introduction

External credit is indispensable to financing firm investment. Accordingly, credit intermediation entails overcoming a number of obstacles, such as contractual incompleteness and asymmetric information.[1] One approach to overcoming these credit constraints, elucidated by the incomplete contracts literature, is to invest in physical assets that can be pledged as collateral (Williamson, 1988; Hart and Moore, 1994). Specifically, tangible assets, such as buildings and structures, equipment, and natural resources, retain greater residual value to lenders in the case that the firm defaults or repudiates the contract (Braun, 2003; Manova, 2012).[2] Conversely, intangible assets, such as human capital (worker and manager training), product and process innovation (research and development), and marketing, tend to be inalienable and firm specific in nature and therefore have less residual value to lenders.[3] Credit constraints therefore bias investment towards tangible assets at the expense of intangible assets, which in turn has repercussions for the environment.

Significant attention has been given to the role of credit constraints in firm investment and performance; however, to date, the consequences for the environment have not been explored. This is the first paper to explore the effect of credit constraints on production-generated pollution emissions. To that end, I develop a theoretical model incorporating

[1]The literature is vast, see Hubbard (1998) and Stein (2001) for survey articles. Empirical studies document that credit constraints bear on firm investment and performance. For example, Midrigan and Xu (2012) find that credit frictions reduce total factor productivity by up to 40 percent, and Hennessy and Whited (2007) find that credit frictions represent 13 and 25 percent of financing costs for large and small firms.

[2]Retaining greater residual value implies that shifting control from firms to creditors is less costly, or equally, that a greater fraction can be pledged as collateral (collateralized debt).

[3]Intangible assets are considered broadly to include all factors contributing to total output not caused by tangible assets. Conventional accounting measures (book value) of assets therefore only partially capture intangible assets defined herein. For example, the book value of intangible assets includes the value of patents but not comprehensive knowledge.

external borrowing to analyze the link between credit constraints and pollution emissions. The predictions of the model are tested using a unique dataset that matches plant measures of creditworthiness and pollution emissions. Both the theory and empirics attest that credit constraints increase pollution emissions.

While several studies have explored the relationship between various measures of financial performance and environmental performance; no study, to my knowledge, has attempted to theoretically or empirically isolate the effect of credit constraints on environmental performance. A recent study by Earnhart and Segerson (2012) (henceforth E&S) is the first paper to theoretically explore various dimensions of financial status on environmental performance, focusing on the effect of profitability, solvency risks, and liquidity, on the efficacy of environmental regulations on reducing emissions.[4] While the study adds to our understanding by distinguishing between various dimensions of financial status, E&S abstract from external borrowing, which is the primary financing source for most firms (Fazzari et al., 1988).[5] This paper incorporates external borrowing that entails satisfying a credit constraint with lenders. Incorporating external borrowing, along with the generalization that firms employ various inputs that are imperfect substitutes, generates the prediction that credit constraints impact the intensity of pollution emissions.

The empirical literature on firm environmental and financial performance does not account for credit constraints and, with the exception of E&S, focuses solely on the role of profitability. E&S conduct an empirical analysis for wastewater discharges of 508 "major" publicly held chemical manufacturing facilities using indirect measures of liquidity and solvency risks.[6] One shortcoming of using only major publicly-held companies (and potential

[4]E&S develop an "crime and punishment" (Becker, 1968) model examining optimal pollution abatement for compliance with an emissions standard in the presence of liquidity and solvency constraints, focusing on the conditional effect of expected punishments on compliance, which is not considered in this paper. E&S do not explicitly model production (abatement is the only decision variable), which is necessary but not sufficient to generate the predictions in this paper.

[5]Fazzari et al. (1988) report that for manufacturing firms the majority of funding is long-term bank debt, except for large firms with over $250 million in assets, which use around 60 percent retained earnings.

[6]E&S use the firm's current ratio as a measure of solvency and the year end cash stock as a measure of liquidity. The empirical analysis also departs from E&S by using a more comprehensive measure of emissions (releases to air, water, landfill) and employing multiple emissions measures capturing both pounds and the

explanation for not finding significant results), is selection bias–publicly held companies have unique capital structures, financing investments mostly through retained earnings and equity, and are therefore less affected by credit and liquidity constraints. This paper takes advantage of a recently-released dataset containing data for both privately and publicly-held plants in all manufacturing industries (nearly 30,000 in total) and a unique plant-level measure of credit constraints, which is a direct measure of the parameter in the theoretical model. I find significant effects of credit constraints on pollution emissions and provide direct evidence of the mechanisms linking credit constraints and emissions.

This paper develops a conceptual model focusing on the partial equilibrium analysis of a representative firm that generates pollution emissions as a byproduct of production. I posit that firms produce a final good using intermediate factors tangible and intangible assets. Financing production of tangible and intangible assets requires external lending, which entails satisfying an incentive compatibility constraint (credit constraint) with a risk-neutral lender. Due to price and production risks, as well as contractual incompleteness and asymmetric information, lenders assign a positive probability to the event that the firm defaults, in which case a fraction of the investment is recovered by the lender. Incentive compatibility therefore requires that the lender's expected return must exceed an exogenous reservation return. The model demonstrates that greater assigned probability to the default state strengthens the credit constraint and increases the incentive to invest in tangible assets, which retain greater residual value in default states. Thus, credit constraints increase the intensity of pollution emissions whenever the intensity of pollution emissions is positively associated with the share of tangible assets in production. Finally, credit constraints might also reduce output implying that net effect of credit constraints on total emissions is an empirical question.

The empirical analysis explores the impact of credit constraints on pollution emissions for a panel of manufacturing plants, using the Environmental Protection Agency's Risk-

health risk of emissions. I also expand the span of the data from 7 to 20 years.

Screening Environmental Indicators and the National Establishment of Time Series, among several other datasets. Specifically, I investigate the impact of credit constraints, using measures of creditworthiness from Dunn and Bradstreet, on several measures of pollution emissions, including total pounds of emissions, the potential risk of emissions to human health, and the actual risk of emissions to human health given the characteristics of the exposed surrounding population. The empirical analysis also estimates the effect of credit constraints on output, thereby distinguishing between "technique" and "scale" effects of credit constraints on pollution emissions. Finally, using the Compustat annual industrial dataset, I explore the intermediate relationships between firm-level credit constraints and the share of tangible assets, and the share of tangible assets and aggregate firm-level emissions.

The results suggest that credit constraints significantly increase pollution emissions (even after accounting for the countervailing scale effect) using both Pooled OLS and Fixed Effects.[7] I find that a one-standard deviation increase in creditworthiness reduces pollution emissions by approximately 4.5 percent. The results are statistically significant and withstand numerous robustness checks, including adding a rich set of controls, employing lagged dependent variables, and instrumental variables. Moreover, heterogeneous effects of credit constraints on pollution emissions are highly consistent with expectations. For example, the impact of credit constraints is particularly acute in industries with greater reliance on external credit. The firm-level analysis validates the intermediate relationships– credit constraints are positively associated with the share of tangible assets, and the share of tangible assets is positively associated with pollution emissions. Finally, because firms own plants in multiple industries, I disentangle the technique and composition effects of the share of tangible assets on pollution emissions and find that the former is the primary effect.[8]

[7] Moreover, the dataset affords significant degrees of freedom, which permits employing industry by year and state by year effects to account for time-variant heterogeneous pollution policies and input and output price shocks.

[8] The technique effect entails an increase in emissions of all plants belonging to the firm (holding the

More broadly, this paper is related to the literature exploring the relationship between financial performance and environmental performance, which contains inconclusive and often contradictory findings. Financial performance is typically a measure of profitability and various, often opposing, mechanisms are proposed. It is therefore not surprising that the results are inconclusive, though there are other potential concerns, such as non-representative, and very small, samples. Gray and Deily (1996) and Shadbegian and Gray (2005) find that more profitable firms are not more likely to comply with environmental standards, whereas Maynard and Shortle (2001) find that more profitable firms are more likely to invest in a clean technology.[9] Earnhart and Lizal (2006, 2010) report seemingly incongruous findings for industrial firms in the Czech Republic. On the one hand, profits are positively associated with air pollution (Earnhart and Lizal, 2006); and on the other hand, value added is negatively associated with air pollution emissions (Earnhart and Lizal, 2010).

Since research and development and manager training are investments in intangible assets, this paper is consistent with empirical studies documenting that more efficient firms have lower abatement costs (Gray and Shadbegian, 1995; Shadbegian and Gray, 2003), as well as pollution emissions (Cui and Ji, 2011). Moreover, improved management is associated with lower energy intensity (Bloom et al., 2010).

The findings of this paper have policy implications for both developed and developing countries. Governments in developed countries routinely intervene in credit markets to reduce credit constraints, such as the loan guarantees by the Small Business Administration in the United States. If these interventions are effective at reducing credit constraints then they might confer environmental benefits, which should be taken into consideration. However, such interventions typically aim at promoting investment in fixed capital assets, such as structures and equipment, which are primarily tangible assets. This paper highlights that

composition of output across plants constant), whereas the composition effect entails an increase in output in plants in pollution-intensive industries.

[9] Gray and Deily (1996) analyze 41 steel plants, Shadbegian and Gray (2005) analyze 116 pulp and paper mills, and Maynard and Shortle (2001) analyze 75 bleached kraft pulp mills.

promoting investment in tangible assets, at the cost of financing intangibles, exacerbates the bias in investment towards tangible assets, which generate greater pollution emissions. Moreover, existing tax policy is also biased towards tangible assets, through various tax incentives and accelerated depreciation rates. Reducing credit constraints for investment in intangible assets and pollution abatement equipment, and eliminating the bias generated through tax policy can therefore mitigate the effects of credit market distortions on pollution emissions. Finally, there are many avenues for reforming the legal and institutional environment in the context of developing countries, such as increasing creditor rights and promoting information sharing through credit bureau registries, to reduce the influence of credit constraints on pollution emissions.

The remainder of this paper is organized as follows. Section 2 presents the conceptual model, generates the primary estimation equation, and outlines the identification strategy. Section 3 describes the data and empirical model specifications, presents the regression analysis and robustness checks, and discusses the findings. Finally, Section 4 concludes.

2 Conceptual Model

This section develops a simple theoretical model exploring the relationship between credit constraints and pollution emissions. The model focuses on the static partial equilibrium analysis of a representative firm that generates pollution emissions as a byproduct of production and relies on raising external credit to finance investments.

Following the standard approach in the environmental economics literature, I model pollution emissions as an additional factor of production.[10] The underlying assumption is that reducing the pollution necessarily entails the diversion of productive inputs towards abatement activities, thereby reducing the availability of inputs to produce the final con-

[10](Cropper and Oates, 1992) survey the environmental economics literature, which largely treats pollution emissions "simply as another factor of production." More recent studies treating pollution emissions as an input include Taylor and Copeland (1994); López (1994); Acemoglu et al. (2012).

sumption good. Incorporating abatement activities as implicit in the production process follows under certain assumptions regarding the abatement and production technologies, which are beyond the scope of this paper to fully address. (See Cropper and Oates (1992) for a discussion of the assumptions generating the result.) The conventional model has been criticized on the basis of incompatibility with materials balance (or conservation laws of mass and energy); however, models consistent with these principles add a significant amount of complexity (Pethig, 2006; Krysiak and Krysiak, 2003). To keep the analysis tractable and to add financing considerations, I use the conventional approach, modeling pollution as an input in production. The implications of employing an framework consistent with materials balance are discussed after presenting the baseline model.

The lending incentive compatibility constraint is similar to Manova (2012), with the generalization that the composition of assets is endogenous. The implications of various generalizations are discussed at several points.

2.1 Production

Firms produce a homogenous final good using two intermediate goods: tangible and intangible assets. Both intermediate assets are produced using variable and fixed inputs, which I refer to as "labor" and "capital." The defining feature is that labor does not require external financing, whereas capital requires external financing. I refer to capital employed in producing tangible and intangible assets as tangible and intangible capital. Production of tangible assets, unlike intangible assets, generates pollution emissions as a byproduct.[11] Production of the final good exhibits constant elasticity of substitution (CES) with an elas-

[11] The terminology tangible and intangible assets bears resemblance to the conventional "dirty" and "clean" goods (Copeland and Taylor, 2004). The assumption that only tangible assets generate pollution emissions is for simplicity; the necessary assumption is that production of tangible assets entails relatively greater pollution emissions than production of intangible assets (Copeland and Taylor (2004), among others, use a similar simplifying assumption).

ticity of substitution $\sigma > 1$.[12] Production is written as

$$q \equiv \phi \left[(1-\gamma) x^{\frac{\sigma-1}{\sigma}} + \gamma y^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where x and y are tangible and intangible assets, respectively.

Production of the intermediate assets, I assume, is Cobb-Douglas with constant returns to scale.

$$x \equiv z^{\alpha} l_x^{\beta} k_x^{1-\alpha-\beta} \tag{2}$$

and

$$y \equiv l_y^{\eta} k_y^{1-\eta} \tag{3}$$

where z is pollution emissions, l_x is labor employed in producing x, and l_y is labor employed in producing y. To facilitate subsequent derivations, I express tangible and intangible capital as $k_x = \theta k$ and $k_y = (1-\theta)k$, where k is the aggregate firm capital and θ is the share of tangible capital.

Consistency with the balance of materials principle would follow from either (i) employing tangible entails more materials in production or (ii) that emissions generated from employing tangible assets require more intensive use of traditional inputs to convert into "abatement residuals" (Pethig, 2006). It seems reasonable to assume that materials exhibit a higher degree of complementarity with tangible inputs vis-à-vis intangible inputs, which would be consistent with balance of materials principle.

2.2 Financing

Labor inputs and pollution "permits" are purchased at exogenous market rates w and τ, respectively. Capital is purchased at an exogenous market rate r, but capital purchases

[12]The CES production is a generalization of the canonical Cobb-Douglas framework (Copeland Taylor, 1994). The parameters γ and ϕ are share and productivity coefficients, respectively. That $\sigma > 1$ is a conventional assumption in similar CES models focusing on clean and dirty inputs (Acemoglu et al., 2012).

must be financed from an external lender. Because the lender has an outside reservation return, financing capital purchases entails satisfying the lender's participation constraint, implying a cost premium of capital whenever the constraint is binding.

Productivity and solvency shocks, as well as contractual incompleteness and asymmetric information, imply that lending entails "default risk." That is, default risk implies that the lender associates an ex-ante subjective probability with the event that the loan will not be repaid, in which case a fraction of the loan is recovered by the lender. The consequence of greater default risk is therefore that risk-neutral lenders will require a higher ex-ante rate of return (interest rate).

2.2.1 Lenders

Lenders are risk neutral and, without loss of generality, have a reservation rate of return normalized to 0.[13] The lender's participation constraint for an arbitrary loan of amount $h > 0$ is therefore

$$-h + (1 - \lambda)Rh + \lambda\xi h \geq 0 \tag{4}$$

where $R \geq 0$ is the (endogenous) ex-ante rate of return to the lender in the case that the firm does not default, $\lambda \in (0, 1)$ is the lender's subjective probability assigned to the default state, and $\xi \in (0, 1)$ is the percentage of the loan that can be pledged as collateral.[14] In other words, ξ is the lender's residual value of the loan. Therefore, the second term is the payoff in the non-default state, while the third term is payoff in the default state. Thus, the participation constraint implies that the loan amount must be exceeded by the lender's expected return.

Because 4 implies that $R > 0$, the lender's participation constraint is binding. I incorporate the lender's participation constraint which creates a link between the firm's credit

[13] The results would not change qualitatively if lenders could earn a market net interest rate $\tilde{r}$.

[14] To be precise, λ is the subjective probability measure associated with the default state, in a discrete sample space consisting of default and non-default states. Because the firm and lender are risk-neutral the second moment of the probability measure is immaterial.

constraint and the cost premium of external credit. Firms make a one-time offer to lenders, varying the ex-ante rate of return to bring the lender to his participation constraint. Lenders participate whenever

$$R \geq \frac{1-\lambda\xi}{1-\lambda} \tag{5}$$

Differences in the fraction of capital that can be pledged as collateral between tangible and intangible capital therefore imply differences in the lender's participation constraint. Recall that a greater fraction of tangible capital, relative to intangible capital, can be pledged as collateral ($\xi_x > \xi_y$).For simplicity, I assume that $\xi_x = 1$ and $\xi_y = 0$, which implies that

$$R_x = 1 \quad \text{and} \quad R_y = \frac{1}{1-\lambda} > 1 \tag{6}$$

where R_x and R_y are the cost premiums associated with financing tangible and intangible capital. Expression (6) demonstrates that financing tangible capital entails no cost premium whenever tangible capital can be entirely pledged as collateral. On the other hand, financing intangible capital entails a cost premium whenever there is a positive probability of default.

2.2.2 Capital Costs

The firm's capital costs consists of the exogenous market cost of capital multiplied by the cost premium of borrowed funds, weighted by the share of tangible and intangible capital purchased. Thus, the per-unit cost of total capital is

$$\psi = r\left[\theta R_x + (1-\theta)R_y\right] \tag{7}$$

Lemma 1: *Investment in intangible capital entails a cost premium, which is increasing in default risk. In particular, tangible and intangible capital costs are given by*

$$r_x = r \quad \text{and} \quad r_y = r\mu \geq r \tag{8}$$

where $\mu = 1 + \lambda/(1-\lambda) > 1$.

Proof: Use (6) in (7) and differentiate (7) with respect to θ and $1-\theta$. $\square$

The variable $\mu > 1$ represents the cost premium associated with the credit constraint, which is monotonically increasing in default risk. Therefore, I refer to an increase in μ as an increase in credit constraints.[15]

2.3 Production Decisions

Firm profit maximization implies the following per-unit cost functions of tangible and intangible assets[16]

$$c_x = \tau^{\alpha} w^{\beta} r^{1-\alpha-\beta} \quad \text{and} \quad c_y = w^{\eta} r^{1-\eta} \mu^{1-\eta} \tag{9}$$

which implies that the per-unit cost of the final good is

$$c_q = \frac{1}{\phi} \left[(1-\gamma)^{\sigma} (c_x)^{1-\sigma} + \gamma^{\sigma} (c_y)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{10}$$

Shepherd's lemma implies that the ratio of tangible to intangible assets is

$$\frac{x}{y} = \left[\frac{1-\gamma}{\gamma} \left(\frac{\mu^{1-\eta} w^{\eta-\beta} r^{\alpha+\beta-\eta}}{\tau^{\alpha}} \right) \right]^{\sigma} \tag{11}$$

I define the above ratio between tangible and intangible assets as "asset tangibility."

Result 1: *Asset tangibility is decreasing in the cost of pollution permits, and increasing in the cost of capital and labor whenever tangible assets employ these factors more intensively than intangible assets. Finally, asset tangibility is increasing in credit constraints. In*

[15] Asymmetric financing costs reported in Lemma 1 are the consequence of asymmetric residual value of assets. Another source of variation, not explicitly modeled, is heterogeneous input risks associated with tangible and intangible assets. If default risk is positively associated with employing intangible assets then incorporating input risks would reinforce Lemma 1.

[16] Because the lender is the residual claimant in the default state, risk does not distort production decisions. The results would be reinforced if the firm were also a residual claimant and tangible assets were less costly to liquidate than intangible assets.

other words, credit constraints distort the optimal asset ratio, leading to over-investment in tangible assets.

Proof: Follows from 11. □

Expression (11) demonstrates that asset tangibility is determined by (i) the production technology, (ii) relative factor prices, and (iii) credit constraints. The focus of this paper is the influence of credit frictions, thus, it is useful to isolate its influence on asset tangibility. That is, constraints

$$\kappa \equiv \frac{x}{y} = \bar{\kappa}\mu^{\sigma(1-\eta)} \tag{12}$$

The value $\bar{\kappa}$ is therefore the prevailing asset ratio absent credit constraints, representing the influence of the production technology and relative factor prices.[17] The residual term represents the distortion generated by credit constraints, which increase endogenous asset tangibility.

2.4 Emissions Intensity

Define emissions intensity as $e = z/q$. Shepherd's Lemma implies that emissions intensity is

$$e \equiv e(\tau, c_x, c_y) = \frac{\alpha c_x}{\phi\tau}\left(\frac{\phi(1-\gamma)c_q}{c_x}\right)^{\sigma} \tag{13}$$

Emissions intensity is therefore determined by the price of pollution permits and the per-unit cost of tangible and intangible assets.

The following Lemma elucidates the intermediate relationship between asset tangibility and emissions intensity.

Lemma 2: *Pollution emissions intensity is determined by asset tangibility, as well as exogenous factor prices and the production technology. Specifically, emissions intensity and*

[17]That is, $\bar{\kappa} \equiv \left[\frac{1-\gamma}{\gamma}\left(\frac{w^{\eta-\beta}r^{\alpha+\beta-\eta}}{\tau^{\alpha}}\right)\right]^{\sigma}$.

asset tangibility are positively related. That is,

$$e \equiv e(\kappa, \tau, w, r) \quad \text{where} \quad \frac{\partial e/e}{\partial \kappa/\kappa} = \frac{\gamma \kappa^{\frac{1-\sigma}{\sigma}}}{\left[(1-\gamma) + \gamma \kappa^{\frac{1-\sigma}{\sigma}}\right]} > 0 \tag{14}$$

Proof: Using expressions (9) to (13) imply that

$$e = (\alpha/\phi)\tau^{\alpha-1} w^{\beta} r^{1-\alpha-\beta} \left[\left((1-\gamma) + \gamma \kappa^{\frac{1-\sigma}{\sigma}}\right)\right]^{\frac{\sigma}{1-\sigma}} \tag{15}$$

□

Expression (15) can be expressed in terms of the frictionless asset tangibility ($\bar{\kappa}$) and the distortion generated by credit constraints using the decomposition in (12). The next result explicates the comparative statics between credit constraints and emissions intensity.

Result 2: *Credit constraints increase emissions intensity. Moreover, pollution emissions intensity can be expressed as the following reduced-form equation*

$$e \equiv e(\mu, \tau, w, r) \quad \text{where} \quad \frac{\partial e/e}{\partial \mu/\mu} = \left(\frac{\sigma(1-\eta)}{\phi}\right)\left(\frac{\gamma \phi c_q}{c_y}\right)^{\sigma-1} > 0 \tag{16}$$

Proof: Follows from (9), (10), and (13) □

Lemma 2 and Result 2, which explicate the intermediate and reduced-form relationships, are the primary empirical predictions of the model.

2.5 Pollution Emissions

The primary result of the conceptual analysis, as demonstrated in the previous section, is that credit constraints increase emissions intensity. Pollution emissions are, of course, the product of emissions intensity and output $z = eq$ (the so-called technique and scale effects). And output is decreasing in credit constraints whenever the firm's supply curve is upward sloping or the final good's demand curve is downward sloping. The assumptions of constant returns to scale and exogenous prices preclude the determination of the scale effect because output cannot be determined when the supply curve is perfectly elastic, unless the demand curve is sloping downward. The effect of credit constraints on pollution emissions, thus, depends on parameters that cannot be known with much degree of certainty and is therefore an empirical question, which will be take up in the subsequent section.

While the impact of credit constraints on pollution emissions is an empirical question, one simple approach to derive sharp predictions for the net effect is to assume that firms face downward sloping demand curves for "differentiated" goods. The rest of the conceptual analysis explores this case in the interest of illustration, not to generate testable predictions. The results would also follow from imposing diminishing returns to scale; however, this would add a great deal of algebraic clutter to the prior results and preclude deriving closed-form solutions. The assumption that demand is downward sloping does not affect any of the previous results and is analytically expedient.

For simplicity, I assume that the firm operates in monopolist competition, implying that it faces a downward-sloping demand curve. Recall, profit maximization in the canonical monopolistic competition model implies a constant markup over marginal cost and equilibrium output (Dixit and Stiglitz, 1977)

$$p = \frac{c_q}{\varrho} \quad \text{and} \quad q = \left(\frac{c_q}{\varrho}\right)^{-\epsilon} \frac{Y}{P^{1-\epsilon}} \tag{17}$$

where p is the price of a good, $\epsilon = 1/(1-\varrho) > 1$ is the elasticity of substitution, Y is total expenditures, and P is the ideal price index.[18]

The effect of credit constraints consists of two analytically distinct effects: a price substitution effect between factor costs of tangible and intangible assets (the technique

[18]Recall the ideal price index for differentiated varieties $v \in V$ is

$$P = \left[\int_{v \in V} p(v)^{1-\epsilon} dv\right]^{\frac{1}{1-\epsilon}}$$

effect) and an output change induced by a change in the marginal cost of the final good (the scale effect). The latter effect implies that credit constraints increase the marginal cost of the final good, leading to upward shift in the supply curve, which in turn decreases output and the demand for pollution emissions.

Result 3: *Credit constraints increase pollution emissions if and only if the production elasticity of substitution is greater than the consumption elasticity of substitution ($\sigma > \epsilon$).*

Proof: Using that $(\partial q/\partial c_q)(c_q/q) = -\epsilon$ from (17) implies that

$$\frac{\partial z/z}{\partial \mu/\mu} = \left(\frac{\sigma - \epsilon}{\sigma}\right) \frac{\partial e/e}{\partial \mu/\mu} \tag{18}$$

□

The intuition for Result 3 is straightforward. First, greater substitutability between tangible and intangible assets in production implies that an increase in the cost of intangible assets induces a significant substitution effect but does not significantly reduce the supply curve of the final good. Second, less substitutability in consumption implies that the demand curve is steeper, implying that a decline in supply leads to a significant price effect, but only a weak scale effect. Thus, greater substitutability in production and less substitutability in consumption implies that scale effect is dominated by the technique effect. And the opposite whenever production exhibits less substitutability than consumption.

2.6 Empirical Model Specification

This section generates the reduced-form model to be estimated. In the Appendix (Section A1.1), I demonstrate that pollution emissions can be expressed by the reduced-form relationship

$$\hat{z} = \hat{q} + \Delta_\mu \hat{\mu} + \Delta_\tau \hat{\tau} + \Delta_w \hat{w} + \Delta_r \hat{r} + \Psi \tag{19}$$

where circumflex denotes relative change and Ψ is the net effect of various production-technology parameters.[19] The Δ parameters represent the elasticity of pollution emissions with respect to various variables. The exact parameters are reported in the Appendix.

The empirical analysis uses plant-level measures of pollution emissions as the dependent variable (z). The primary variable of interest is the elasticity of emissions with respect to credit constraints Δ_{μ}, which is positive from Result 2. Because credit constraints (μ) are monotonically increasing in the subjective probability of default (λ), an ideal measure of credit constraints is not the actual risk of default, which is unobservable, but the value that lenders assign to default. Because lenders rely on measures of creditworthiness to determine credit risk, I use plant-level measures of creditworthiness as a measure for credit constraints. Since creditworthiness is inversely related to credit constraints, the expect sign of the coefficient is negative.

I use plant-level sales (deflated by industry) for output (q) and state by year and industry by year fixed effects to control for pollution policy and market factor prices (τ, w, and r).[20] Employing state by year and industry by year effects also controls for all time-varying unobservable factors at the industry and state levels that influence emissions. This includes, for example, technical change and demand shocks that influence specific industries and states over time. Finally, production intensity and share parameters ($\gamma, \sigma, \alpha, \beta, \eta$) are accounted for using plant Fixed Effects and industry by year effects, while factor productivity (ϕ) is accounted for using a plant-level measure of productivity. In sum, I control for Ψ using plant productivity, industry by year effects, and plant Fixed Effects. Employing plant Fixed Effects also controls for all time-invariant unobservable factors. The remaining empirical issues are discussed in the subsequent section.

[19] Relative change in pollution emissions, for example, describes $\hat{z} = dz/z$. Recall q is output, μ is credit constraints (increasing transformation of default risk), and τ, w, and r, are the market prices of emissions, labor, and capital, respectively. The production technology parameters are $\Psi \equiv \Psi(\phi, \gamma, \sigma, \alpha, \beta, \eta)$.

[20] The ad-valorem emissions tax is broadly-defined to include all potential costs of emissions, such as liability threats and pressure from consumers and investors, which are the subject of studies investigating "self-regulation" (Anton et al., 2004).

3 Empirical Analysis

3.1 Data Description

The empirical analysis explores the impact of credit constraints on plant-level pollution emissions for manufacturing plants (Standard Industrial Classifications 20-39) in the United States over two decades (1990–2009). The unit of observation is a plant (also known as establishment or facility), which is a single physical location that produces or distributes goods and services. Firms are dissimilar from plants because firms often own or control several plants, which might be geographically dispersed. Additionally, the relationships between asset tangibility and pollution emissions, and credit constraints and asset tangibility, are investigated using firm-level data.

I rely on four data sources, which provide a unique dataset. First, I use the Environmental Protection Agency's (EPA) Risk-Screening Environmental Indicators (RSEI) as a measure of plant-level pollution emissions. Second, I match the RSEI emissions data with the Dunn and Bradstreet's (D&B) National Establishment Time Series (NETS) data. The NETS is a longitudinal plant database containing information on plant sales, employment, location, and a number of other characteristics. In particular, the NETS also contains plant-level measures of creditworthiness, compiled by D&B's DUNS Marketing Information archive. Third, I rely on the Compustat annual industrial database, which contains detailed firm-level data for publicly-held companies. Since a subset of plants in the RSEI dataset are owned by Compustat firms, it is possible to match detailed financial data with plant-level emissions. Finally, I deflate plant sales using the National Bureau of Economic Research NBER-CES Manufacturing Industry Database by Bartelsman and Gray (1996). See Table 5 for a terse list of all variables, sources, and descriptions.

3.1.1 Pollution Emissions

This paper uses plant-level pollution emissions generated by the EPA's RSEI. The RSEI uses chemical release data from the EPA's Toxic Release Inventory (TRI) to assess the aggregate damages caused by a plant's pollution emissions. The TRI is an annual collection of approximately 650 toxic chemicals, including the quantity and disposal media (air, water, landfill, etc.) of each chemical released. Most empirical studies are based on pounds of all chemical releases, or pounds of various subgroups of chemical releases. Using pounds of releases is problematic because chemicals are very heterogeneous, even within various subgroups.

The RSEI accounts for the chemical toxicity, the fate and transport of the chemical, the pathway of human exposure, and the population exposed using epidemiological and demographic information. It generates three primary measures of pollution emissions: Pounds, Hazard, and Risk. Pounds of emissions is, simply, the unweighted sum of all chemical releases. Hazard emissions weights each chemical released by its toxicity level, as measured by epidemiological studies. Risk emissions incorporates toxicity and the disposal media of each chemical, coupled with population characteristics of the surrounding area exposed (from the U.S. Census Bureau). Each chemical is therefore weighted by the fate and transport in the environment, the pathway of human exposure, and the population and sensitivity of exposed populations.

From a normative point of view, Risk emissions is arguably the most important measure of pollution emissions. One problematic feature of using Risk emissions, from a descriptive point of view, is that it is influenced by extraneous factors (e.g., population characteristics). This paper employs all three measures of pollution emissions, focusing primarily on Hazard emissions.

Plants are required to report all of the approximately 650 toxic chemical releases and release media under the Emergence Planning Community Right-to-Know Act (EPCRA) of 1986. The EPCRA applies to all manufacturing plants that employ at least ten employees and release at least one of the covered toxic chemicals in excess of the designated threshold. Releases are self-reported and, under the EPCRA, the EPA can assess a maximum civil penalty of $25,000 per violation for not reporting or misreporting releases, but plants are not penalized for the amount of releases reported.[21] Plants, therefore, have an incentive to accurately report their emissions.

The TRI has become the primary source by which researchers, regulators, and environmentalists, assess plant-level environmental performance; however, a number of shortcomings have been pointed out. It is beyond the scope of this paper to address these issues adequately and I refer to Marchi and Hamilton (2006) for a paper devoted to exploring the accuracy of the TRI. The primary concern is that, because the data are self-reported, emissions might not be reported accurately. Misreporting might be the consequence of devoting insignificant effort to measurement or due to deliberate misreporting.[22] As mentioned, plants are not penalized for the amount of releases reported; however, there might be an incentive to misreport if public approbation or other perceived costs outweigh the expected penalty associated with misreporting. While some misreporting is quite likely, Marchi and Hamilton (2006) only find evidence of misreporting in two, of the twelve investigated, chemicals. Similarly, the EPA investigated reductions in reported emissions and found that at least half, and likely more, of the reductions could be attributed to actual reductions in emissions (EPA, 2012).

Another drawback to using the TRI is the absence of several important pollutants, including sulfur dioxide (SO_2) and mono-nitrogen dioxides (NO_x), which are "criteria pollutants" regulated by the EPA under the National Ambient Air Quality Standards. The TRI dataset does include a number of chemicals classified as volatile organic compounds

[21] For the period 1990-1999, the EPA pursued 2,309 administrative actions against plants under the EPCRA and assessed $15,000 in criminal penalties, $12,957 in civil judicial penalties, and $3,525,780 in administrative penalties (EPA, 2001). In fiscal year 2001, the EPA conducted 321 environmental compliance inspections for TRI reporting and pursued 2,309 administrative actions against plants under the EPCRA (Marchi and Hamilton, 2006).

[22] The EPCRA does not require uniform monitoring practices and explicitly states that plants need not devote substantial resources to monitoring emissions (Marchi and Hamilton, 2006).

(VOCs), particulate matter (PM), lead (Pb), and many other toxic chemicals. The comprehensive measure of pollution emissions employed in this study therefore, while not exhaustive of all important pollutants, does include a broad set of important pollutants.

3.1.2 Plant Characteristics

The RSEI emissions data is matched to longitudinal plant data from the NETS. The NETS is proprietary data compiled by Walls and Associates from D&B's credit monitoring and marketing information archives. The NETS essentially covers all plants and firms in the United States, beginning in 1990 and extending to 2010. I match the RSEI emissions data, which contains the EPA's facility identification numbers reported in the TRI, using a correspondence I created in collaboration with Walls and Associates.[23]

This paper employs a measure of creditworthiness from the NETS as a measure of financial constraints. The NETS contains annual plant measures of creditworthiness from D&B, called PayDex Scores, which are generated using payment history from all relevant credit and business relationships, such as suppliers and vendors. PayDex Scores range between 0 and 100 (in integer values) in ascending order of creditworthiness. According to D&B, the Score is a measure of both late payment and default risk, where a score above 80 indicates low risk and below 50 indicates high risk.[24] The NETS dataset contains annual minimum and maximum Credit Scores. I use the maximum Credit Score because it is plausible that plants would attempt to access credit at their peak credit score, or at least would not attempt to access credit immediately after a downturn in their Credit Score.[25]

[23]The correspondence matches significantly more plants than previous studies: 414,602 of 453,224 (91 percent) of plant-year observations in the RSEI dataset were matched (missing values further reduce the sample size as I will discuss in the subsequent section). Previous studies have matched the two datasets using the EPA's facility identification numbers and D&B numbers (DUNS); however, the DUNS numbers in the TRI are highly inaccurate. For example, many DUNS are repeated across plants because the number belongs to the plant's parent, which is shared among several plants. Moreover, the EPA often assigns multiple facility identification numbers to the same plant over the 1990-2009 period for numerous reasons. Generating the correspondence entailed examining every non-unique match, using data provided by Walls and Associates on plant births and deaths and plant relocations. Only plants that could be assigned a unique match between the two datasets are included.

[24]For more information on PayDex Scores, see http://paydex.net/.

[25]Certainly, an argument might be made that the minimum Credit Score should be used because creditors

Because it is not unambiguous that the maximum should be used, I replicate the baseline results using both the minimum and the mean.

The PayDex Score is an ideal measure of credit constraints for several reasons. While most empirical analyses employ indirect measures of credit constraints, Paydex Scores are direct measures of credit constraints and, importantly, are determined by an institution external to the firm.[26] Second, credit scores are the yardstick by which creditors access creditworthiness, which implies that it accords particularly well with the conceptual model. Only a few studies employ credit scores as a measure of credit constraints because they are typically not included in most datasets. One exception is Muûls (2008), who uses European Coface credit scores for Belgian firms to explore the impact of access to credit on exporting decisions. Muûls (2008) demonstrates that the Coface credit scores generate the same ordinal measure of credit constraints as conventional measures of credit constraints. For similar reasons as mentioned above, Muûls (2008) argues that using credit scores has many advantages over conventional measures, although there are only modest differences in practice.

The NETS also contains information on plant sales, employment, industry, location, and numerous other variables. The primary variables employed are Sales, deflated by industry deflators from Bartelsman and Gray (1996), and Labor Productivity, calculated as the ratio of sales to employees. Other variables include legal status (Corporation, Proprietorship, Partnership, or Non-Profit), trade status (Exporter, Importer, Both), Age of the plant, Public Ownership, Corporate Ownership, Foreign Owned, Move Often, Change Industry, Minority Owned, Women Owned, and CEO is a Woman. The NETS also contains information on whether the plant has a parent headquarters or is a parent headquarters.

Neumark et al. (2011) investigate the quality of the NETS data and find the accuracy of

might place more weight on the minimum (if available) rather than maximum score. Similarly, creditors might use some combination of the maximum and minimum.

[26]Indirect measures of credit constraints include, firm size, age, dividend policy, bond rating, debt-to-asset ratios, and interest coverage ratios. See Claessens and Tzioumis (2006) for an overview of the various measures of firms' access to finance.

the employment data is of similar quality as the Current Population Survey (CPS) and the Current Employment Statistics (CES) Payroll data. The primary drawback to the NETS is that it does not include information on capital stocks, precluding the possibility of estimating a production function. Also, the NETS is not a census and it is therefore not suitable to investigating plant births and deaths.

3.1.3 Firm Characteristics

The Standard and Poor's Compustat annual industrial database contains detailed firm-level financial data for publicly-held companies, beginning in 1950 and ending in 2010. The data are matched using the ultimate parent headquarters company name in the NETS dataset and addresses are used to corroborate the match.[27]Employing plant and firm-level variables entails several drawbacks. First, publicly-held companies have unique capital structures and tend to be less influenced by credit constraints, resulting in sample selection bias. Second, aggregate firm-level data cannot be attributed to particular plants and emissions data are only available for the subset of plants that report emissions to the EPA, potentially resulting in measurement error.

While the plant-level results are the primary emphasis, the firm-level analysis shed light on several complementary questions. First, I investigate if greater firm-level asset tangibility is associated with greater pollution emissions across all plants. Second, I explore if measures of firm-level credit constraints are associated with asset tangibility. As far as I know, this is the first paper to empirically explore the relationship between credit constraints and asset tangibility, though a complete analysis of the relationship is beyond the scope of this paper.[28]

Asset Tangibility is defined, following Braun (2003) and Manova (2012), as the share

[27]The matched dataset consists of 1,053 firms and 9,517 plants.

[28]A recent working paper (Chen, 2013) theoretically and empirically demonstrates that industries with higher asset intangibility are particularly affected by credit constraints because intangible assets cannot be pledged as collateral. However, Chen (2013) does not consider the possibility that firms might adjust asset composition in order to mitigate credit constraints.

of net property, plant, and equipment in total book-value assets. I use standard measures of credit constraints, including the Current Ratio (Current Assets to Current Liabilities) and the Cash to Total Assets Ratio. The ratio of Total Liabilities to Total Assets is employed as a proxy for long-run solvency. Additional controls include the Market to Book Ratio, the Sales to Assets Ratio, and Return on Assets (Earnings Before Interest and Taxes to Total Assets).

3.2 Summary Statistics

The data consists of an unbalanced panel of manufacturing plants in 2-digit Standard Industrial Classification (SIC) 20 to 39, starting in 1990 and ending in 2009.[29] The RSEI dataset does not distinguish between missing and zero-valued emissions; hence, I exclude all plants with non-positive value of emissions. I also exclude plants with missing values recorded for Sales, Labor Productivity, and Credit Score.[30] The final sample consists of 29,817 plants and 248,153 plant-year observations. The median number of years in the sample is 7 years.

The three measures of pollution emissions are Pounds, Hazard, and Risk. Pounds is denominated in pounds, but Hazard and Risk emissions are not denominated in meaningful units. All emissions are highly skewed, hence, I apply a log transformation. The transformed data are single-peaked and roughly symmetrical, as demonstrated in Figure 1. Table 1 demonstrates that the three measures are highly correlated: Pounds emissions explain roughly 51 percent of Hazard emissions and 39 percent of Risk emissions. Moreover, Hazard emissions explain roughly 68 percent of Risk emissions. Table 1 demonstrates that the

[29] I extend the RSEI dataset from 1996 to 1990 by manually removing the raw data in the RSEI software and replacing it with previous files provided by the EPA upon request.

[30] Excluding plants with zero emissions or missing values potentially engenders selection bias because selection is non-random. Truncation of plants with emissions below the threshold is also a potential source of bias, particularly if omitted plants also have systematically lower credit scores. Unfortunately, there are numerous reasons plants are not included in the sample, precluding conventional approaches to mitigating the problem. As far as I know, no studies using the RSEI dataset have discussed the implications of selection bias or attempted to grapple with potential bias. Figure 1 does not, however, display compelling evidence of truncation.

levels of emissions are highly correlated with the intensities (Emissions divided by Sales) of emissions (the levels explain 87, 96, and 94 percent of the intensities for Pounds, Hazard and Risk, respectively).

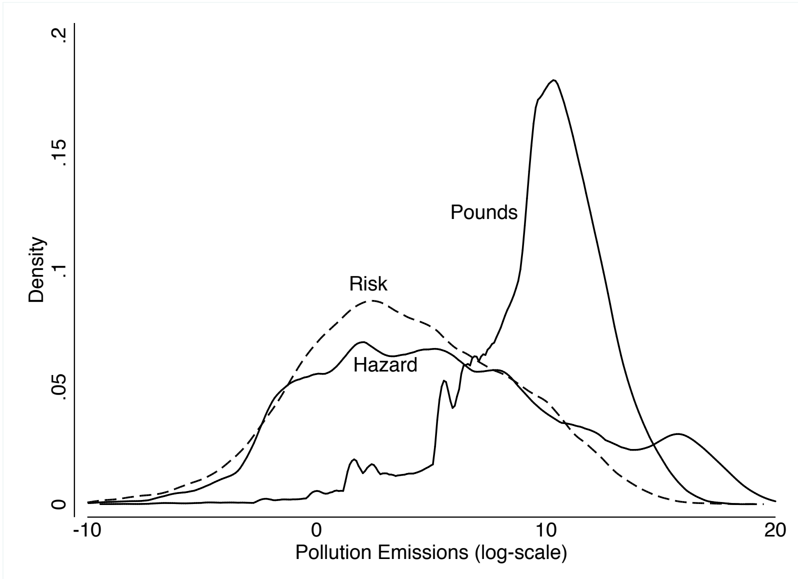

Figure 1: Distribution of Pounds, Hazard, and Risk emissions

Table 1: Pollution Emissions Cross-Correlations

Variables	Pounds	Hazard	Risk	Pounds*	Hazard*	Risk*
Pounds	1.0000					
Hazard	0.5127	1.0000				
Risk	0.3941	0.6729	1.0000			
Pounds*	0.8748	0.4048	0.3205	1.0000		
Hazard*	0.4551	0.9638	0.6493	0.4813	1.0000	
Risk*	0.2995	0.5898	0.9428	0.3980	0.6584	1.0000

Notes: *Indicates emissions intensity (emissions/sales). All variables in logarithms.

Table 2 reports summary statistics (mean and standard deviation) by 2-digit SIC industry. Emissions is log-transformed Hazard emissions. Primary Metals and Industrial Machinery are the dirtiest industries, whereas Leather and Food are the cleanest industries. Table A2 in the Appendix reports normalized summary statistics by 2-digit SIC for Pounds, Hazard, and Risk, emissions. Both tables demonstrate that there is significant variation in pollution emissions, both between and within industries. For example, Table A2

Table 2: Summary Statistics by 2-digit SIC Industry: Mean and (Std. Deviation)

	Emissions		Credit Score		Sales		Productivity	
Food	1.85	(3.79)	77.53	(4.96)	16.47	(1.57)	11.40	(0.72)
Tobacco	5.11	(3.97)	75.19	(6.96)	19.49	(1.69)	12.27	(0.24)
Textiles	2.81	(4.59)	76.12	(5.78)	16.54	(1.57)	11.21	(0.46)
Apparel	3.58	(4.73)	75.53	(5.26)	16.34	(1.45)	11.23	(0.39)
Lumber	3.47	(4.25)	78.12	(5.17)	16.12	(1.23)	11.11	(0.42)
Furniture	2.98	(4.45)	75.78	(6.59)	16.36	(1.20)	11.06	(0.41)
Paper	4.82	(4.90)	75.59	(5.93)	16.61	(1.36)	11.36	(0.56)
Printing	2.53	(3.40)	76.60	(6.32)	16.31	(1.36)	11.19	(0.48)
Chemicals	4.69	(5.14)	74.15	(6.26)	15.72	(1.36)	11.53	(0.61)
Petroleum and Coal	5.91	(5.52)	75.27	(6.24)	15.65	(1.57)	11.32	(0.84)
Rubber and Plastics	3.22	(4.56)	74.47	(6.68)	15.90	(1.31)	11.25	(0.46)
Leather	0.75	(6.12)	76.53	(5.76)	16.46	(1.15)	10.85	(0.36)
Stone, Clay, and Glass	4.75	(6.16)	75.67	(5.98)	15.94	(1.38)	11.40	(0.51)
Primary Metals	8.57	(5.77)	74.76	(6.45)	16.19	(1.37)	11.46	(0.60)
Fabricated Metal	7.30	(5.91)	74.42	(6.80)	15.60	(1.29)	11.08	(0.65)
Industrial Machinery	8.25	(6.58)	73.44	(6.21)	16.52	(1.50)	11.40	(0.65)
Electronics	5.99	(4.66)	73.06	(6.38)	17.17	(1.70)	11.92	(0.98)
Transportation Equipment	7.32	(6.28)	72.89	(6.95)	17.36	(1.65)	11.72	(0.49)
Instruments	5.31	(5.73)	73.78	(5.65)	17.17	(1.47)	11.76	(0.56)
Misc. Manufacturing	3.78	(5.27)	75.26	(6.73)	16.27	(1.49)	11.51	(0.68)
Total	5.72	(5.78)	74.54	(6.45)	16.23	(1.54)	11.43	(0.69)

Notes: Emissions is log Hazard emissions. Sales is log deflated sales and Productivity is Sales to log employees (Labor Productivity).

shows that 6 out of 20 industries have greater within-industry standard deviations than the standard deviations across industries (normalized to unity).

The mean Credit Score is 74.5 and the associated standard deviation is 6.45 (Table 2). Recall, D&B classify plants with Credit Scores above 80 as being low risk of default, thus, most plants have Credit Scores indicating at least some risk of default. Table 2 also reports summary statistics for Sales and Productivity, where Productivity is defined as Sales divided by the number of employees.

The within-plant standard deviation in Hazard emissions is 2.38, whereas the between-plant standard deviation is 5.41 (not reported). Similarly, the within-plant standard deviation in Credit Score is 4.63, whereas the between-plant standard deviation is 5.51. Thus, there is significant variation of the primary variables of interest, both within and between plants.

3.3 Baseline Regression Analysis

3.3.1 Model Specification

The motivation for the model specification is discussed in Section 2.6. The baseline model is the following

$$\begin{aligned} \text{Emissions}_{psit} = \ & \delta_1 \, \text{Credit Score}_{psi\,t-1} + \delta_2 \ \text{Sales}_{psit} + \\ & \delta_3 \, \text{Labor Productivity}_{psit} + \nu_{st} + \nu_{it} + u_{psit} \end{aligned} \tag{20}$$

where p indexes plants, s indexes states, i indexes industry, and t indexes time. Year by state and year by industry (2-digit SIC) effects are captured by the variables ν_{st} and ν_{it}, respectively.

I express all variables in logarithms, with the exception of Credit Score. Hence, δ_2 and δ_3 are elasticities. Because Credit Score is not an ordinal measure, I use Credit Score as a linear variable, although I explore a number of non-linear specifications as a robustness check. The coefficient δ_1 is therefore the percentage change in Emissions due to a 1-point increase in Credit Score. Because the impact of Credit Score is not immediate, I use Credit Score with a 1-year lag.[31] All other variables are contemporaneous.

I denote all of the explanatory variables as X_{psit}. As usual, the composite error term consists of a plant-specific and a random component, $u_{psit} = \alpha_{psi} + \varepsilon_{psit}$. Recall, employing Pooled Ordinary Least Squares (Pooled OLS) requires $E(\varepsilon_{psit}|X_{psit}) = 0$. However, it it likely that, for example, plants with better unobservable management might produce higher Credit Scores and lower Emissions, even after controlling for Labor Productivity, which would violate this assumption. Employing plant Fixed Effects (henceforth, Fixed Effects), relaxes this assumption, requiring that $E(\varepsilon_{psit}|\alpha_{psi}, X_{psit}) = 0$.[32] Fixed Effects allows the random error component to be correlated with the plant time-invariant component, but

[31] The results are nearly identical using 2 and 3 year moving averages, available upon request.

[32] To be precise, Fixed Effects refers to the mean-difference model combined with the least squares dummy variables model (state by year and industry by year dummy variables).

requires that X_{psit} be uncorrelated with $(u_{psit} - \alpha_{psi})$. This paper employs both Pooled OLS and Fixed Effects. Because it is likely that the error term is correlated over time for a given plant, I use cluster-robust standard errors that cluster on plants.

Figure (2) plots predicted Hazard emissions (vertical scale) over Credit Scores (horizontal scale) using Credit Score as a set of indicator variables (98 dummies ranging between 2 and 99) using Pooled OLS.[33] Predicted Pounds and Risk emissions follow a similar pattern and the graphs can be found in the Appendix (Figures A1 and A2). For Credit Scores less than 70, there appears to be no effect on Hazard emissions; however, starting around 70 and ending around 80, there appears to be a significant effect on Hazard emissions.

That there is a precipitous drop between 75 and 80 is consistent with expectations given that D&B explicitly establish categories for risk (for example, a credit score of 80 and above is classified as "Low risk").[34] Creditors might rely on the categories established by D&B for credit approvals or for setting rates in particular and lending terms in general, though this assertion cannot be verified.

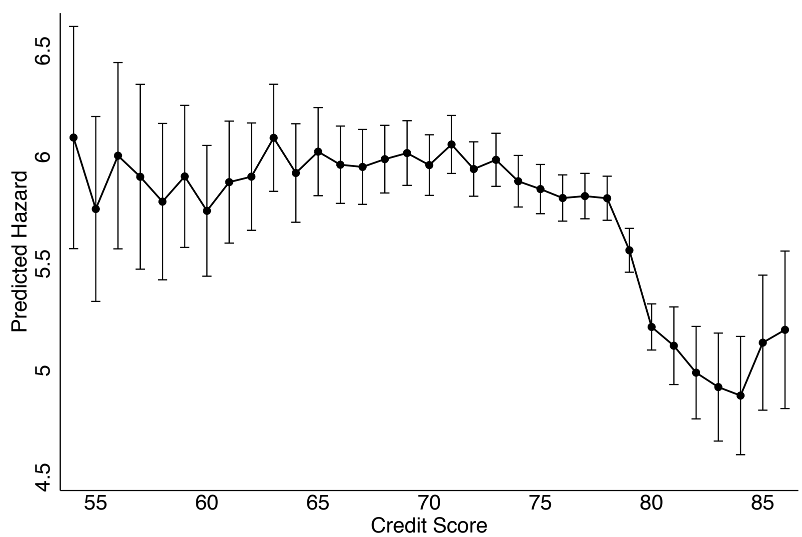

Figure 2: Predicted Hazard Emissions and 95% Confidence Interval

[33]The figure omits the bottom and top 1 percent of Credit Scores because the confidence intervals overwhelm the graph. The predicted values are at the sample values and then averaged (average marginal effect). The figure is similar using Fixed Effects, although the drop is less precipitous, as the regression analysis demonstrate.

[34]Information on categories can be found at http://mycredit.dnb.com/glossaries/paydex/.

3.3.2 Results

Table 3 reports Pooled OLS and Fixed Effects estimations, using Pounds, Hazard, and Risk emissions, as dependent variables. In all specifications, Credit Score has a negative and statistically significant (1 percent significance level) impact on Emissions.[35] Specifically, increasing Credit Score by 1 point reduces Hazard emissions by 3.1% using Pooled OLS and 0.7% using Fixed Effects. The impact of Credit Score is greatest for Hazard emissions and least for Pounds emissions using both Pooled OLS and Fixed Effects. Because unobservable time-invariant plant characteristics are likely to be positively (negatively) correlated with Emissions and negatively (positively) correlated with Credit Score, the magnitude of the impact of Credit Score suggested by Pooled OLS is likely to be biased upwards. Thus, Fixed Effects estimates are likely more precise.

The impact of Sales on Emissions is positive and significant at the 1 percent significance level. The elasticity of Emissions with respect to Sales ranges between 0.62 and 0.99 using Pooled OLS, and between 0.09 and 0.14 using Fixed Effects. Therefore, it is possible to rule out homogeneity of degree one ($\delta_2 = 1$) for Fixed Effects, but not for Pooled OLS. This result is consistent with the handful of studies demonstrating that larger producers tend to generate less emissions per unit of output than smaller producers (Harrison and Antweiler, 2003). Both the Pooled OLS and Fixed Effects estimates suggest that an increase in Labor Productivity significantly reduces Emissions (1 percent significance level, except in one specification).[36]

[35]The sensitivity of the results to using the maximum Credit Score, rather than the minimum or the mean, is addressed in section A1.2 in the Appendix.

[36]Because not all factors of production are included in Labor Productivity, it is impossible to distinguish between the effect of changes in the production-possibility frontier (technical change) and movements along the same frontier (factor substitution).

Table 3: Pollution Emissions using Pooled OLS and Fixed Effects

	Pooled OLS			Fixed Effects		
	Pounds	Hazard	Risk	Pounds	Hazard	Risk
Credit Score	–0.0102†	–0.0327†	–0.0216†	–0.0033†	–0.0070†	–0.0038†
	(0.0017)	(0.0035)	(0.0030)	(0.0009)	(0.0014)	(0.0014)
Sales	0.6334†	0.9902†	0.6885†	0.0973†	0.1384†	0.1037†
	(0.0131)	(0.0250)	(0.0211)	(0.0110)	(0.0185)	(0.0166)
Labor Productivity	–0.4492†	–0.6127†	–0.4004†	–0.1199†	–0.2018†	–0.0530
	(0.0286)	(0.0541)	(0.0458)	(0.0294)	(0.0418)	(0.0416)
Adj. R-sq	0.146	0.202	0.098	0.034	0.026	0.029
R-sq (within)				0.039	0.031	0.035
R-sq (between)				0.000	0.001	0.003
R-sq (overall)				0.000	0.001	0.004
Plants	29,817	29,636	27,092	29,817	29,636	27,092
Observations	248,153	246,324	219,095	248,153	246,324	219,095
State×Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. Credit Score is lagged one year. All variables are in log-scale, except Credit Score, which is an ordinal measure.

3.4 Further Empirical Analyses

One of the primary concerns of identification is the confounding effects of omitted variables. For example, adept managers might be associated with less pollution emissions and higher credit scores, resulting in omitted variable bias. In this case, the model would compensate for the missing factor (managerial skill) by over-estimating the impact of Credit Score. Employing Fixed Effects accounts for time-invariant managerial skill; however, it is possible that changes in managerial skill might be associated with changes in credit scores.

Other concerns include reverse causality and measurement error. Reverse causality entails that changes in Credit Score are associated with future changes in Emissions, while measurement error entails that changes in Credit Score are associated with changes in systematic misreporting. For example, reverse causality would arise if anticipation of future pollution regulations influenced current decisions that bear on the plant's Credit Score.[37]

[37]The industry by year and state by year effects account for anticipated and realized regulations. Reverse causality would require that the regulation entails heterogeneous anticipation effects within industries and that the heterogeneous effects are correlated with changes in creditworthiness.

The remainder of this section focuses on addressing the problem of omitted variable bias, as well as reverse causality and measurement error, by exploring heterogeneous effects and employing additional control variables. Alternative approaches using Lagged Dependent Variables and Instrumental Variables are presented in the subsequent section.

3.4.1 Heterogeneous Effects

This section generates several predictions concerning heterogeneous effects of Credit Score on Emissions. For example, I predict that the impact of Credit Score will be greater for plants in industries with greater dependency on external financing. The thought experiment to consider is whether potential omitted variables might also result in the predicted heterogeneous effects. Exploring heterogeneous effects does not, of course, rule out the possibility of bias associated with omitted variables. However, detecting systematic heterogeneous effects that are consistent with *a priori* predications adds confidence that the results are not merely the consequence of omitted variables.

There are many potential sources of heterogeneity and I discuss the most relevant sources in, more or less, ascending order of relevance. Several sources of heterogeneity are not presented because meaningful (convincing) hypothesis cannot be generated. While it cannot be ruled out that the heterogeneous effects are also generated by omitted variables, there is no *a priori* reason to expect an association between the various sources of heterogeneity and the degree of bias. In each case discussed below, the predicted associations with the impact of Credit Score of Emissions are negative, which implies that the expected sign of the interaction with Credit Score is positive (as indicated in the parentheses).

1. **Industry Current Ratio (+):** Plants in industries with a lower Current Ratio are more liquidity constrained and dependent on external financing.[38]

[38] Industry Current Ratio is at the 4-digit SIC-level, calculated as the mean ratio of Current Assets to Current Liabilities for Compustat Firms. Rajan and Zingales (1998) and Manova (2012) contend that industry-level variation in liquidity constraints reflects exogenous technological features.

2. **Corporate Ownership>50% (+):** Belonging to a corporation confers a number of benefits that obviate credit constraints. First, corporations tend to have greater liquidity, at least in absolute terms, due to being larger than non-corporations. Greater liquidity reduces dependency on external financing and affords greater flexibility to allocate funds across plants.[39] Moreover, the assets of the corporation can be used as collateral, which reduces the risk to creditors. Finally, corporations have transferrable ownership, which reduces the cost of defaulting.

3. **Headquarters Size (+):** Headquarters Size is a categorical variable indicating the size of the plant's parent headquarters, in terms of the number of plants reporting that headquarters as a parent. The categories include (i) plant has no parent headquarters, (ii) plant has a "small" parent headquarters (1-3 plants), (iii) plant has a "large" parent headquarters (4 or more plants). For similar reasons as corporate ownership, having a large headquarters confers greater liquidity and collateral to be pledged to creditors.

4. **Sales (+):** Plants that are larger have more assets to pledge as collateral and greater liquidity.

5. **Public Facility (+):** All else constant, lenders might believe that public facilities are less likely to default. Moreover, public facilities might have access to credit that is not available to private plants.

Table A3 demonstrates that all of the hypotheses are supported. Apart from inclusion of interactive terms, the specification is identical to Table 3, column 2.[40] The interactive terms are either indicator variables (dummy or categorical variable used as a set of dummies) or terciles based on continuous variables (denoted $\mathcal{T}$). The omitted category for the terciles is the first tercile (the bottom one-third of the distribution). The variables employed

[39]For example, plants belonging to large corporations are less vulnerable to solvency shocks because the corporation can absorb shocks to individual plants by reallocating funds across plants.

[40]To save space, I do not include the Fixed Effects estimates. The results are similar; however, several of the interactive terms are not significant, while all of the Credit Score estimates are significant at the 1 percent significance level.

interactively are also used as controls in all specifications, but only the interacted estimates are reported (the subsequent section reports all of the direct effects). To summarize, the impact of Credit Score on Emissions is heterogeneous and depends on the Current Ratio, Corporate Ownership, Headquarters Size, Sales, and Public Facility. All of the interactive terms have the predicted signs and are statistically significant at the 1 percent significance level.

3.4.2 Restricted Samples

In this section, I restrict the sample to strictly nested subsets of plants. For large corporations, it is plausible that lenders rely less on the D&B credit score and more on credit scores that are assigned to publicly-traded firms (e.g., S&P, Moody's). Moreover, a richer set of financial and historical data are available for large corporations, which might be given greater weight for assessing risk. Therefore, I restrict the sample to only privately-owned plants, excluding all publicly-held corporations. Second, among the privately-owned plants, I restrict the sample to plants that do not belong to a larger parent company. The reason is two-fold: (1) to eliminate plants belonging to large private conglomerates (e.g., Koch Industries) and (2) to reduce the potential for bias in the standard errors associated with firm-level shocks. Finally, among the stand-alone plants, I restrict the sample to plants with annual deflated sales less that $5 million dollars. Narrowing the sample to plants that do not belong to larger conglomerates and that are relatively small increases excludes plants that are not dependent on the D&B credit score. Therefore, we expect that each restriction should increase the effect of creditworthiness on pollution emissions. Additionally, we might expect that a decrease in the standard errors, though the restriction does reduce the sample size, thereby reducing degrees of freedom.

The results for the restricted samples are reported in Table A4 in the Appendix. The sample restrictions are strictly nested, starting with excluding publicly-held firms, congolmerates (plants with independent parent company), and average deflated sales exceeding $ 10 million. As expected, the impact of Credit Score on Hazard Emissions is greater in restricted subsamples. Restricting the sample to privately-held, non-conglomerates, and average annual sales less than $10 million increases the impact of Credit Score on Hazard emissions from -0.007 to -0.012. Moreover, restricting the sample increases the goodness-of-fit as indicated by the adjusted R-squared.

3.4.3 Added Controls

A common approach to demonstrating the exogeneity of explanatory variables, in the absence of experimental or quasi-experimental data, is by assessing whether the point estimates are sensitive to the inclusion of additional control variables. This approach has been employed, informally, for several decades and has been recently formalized by Altonji et al. (2005). The aim of the approach is to select a full range of observables that have significant explanatory power to account for the full range of observable and unobservable factors. Of course, employing observables to make inferences about omitted variable bias, as the authors point out, should be used with caution.

One shortcoming of the NETS is that many of the variables are time-invariant, precluding the use of plant Fixed Effects.[41] Therefore, I use Pooled OLS and Random Effects, which allows for the estimation of time-invariant variables.

The following sets of added controls are employed: (1) ownership characteristics, (2) internationalization, (3) firm dynamics, and (4) various plant features (see Table 5 for a description of variables). Ownership characteristics include dummy variables for Corporate Ownership>50% and Public Facility, and categorical variables indicating Legal Status (Corporation, Partnership, or Non-Profit), the size of the Plant's Headquarters (Small or Large Headquarters), and if the Plant is Headquarters (Small or Large Headquarters). The omitted categories are plants without distinct Headquarters and plants that are not

[41] In some cases, the variables are time-invariant because they do not in fact change over time (e.g., Legal Status), whereas, in other cases, the variables might change over time, but the data are only collected at one point in time (e.g., CEO gender).

the Headquarters to other plants, respectively. Internationalization includes Trade status (Importer, Exporter, Both) and a dummy variable for Foreign Owned. Firm dynamics include plant Age (quadratic polynomial), lagged Sales Growth and Productivity Growth, and dummy variables indicating Move Often and Industry Change. Finally, plant features include dummy variables indicating if the plant is Minority Owned, Women Owned, is Cottage designated, and a categorical variable for Executive gender ("both" is omitted category).

The results for the Added Controls regressions using Hazard emissions as a dependent variable are reported in Tables A5 and A6 in the Appendix. In all specifications, Credit Score is negative and significant at the 1 percent significance level. The point estimate in the baseline Pooled OLS model suggests that a one-point increase in Credit Score reduces Hazard emissions by 3.1%, while the added controls suggest that the reduction ranges between 4.4% and 5.6%. The point estimate in the baseline Fixed Effects model implied that one-point increase in Credit Score reduces Hazard emissions by 0.70%, while the added controls using Random Effects imply that the reduction ranges between 0.67% and 0.79%. The Random Effects estimates are therefore remarkably similar to the Fixed Effects estimates after controlling for observables, and the point estimates are not influenced by the inclusion of added controls. This suggests that the explanatory variables are uncorrelated with the error term after accounting for observables.

3.5 Alternative Identifying Assumptions

This section employs alternative identifying assumptions as an additional robustness check. The objective is to demonstrate that the results are broadly similar using plausible alternative models. Specifically, I employ lagged dependent variables and Instrumental Variables. The key is not necessarily that the alternative identifying assumptions are more realistic, but that the alternatives are different and therefore have different shortcomings. If the results are similar across a variety of identifying assumptions then it reduces the likelihood that the results are affected by one particular shortcoming.

3.5.1 Lagged Dependent Variable

A common alternative to the Fixed Effects model is employing Lagged Dependent Variables (LDV). The former is suitable whenever the most important omitted variables are time-invariant, whereas the latter is suitable whenever the most important omitted variables are time-variant. The identifying assumption using Lagged Dependent Variables is that $E(\varepsilon_{psit} \mid Y_{psi\,t-1}, X_{psit}) = 0$, where $Y_{psi\,t-1}$ represents lagged Emissions. Employing LDV accounts for all lagged time-varying omitted variables, such as capital stocks and accumulated manager and worker skills.

In the presence of time-invariant and time-variant omitted variables, a more general model can be employed that includes both lagged dependent variables and unobservable fixed effects. Estimation entails differencing to eliminate the fixed effect, which implies that the differenced residual is correlated with the lagged dependent variable. The conventional approach to solving the problem is to use the two-year-lagged dependent variable as an instrument for the lagged-difference dependent variable.[42]

Table A7 reports variations of the LDV and First Difference models for Hazard emissions. All estimations use a similar set of covariates as the estimations in Table 3 and use cluster-robust standard errors that are clustered on plants. The first column performs Pooled OLS using a lagged dependent variable, without plant fixed effects. The second column employs a First Difference model without a lagged (difference) dependent variable (for comparison), while the third column employs a First Difference model with a lagged dependent variable.[43] Finally, the fourth column is similar to the third column, except for using a two-year-lagged dependent variable as an instrument for the lagged-difference

[42] This remedy is, of course, not without additional assumptions, which are beyond the scope of this section. For details and examples, see Holtz-Eakin et al. (1988).

[43] Using a First Difference model also provides a robustness check as the identifying assumption is slightly weaker. Recall, the Fixed Effects identifying assumption (strict exogeneity) is that all $\varepsilon_{psit} - \bar{\varepsilon}_{psi}$ are uncorrelated with contemporaneous, past, and future $X_{psit} - \bar{X}_{psi}$ (where over-bar represents the plant mean). The First Difference permits future values of the regressors to be correlated with the error (weak exogeneity).

dependent variable (2SLS).

Guryan (2004) points out that Fixed Effects overstates coefficient estimates if LDV is the correct specification, whereas LDV understates coefficient estimates if Fixed Effects is the correct specification. Thus, FE and LDV therefore bound the causal effect above and below, respectively. Table A7 demonstrates that a one-point increase in Credit Score reduces Emissions by 0.34% (significant at 1 percent significance level), which implies that the effect of Credit Score is bounded between 0.34% and 0.70%. The First Difference model implies that a one-point increase in Credit Score reduces emissions by 0.39% (significant at the 1 percent level). Columns 3 and 4 indicate that the point estimates of Credit Score using both lagged dependent variables and unobservable fixed effects are smaller in magnitude compared to the Fixed Effects and LDV models (point estimate for the First Difference is significant at the 5 percent level, whereas the First Difference using 2SLS is insignificant).

3.5.2 Instrumental Variables

Instrumental Variables (IV) is the most common approach to addressing the bias associated with endogeneity. For example, changes in managerial quality might be correlated with changes in Credit Score, as well as changes in Emissions, resulting in endogeneity. The credibility of the IV approach for overcoming the potential endogeneity of Credit Score hinges on identifying a set of instruments correlated with Credit Score, but not correlated with the corresponding error term. This means that the instrument should be correlated with Credit Score, but should not be correlated with changes in managerial quality, for example. Because instruments are typically difficult to identify, and the case of this study is no exception, I emphasize the use of Instrumental Variables as one of a battery of robustness checks. I propose two instruments, which I discuss in turn.

First, I use the average annual Credit Score of the city in which the plant is located, excluding the Credit Score of the plant. Plants are more likely to borrow from creditors and to establish business relationships within the geographical vicinity of the plant.[44] Exogenous geographical variation is produced from the proclivity of lenders and businesses to strictly report late payments, or to pardon credit infractions, and the plant's "exposure" to these lenders. Since the average Credit Score of the city does not directly influence Emissions and it is independent of plant-level factors that influence Credit Score, the orthogonality assumption depends on whether the instrument is correlated with other factors that influence Emissions. For example, if more-educated cities tend to have higher Credit Scores and stricter local environmental regulations then the exclusion restriction would not hold.[45]

Second, I use the range, within a given year, between the minimum and maximum credit scores. The range will be correlated with the maximum credit score and uncorrelated with the corresponding error term under two conditions. First, it should not influence creditworthiness directly. For example, if creditors use the variability of the plant's credit score to assess creditworthiness then using the range as an instrument would be problematic. Second, it should not be correlated with unobservable factors that impact pollution emissions, such as management quality. If management quality influences the range of the plant's credit score then the instrument would not satisfy the exclusion restriction.

Table A8 in the Appendix reports the 2SLS estimates using Pooled OLS and Fixed Effects and Hazard emissions as the dependent variable. All estimations use cluster-robust standard errors that are clustered on plants. As instruments, the first and fourth columns use the range between the maximum and minimum Credit Score, the second and fifth columns use the average Credit Score in which the plant is located, and the third and sixth columns use both instruments. The first-stage F-tests indicate that the instruments are strong predictors of Credit Score. In the case where an over-identification test can be performed, the Hansen J stat (p-value) does not reject over-identification, indicating that the instruments

[44]Reports from business relationships are also reported to the D&B since businesses often extend credit to other businesses by allowing weeks, or even months, to lapse between the delivery of goods and services and ultimate payment.

[45]Moreover, plants in high-income and more-educated cities might have a greater incentive to underreport emissions since more of the surrounding population is aware of the reported emissions.

are not correlated with the error term, as desired. Finally, the Wu-Hausman F-test is not rejected in most cases (four of six), suggesting that Credit Score is not in fact endogenous. All of the results have the expected sign and employing 2SLS increases the magnitude of the point estimates by a factor of two. As is often the case, employing Instrumental Variables, with cluster-robust standard errors, significantly increases the size of the standard errors. Nevertheless, the Credit Score estimates are significant at the 1 percent significance level in two of six specifications, and significant at least at the 10 percent significance level in an additional two specifications.

3.6 Addressing the Joint Determination of Output

This section addresses two distinct, though related, issues. First, Sales and Emissions are jointly determined, which is a potential source of bias. Second, because Credit Score might impact Sales, determining the relationship between Credit Score and Sales is necessary to determine the net effect of Credit Score on Emissions. As the conceptual model demonstrates, the scale and technique effects influence pollution emissions in opposing directions. Thus, this section is interested in "adding-up" the two effects in order to determine which one dominates.[46]

One approach to adding-up the scale and technique effects is to simply regress Credit Score on Sales. Towards this end, I use a similar approach as before, using Sales as a dependent variable and lagged Credit Score as an independent variable. Table A9 in the Appendix, column 1, estimates the determinants of Sales, using Fixed Effects and an identical set of year by industry and year by state controls as the previous estimations. The results suggest that a 1 point increase in Credit Score increases Sales by 0.13% (significant

[46]To be clear, "adding-up" refers to adding the two partial derivatives comprising the total derivative of Emissions with respect to Credit Score. That is,

$$\frac{dz/z}{d\lambda/\lambda} = \frac{\partial z/z}{\partial q/q}\frac{\partial q/q}{\partial \lambda/\lambda} + \frac{\partial z/z}{\partial \lambda/\lambda}$$

where z and λ denote pollution emissions and financial constraints. I use the terms scale and technique effects to represent the first and second terms on the right hand side, respectively.

at the 1 percent significance level). Column 2 in Table A9 instruments for Credit Score using the two instruments discussed in the previous section. The Credit Score estimate remains positive and significant at the 1 percent significance level.[47]

I employ a number of approaches to econometrically address the joint determination of output. First, I rely on plant Fixed Effects to control for baseline plant size, and exclude Sales in the regressions. This approach is common in studies investigating the short-run impacts of exogenous policy changes using a difference-in-differences approach, but it might result in substantial omitted variable bias for longer panels. Second, I instrument for Sales and Labor Productivity, using the lagged difference of each as instruments. The primary drawback of this approach, as many studies have pointed out, is that using internal instruments presents a number of concerns, which are beyond the scope of this paper to address.

Table A9, column 3, reports the coefficient estimates, for the specification excluding Sales from the model. As expected, the impact of Credit Score is smaller if Sales is omitted because the estimate reflects the net technique and scale effects. The exclusion of Sales reduces the Credit Score estimate from -0.70% to -0.55% (significant at the 5 percent significance level). Column 4 of Table A9 instruments for Sales and Labor Productivity, but not Credit Score, and the Credit Score estimate (-0.55%) is remarkably similar to the regression excluding Sales and Labor Productivity (column 3 of same table). This suggests that excluding Sales does not result in significant omitted variable bias. Column 5 of Table A9 instruments for Credit Score, Sales, and Labor Productivity, using the instruments for Sales and Labor Productivity from Table A9, column 4, and the instruments for Credit Score from Table A8, column 6. In this specification, the point estimate (-1.53%) is significant at the 10 percent level and similar to the corresponding estimate that does not instrument for Sales (-2.10%, c.f. Table A8, column 6).

[47]The instruments pass both the weak and over-identification tests.

3.7 Adding-Up the Technique and Scale Effects

Using the results in the previous section, it is possible to determine the net effect of Credit Score on Emissions. This section performs a simple back-of-the-envelope calculation using the results in the previous sections to roughly compare the technique and scale effects. Using the Fixed Effects estimates, increasing Credit Score by one point reduces emissions, via the technique effect, by roughly 0.70%. On the other hand, increasing Credit Score by one point increases Sales by roughly 0.13%. Thus, if increasing Sales by one percent increases Emissions by 0.14% (c.f. Table 3, column 5) then increasing Credit Score by one point increases Emissions, via the scale effect, by 0.13*0.14=0.018%. Therefore, it appears that the technique effect vastly overwhelms the scale effect. That is, an increase in Credit Score by one point reduces emissions by approximately 0.68%.

The conclusion that the technique effect dominates the scale effect holds even if we suppose that the estimated scale effect is significantly underestimated. For example, suppose that the elasticity of emissions with respect to output were equal to one, as implied by a constant returns to scale production technology. Under this assumption, an increase in Credit Score by one point would increase emission, via the scale effect, by 0.13%, implying that the net effect is a reduction by 0.58%.[48] Thus, it is highly unlikely that the net effect of financial constraints is to decrease pollution emissions.

3.8 Firm-Level Analysis

Exploring the intermediate relationship between credit constraints and pollution emissions is hindered by the fact that the composition of assets is not reported at the plant level and pollution emissions are only reported at the plant level. The aim of this section is twofold. First, to explore the relationship between firm-level asset tangibility and aggregate firm-level pollution emissions. Second, to explore the relationship between credit constraints

[48] In fact, the elasticity of emissions with respect to output would need to be greater than 5 in order for the scale effect to dominate the technique effect.

and asset tangibility.

Table A11 in the Appendix reports that the typical firm has roughly 14 plants that, in sum, produce 4 product varieties (8 digit SIC) in 2.4 industries (4 digit SIC). Moreover, plants within the same firm exhibit marked variation: the standard deviations of Emissions and Credit Score are 4.1 and 4.6, respectively. For comparison, the standard deviation among all plants in the sample is 6.5 and 5.7, respectively (cf. Table 2).

3.8.1 Asset Tangibility and Emissions

This section explores the intermediate relationship between Asset Tangibility and Emissions. Towards this end, I estimate the following model

$$\sum_{p=1}^{p_f} \text{Emissions}_{pfit} = \delta_4 \text{Asset Tangibility}_{fit} + +\delta_5 \sum_{p=1}^{p_f} \text{Sales}_{pfit} + \\ \delta_6 (1/p_f) \sum_{p=1}^{p_f} \text{Credit Score}_{pfit-1} + \Gamma'_{fit}\Omega + \vartheta_{it} + u_{fit} \qquad (21)$$

where f indexes firms, i indexes industries, t indexes year, and p_f is the number of plants in firm f.

The dependent variable is the sum of Hazard emissions across all plants in a given year. Asset Tangibility is the firm-level ratio of tangible assets (structures, equipment, natural resources) to total book value assets. Sales is the sum and Credit Score is the mean across all plants. Additional firm-level variables include measures of credit constraints, including the Current Ratio and the Cash to Assets Ratio. Additional controls include the Liabilities to Assets Ratio, which is a measure of long-run solvency, and the Market to Book Ratio and the Sales to Assets Ratio, which are measures of potential and actual profitability, respectively.[49] The variable ϑ_{it} accounts for industry by year effects. I use both Pooled OLS and Fixed Effects with cluster-robust standard errors that are clustered on firms.

[49] The results are similar including Return on Assets as an additional control for profitability, though missing values reduce the sample size. The Market to Book Ratio includes intangible assets, which are sometimes excluded because they possess no resale value.

The primary variable of interest is δ_4, the elasticity of Emissions with respect to Asset Tangibility. Because emissions data are not reported for every plant (many plants do not release any toxic chemicals), the interpretation of δ_4 is the impact on reported emissions. Section 3.1 discusses potential selection and measurement error bias associated with the firm-level analysis. In particular, p_f represents only a subset of plants, whereas firm-level variables are aggregate for all plants. The direction of the bias therefore depends on the differences between plants in the sample and out of the sample and the direction of the bias is unclear.[50]

Table 4 reports that Asset Tangibility is positively associated with Hazard emissions using both Pooled OLS and Fixed Effects. In particular, using Fixed Effects, a one-percent increase in Asset Tangibility is associated with an increase in Emissions ranging between 0.36 percent and 0.43 percent. While the impact of Credit Score is similar in magnitude to the results in the previous sections, the effect is no longer significant. One interpretation, which is predicted by the model, is that credit constraints do not influence Emissions beyond their influence through Asset Tangibility. However, as mentioned, Credit Score is measured with an error since not all plants are included and the sample of plants might not be representative. Pooled OLS suggests that credit constraints (Current Ratio and Cash/Assets) increase Emissions, whereas Fixed Effects suggests that credit constraints do not influence Emissions.

[50] A potential source of bias is that the error term consists of the emissions of plants not in the sample. Since reporting emissions to the EPA is a necessary condition for being in the sample, it is likely that plants not in that sample generate less emissions on average. The direction of the bias therefore depends on the correlation between Asset Tangibility and the emissions of plants not in the sample.

Table 4: Firm-Level Determinants of Aggregate Hazard Emissions

	Pooled OLS				Fixed Effects			
Asset Tangibility	1.3863†	1.3849†	1.1983†	1.2526†	0.4583**	0.4550**	0.4330**	0.3545**
	(0.3143)	(0.3139)	(0.3168)	(0.3118)	(0.1792)	(0.1796)	(0.1792)	(0.1756)
Sales	1.0009†	1.0012†	1.0128†	0.9850†	0.4295†	0.4297†	0.4307†	0.4152†
	(0.1211)	(0.1211)	(0.1188)	(0.1220)	(0.0814)	(0.0816)	(0.0819)	(0.0821)
Total Assets	0.8200†	0.8190†	0.8221†	0.8807†	0.2929*	0.2945*	0.2848*	0.4236**
	(0.1348)	(0.1347)	(0.1405)	(0.1562)	(0.1547)	(0.1547)	(0.1551)	(0.1670)
Credit Score		–0.0155	–0.0124	–0.0121		–0.0082	–0.0080	–0.0086
		(0.0301)	(0.0301)	(0.0293)		(0.0126)	(0.0126)	(0.0126)
Current Ratio			0.0661	1.0442†			–0.0503	–0.0347
			(0.3626)	(0.3900)			(0.1713)	(0.1796)
Cash/Assets			–0.4491†	–0.3556†			–0.0241	–0.0401
			(0.1053)	(0.1031)			(0.0437)	(0.0439)
Liabilities/Assets				1.4585†				–0.1342
				(0.4498)				(0.2454)
Market/Book Ratio				–0.2125				0.1813**
				(0.1851)				(0.0806)
Sales/Assets				0.5366				0.4796**
				(0.4395)				(0.2092)
R-sq	0.372	0.372	0.380	0.388	0.063	0.063	0.063	0.067
R-sq (within)					0.106	0.106	0.106	0.110
R-sq (between)					0.195	0.190	0.211	0.221
R-sq (overall)					0.184	0.184	0.200	0.204
Firms	785	785	785	785	785	785	785	785
Observations	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Industry×Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on firms. The dependent variable is the sum of Hazard emissions across all plants. Sales is the sum and Credit Score is the mean across all plants. Asset Tangibility is the firm-level ratio of Tangible Assets (Plant, Equipment, and Natural Resources) to Total Assets. The remainder of the variables are at the firm-level. All of the variables are in log-scale, except Credit Score. The following variables are lagged one year: Current Ratio, Cash/Assets, Liabilities/Assets, Market/Book Ratio, and Sales/Assets.

3.8.2 Decomposing the Technique and Composition Effects

Since firms own plants in multiple industries, the effect of Asset Tangibility on Emissions consists of technique and composition effects. This section tests the null hypothesis that Asset Tangibility influences the composition of output across sectors. Rejection of the null suggests that the effect of Asset Tangibility on Emissions represents plant-level technique effects. Towards this end, I estimate the following model

$$\sum_{p=1}^{p_f}\left(\frac{\text{Emissions}_{it}}{\text{Sales}_{it}}\right)\text{Sales}_{pfit} = \tilde{\delta}_4\text{Asset Tangibility}_{fit} + \tilde{\delta}_5\sum_{p=1}^{p_f}\text{Sales}_{pfit} + \tilde{\delta}_6(1/p_f)\sum_{p=1}^{p_f}\text{Credit Score}_{pfit-1} + \Gamma'_{fit}\tilde{\Omega} + \tilde{\vartheta}_{it} + \tilde{u}_{fit} \quad (22)$$

where f indexes firms, i indexes industries, t indexes year, and p_f is the number of plants in firm f. The left hand side is the sum of plant sales (output) multiplied by the average industry (4-digit SIC) pollution intensity. Changes in the dependent variable therefore reflect changes associated with the composition of production but not the intensity of production within sectors. The dependent variable is log-transformed and the explanatory variables are identical to the set discussed in the previous section (3.8.1).

Table A12 in the Appendix reports that Asset Tangibility does not influence the composition of production after accounting for firm-level controls and using Fixed Effects. Moreover, using Fixed Effects, the standard errors of Asset Tangibility are roughly similar to the corresponding standard errors in the previous section and it can be ruled out that the coefficient estimates are similar to the corresponding estimates in the previous section (at the 10 percent significance level). Thus, the results suggest that the impact of Asset Tangibility on Emissions is achieved as a consequence of technique effects.

3.8.3 Credit Constraints and Asset Tangibility

This section demonstrates that credit constraints distort investment towards greater asset tangibility. Thus, I estimate the following

$$\begin{aligned} \text{Asset Tangibility}_{fit} = \; & \delta_7 \, \text{Current Ratio}_{fi\,t-1} + \delta_8 \, \text{Cash/Assets}_{fi\,t-1} + \\ & \delta_9 \, \text{Liabilities/Assets}_{fi\,t-1} + \Lambda'_{fit} X + \vartheta_{it} + u_{fit} \end{aligned} \tag{23}$$

where f indexes firms, i indexes industries, and t indexes year. X is a vector of additional firm controls, which are included in some estimations, including the Market to Book Ratio, Sales to Assets Ratio, and Return on Assets. The variable ϑ_{it} accounts for industry by year effects. All variables are in logs and all explanatory variables are lagged one year. I use both Pooled OLS and Fixed Effects with cluster-robust standard errors that are clustered on firms.

Because this section focuses on intermediate relationship between credit constraints and asset tangibility, it is not necessary to restrict the sample to firms reporting emissions, which significantly increases the sample size. Only firms in similar SIC industries as the previous estimations are included in the sample. The primary variables of interest are measures of credit constraints, including the Current Ratio and Cash to Assets Ratio.

Table A13 in the Appendix reports the determinants of Asset Tangibility using Pooled OLS and Fixed Effects. Columns 1 and 3 are the baseline specifications and columns 2 and 4 add additional firm controls. In all specifications, the coefficient estimates for Current Ratio and Cash/Assets have the expected signs and are significant at the 1 percent significance level. Specifically, the elasticity of Asset Tangibility with respect to the Current Ratio is -0.041, and the elasticity with respect to Cash/Assets is -0.039 (column 4). The results therefore demonstrate that credit constraints increase asset tangibility.

Using the Fixed Effects results from Table A13 (column 4) and Table 4 (column 8) indicate that the partial impact of a 1 percent increase in the Current Ratio and the Cash to Assets Ratio reduces Emissions via reducing Asset Tangibility by 4*0.35=1.4 percent. This result entails imprecision as, in addition to selection and measurement error bias as discussed earlier, the impact of credit constraints on Asset Tangibility estimated in Table A13 might not be representative of the subsample of firms estimated in Table 4.[51]

3.9 Discussion of Results

The empirical analysis demonstrates that credit constraints increase pollution emissions, even after accounting for the countervailing scale effect. Moreover, the effect appears quantitatively large and statistically significant. While the results are robust with respect to several modeling and identification assumptions, the data are not experimental and therefore do not support strong conclusions about causality. I therefore consider several possible interpretations of the results. The first interpretation, as this paper advances, is that credit constraints casually influence asset tangibility, thereby increasing pollution emissions.

The second interpretation is that credit constraints are correlated with some unobservable factor that influences pollution emissions. While the primary focus of the robustness checks were aimed at mitigating the problem of omitted variable bias, I cannot rule out this interpretation. However, it is unlikely that the results would pass a battery of robustness checks unless credit constraints accounted for at least part of the estimated effects. Moreover, the results are consistent using firm-level analysis and examining the intermediate relationships. Thus, while the results might reflect some degree of omitted variable bias, there is significant evidence that credit constraints have at least some causal role in generating pollution emissions.

The third interpretation is that credit constraints do causally impact pollution emissions, but for reasons not explicated herein. For example, credit constraints might reduce

[51] Estimating the models in A13, which includes 108,239 firms, for the 785 firms estimated in Table 4 results in insignificant coefficient estimates for Asset Tangibility due to the small sample size. It is of course possible to simultaneously estimate the models in Table A13 and Table 4. However, the identifying assumptions cannot be convincingly satisfied. The results for estimating both equations simultaneously using 2SLS approaches are mostly insignificant.

expenditures on pollution abatement capital.[52] While I demonstrate that credit constraints influence asset tangibility and that asset tangibility influences pollution emissions, it is difficult to assess the contribution of the asset tangibility channel due to limited plant-level data. The finding that credit constraints do not influence pollution emissions after controlling for asset tangibility suggests that asset tangibility is the primary channel in which credit constraints influence pollution emissions. However, it is possible that asset tangibility represents one of potentially several other channels that influence pollution emissions and it is the task of future research to disentangle these effects. In any case, the conclusions of the paper and the policy implications remain.

4 Conclusion

This paper is the first to explore the relationship between credit constraints and production-generated pollution emissions. Towards this end, I develop a conceptual model demonstrating that credit constraints distort the composition of assets towards over-investment in tangible assets at the expense of intangible assets, thereby increasing the intensity of pollution emissions.

This paper investigates the impact of credit constraints on pollution emissions using plant-level pollution emissions and unique plant-level measures of creditworthiness. The results suggests that credit constraints significantly increase pollution emissions–a one standard deviation in creditworthiness reduces pollution emissions by 4.5 percent. The results are statistically significant using both Pooled OLS and Fixed Effects and withstand numerous robustness checks, including exploring heterogeneous effects, added controls, lagged dependent variables, and instrumental variables. I find that while credit constraints also re-

[52] While pollution abatement expenditures might have more direct effects on pollution emissions, expenditures represent only 3.3% of capital expenditures and 0.4% of operating costs (Becker, 2005). On the other hand, I find that the share of tangible assets is roughly 30 percent among all firms and, more importantly, that there is significant variation within industries (standard deviations range between 7 and 16 percentage points by industry). Thus, a change of one (within-industry) standard deviation in Asset Tangibility has the potential to significantly influence emissions, as the empirical analyses corroborate.

duce output, the net effect of credit constraints on pollution emissions is positive. Finally, I corroborate the plant-level results and validate the proposed mechanism by demonstrating that firm-level asset tangibility is positively associated with pollution emissions and that firm-level credit constraints are positively associated with asset tangibility. In sum, this paper presents strong evidence that credit constraints have at least some causal effect on pollution emissions.

There are many avenues for future research. First, future research should attempt to identify sources of exogenous variation in credit constraints to rule out potential bias. Second, studies should attempt to disentangle the effect of real solvency risks on the one hand and asymmetric information and imperfect property rights on the other hand. While the conceptual analysis suggests that all factors increasing the perceived riskiness of lending will increase the intensity of pollution emissions, extrapolation of the results to all causes of credit constraints should not be taken for granted. Third, future studies should explore the impact of credit constraints on the extensive margin–that is, the impact on firm entry and exit. An important channel in which credit constraints might influence aggregate pollution emissions is by preventing firms that employ more intangible assets from entering the market. Thus, overlooking the extensive margin understates the impact of credit constraints on aggregate pollution emissions. Finally, determining the impact of credit constraints on the extensive margin will shed light on the general equilibrium effects of credit constraints, which is necessary to evaluate the welfare impacts of credit constraints on the environment.

A1 Appendix

A1.1 Derivation of Estimation Equation

This section derives expression 19. Let Ψ with various subscripts represent production-technology parameters. Using equation 13 implies that

$$\hat{e} = (1-\sigma)\hat{c}_x + \sigma\hat{c}_q + \Psi_1 \tag{24}$$

Using equation 9 implies that

$$\hat{c}_q = \gamma\left(\frac{c_q\gamma\psi}{c_y}\right)^{\sigma-1}\hat{c}_y + (1-\gamma)\left(\frac{c_q(1-\gamma)\psi}{c_x}\right)^{\sigma-1}\hat{c}_x + \Psi_2 \tag{25}$$

Moreover, using equation 10 implies that

$$\hat{c}_y = \eta\hat{w} + (1-\eta)\hat{r} + (1-\eta)\hat{\mu} \quad \text{and} \quad \hat{c}_x = \alpha\hat{\tau} + \beta\hat{w} + (1-\alpha-\beta)\hat{r} \tag{26}$$

Recall that $\hat{z} = \hat{e} + \hat{q}$. Using 25 and 26 in 24 implies that

$$\hat{z} = \ \hat{q} + \Delta_\mu\hat{\mu} + \Delta_\tau\hat{\tau} + \Delta_w\hat{w} + \Delta_r\hat{r} + \Psi \tag{27}$$

where

$$\begin{aligned}
\Delta_\mu =& \left(\frac{\sigma(1-\eta)}{\phi}\right)\left(\frac{c_q\gamma\phi}{c_y}\right)^{\sigma-1} \\
\Delta_\tau =& \alpha\left((1-\sigma) + \sigma(1-\gamma)\left(\frac{(1-\gamma)c_q\phi}{c_x}\right)^{\sigma-1}\right) - 1 \\
\Delta_w =& \beta\left((1-\sigma) + \sigma(1-\gamma)\left(\frac{(1-\gamma)c_q\phi}{c_x}\right)^{\sigma-1}\right) + \eta\left(\sigma\gamma\left(\frac{\gamma\phi c_q}{c_y}\right)^{\sigma-1}\right) \\
\Delta_r =& (1-\alpha-\beta)\left((1-\sigma) + \sigma(1-\gamma)\left(\frac{(1-\gamma)c_q\phi}{c_x}\right)^{\sigma-1}\right) + (1-\eta)\left(\sigma\gamma\left(\frac{\gamma\phi c_q}{c_y}\right)^{\sigma-1}\right)
\end{aligned}$$

Table 5: Variable Descriptions

Variable	Description
Plant Pollution Emissions (*Source: EPA's Risk Screening Environmental Indicators*)	
Pounds	Unweighted sum of all chemical releases reported in the EPA's Toxic Release Inventory (TRI) into all disposal media (air, water, landfill).
Hazard	Sum of all chemical releases, weighted by human toxicity and disposal media, according to epidemiological studies.
Risk	Sum of all chemical releases, weighted by the toxicity and disposal media (Hazard), and the transport and fate of the chemical in the environment, the pathway of human exposure, and the number and type of people geographically exposed.
Plant-Level Data (*Source: National Establishment Time Series*)	
Credit Score	D&B Paydex credit score, ranging from 0 to 100 in ascending order of creditworthiness.
Sales	Sales in constant 2008 US$ deflated by the 4-digit SIC value of shipments deflator.
Labor Productivity	Sales total employees.
Firm Financial Data (*Source: Compustat Industrial Data*)	
Asset Tangibility	Ratio of tangible assets, which includes facilities and infrastructure, equipment, and natural resources, total assets.
Current Ratio	Ratio of Current Assets to Current Liabilities.
Cash/Assets	Ratio of Cash total Assets.
Liabilities/Assets	Total Liabilities total Assets. Proxy for solvency.
Market/Book Ratio	Ratio of Market Value to Book Value of Total Assets.
Return on Assets	Ratio of Earnings Before Interest and Taxes total Assets.
Additional Plant-Level Data (*Source: National Establishment Time Series*)	
Corp. Own.>50%	Dummy indicating corporation that is more that 50% owned by another corporation.
Public Facility	Dummy indicating public facility.
Legal Status	Categorical variable of Corporation, Proprietorship, Partnership, or Non-Profit. Corporation is the omitted category in the regressions.
Plant is HQs	Categorical variable for the number of plants listing this plant as headquarters. Small HQs indicates 1-3 plants list this and Large HQs indicates 4 or more (0 omitted category).
Plant's HQs	Categorical variable for the number of plants listing the same headquarters. Small Parent HQs indicates 1-3 plants list similar headquarters and Large Parent HQs indicates 4 or more (0 is omitted category).
Foreign Owned	Dummy indicating foreign owned.
Trade	Categorical variable for Importer, Exporter, or Import and Export.
Age	Year - Year Started, reported by the plant.
Move Often	Dummy indicating moved more than once in the sample.
Industry Change	Changed 3-digit SIC at least once.
Minority	Dummy indicating minority owned.
Women Owned	Dummy indicating controlling interest in firm held by woman.
Cottage	Dummy indicating private business with less than 3 employees.
Executive	Categorical variable indicate Female CEO, Male CEO, omitted category is "Either".

A1.2 Credit Score Sensitivity

This short section demonstrates that the results are robust to using the minimum and mean [0.5*(max+min)] values. Because D&B establishes categories for risk, I also employ Credit Score as an indicator variable for blocks of scores. In particular, I use indicator variables for Credit Score less than 70, between 70 and 74, between 75 and 79, and greater than 80.[53]

Table A1 reports the estimated coefficients using Pooled OLS and Fixed Effects, where the dependent variable is Hazard emissions. Using the minimum credit score reduces the Credit Score point estimate by roughly 50 percent, but the estimate remains significant at the 1 percent level in both specifications. Using Credit Score indicators corroborate that an increase in Credit Score reduces pollution emissions. In both Pooled OLS and Fixed Effects, the indicator estimates are jointly significant at the 1 percent significance level using an F-test (p-values are reported in the Table).

[53]The results are similar using a single dummy for above 80, using blocks of 10, and various other specifications. One website emphasizes a single category (80 and above indicates "low risk") (see: http://mycredit.dnb.com/glossaries/paydex/), whereas another website emphasizes blocks of 10 (see: http://paydexscore.net/paydex-score-chart/).

Table A1: Credit Score Sensitivity Analysis: Alternative Credit Measures (Dependent Variable: Hazard Emissions)

	Pooled OLS			Fixed Effects		
Credit Score (minimum)	–0.0180†			–0.0025**		
	(0.0024)			(0.0010)		
Credit Score (mean)		–0.0269†			–0.0051†	
		(0.0031)			(0.0014)	
I{Credit Score $\in [70, 74]$}			0.0270			–0.0276
			(0.0501)			(0.0224)
I{Credit Score $\in [75, 79]$}			–0.1848†			–0.0614†
			(0.0559)			(0.0236)
I{Credit Score $\in [80, 199]$}			–0.8442†			–0.1354†
			(0.0695)			(0.0294)
R-sq	0.207	0.207	0.209	0.031	0.031	0.031
Adjusted R-sq	0.202	0.202	0.204	0.026	0.026	0.026
Plants	29,636	29,636	29,636	29,636	29,636	29,636
Observations	246,324	246,324	246,324	246,324	246,324	246,324
Credit group F-test (p-val)			0.000			0.000

Notes: Significance levels: *0.10, **0.05, and †0.01. Credit Score (minimum) is the minimum credit score for a given year and Credit Score (mean) is half the sum of the min and max. I{ Score $\in [70, 74]$} is an indicator variable if Credit Score is in the range $[70, 74]$. I{Score $\in [0, 69]$} is the omitted category. The Credit group F-test tests the joint significance of the Credit Score indicators. All estimations use cluster-robust standard errors that are clustered on plants. All models include state$\times$year and industry$\times$year effects. All variables are in log-scale, except Credit Score, which is an ordinal measure.

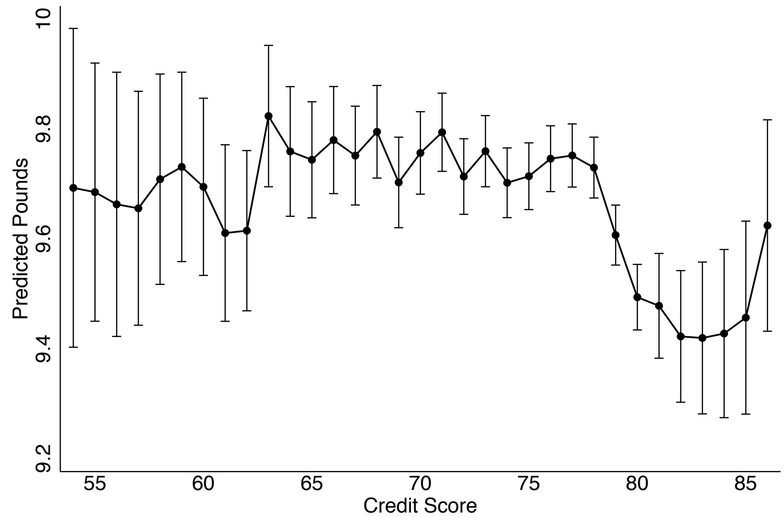

Figure A1: Predicted Pounds Emissions and 95% Confidence Interval

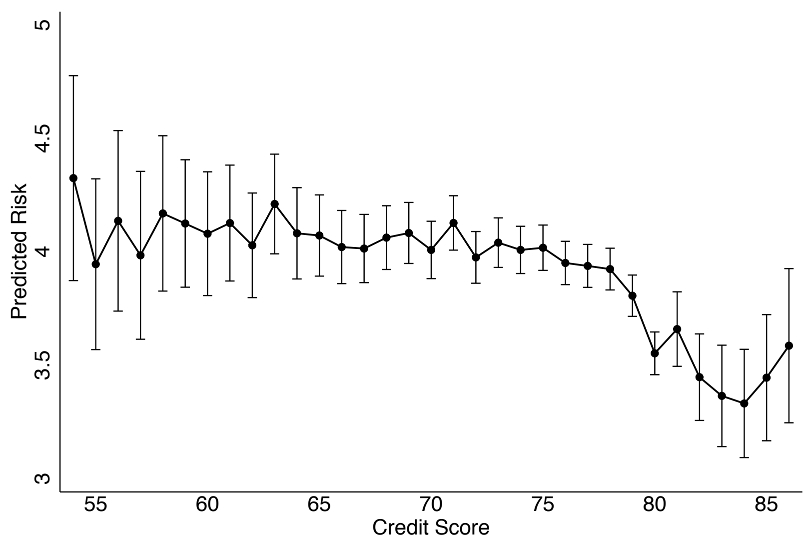

Figure A2: Predicted Risk Emissions and 95% Confidence Interval

Table A2: Standardized Summary Statistics by 2-digit SIC industry: Mean and (Std. Deviation)

	Pounds				Hazard				Risk			
	Emissions		Intensity		Emissions		Intensity		Emissions		Intensity	
Food	-0.06	(1.00)	-0.14	(1.06)	-0.67	(0.66)	-0.73	(0.71)	-0.31	(0.78)	-0.39	(0.83)
Tobacco	0.66	(0.43)	-0.40	(0.68)	-0.11	(0.69)	-0.69	(0.71)	-0.04	(0.91)	-0.74	(1.05)
Textiles	-0.29	(1.06)	-0.39	(1.17)	-0.50	(0.79)	-0.57	(0.82)	-0.31	(0.88)	-0.37	(0.88)
Apparel	-0.31	(0.85)	-0.35	(0.95)	-0.37	(0.82)	-0.40	(0.88)	0.05	(0.91)	0.01	(0.98)
Lumber	-0.30	(1.14)	-0.26	(1.16)	-0.39	(0.73)	-0.38	(0.74)	-0.31	(0.82)	-0.28	(0.82)
Furniture	0.18	(0.69)	0.14	(0.73)	-0.47	(0.77)	-0.51	(0.76)	-0.28	(0.74)	-0.30	(0.73)
Paper	0.26	(1.15)	0.13	(1.12)	-0.16	(0.85)	-0.23	(0.82)	0.10	(0.97)	0.02	(0.92)
Printing	0.09	(0.73)	0.07	(0.73)	-0.55	(0.59)	-0.58	(0.61)	-0.27	(0.71)	-0.30	(0.71)
Chemicals	0.01	(1.04)	0.17	(0.98)	-0.18	(0.89)	-0.09	(0.86)	0.07	(1.00)	0.18	(0.96)
Petroleum and Coal	-0.22	(1.27)	-0.03	(1.13)	0.03	(0.95)	0.14	(0.93)	0.34	(1.12)	0.46	(1.06)
Rubber and Plastics	-0.06	(0.86)	0.05	(0.86)	-0.43	(0.79)	-0.38	(0.77)	-0.30	(0.86)	-0.22	(0.86)
Leather	-0.05	(0.75)	-0.13	(0.85)	-0.86	(1.06)	-0.92	(1.10)	-0.81	(0.99)	-0.85	(1.02)
Stone, Clay, and Glass	-0.60	(1.38)	-0.51	(1.34)	-0.17	(1.07)	-0.12	(1.02)	-0.06	(1.03)	0.01	(0.95)
Primary Metals	0.14	(1.08)	0.15	(1.01)	0.49	(1.00)	0.51	(0.97)	0.32	(0.97)	0.32	(0.93)
Fabricated Metal	0.06	(0.85)	0.27	(0.85)	0.27	(1.02)	0.39	(1.02)	0.16	(1.06)	0.29	(1.06)
Industrial Machinery	0.04	(0.82)	-0.06	(0.87)	0.44	(1.14)	0.39	(1.16)	0.00	(1.09)	-0.07	(1.11)
Electronics	-0.04	(1.01)	-0.35	(1.04)	0.05	(0.81)	-0.12	(0.85)	-0.19	(0.90)	-0.40	(0.91)
Transportation Equipment	0.24	(0.82)	-0.13	(0.84)	0.28	(1.09)	0.08	(1.07)	0.10	(1.06)	-0.15	(1.01)
Instruments	-0.15	(0.98)	-0.46	(1.02)	-0.07	(0.99)	-0.24	(1.02)	-0.23	(1.04)	-0.44	(1.06)
Misc. Manufacturing	-0.06	(0.86)	-0.07	(0.91)	-0.34	(0.91)	-0.35	(0.92)	-0.30	(0.95)	-0.31	(0.96)
Total	0.00	(1.00)	0.00	(1.00)	0.00	(1.00)	0.00	(1.00)	0.00	(1.00)	0.00	(1.00)

Notes: Emissions is log emissions and Intensity is log emissions to log deflated Sales. All values are standardized with zero mean and unity standard deviation.

Table A3: Heterogeneous Effects Using Pooled OLS (Dep Var: Hazard emissions)

Credit Score	–0.0335†	–0.0344†	–0.0401†	–0.0419†	–0.0417†
	(0.0035)	(0.0037)	(0.0035)	(0.0035)	(0.0037)
$\mathcal{T}_2$ Current Ratio×Credit	0.0033†				
	(0.0008)				
$\mathcal{T}_3$ Current Ratio×Credit	0.0043†				
	(0.0010)				
Corporate Ownership>50%×Credit		0.0028†			
		(0.0011)			
Small HQs×Credit			0.0078†		
			(0.0014)		
Large HQs×Credit			0.0173†		
			(0.0011)		
$\mathcal{T}_2$ Sales ×Credit				0.0137†	
				(0.0011)	
$\mathcal{T}_3$ Sales×Credit				0.0248†	
				(0.0017)	
Public Facility×Credit					0.0096†
					(0.0010)
Adjusted R-sq	0.2327	0.2326	0.2395	0.2366	0.2354
Plants	28,801	28,801	28,790	28,801	28,801
Observations	237,984	237,984	237,961	237,984	237,984

Notes: Significance levels: *0.10, **0.05, and †0.01. $\mathcal{T}_2$ is a dummy equal to one if the continuous variable is in the second tercile, and so on. All variables interacted with Credit are also included as control variables (not reported). All estimations use cluster-robust standard errors that are clustered on plants. All models include state×year and industry×year effects.

Table A4: Nested Restricted Samples using Fixed Effects (Dep Var: Hazard emissions)

Excluded Plants:	Publicly-held	Conglomerate	Sales>$10mil
Credit Score	–0.0079 †	–0.0084†	–0.0112 †
	(0.0010)	(0.0013)	(0.0018)
Adjusted R-sq	0.281	0.293	0.312
Plants	16,529	9,899	6,163
Observations	132,007	76,133	45,489

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. All models include state×year and industry×year effects. The sub-samples are strictly nested. The first column excludes all publicly-held plants, the second excludes all conglomerates (plants with parent company), and the third excludes all plants with average annual sales greater than $5 million deflated US dollars.

Table A5: Added controls (Part I) using Pooled OLS (POLS) and Random Effects (R-E) (Dependent Variable: Hazard Emissions)

	POLS	R-E	POLS	R-E
Credit Score	–0.0437†	–0.0071†	–0.0490†	–0.0079†
	(0.0038)	(0.0015)	(0.0037)	(0.0014)
	Ownership Characteristics			
Corporate Ownership >50%	0.3919†	0.6014†		
	(0.1019)	(0.0894)		
Public Facility	0.4666†	0.5761†		
	(0.0924)	(0.0832)		
Legal Status				
Partnership	0.5138†	0.7735†		
	(0.1360)	(0.1191)		
Proprietorship	–0.5317	–0.5409		
	(0.5935)	(0.5041)		
Non-Profit	–2.3320†	–2.5641†		
	(0.4959)	(0.4469)		
Plant's Headquarters				
Small HQs	–0.0237	0.0724		
	(0.1109)	(0.0964)		
Large HQs	–0.1723	–0.2269		
	(0.1598)	(0.1410)		
Plant is Headquarters				
Small HQs	0.3036**	0.2842†		
	(0.1255)	(0.1084)		
Large HQs	0.5497†	0.6796†		
	(0.1064)	(0.0921)		
			Internationalization	
Foreign Owned			0.0614	0.3509†
			(0.0944)	(0.0884)
Trade				
Importer			0.8760†	1.3878†
			(0.0862)	(0.0777)
Exporter			0.0509	0.2814†
			(0.0991)	(0.0882)
Import and Export			0.7740†	1.2116†
			(0.1340)	(0.1241)
Adjusted R-sq	0.113		0.113	
R-sq (within)		0.005		0.005
R-sq (between)		0.063		0.065
R-sq (overall)		0.063		0.057
Plants	27,031	27,031	28,799	28,799
Observations	223,873	223,873	238,062	238,062

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. All models include state $\times$ year and industry $\times$year effects. See text for variable descriptions.

Table A6: Added controls (Part II) Using Pooled OLS (POLS) and Random Effects (R-E) (Dependent Variable: Hazard Emissions)

	POLS	R-E	POLS	R-E
Credit Score	–0.0555†	–0.0067†	–0.0484†	–0.0077†
	(0.0045)	(0.0016)	(0.0043)	(0.0016)
	Plant Dynamics			
Age	–0.0066	–0.0190†		
	(0.0041)	(0.0035)		
Age^2	0.0001**	0.0001†		
	(0.0000)	(0.0000)		
Sales growth	–0.4602†	–0.0685†		
	(0.0289)	(0.0132)		
Productivity Growth	0.1192*	–0.0111		
	(0.0676)	(0.0247)		
Move Often	–0.1053	–0.3344		
	(0.2263)	(0.2035)		
Industry Change	0.0226	0.0733		
	(0.0962)	(0.0867)		
			Plant Features	
Minority			–1.1151†	–1.0678†
			(0.3500)	(0.2963)
Women Owned			–0.4196*	–0.7765†
			(0.2177)	(0.1881)
Cottage			–0.4893	0.8597
			(1.3593)	(1.4879)
Executive				
Female CEO			–0.6607**	–0.5319**
			(0.2704)	(0.2440)
Male CEO			0.0774	0.1657
			(0.1825)	(0.1690)
Adjusted R-sq	0.114		0.112	
R-sq (within)		0.001		0.005
R-sq (between)		0.069		0.066
R-sq (overall)		0.062		0.055
Plants	22,323	22,323	20,910	20,910
Observations	171,042	171,042	187,633	187,633

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. All models include state×year and industry×year effects. See text for variable descriptions.

Table A7: Hazard Emissions using Lagged Dependent Variables (LDV)

	OLS	First Differences		
Credit Score	–0.0034†			
	(0.0007)			
Δ Credit Score		–0.0039†	–0.0019**	–0.0016
		(0.0009)	(0.0009)	(0.0012)
Plants	26,515	25,831	23,665	23,665
Observations	215,234	207,981	183,480	183,480
LDV	Yes	No	Yes	Yes
2SLS	No	No	No	Yes

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. All models include state×year and industry×year effects. 2SLS indicates that the lagged-difference Emissions are instrumented using two-year-legged Emisisons.

Table A8: 2SLS Using Pooled OLS and Fixed Effects (Dep Var: Hazard Emissions)

	2SLS–Pooled OLS			2SLS-Fixed Effects		
Credit Score	–0.0409	–0.1060†	–0.0902†	–0.0264**	–0.0003	–0.0213*
	(0.0308)	(0.0306)	(0.0251)	(0.0124)	(0.0301)	(0.0118)
Sales	0.9178†	0.8801†	0.8856†	0.1392†	0.1371†	0.1381†
	(0.0268)	(0.0277)	(0.0269)	(0.0185)	(0.0190)	(0.0190)
Labor Productivity	–0.8048†	–0.8070†	–0.8139†	–0.1003**	–0.1155†	–0.1083**
	(0.0556)	(0.0575)	(0.0569)	(0.0410)	(0.0439)	(0.0430)
R-sq	0.051	0.042	0.045	–0.000	0.001	0.000
Plants	29,636	27,806	27,806	26,209	24,510	24,510
Observations	246,324	227,123	227,123	242,897	223,827	223,827
First-stage F-test	801.7	790.5	736.7	875.0	260.4	543.4
Overidentification Test (p-val)			0.214			0.405
Endogeneity Test (p-val)	0.702	0.012	0.025	0.121	0.823	0.161

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on plants. All models include state×year and industry×year effects. The Overidentification Test is the Hansen J stat (p-val) and the Endogeneity Test is the Wu-Hausman F-Test (p-val). See text for description of instruments used. All variables are in log-scale, except Credit Score, which is an ordinal measure.

Table A9: Addressing Endogeneity of Sales using Fixed Effects

	Dep Var: Sales		Dep Var: Hazard Emissions		
Credit Score	0.0013†	0.0123†	–0.0055†	–0.0056†	–0.0153
	(0.0004)	(0.0022)	(0.0013)	(0.0015)	(0.0119)
Sales				0.1446†	–0.0024
				(0.0279)	(0.0372)
Labor Productivity				–0.2688†	–0.1519*
				(0.0661)	(0.0881)
Plants	29,817	21,694	35,299	23,620	19,785
Observations	248,153	189,566	294,678	210,397	168,315
2SLS	No	Yes	No	Yes	Yes
Overidentification Test (p-val)		0.793			0.749
Endogeneity Test (p-val)		0.000		0.001	0.066
First-stage F-test					
Credit Score		867.7			227.1
Sales				3461.2	257.4
Labor Productivity				283.1	26.7

Notes: Significance levels: *0.10, **0.05, and †0.01. All models include Fixed Effects and state×year and industry×year effects. Over-identification Test is the Hansen J Stat (p-value) and the Endogeneity Test is the Wu-Hausman Test (p-value).

Table A10: Firm-Level Summary Statistics: Mean and (Std. Deviation)

	Emissions		Sales		Asset Tangibility		Credit Score	
Food	5.31	(4.48)	18.93	(1.81)	0.35	(0.15)	77.54	(3.86)
Tobacco	6.47	(2.56)	19.04	(1.71)	0.11	(0.05)	75.82	(1.86)
Textiles	5.73	(5.29)	17.79	(1.36)	0.35	(0.12)	76.84	(5.07)
Apparel	2.02	(4.94)	17.30	(0.12)	0.20	(0.05)	70.14	(7.40)
Lumber	6.58	(5.01)	17.59	(1.26)	0.44	(0.18)	78.32	(4.24)
Furniture	7.72	(6.90)	18.50	(1.60)	0.25	(0.09)	74.40	(4.68)
Paper	9.87	(4.56)	18.71	(1.50)	0.52	(0.15)	75.87	(3.40)
Printing	2.63	(3.60)	16.70	(0.80)	0.47	(0.12)	78.16	(4.07)
Chemicals	10.86	(6.23)	18.33	(1.95)	0.31	(0.15)	73.65	(3.96)
Petroleum and Coal	14.22	(3.71)	18.01	(1.61)	0.54	(0.16)	74.92	(2.49)
Rubber and Plastics	6.44	(6.60)	17.53	(1.98)	0.34	(0.12)	75.59	(4.77)
Stone, Clay, and Glass	10.58	(5.47)	17.81	(1.58)	0.42	(0.16)	76.98	(5.20)
Primary Metals	15.09	(4.61)	18.76	(1.62)	0.36	(0.14)	74.28	(3.62)
Fabricated Metal	12.80	(5.86)	17.76	(1.97)	0.29	(0.14)	74.08	(5.10)
Industrial Machinery	12.10	(6.05)	18.38	(1.60)	0.23	(0.11)	73.22	(4.08)
Electronics	8.67	(5.45)	19.15	(2.26)	0.27	(0.13)	73.09	(4.55)
Transportation Equipment	12.17	(6.92)	19.09	(1.75)	0.28	(0.12)	72.36	(4.08)
Instruments	9.22	(6.33)	18.33	(1.76)	0.23	(0.11)	74.27	(3.81)
Misc. Manufacturing	7.16	(6.62)	17.98	(1.75)	0.24	(0.07)	74.72	(5.52)
Total	10.28	(6.34)	18.51	(1.90)	0.30	(0.15)	74.14	(4.46)

Notes: Emissions is the sum Hazard emissions across all plants. Sales is the sum t and Credit Score is the mean across all plants. Asset Tangibility is the firm-level ratio of Tangible Assets (Plant, Equipment, and Natural Resources) to Total Assets. Emissions and Sales are in log scale.

Table A11: Additional Firm-Level Summary Statistics: Mean and (Std. Deviation)

	#Plants		#Industries		#Products		σ_f Emissions		σ_f Credit		Current Ratio		Cash/Assets	
Food	26.52	(28.62)	2.27	(2.28)	4.55	(4.72)	2.47	(1.41)	4.02	(2.21)	2.35	(2.68)	0.04	(0.07)
Tobacco	16.78	(6.64)	2.22	(0.67)	4.13	(1.89)	2.83	(1.69)	5.48	(2.32)	1.15	(0.26)	0.13	(0.14)
Textiles	4.90	(5.44)	1.28	(0.83)	1.90	(1.36)	3.85	(2.51)	2.92	(2.24)	2.86	(1.17)	0.04	(0.05)
Apparel	1.14	(0.38)	1.00	(0.00)	1.00	(0.00)					2.35	(0.57)	0.06	(0.07)
Lumber	10.47	(10.11)	1.83	(1.52)	2.90	(3.24)	2.61	(1.41)	4.38	(2.25)	2.42	(1.02)	0.08	(0.08)
Furniture	18.66	(19.40)	2.44	(3.53)	4.41	(5.21)	2.82	(1.74)	4.85	(2.82)	2.48	(1.14)	0.04	(0.05)
Paper	19.85	(36.19)	2.51	(3.69)	5.17	(9.72)	3.92	(1.49)	4.29	(2.36)	1.77	(0.60)	0.03	(0.04)
Printing	3.49	(0.94)	1.59	(0.79)	1.79	(0.73)	2.46	(2.36)	5.05	(4.53)	1.65	(0.77)	0.03	(0.06)
Chemicals	19.19	(33.32)	2.80	(3.80)	5.08	(9.03)	4.49	(1.87)	4.87	(2.50)	2.62	(3.41)	0.08	(0.10)
Petroleum and Coal	18.98	(13.93)	2.24	(1.87)	3.46	(2.29)	4.34	(1.12)	5.29	(2.16)	1.51	(0.64)	0.05	(0.05)
Rubber and Plastics	7.37	(9.04)	1.31	(1.14)	2.01	(2.24)	3.21	(2.11)	4.06	(2.46)	2.05	(0.81)	0.04	(0.05)
Stone, Clay, and Glass	16.62	(27.40)	2.55	(3.50)	3.75	(6.40)	3.81	(2.24)	4.03	(3.24)	2.65	(1.80)	0.06	(0.06)
Primary Metals	14.07	(18.77)	2.95	(3.53)	5.08	(6.39)	4.59	(2.05)	4.90	(3.02)	2.50	(1.14)	0.04	(0.06)
Fabricated Metal	14.12	(15.37)	2.64	(3.34)	4.24	(5.23)	4.31	(2.37)	5.22	(2.86)	2.31	(1.48)	0.05	(0.07)
Industrial Machinery	9.35	(9.04)	2.01	(2.01)	3.10	(2.97)	4.71	(2.55)	4.30	(2.42)	2.42	(1.37)	0.07	(0.08)
Electronics	10.66	(20.24)	1.98	(3.01)	3.18	(6.08)	3.40	(2.20)	4.12	(2.45)	3.06	(2.22)	0.11	(0.11)
Transportation Equip.	18.42	(26.97)	3.23	(3.68)	5.30	(6.90)	4.88	(2.26)	5.23	(2.50)	2.07	(1.48)	0.07	(0.09)
Instruments	9.35	(11.79)	2.38	(2.44)	3.35	(3.88)	4.51	(2.30)	4.34	(2.87)	2.77	(2.01)	0.09	(0.09)
Misc. Manufacturing	4.06	(3.41)	1.11	(1.07)	1.61	(1.58)	3.98	(2.17)	3.11	(3.35)	2.56	(1.08)	0.09	(0.10)
Total	14.09	(22.89)	2.38	(3.07)	3.97	(6.20)	4.11	(2.22)	4.56	(2.64)	2.51	(2.07)	0.07	(0.09)

Notes: # Plants is the number of plants under a firm. #Industries and #Products is the number of distinct 4- and 8-digit SIC industries in which the firm's plants produce. σ_f is the within-firm Standard Deviation (over time and across plants). The remainder of the variables are at the firm level.

Table A12: Firm-Level Determinants of the Composition of Production

	Pooled OLS				Fixed Effects			
Asset Tangibility	0.6433**	0.6425**	0.4238	0.4580*	0.0888	0.0909	0.0757	0.0406
	(0.2695)	(0.2694)	(0.2699)	(0.2673)	(0.1815)	(0.1810)	(0.1839)	(0.1814)
Sales	1.3295†	1.3296†	1.3422†	1.3113†	1.1851†	1.1850†	1.1857†	1.1825†
	(0.0951)	(0.0951)	(0.0916)	(0.0904)	(0.0666)	(0.0666)	(0.0664)	(0.0662)
Credit Score		–0.0091	–0.0025	–0.0042		0.0054	0.0056	0.0058
		(0.0219)	(0.0213)	(0.0214)		(0.0101)	(0.0102)	(0.0101)
Total Assets	0.2936†	0.2930†	0.2646†	0.3448†	0.1792*	0.1781*	0.1715*	0.2319**
	(0.0956)	(0.0955)	(0.0996)	(0.1090)	(0.0989)	(0.0988)	(0.0996)	(0.1103)
Current Ratio			–0.2084	0.5221*			–0.0374	0.0506
			(0.2598)	(0.2982)			(0.1143)	(0.1262)
Cash/Assets			–0.4283†	–0.3638†			–0.0155	–0.0237
			(0.0845)	(0.0831)			(0.0362)	(0.0361)
Liabilities/Assets				0.9494†				0.1215
				(0.3540)				(0.1729)
Market/Book Ratio				–0.1719				0.1246*
				(0.1269)				(0.0705)
Sales/Assets				0.6580**				0.2278
				(0.3219)				(0.1704)
R-sq	0.510	0.510	0.522	0.528	0.291	0.291	0.291	0.293
R-sq (within)					0.291	0.291	0.291	0.293
R-sq (between)					0.232	0.195	0.206	0.246
R-sq (overall)					0.270	0.232	0.235	0.274
Firms	785	785	785	785	785	785	785	785
Observations	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on firms. The dependent variable is the sum of plant-level sales multiplied industry intensity of the plant across all firms. Sales is the sum and Credit Score is the mean across all plants. Asset Tangibility is the firm-level ratio of Tangible Assets (Plant, Equipment, and Natural Resources) to Total Assets. The remainder of the variables are firm-level. All of the explanatory variables are lagged one year and all variables are in log-scale, except Credit Score.

Table A13: Determinants of Firm-Level Asset Tangibility

	Pooled OLS		Fixed Effects	
Current Ratio	–0.0760†	–0.2953†	–0.0402†	–0.0409†
	(0.0166)	(0.0201)	(0.0112)	(0.0126)
Cash/Assets	–0.2058†	–0.1125†	–0.0379†	–0.0386†
	(0.0051)	(0.0051)	(0.0031)	(0.0029)
Liabilities/Assets	0.0140	0.0434**	–0.0538†	–0.0059
	(0.0171)	(0.0207)	(0.0125)	(0.0140)
Market/Book Ratio		–0.1228†		–0.0281†
		(0.0075)		(0.0043)
Sales/Assets		–0.0434*		0.1199†
		(0.0224)		(0.0182)
Return on Assets		0.0814†		–0.0034
		(0.0067)		(0.0037)
R-sq	0.120	0.149	0.007	0.026
R-sq (between)			0.160	0.146
R-sq (overall)			0.095	0.091
Firms	9,641	6,626	9,641	6,626
Observations	108,239	65,774	108,239	65,774

Notes: Significance levels: *0.10, **0.05, and †0.01. All estimations use cluster-robust standard errors that are clustered on firms. Asset Tangibility is the ratio of Tangible Assets to Total Assets, Current Ratio is Current Assets to Current Liabilities, Assets are Total Assets.

Chapter 2: Are Credit Constraints Bad for the Environment? Theory and Cross-Country Evidence

1 Introduction

Credit market imperfections are a pervasive feature in most, if not all, economies (for a survey, see Browning and Lusardi, 1996).[1] The result is an excess of demand, or rationing, of loanable funds, which prevents firms and households from financing investments (Stiglitz and Weiss, 1981; Aghion and Bolton, 1992; many others). Investment in human capital, in particular, is affected by credit market imperfections as human capital cannot be collateralized (Hart and Moore, 1994). Due to positive externalities associated with investment in human capital and health (Lucas, 1988; Moretti, 2004), significant attention has been given to the role of credit constraints in economic performance (Levine, et al., 2000; Beck, et al., 2000). However, no studies have systematically explored the effect of credit constraints on the environment.

This paper explores the relationship between credit constraints and the environment by developing a simple theoretical model and testing the main results. I emphasize credit constraints impinging on investment in human capital, which in turn orients production towards more pollution-intensive industries, and promotes greater pollution intensity in these industries. Two reasons motivate the particular, but not exclusive, emphasis on investment in human capital. First, credit market imperfections are particularly relevant to investment in human capital (Hart and Moore, 1994).[2] Second, human capital is a precursor to

[1]That households are affected by credit constraints, even in high-income countries, is empirically supported. For example, Grant (2007) estimates that nearly one-third of households in the US are credit constrained and that credit constraints affect young households to an even larger extent.

[2]This is evidenced, indirectly, by significant variation in returns to eduction across countries (Psacharopoulos, 2004), including remarkably high returns in developing countries to programs alleviating credit constraints (e.g., conditional cash transfers). On the other hand, physical and financial capital can be collateralized much easier and can be concentrated within firms, thereby circumventing transactions costs

the development of clean industries, including information technology sectors, high-tech manufacturing, fiber optics, research institutions, and universities (Antweiler, et al., 2001; Aghion and Howitt, 1998).Overcoming credit constraints is, therefore, crucial for achieving sustainable growth based on advancing human capital and knowledge, and the lack of systematic evidence of the relationship between credit constraints and pollution is thus surprising.

This paper contributes to the literature exploring the relationship between economic development and environmental performance, including the environmental Kuznets curve (EKC) literature. The primary explanations advanced for the EKC are (1) sources of growth, (2) income effects, (3) threshold effects, and (4) increasing returns to abatement.[3] This paper is most closely related to sources of growth explanations, which postulate that structural change transforms the composition of output from resource and pollution-intensive goods to human-capital-intensive goods. A precursor to this transformation is, therefore, overcoming credit constraints, especially for poor countries, which lack sufficient savings to finance investments. Moreover, because developing countries typically have weak property rights, imperfect contract enforcement, unstable political institutions, underdeveloped information systems, among other problems, credit markets typically perform poorly (Banerjee, 2005). Thus, if economic growth translates into improved institutions, which in turn facilitates greater financial intermediation, then credit markets are a possible channel through which the EKC is manifested. The focus on credit constraints is however absent in the literature and the predictions are not necessarily identical as countries with similar income may face dissimilar credit market imperfections.

A limited number of recent studies have examined the effect of financial development on environmental performance (Dasgupta et al., 2001; Dasgupta et al., 2006; Tamazian et

associated with underdeveloped credit markets. As a result, the marginal product of capital displays very little variation across countries after accounting for all inputs (Caselli, 2006).

[3]For a survey of the literature, see Copeland and Taylor (2004) or Stern (2004). Example of papers by explanation are (1) Grossman and Krueger, 1995; (2) López, 1994; (3) Seldon and Song, 1994; Stokey, 1998; and (4) Andreoni and Levinson, 2000.

al., 2009; and Tamazian and Rao, 2010). Tamazian et al. (2009) posit that financial development reduces financing costs, including the cost of investment in environmental projects, and find that financial development and CO_2 emissions are negatively related. Similarly, Tamazian and Rao (2010) show that financial development is especially important for local and state governments as many environmental projects are undertaken by the public sector. Finally, López and Islam (2011) show that fiscal spending aimed at reducing market failures, including credit market imperfections, reduces pollution, which provides indirect evidence that credit market imperfections increase pollution.[4]

This paper develops a theoretical model by extending the two sector, general equilibrium framework used in the trade and the environment literature to include credit constraints that bear on investment and production decisions. The primary insight of the model is that if credit constraints are particularly acute for investment in human capital, as opposed to physical capital, then credit constraints increase pollution emissions through composition and technique effects. That is, because production of dirty goods is physical-capital intensive, whereas production of clean goods is human-capital intensive, constraining human capital investment draws resources from the clean sectors, leading to a more than proportional expansion of output in the dirty sectors and an absolute decline in output in clean sectors sectors. Thus, for a constant pollution intensity (pollution per unit of dirty good produced), a decrease in human capital increases pollution via the composition effect (share of dirty goods in output). A decrease in human capital might also engender an endogenous policy response, leading to laxer environmental regulations, which increases pollution intensity via the technique effect whenever environmental quality is a normal good.

The main prediction of the model is supported for air pollutants sulfur dioxide (SO_2) and lead, using pollution measures from the World Health Organization's Automated Meteorological Information System for about 150 cities in 45 countries. Following the financial

[4]It is not possible to assess, however, whether the empirical relationship between fiscal spending and pollution is via reducing credit market imperfections or some other channel.

development and growth literature, I use private credit as a proxy for credit constraints, as well as variation in the legal rights of creditors against defaulting debtors (bankruptcy laws) and the existence of credit bureau registries. The empirical results demonstrate that credit constraints increase air pollution using a reduced-form approach. Furthermore, using a two-stage procedure where private credit and human capital are determined in the first stage, I find that credit constraints reduce private credit and human capital, which, in turn, increases pollution. The results are robust with respect to additional control variables and various sensitivity checks.

This paper has several important policy implications, especially in the context of developing countries. Because developing countries typically exhibit imperfect contract enforcement and underdeveloped informational systems, reforming the legal and institutional environment, such as reforms increasing creditor rights and promoting informational sharing through establishing credit bureau registries, might represent a "win-win" policy intervention as reducing credit constraints also promotes economic growth (Levine, 2000). That is, the benefits of reducing credit market imperfections are even greater than previously understood. An important caveat highlighted in this paper is that reforms must overcome credit market imperfections affecting investment in human capital, which are typically more difficult to overcome. Increasing capital inflows through financial market liberalization might be counterproductive for improving environmental performance if the majority of households are unable to access credit. Therefore, policies promoting capital accumulation should be coupled with policies reducing credit constraints to households and targeting investment in human capital.

The remainder of this paper consists of a conceptual model (Section 2), empirical model and results (Section 3), and conclusion (Section 4).

2 Model

The conceptual model elaborates the standard two-sector model with pollution emissions developed by Copeland and Taylor (2004). I consider a small open economy, producing two final goods (a "clean" and a "dirty" good) with physical capital and human capital as primary factors. The dirty good uses pollution as factor of production and is physical-capital intensive, whereas the clean good does not use pollution as a factor of production and is human-capital intensive. The model spans two periods to capture the effect of credit constraints on investment and production decisions.

Considering pollution as an additional factor of production is the standard approach in the environmental economics literature;[5] however, the approach has been criticized on the basis of incompatibility with materials balance principle (or conservation laws of mass and energy) (Pethig, 2006). While adding a significant amount of complexity, the standard model can be generalized to a framework consistent with materials balance principle by incorporating materials explicitly in the production function, with an accompanying abatement technology to convert materials into production residuals (harmful pollution) and abatement residuals (non-harmful discharges). All else equal, a sufficient assumption to ensure that the physical-capital intensive sector is pollution intensive is that materials and physical capital exhibit greater complementarity, implying that the physical-capital intensive sector uses materials and therefore generates more pollution.

The model demonstrates that credit constraints reduce investment in human capital, which in turn promotes production of dirty goods over clean goods, thereby increasing pollution. The result is demonstrated under both exogenous and endogenous environmental policy.

[5] Cropper and Oates (1992) survey the environmental economics literature, which largely treats pollution emissions "simply as another factor of production." More recent studies treating pollution emissions as an input include Copeland and Tylor (1994) and Lòpez (1994), and Acemoglu et al. (2012).

2.1 Production

Consider a small open economy, producing two goods, X and Y, which are produced with a constant returns to scale technology using two primary factors, physical and human capital, K and L. Good Y is treated as the numeraire and p denotes the price of good X. For simplicity, production of X entails pollution, but production of Y does not. I assume pollution reduces the utility of consumers, but does not affect production.

Production of good Y is

$$Y = H(K_y, L_y) \tag{1}$$

where H is increasing, linearly homogenous, and concave.

For analytical convenience, pollution is treated as an input in production of good X, rather than as a joint output. Production of good X is given by

$$X = Z^{\alpha}[F(K_x, L_x)]^{1-\alpha}, \quad 0 < \alpha < 1 \tag{2}$$

where $Z < F$ whenever firms undertake abatement and $Z = F$ whenever abatement does not occur. Thus, $Z \leq F$. Similarly, F is increasing, linearly homeogeneous, and concave.

The government taxes pollution or issues an equivalent number of pollution permits. Assuming some abatement is undertaken, perfect competition implies that the pollution intensity of the dirty sector is given by

$$e \equiv \frac{z}{x} = \frac{\alpha p}{\tau} < 1 \tag{3}$$

where τ is the price of pollution permits.

Full employment of primary factors implies that output can be expressed in terms of aggregate factor endowments and prices

$$x = x(p, \tau, K, L) \quad \text{and} \quad y = y(p, \tau, K, L) \tag{4}$$

Moreover, perfect competition implies that national income can be expressed as the maximum value function

$$G(p, K, L, z) = \max_{x,y}\{px + y : (x, y) \in T(K, L, z)\} \tag{5}$$

where T represents the feasible technology set.

2.2 Producer-Consumers

Suppose the economy admits a representative producer-consumer with preferences over consumption goods and environmental quality. Utility is homethetic and strongly separable in consumption and the environment. Without loss of generality, suppose the price of good X is also normalized to unity. Indirect utility is given by

$$V(I, z) = v(I) - h(z) \tag{6}$$

where I represents real disposable income. As conventional, I assume that $v' > 0$, $v'' < 0$, $h' > 0$, and $h'' > 0$.

The representative agent lives for two periods. In period 0, she borrows in order to invest in human capital (schooling) and to purchase consumption goods. In period 1, she produces the two final goods using human capital determined in the previous period and a fixed supply of physical capital purchased on a spot market. Further, she repays the loan with interest and consumes her remaining income. Lifetime utility is therefore given by

$$W = v(I_0) + \rho(v(I_1) - h(z)) \tag{7}$$

where $0 < \rho < 1$ is the discount factor. I assume all generations inherent an exogenous level of pollution in period 0, which does not affect equilibrium choices due to strong seperability of preferences.

The representative agent therefore faces the following set of budget constraints

$$I_0 = B - qL \tag{8}$$

$$I_1 = G(K, L, z) - (1 + r)B \tag{9}$$

where B represents the net asset position at the end of period 0 (borrowing), q represents the cost of investing in human capital (inverse of productivity of investment), (1+r) represents the gross interest rate, and G is real national income.

2.3 Credit Constraints

As mentioned, I presume that human capital is the only asset that is potentially subject to a borrowing constraint. In general, investment in both types of assets might be influenced by credit constraints. Typically, credit constraints are generated by the preclusion of using the asset as collateral (either as a consequence of imperfect property rights or the inalienability of the asset), thereby increasing the risk of lending from the lenders point of view. Therefore, because human capital is more difficult to pledged as collateral, credit constraints are likely to be tighter on investment in human capital. The qualitative results would follow under the more general assumption that credit constraints are relatively more binding for investment in human capital than physical capital. For simplicity and clarity, I assume that only investment in human capital is influenced by credit constraints.

The representative agent faces a borrowing constraint such that her net asset position in period 0 cannot exceed a fixed fraction of the present value income. That is,

$$B \leq \theta \frac{G(K, L, z)}{1 + r} \tag{10}$$

Maximization with respect to borrowing therefore implies

$$\frac{\partial v}{\partial I_0} = \rho \frac{\partial v}{\partial \tilde{I}_1}(1+r) + \lambda_B \tag{11}$$

where $\lambda_B \geq 0$ is the shadow value of borrowed assets. In comparison, the optimal unconstrained ($\lambda_B = 0$) borrowing satisfies

$$\frac{\partial v}{\partial \tilde{I}_0} = \rho \frac{\partial v}{\partial \tilde{I}_1}(1+r) \tag{12}$$

where tilde represents the unconstrained optimal. It is straightforward to show that $\lambda_B > 0$ implies $I_0/I_1 < \tilde{I}_0/\tilde{I}_1$. That is, the ratio of disposable income in period 0 to period 1 is less for credit constrained individuals. To derive sharp results for the effect of credit constraints on investment in human capital, additional structure is required.

Producer-Consumer Assumptions

A1. The credit constraint is binding: $\lambda_B > 0$

A2. The elasticity of marginal utility with respect to income is greater than unity: $-\frac{v''}{v'}I \geq 1$

Assumption A1 is necessary for credit constraints to be interesting and assumption A2 is supported by some empirical evidence (Layard et al., 2008). I assume that the representative agent treats factor prices and the credit constraint as exogenous (investing in human capital does not relax her credit constraint).

Because the credit constraint is binding, we can substitute $B = \theta G/(1+r)$ and solve for the optimal credit-constrained investment in human capital directly. Thus the first order condition for an interior solution is given by

$$q\frac{\partial v}{\partial I_0} = \rho \frac{\partial v}{\partial I_1}(1-\theta)w \tag{13}$$

where the wage rate of human capital is the first derivative of the national income function with respect to human capital $w = G_L$.

Result 1: *Investment in human capital is decreasing in the extent that households are credit constrained.*

Proof: Using the envelope theorem implies

$$\frac{dL}{d\theta} = \frac{-q\frac{\partial^2 v}{\partial I_0^2}\frac{G}{1+r} + \rho w\left[-I_1\frac{\partial^2 v}{\partial I_1^2} - \frac{\partial v}{\partial I_i}\right]}{\mathcal{H}} > 0 \tag{14}$$

where $\mathcal{H} > 0$ by the second-order condition.

Result 1 follows from concavity of indirect utility and assumption A2. Thus, Result 1 implies L is an increasing function of θ.

2.4 Pollution with Exogenous Environmental Policy

In this section, I consider the effect of credit constraints on pollution via investment in human capital. I hold the price of pollution permits constant ($\tau = \bar{\tau}$) to focus attention on the role of investment in human capital. Because environmental policy is exogenous, pollution can be decomposed into the so-called "scale" and "composition" effects according to the following expression

$$z = \bar{e}GS \tag{15}$$

where G is real national income (scale effect), and $S = x/G$ is the income share of industries producing good X (composition effect). Because the price of pollution permits are constant the emission intensity is also a fixed parameter. Thus, a percentage change in pollution can be represented as

$$\hat{z} = \hat{G} + \hat{S} \tag{16}$$

where $\hat{z} = dz/z$ and so on. The following assumption drives the main result.

Production Assumptions

A3. Sector X is capital-intensive relative to sector Y: $K_x/L_x > K_y/L_y$.

Aassumption A3 is strongly supported by some empirical evidence (Antweiler et al. 2001).

Result 2: *Under an exogenous environmental policy, pollution is decreasing in human capital.*

Proof: By the Rybczinski theorem, an increase in human capital stimulates the human-capital intensive sector, drawing factors from the dirty sector to the clean sector. That is,

$$\hat{z} = \epsilon_{xL}\hat{L} < 0 \tag{17}$$

where the term $\epsilon_{xL} < 0$ is the elasticity of output of good X with respect to human capital.

Using that $\hat{G} = s_L\hat{L} + s_z\hat{z}$, where s_L represents the labor's share of national income and s_z represents pollution's share, the reduced-form relationship between pollution and income is given by

$$\hat{z} = \frac{\epsilon_{xL}}{s_L + s_z\epsilon_{xL}}\hat{G} \tag{18}$$

where $s_L + s_z\epsilon_{xL}$ represents the elasticity of national income with respect to human capital, which is positive. That is, an increase in human capital decreases pollution and thus decreases income, but the net effect of an increase in human capital is strictly positive.

2.5 Pollution with Endogenous Environmental Policy

In this section, I consider the effect of credit constraints on pollution via investment in human capital, allowing for an endogenous policy response. I assume, for simplicity, that environmental policy is chosen to maximize utility. A well-known result in the environmental economics literature (López, 1994) is that marginal national income from an increase in pollution should equal the marginal rate of substitution between pollution and income (marginal damage in terms of income). That is,

$$G_z = MD(p, I, z) \tag{19}$$

where $MD = h'/v'$. Moreover, perfect competition implies that aggregate pollution satisfies $\tau = G_z$

Result 3: *Under an endogenous environmental policy, pollution is decreasing in human capital.*

Proof: Using the envelope theorem implies

$$\frac{dz}{dL} = \frac{G_{zl} - MD_I G_L}{MD_I G_z + MD_z - G_{zz}} \tag{20}$$

where subscript denotes partial derivatives. The denominator is positive by the second order condition.[6] The first term in the numerator represents the marginal change in the price of pollution permits with respect to human capital. That is, $G_{zL} = \partial\tau/\partial L$. Recall an increase in human capital diverts resource from the dirty sector by the Rybczinski theorem, which implies that the demand for pollution permits falls. The downward shift in the demand for pollution permits implies that the optimal price of pollution permits falls, $G_{zL} < 0$. Concavity of utility with respect to income and convexity with respect to pollution implies $MD_I > 0$ and $G_L = w > 0$. Thus, the numerator is strictly negative.

Result 4: *Under both exogenous and endogenous environmental policy, credit constraints increase pollution emissions.*

Proof: Follows from linking Results 1 and 2 in the case of exogenous environmental policy and Results 2 and 3 in the case of endogenous environmental policy.

Result 4 provides the primary empirical question to be tested. The reduced-form relationship between credit constraints and pollution emissions is given by

[6] This can be easily verified. MD_I is positive since $v'' < 0$ and similarly MD_z is positive since $h'' > 0$. Finally, concavity of the national income with respect to factor inputs is a standard result for income functions.

$$\frac{dz}{d\theta} = \frac{\partial z}{\partial L}\frac{dL}{d\theta} < 0 \tag{21}$$

where $\partial L/\partial\theta > 0$ is expressed in Result 1 and $\partial z/\partial L < 0$ is expressed in Results 2 and 3.

3 Empirical Analysis

3.1 Data

This section discusses the primary variables used. See Table (1) for complete list of sources and brief descriptions.

3.1.1 Credit Constraints

Two complementary approaches are used to investigate the impact of credit constraints on the environment.

First, private credit is used as a proxy for credit constraints. Private credit is the value of deposit money bank credit to the private sector.8 This measure includes credit to the private sector, as opposed to credit to governments, public enterprises, and central banks. While private credit does not directly measure credit constraints, several studies have interpreted private credit as a measure of financial intermediary development, including the mitigation of information and transaction costs and credit constraints. For example, private credit is a standard indicator in the financal development and growth literature and several studies have demonstrated that countries with higher levels of private credit experience faster economic growth and reduced poverty (Beck, Levine, and Loayza, 2000; Beck, Demirgüç-Kuntand Levine, 2007). The data are from Beck and Demirgüç-Kunt(2009) and are maintained by the World Bank for the years 1960 to 2010 for almost all country-years with air pollution data.

Second, following the theoretical literature on credit constraints, proxies for the "power" of creditors and informational asymmetries are used. Theories of credit constraints advance two main explanations. Firstly, lenders will be reluctant to lend to potential borrowers whenever their power to force repayment are circumscribed (Townsend, 1979; Aghion and Bolton, 1992; Hart and Moore, 1994).[7] Secondly, lenders will be reluctant to lend to borrowers whenever informational asymmetries exists. Thus, lenders will be more willing to extend credit whenever they know more about potential borrowers, including past credit histories and current indebtedness (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). These views are, of course, not mutually exclusiveÐboth power and information may play a role in credit constraints.

Motivated by power and informational theories of credit constraints, this paper uses variation in the legal rights of creditors against defaulting debtors (bankruptcy laws) and the existence of credit bureau registries as variation in credit constraints. The legal rights of creditors is an indicator variable indicating whether "secured creditors are able to seize their collateral after the petition for reorganization is approved" (Djankov et al., 2007). These bankruptcy laws were originally investigated by La Porta et al. (1997, 1998), and were significantly expanded and updated by Djankov et al. (2007). Credit registries provide information on a borrower's credit history and current indebtedness to lenders. Jappelli and Pagano (2002) show that credit registries are important determinants of credit availability. Because the value of credit agencies increases over time as additional years of credit histories are amassed and trust is consolidated, the number of years elapsed since the establishment of a nation's credit agency is employed as a proxy variable. The number of years squared is also used to reflect diminishing marginal value over time.

3.1.2 Air Pollution

Because the theoretical model is applicable to production-generated pollution, I focus on pollution emanating from production, rather than pollution emanating from consumption.

[7]The cited studies are the pioneering theoretical contributions. The literature is quite large and there are many more studiesÐboth empirical and theoretical.

López and Islam (2011) show that among air pollutants with consistent data (sulfur dioxide, lead, ozone, volatile organic compounds, and carbon monoxide), sulfur dioxide (SO_2) and lead are the main air pollutants generated from production sources.[8] The majority of SO_2 and lead pollution are generated as a by-product of electricity generation and industrial processes.

Data for air pollution (SO_2 and lead) are from the World Health Organization (WHO) Automated Meteorological Information System (AMIS), which is provided by the US Environmental Protection Agency (EPA). This data set has been used extensively in the literature and provides the most consistent measures of air pollution across countries and time. The data span from 1986 to 1999 and include 44 countries and 321 sites for SO_2 and 36 countries and 154 sites for lead. See Table (2) for a list of countries.

3.1.3 Additional Covariates

This paper follows López and Islam (2011) for choosing the remaining proxy variables. I use the Barro and Lee (2010) measure of human capital (L), which is piecewise linear function of the average number of years schooling. Investment as a percent of GDP is used as a proxy for physical capital, household consumption per capita for the income effect, GDP per land area for the scale effect, and an index of trade policy openness for the price index. Because there is not consistent data for the price of pollution, several indices of political institutions are used as proxies, including an index of democracy (Polity IV database) and regime stability (number of years since last regime change). GDP per capita growth controls for the capacity of institutions to adapt to a growing economy. Additional controls are discussed in the sensitivity analysis.

[8] López and Islam (2011) calculate the share of pollution emanating from (1) production, (2) consumption, or (3) both. The break-down for SO_2 is 80%, 2%, and 18%, whereas lead is 56%, 0%, and 44%

3.1.4 Summary Statistics

Table (3) presents the summary statistics for the main variables of interest and Table (4) presents the mean values for all variables by private credit quartile.[9] For example, the first column represents the mean values for all variables with private credit less than first quartile of the distribution. The values for private credit represent the mean of the quartile (not the quartile cut-offs). From Table (4), air pollution and human capital are increasing in private credit from the lowest quartile to the second quartile and then monotonically decreasing to the highest quartile.

Creditor Rights is a dummy variable indicating whether creditors can legally seize their collateral and Credit Bureau is the number of years since the establishment of a credit bureau registry. For the lowest private credit quartile, 28 percent of countries have creditor rights, whereas 69 percent of countries have creditor rights for the highest quartile. Similarly, credit bureau appears to be strongly related to private credit. Among the countries in the sample, seven do not have credit bureau registries at any point during span of the sample. Finally, private credit appears to be positively related to GDP per capita and positively related to the quality of political institutions.

3.2 Estimation Specification and Results

The baseline analysis employs the following linear estimation model is employed

$$\ln z_{ijt} = \beta_1 \theta_{jt-1} + \beta_2 \ln L_{jt-1} + \beta_3 \ln K_{jt-1} + \chi'_{jt}\Gamma + \eta_t + \epsilon_{ijt} \tag{22}$$

where i indexes pollution site stations, j indexes countries, and t indexes years. The variable z_{ijt} is pollution concentration (SO_2 and lead) at site i in country j, at time t.

Equation (22) is estimated using Ordinary Least Squares (OLS), Random Site Effects (RSE), and Fixed Site Effects (FSE) for sulfur dioxide (SO_2) and lead. RSE and FSE

[9] Quartile refers to blocks of 25% of the data.

control for unobservable site characteristics (random and fixed effects).

Tables (5) and (6) present the coefficient estimates for the dependent variables lead and SO_2 concentration, respectively. Specifications (1) - (3) use private credit as variation in credit constraints, whereas specification (4) uses proxies for credit constraints. As mentioned, the proxy variables include an indicator variable for whether creditors are permitted to seize their collateral after bankruptcy (Creditor Rights) and the number of years elapsed since the establishment of a credit bureau registry (Credit Bureau).

Recall the number of sites measuring lead is significantly smaller than the number of sites measuring SO_2, and the samples are not strictly nested. The R-squared is commensurate with previous studies, demonstrating that the goodness-of-fit is satisfactory in all specifications. The R-squared appears higher for the lead model, which might be due to a number of factors. The RSE over identification test casts doubt on the random effects orthogonality assumptions; thus, FSE results are perhaps more reliable.

As predicted by the model, the estimates for human capital are negative and significant at conventional significance levels, with the exception of the OLS specifications. Due to unobservable characteristics across both countries and sites, OLS estimates are likely to suffer from severe bias. The human capital estimates for lead are all significant at the 1 percent level, with the exception of one specification which is significant at the 5 percent level. Moreover, the human capital estimates for SO_2 are all significant at the 1 percent level. The estimates for human capital in the FSE specification range between -1.6 and -3.1 for lead, and between -0.7 and -0.9 for SO_2 concentration.

Using specification (3), the interpretation of the FSE estimates for human capital imply that an increase in the human capital index by 1 unit reduces lead and SO_2 pollution concentrations by 160 and 70 percent, respectively. Moreover, an increase in human capital by one standard deviation reduces lead and SO_2 pollution concentrations by approximately 0.54 and 0.22 standard deviations at the mean. The estimates therefore indicate that human capital is an important determinant of air pollution, both in terms of statistical significance and quantitative magnitude.

Similarly, the estimates for private credit are negative and significant at all conventional significance levels, with the exception of the OLS estimates and the RSE estimates for SO_2 concentration. Specification (3) implies that a 10 percent increase in private credit reduces lead and SO_2 concentrations by 6.8 and 2.4 percent, respectively. Moreover, an increase in private credit by one standard deviation reduces lead and SO_2 pollution concentration by approximately 1.38 and 0.49 standard deviations at the mean, respectively. Thus, the estimates indicate that private credit is an important determinant of air pollution.

The estimates for creditor rights are mostly insignificant, whereas the estimates for credit bureau are negative and significant at all significance levels. The squared term is positive, as expected from decreasing marginal value over time, but only significant in one specification. That creditor rights is insignificant can be interpreted in a number of ways. One interpretation is that credit constraints are not, in fact, determined by the particular bankruptcy laws considered. Another interpretation is that bankruptcy laws are relevant to credit constraints only insofar as credit constraints impinge on investment in human capital. In other words, the impact of credit constraints on pollution is only via investment in human capital. Thus, credit constraints do not influence pollution after controlling for the level of human capital. Using a two-stage procedure (section 3.5.2) and a back-of-the envelope calculation implies that roughly 90 percent of the impact of bankruptcy laws on pollution are via investment in human capital, which suggests that the latter explanation is plausible.

The estimates of the remaining variables are mostly consistent with the literature, but very few are significant after controlling for fixed effects. The estimates for GDP to land size (proxy for the scale effect) in the FSE specifications are mostly positive and significant as expected, although one is negative and several are insignificant. The estimates for household consumption (proxy for income effect) are positive and significant in several specifications, contrary to expectations.[10] The political economy variables indicate that

[10]López and Islam (2011) also find a positive income effect.

greater democracy and stability are associated with less pollution; however, the relationship is not particularly robust. The remaining variables do not appear to be significant or have contradictory signs.

3.2.1 Seemingly Unrelated Regressions (SURE)

While the model can be estimated equation-by-equation for lead and SO_2, the estimates are in general not as efficient when the error terms are correlated, which suggests employing seemingly unrelated regression equation (SURE) estimations. Because the number of site-year observations with both lead and SO_2 data are limited, the efficiency gained from employing SURE may not outweigh the efficiency loss due to restricting the sample. This sample restriction might also exacerbate selection bias.

Table (9) presents the estimates using SURE. Because each equation contains exactly the same set of regressors, the coefficients should not change from the equation-by-equation estimates. Similar to the equation-by-equation estimations, all of the estimates for private credit and credit constraint proxies are negative and significant at the 1 percent level, with the exception of one estimate, which is significant at the 5 percent level. The estimates for human capital, especially for SO_2, are significantly larger using SURE, which is purely a consequence of selection bias, whereas the estimates for private credit are relatively unchanged.

3.3 Sensitivity Analysis

While the FSE estimations control for time-invariant unobservable site characteristics, the presence of time-varying omitted variables could bias the estimated coefficients. To mitigate omitted variable bias, this paper employs a procedure referred to as added controls. The added controls approach (Altonji et al. 2005) employs several sets of additional control variables in turn to reduce the possibility of omitted variable bias. The controls chosen need not be directly related to the dependent variable, but should be correlated with omitted variables. An increase in the goodness-of-fit of the model with added controls, while maintaing consistent estimates of the variables of interest, reduces the likelihood of bias due to omitted variables.

Because inequality exacerbates credit market imperfections (Aghion et al., 1999), heterogeneous effects are explored by income GINI coefficients.[11] This serves as both a robustness check and as a further avenue of exploration. Finally, I employ iteratively reweighted least squares (IRWLS) to mitigate the influence of outliers.

3.3.1 Added Controls

Several studies find that political institutions (Deacon, 2009), financial development (Tamazian et al., 2009), and demography and income (Copeland and Taylor, 2004), are related to pollution, either as a consequence of promoting economic development or the provision of environmental services.[12] The added controls sensitivity analysis introduces a set of control variables for each of the aforementioned determinants in turn.

The variables included in the political institutions controls (Governance) include a nationÕs Polity score, which is a standard measure of governance ranging from -10 (most autocratic) to +10 (most democratic) and a dummy for proportional representation. Foreign direct investment and deposit bank assets (Finance) are associated with economic performance in general and investment in particular, but are not directly related to credit constraints. Finally, GDP per capita (additional proxy for income), life expectancy at birth, population, and population density (Demography and Income) are likely correlated with household characteristics, such as environmental and consumption preferences, which affect pollution emanating from consumption, rather than pollution emanating from production.

[11] Aghion et al. (1999) survey the literature on inequality and growth. One possible explanation, among many, for the result is that human capital formation depends on fixed factors and therefore exhibits diminishing returns.

[12] Demography and income are related to the EKC literature, which was discussed in the introduction. Copeland and Taylor (2004) provides a survey of the literature.

Table (8) reports the estimates for private credit using the baseline FSE specification and added sets of controls.[13] Note that adding additional controls reduces the number of observations due to missing variables, which might exacerbate selection bias. In all specifications, the added controls increase the goodness-of-fit (adjusted R-squared), although only modestly.[14] The estimates for human capital are negative and significant at conventional significance levels (ranging between 1 percent and 10 percent significance levels). The estimates for private credit are negative and significant at the 1 percent significance level, except in one specification, which is significant at the 10 percent significance level.

3.3.2 Further Robustness Checks

Table (9) reports estimates using iteratively reweighted least squares (IRWLS) and exploring heterogeneous effects. IRWLS mitigates the influence of outliers using a maximum likelihood estimator for a general linear model. The estimates for human capital and credit are significant at conventional significance levels.

Next, private credit is interacted with a dummy for sites in countries with income GINI coefficients above the median in 1980, which estimates the elasticity of pollution for sites in countries with income inequality above and below the median.[15] The estimated elasticities for private credit for SO_2 and lead concentrations in countries with income inequality below the median are -0.27 and -0.29, whereas the elasticity for countries with income inequality above the median are -0.39 and -0.94, respectively. The SO_2 estimate for countries with income inequality above the median is significant at all conventional significance levels but it is not significantly different from the estimate for countries with income inequality below the median. The lead estimate for countries above the median is significant at all

[13] The results are similar using the proxies for credit constraints (not reported). The sensitivity analysis employs the identical set of controls as the FSE specification reported in Tables (5) and (6).

[14] The adjusted R-squared without added controls varies across specifications because the estimations are performed only on the observations without missing data for the added controls. Thus, the comparison of the adjusted R-squared is for identical samples.

[15] If a nationÕs income GINI coefficient is unavailable in 1980, the first available year is used. Most countries do not have annual data for this variable (it is typically calculated from census data); thus, the effect of income inequality cannot be identified in models employing fixed effects.

significance levels and it is significantly different from the coefficient estimate for countries below the median. Thus, the impact of private credit on pollution is more than double in countries with higher income inequality for lead concentration.

3.4 Two-Stage Procedure

Employing a two-stage procedure achieves two objectives. First, human capital and private credit are determined by a number of factors that are unobservable and potentially related to pollution. Thus, instrumental variables mitigates the problem of endogeneity. Second, employing a two-stage procedure can shed light on the impact of credit constraints on pollution via investment in human capital.

Consider the following first-stage equation

$$\ln L_{jt} = Q'_{jt}\tilde{\Omega} + \chi'_{jt}\tilde{\Gamma} + \tilde{\nu}_i + \tilde{\eta}_t + \tilde{\varepsilon}_{jt} \tag{23}$$

where L_{jt} is human capital and Q_{jt} is a vector of excluded instruments and the other variables are identical to (24). Similarly, private credit is given by

$$\ln \theta_{jt} = Q'_{jt}\Omega + \chi'_{jt}\breve{\Gamma} + v_i + n_t + u_{jt} \tag{24}$$

The predicted values are then used in the second stage estimations using several approaches. First, I use the predicted value of human capital, along with either private credit or proxies for credit constraints, in the second stage equation. That is,

$$\ln z_{ijt} = \zeta \ln \theta_{jt} + \psi \widehat{\ln L_{jt}} + \chi'_{ijt}\Gamma + \nu_{ij} + \eta_t + \varepsilon_{ijt} \tag{25}$$

where θ represents either private credit or proxies for credit constraints. Second, I use both the predicted values of human capital and private credit in the second stage equation. That is,

$$\ln z_{ijt} = \zeta \widehat{\ln \theta_{jt}} + \psi \widehat{\ln L_{jt}} + \chi'_{ijt}\Gamma + \nu_{ij} + \eta_t + \varepsilon_{ijt} \tag{26}$$

3.4.1 Selection of Instruments

Estimation of (27) requires a set of instruments correlated with human capital, but not correlated with the error term in (27). Similarly, estimation of (28) requires a set of instruments correlated with human capital and private credit, but not correlated with the corresponding error term. Equation (27) is estimated using lagged (35 years) human capital as an instrument for human capital. Longer lags are desirable to reduce the likelihood that the instrument is correlated with the error term, assuming the variable is not a weak instrument. The lagged value squared is also used to improve goodness-of-fit and to allow for an over identification test. The underlying assumption is that lagged human capital is correlated with pollution only insofar as it is correlated with contemporaneous human capital.

Equation (28) is estimated using the proxies for credit constraints, as well as lagged human capital. The underlying assumption is that credit laws and credit bureau registries influence pollution only insofar as they are related to private credit. One concern is that political economy factors shape both environmental policy and laws influencing creditor rights. La Porta et al. (1997, 1998) and Djankov et al. (2007) argue that legal origin as well as culture and religion are important determinants of both creditor laws and the presence of credit registries. Economic development certainly plays an important role in determining credit laws and institutions, as well as government policies more generally. Using the number of years since the establishment of a nationÕs credit bureau, however, reduces the possibility that both are simultaneously determined due to separation of time. Finally, because there are more excluded instruments than endogenous variables, an over identification test can be performed to provide suggestive evidence of exogeneity.

3.4.2 2SLS Results

Table (10) presents the coefficient estimates using two-stage least squares (2SLS). Panel A reports the second-stage results, whereas Panel B reports the first-stage results. Variables under the Endogenous Variables title in Panel A are instrumented variables, whereas variables under the Exogenous Variables title in Panel A are treated as exogenous (reduced form) in the second stage. All specifications treat human capital as endogenous, using lagged human capital as an instrument. Specifications (1) and (4) use private credit as an exogenous variable in the second stage, whereas specifications (2) and (5) use proxies for credit constraints as exogenous variables in the second stage. Finally, specifications (3) and (6) treat human capital and private credit as endogenous, using the proxies for credit constraints as excluded instruments.

The first-stage estimates suggest that the instruments are relevant as evidenced by the test of joint significance. The robust F-test exceeds all conventional tests for weak instruments. Note that only the robust joint F-test, not the coefficient estimates, for lagged human capital are reported to save space.

Consistent with the previous results, private credit and credit bureau are negatively related to pollution when employed as exogenous variables in the second equation. The estimates for human capital are all negative and significant at all conventional significance levels SO_2. However, only one of the three estimates for human capital is significant for the lead (significant at the 1 percent level).

Because the endogenous variables are over identified in all specifications, an over-identification test can provide suggestive evidence of exogeneity of the excluded instruments. The over-identification test is not rejected in all specifications, except for two specifications (2 and 5), suggesting that the instruments are not endogenous. One possible reason the over-identification test is rejected in specifications (2) and (5) (and not in the others) is that lagged human capital is correlated with components of contemporaneous private credit that are not accounted for by the excluded instruments. After controlling for private credit, however, lagged human capital is no longer correlated with the error term.

The first-stage estimates demonstrate a number of relationships. First, the proxies for credit constraints are important determinants of private credit. In all specifications, the relationships between the credit constraint proxies and private credit are positive and significant at all conventional significance levels. Second, the proxies for credit constraints are also important determinants of human capital. The relationship between the credit constraint proxies and human capital are positive and significant at the 1 percent significance level, with one exception that is significant at the 5 percent significance level (specification 3).

While the point estimates in the first stage may be imprecise, it is possible to derive the contribution of credit constraints on pollution via investment in human capital using a back-of-the-envelope calculation. Using specification (3), the impact of collateral laws (increase from 0 to 1) via human capital on SO_2 concentration represents roughly 90 percent of the total impact of collateral laws on SO_2. Similarly, the impact of credit bureau (increase in one year elapsed) via human capital on SO_2 represents roughly 26 percent of the total impact of credit bureau agencies on SO_2. Thus, the impact of collateral laws and a one-year increase in credit bureau via human capital represents roughly 63 percent of the total impact on SO_2 concentration. The results indicate that the impact of credit constraints via in pollution is an important component of the total effect of credit constraints on pollution. This also sheds light on possible explanations why the estimates for collateral laws are not significant in the reduced-form specifications after controlling for human capital.

3.5 Summary of Findings

Based on the fixed site effects (FSE), the reduced-form results generally support the following conclusions:

1. Aggregate human capital is negatively related to pollution
2. Aggregate private credit is negatively related to pollution (partial effect)
3. Proxies for credit constraints, including bankruptcy laws and the presence of credit bureau agencies, are positively related to pollution

Based on the two-stage procedure, the results generally support the following conclusions:

1. The partial effects in the single-stage procedure are supported using a two- stage procedure
2. Credit constraints are negatively associated with private credit and investment in human capital

4 Conclusion

This paper is the first to explore the effect of credit constraints on the environment. I develop a simple theoretical model where credit constraints impinge on investment in human capital, which in turn orients production towards sectors employing pollution more intensively. Moreover, the effect of credit constraints on the environment is reinforced by endogenous environmental policies, which offset the reduction in human capital by devoting less resources to abatement.

The main insight of the model is explored using production-generated air pollution (SO_2 and lead concentration), measured at over 250 sites across both low and high-income countries. The results suggest that credit constraints increase pollution via investment in human capital as well as other channels. These results pass a battery of sensitivity analysis using a rich set of added controls, seemingly unrelated equation estimations, and various other sensitivity checks. Furthermore, using a two-stage procedure demonstrates the intermediate relationship between credit constraints and human capital.

Table 1: Variable Descriptions

Variable	Description	Available	Source
SO_2	Sulfur Dioxide concentration, micrograms per cubic meter	1986-1999	WHO-AMIS
Lead	Lead, micrograms per cubic meter	1986-1999	WHO-AMIS
Human Capital	Human Capital Index, methodology by Hall and Jones, 1999	1960-2010	Barro and Lee (2010)
Credit	National private credit by deposit money banks	1960-2010	Beck and Demirgüç-Kunt (2012)
Investment	Gross Capital Formation	1950-2010	Penn World Tables (2012)
Government Consumption	Share of Government Consumption Expenditures	1950-2010	Penn World Tables (2012)
Household Consumption	Market value of all final goods and services purchased by households and imputed rents	1960-2010	World Bank, World Development Indicators (WDI)
Growth GDP	Real GDP per capita Growth in 2005$	1960-2010	WDI
Ratio GDP to Land Area	Ratio of GDP per capita to Land Area (km^2)	1960-2010	WDI
Openness Index	Exports + Imports as percentage of GDP	1950-2010	Penn World Tables
Index of Democracy	Index composed of competitiveness of political participation, openness and competitiveness of executive recruitment, and constraints on the chief executive (additive eleven-point scale 0-10). (DEMOC)	1800-2010	Polity IV (2010) (www.systemicpeace.org/inscr)
Regime Stability	The number of years since the most recent regime change or the end of transition period defined by the lack of stable political institutions	1800-2010	Polity IV
Polity Score	Composite Index of Index of Democracy and Index of Autocracy (subtracting autocracy score from democracy score), ranging from +10 (strongly democratic) to -10 (strongly autocratic) (POLITY2)	1800-2010	Polity IV
Proportional Representation	Indicator variable for proportional representation	1975-2010	Keefer, P. Database of Political Institutions, World Bank (2009)
Tax Receipts	Total government tax revenue	1960-2010	WDI
Foreign Direct Investment	Net inflows of foreign direct investment	1960-2010	WDI
Primary School Completion Rate	Primary completion rate, total (% of relevant age group)	1960-2010	WDI
Life Expectancy	Life expectancy at birth, total (years)	1960-2010	WDI
Population	Total Population	1960-2010	WDI
Poplulation Density	Population per land area (km^2)	1960-2010	WDI
Site Characteristics	Dummy variables indicating site is located in city centre, commercial, industrial, residential, or other	1986-1999	WHO-AMIS
Creditor Rights	Indicator variable indicating whether the laws permit secured creditors to seize their collateral after bankruptcy	1978-2003	Djankov et al. (2007)
Credit Bureau	The number of years elapsed since the establishment of a private credit bureau registry	1978-2003	Djankov et al. (2007)

Table 2: List of countries in SO_2 and lead estimations (and # observations)

SO_2				Lead			
Argentina	29	Japan	57	Argentina	8	Japan	54
Australia	43	Korea, Rep.	100	Australia	55	Korea, Rep.	40
Austria	36	Kuwait	18	Belarus	7	Kuwait	11
Belgium	46	Latvia	55	Belgium	8	Latvia	35
Brazil	101	Lithuania	153	Bulgaria	78	Lithuania	39
Bulgaria	78	Mexico	161	Canada	41	Mexico	72
Canada	44	New Zealand	27	China	39	New Zealand	39
Chile	15	Peru	4	Costa Rica	15	Nicaragua	3
China	344	Philippines	20	Croatia	35	Panama	9
Colombia	12	Portugal	18	Denmark	6	Peru	4
Costa Rica	5	Romania	32	Ecuador	3	Portugal	14
Croatia	42	South Africa	55	El Salvador	15	Romania	12
Cuba	8	Spain	58	Finland	27	South Africa	18
Denmark	6	Sweden	2	France	11	Switzerland	19
Ecuador	47	Switzerland	28	Germany	92	Thailand	21
Estonia	3	Thailand	7	Guatemala	24	United Kingdom	34
Finland	32	Turkey	99	Honduras	18	United States	22
France	148	United Kingdom	124	India	68	Venezuela, RB	30
Germany	247	United States	26				
Greece	38	Uruguay	5				
Hungary	58	Venezuela, RB	4				
India	279						

Table 3: Summary Statistics: Main Variables

	Mean	S.D.	Min	Q_1	Median	Q_3	Max
SO_2	37	43	0	12	23	43	430
Lead	0.25	0.37	0.00	0.06	0.13	0.28	3.84
Credit (per capita)	8,608	17,287	7	767	2,113	8,585	117,381
Human Capital	2.4	0.5	1.5	2.0	2.5	2.8	3.5
Creditor Rights (dummy)	0.47	0.50	0.00	0.00	0.00	1.00	1.00
Credit Bureau (years)	15.2	23.7	0.0	0.0	1.0	22.0	99.0

Table 4: Summary Statistics by Credit Quartile: All variables by mean

Credit Quartile	$\mathbf{Q}_1$	$\mathbf{Q}_2$	$\mathbf{Q}_3$	$\mathbf{Q}_4$	Average
SO2 (micrograms/meter)	35	57	33	23	37
Lead (micrograms/meter)	0.16	0.51	0.21	0.12	0.24
Credit (per capita)	283	1,292	4,426	29,212	8,608
Human Capital	2.53	2.03	2.43	2.67	2.42
Creditor Rights (dummy)	0.28	0.38	0.52	0.69	0.46
Credit Bureau (years)	0.2	9.8	21.0	30.4	15.2
GDP (per capita)	728	3,571	12,222	22,198	9,561
Investment (%GDP)	23.4	20.9	21.9	22.6	22.2
Government Consumption (%GDP)	13.5	8.9	7.2	7.1	9.3
Household Consumption (per capita)	458	2,197	7,240	13,119	5,737
Growth GDP	5.9	3.7	3.2	2.2	3.7
GDP to Area (thousands)	90	196	1,306	4,617	1,523
Openness Index	30	39	46	41	39
Index of Democracy	6.1	5.8	7.2	9.8	7.1
Regime Stability	33	12	47	53	35
Polity Score	4.2	5.3	8.6	9.8	6.7
Proportional Representation	0.96	0.98	0.82	0.57	0.82
Tax Receipts (% GDP)	9.3	12.8	15.1	17.2	12.9
Foreign Direct Investment	1.1	2.5	1.5	1.2	1.6
Deposit Bank Assets (%GDP)	41	40	69	126	68
Primary School Completion Rate	92	94	98	97	95
Life Expectancy	64	70	74	77	71
Population (millions)	741	184	40	70	260
Population Density	199	63	131	200	148
Income GINI	34	47	45	32	42

Table 5: Lead estimates using Ordinary Least Squares (OLS), Random Site Effects (RSE), and Fixed Site Effects (FSE)

	(1) OLS	(2) RSE	(3) FSE	(4) FSE
Human Capital	-0.214	-0.823***	-1.600**	-3.082***
	(0.182)	(0.294)	(0.646)	(0.699)
Credit	-0.148***	-0.270***	-0.683***	
	(0.039)	(0.053)	(0.090)	
Creditor Rights				0.089
				(0.129)
Credit Bureau				-0.141***
				(0.021)
Credit Bureau (squared)				0.002***
				(0.000)
Investment	-0.209*	0.332**	-0.482**	-0.460**
	(0.119)	(0.160)	(0.205)	(0.188)
Government Consumption	-1.368***	-0.292	-0.418	-0.101
	(0.151)	(0.215)	(0.323)	(0.187)
Household Consumption	-0.348***	0.297*	2.187***	2.062***
	(0.095)	(0.156)	(0.719)	(0.670)
GDP growth	-0.008	0.012	-0.018**	-0.004
	(0.012)	(0.007)	(0.008)	(0.007)
GDP to Area	0.111**	0.077	1.242**	-0.129
	(0.046)	(0.097)	(0.621)	(0.643)
Openness Index	0.011***	-0.000	-0.010*	-0.001
	(0.003)	(0.003)	(0.005)	(0.003)
Democracy Index	-0.013***	-0.001	0.004	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Regime Stability	-0.002*	-0.003*	-0.011***	-0.007*
	(0.001)	(0.002)	(0.004)	(0.004)
R^2	0.444	0.555	0.597	0.551
Observations	692	692	692	759
Number of sites	133	133	133	136
Sargan-Hansen Test (p-value)		0.000		

Note: All estimations include year dummies and OLS includes site-specific characteristics (dummies for city centre, commercial, industrial, residential, or other). All prices in 2005 US$. Human capital methodology by Hall and Jones (1999). Credit is private credit by deposit money banks. Creditor Rights is an dummy variable indicating whether creditors are permitted to seize their collateral after bankruptcy. Credit Bureau is the number of years elapsed since the establishment of a private credit bureau registry. Human Capital, Credit, Creditor Rights, Credit Bureau, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, and all institutional indices. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: SO_2 estimates using Ordinary Least Squares (OLS), Random Site Effects (RSE), and Fixed Site Effects (FSE)

	(1) OLS	(2) RSE	(3) FSE	(4) FSE
Human Capital	0.038	-0.528***	-0.655***	-0.943***
	(0.099)	(0.140)	(0.243)	(0.258)
Credit	0.102***	-0.032	-0.242***	
	(0.028)	(0.029)	(0.053)	
Creditor Rights				-0.049
				(0.055)
Credit Bureau				-0.059***
				(0.010)
Credit Bureau^2				0.000
				(0.000)
Investment	-0.195	0.341***	0.130	0.068
	(0.121)	(0.086)	(0.117)	(0.092)
Government Consumption	-0.637***	-0.206**	-0.050	0.118
	(0.073)	(0.096)	(0.129)	(0.094)
Household Consumption	-0.211***	0.031	-0.011	0.813***
	(0.038)	(0.065)	(0.318)	(0.313)
GDP growth	0.017**	0.018***	0.007	0.010***
	(0.008)	(0.003)	(0.004)	(0.004)
GDP to Area	0.019	0.053	0.737***	-0.545*
	(0.019)	(0.050)	(0.254)	(0.282)
Openness Index	-0.001	-0.004	-0.001	0.005***
	(0.002)	(0.002)	(0.003)	(0.002)
Democracy Index	-0.015***	-0.003*	-0.001	-0.002
	(0.004)	(0.001)	(0.002)	(0.001)
Regime Stability	-0.003***	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
R^2	0.233	0.221	0.208	0.223
Observations	1,831	1,831	1,831	2,071
Number of sites	293	293	293	294
Sargan-Hansen Test (p-value)		0.000		

Note: All estimations include year dummies and OLS includes site-specific characteristics (dummies for city centre, commercial, industrial, residential, or other). All prices in 2005 US$. Human capital methodology by Hall and Jones (1999). Credit is private credit by deposit money banks. Creditor Rights is an dummy variable indicating whether creditors are permitted to seize their collateral after bankruptcy. Credit Bureau is the number of years elapsed since the establishment of a private credit bureau registry. Human Capital, Credit, Creditor Rights, Credit Bureau, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, and all institutional indices. Standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 7: Seemingly Unrelated Estimation (SURE) of SO_2 and Lead

	(SURE I)		(SURE II)	
Variables	SO_2	Lead	SO_2	Lead
Human Capital	-4.412***	-2.196***	-3.467***	-2.241***
	(0.711)	(0.746)	(0.698)	(0.759)
Credit	-0.184**	-0.775***		
	(0.087)	(0.091)		
Creditor Rights			-0.104	0.006
			(0.106)	(0.115)
Credit Bureau			-0.042**	-0.136***
			(0.017)	(0.019)
Investment	-0.069	-0.465**	-0.114	-0.576***
	(0.199)	(0.209)	(0.171)	(0.186)
Government Consumption	-1.004***	-0.539*	0.008	-0.411**
	(0.272)	(0.286)	(0.154)	(0.168)
Household Consumption	1.074	1.140	1.536***	2.777***
	(0.735)	(0.771)	(0.594)	(0.646)
GDP growth	0.004	-0.022***	0.004	-0.004
	(0.007)	(0.007)	(0.006)	(0.007)
GDP to Area	0.546	3.037***	-0.687	-0.668
	(0.600)	(0.629)	(0.553)	(0.602)
Openness Index	-0.004	0.004	0.005*	0.002
	(0.005)	(0.005)	(0.002)	(0.003)
Democracy Index	-0.002	0.005**	-0.005**	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Regime Stability	-0.013***	-0.015***	-0.003	-0.013***
	(0.005)	(0.005)	(0.004)	(0.004)
R^2	0.922	0.933	0.910	0.912
Observations	468	468	532	532

Note: All estimations include year dummies and OLS includes site-specific characteristics (dummies for city centre, commercial, industrial, residential, or other). All prices in 2005 US$. Human capital methodology by Hall and Jones (1999). Credit is private credit by deposit money banks. Creditor Rights is an dummy variable indicating whether creditors are permitted to seize their collateral after bankruptcy. Credit Bureau is the number of years elapsed since the establishment of a private credit bureau registry. Human Capital, Credit, Creditor Rights, Credit Bureau, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, and all institutional indices. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: Robustness checks (added controls) using Fixed Site Effects (FSE)

Variables	(1) SO_2	(2) Lead	(3) SO_2	(4) Lead	(5) SO_2	(6) Lead
Human Capital	-0.431*	-2.636***	-0.693**	-2.937***	-0.485*	-1.687**
	(0.239)	(0.727)	(0.288)	(0.785)	(0.248)	(0.678)
Credit	-0.290***	-0.572***	-0.298***	-0.247*	-0.299***	-0.674***
	(0.054)	(0.109)	(0.065)	(0.134)	(0.056)	(0.099)
	Governance					
Polity Score	-0.044***	-0.010				
	(0.013)	(0.023)				
Proportional Representation	1.116***	-0.310				
	(0.148)	(0.189)				
			Finance			
Foreign Direct Investment			0.007	0.059**		
			(0.015)	(0.027)		
Deposit Assets			0.137	-0.509***		
			(0.088)	(0.183)		
					Demography & Income	
GDP					-5.358***	4.916***
					(0.875)	(1.587)
Life Expectancy					-0.130***	0.078
					(0.029)	(0.078)
Population					-3.652**	2.693
					(1.536)	(3.037)
Population Density					-0.008***	0.004
					(0.002)	(0.006)
Adjusted R^2	0.161	0.534	0.029	0.531	0.101	0.549
Adjusted R^2 (w/o added controls)	0.111	0.528	0.028	0.524	0.072	0.522
Observations	1,636	656	1,762	658	1,831	692
Number of sites	267	130	292	132	293	133

Note: All estimations include year dummies and OLS includes site-specific characteristics (dummies for city centre, commercial, industrial, residential, or other). All prices in 2005 US$. Human capital methodology by Hall and Jones (1999). Credit is private credit by deposit money banks. Creditor Rights is an dummy variable indicating whether creditors are permitted to seize their collateral after bankruptcy. Credit Bureau is the number of years elapsed since the establishment of a private credit bureau registry. Human Capital, Credit, Creditor Rights, Credit Bureau, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, Primary School Completion Rate, Life Expectancy, and Population Density and all institutional indices. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: Iteratively Reweighted Least Squares (IRWLS) and Heterogeneous Effects

	IRWLS		Heterogeneous Effects	
	(1)	(2)	(3)	(4)
	SO_2	Lead	SO_2	Lead
Human Capital	-0.331*	-0.947*	-0.632**	-0.975
	(0.196)	(0.488)	(0.296)	(0.796)
Credit	-0.472***	-0.752***	-0.267***	-0.289**
	(0.043)	(0.064)	(0.068)	(0.115)
Credit × High Income GINI			-0.122	-0.647***
			(0.080)	(0.151)
Investment	-0.204**	-0.800***	0.141	-0.332*
	(0.093)	(0.149)	(0.126)	(0.199)
Government Consumption	0.163	-0.676***	-0.182	-0.553*
	(0.103)	(0.233)	(0.148)	(0.327)
Household Consumption	0.624**	1.777***	0.211	1.541**
	(0.255)	(0.529)	(0.337)	(0.686)
GDP growth	-0.006*	-0.025***	0.005	-0.011
	(0.003)	(0.006)	(0.004)	(0.008)
GDP to Area	0.870***	2.166***	0.732***	1.723***
	(0.203)	(0.451)	(0.271)	(0.601)
Openness Index	0.004**	-0.009**	-0.002	0.004
	(0.002)	(0.004)	(0.003)	(0.005)
Democracy Index	0.001	0.004**	-0.000	0.005**
	(0.001)	(0.002)	(0.002)	(0.002)
Regime Stability	-0.000	-0.010***	-0.001	-0.012***
	(0.001)	(0.003)	(0.002)	(0.004)
R^2	0.944	0.959	0.216	0.646
Observations	1,686	628	1,643	618
Number of sites			284	123

Note: All estimations include year dummies. All prices in 2005 US$. All estimations use identical controls as baseline model (omitted from table to save space). Credit is private credit by deposit money banks. Deposit Bank Assets is Deposit Bank Money Assets. Credit, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, Primary School Completion Rate, Life Expectancy, and Population Density and all institutional indices. Robust errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 10: Pollution estimates using 2SLS

Dependent Variables	(1) SO_2	(2) SO_2	(3) SO_2	(4) Lead	(5) Lead	(6) Lead
Panel A: 2SLS						
Endogenous Variables:						
Human Capital	-3.634***	-3.881***	-2.682***	-1.588	-4.805***	-0.412
	(0.643)	(0.558)	(0.729)	(1.368)	(1.237)	(1.011)
Credit			-0.643***			-0.916***
			(0.152)			(0.111)
Exogenous Variables:[a]						
Credit	-0.261***			-0.638***		
	(0.058)			(0.087)		
Collateral Laws		0.018			-0.032	
		(0.060)			(0.128)	
Credit Bureau		-0.029***			-0.087***	
		(0.009)			(0.020)	
Over-identification p-value	0.475	0.041	0.442	0.579	0.052	0.121
Observations	1665	1821	1663	615	682	615
Number of Sites	265	267	264	110	113	110

Panel B: First Stages						
Human Capital Instruments:[b]						
Collateral laws			0.028***			0.024***
			(0.008)			(0.008)
Credit Bureau			0.006**			0.011***
			(0.002)			(0.002)
F-test (robust)	26.00	20.81	20.52	16.86	19.45	43.85
Credit Instruments:						
Collateral laws			0.126***			0.286***
			(0.030)			(0.056)
Credit Bureau			0.073***			0.105***
			(0.008)			(0.018)
F-test (robust)			22.29			22.14

Note: Specifications (1), (2), (4), and (5) instrument for only Human Capital, whereas specifications (3) and (6) instrument for both Human Capital and Credit. [a]Exogenous Variables indicates that variables are used (directly) in the second stage (not instrument). [b]Lagged human capital (35 years) and its squared term are used as excluded instruments (coefficients not reported). All estimations include year dummies and identical controls as baseline model (omitted from table to save space). All prices in 2005 US$. Human capital methodology by Hall and Jones (1999). Credit is private credit by deposit money banks. Creditor Rights is an dummy variable indicating whether creditors are permitted to seize their collateral after bankruptcy. Credit Bureau is the number of years elapsed since the establishment of a private credit bureau registry. Human Capital, Credit, Creditor Rights, Credit Bureau, Investment, and Government Consumption are lagged one year. All variables are in log form, except Growth GDP, Openness Index, and all institutional indices. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Chapter 3: Do Tax Cuts Encourage Rent Seeking by Top Corporate Executives? Theory and Evidence

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1. Introduction

The soaring top income shares in the United States (the so-called "one percent") have ignited significant controversy in both public opinion and academic discourse. Adding fuel to the flames is the growing sense of incompetence, corruption, and greed, of corporate executives, especially in the financial sector, exposed in the wake of the great recession. Lavish pay, coupled with yawning federal budget deficits and shrinking public services, has generated growing public support for greater taxation on the rich. Defenders of the one percent point out the "big tradeoff" between equality and efficiency.[1] Since economic growth and job creation after the recession has been tepid, a particularly pressing policy question is how much money is lost or "leaked" as a consequence of taxing top income earners.

It is well known that incomes are far less equal today than previous generations. Perhaps the most cited figure is the doubling of the share of the top 1 percent from less than 10 percent in the 1970s to over 20 percent the late 2000s (Piketty and Saez, 2003). The rise in top income shares is largely driven by income growth of executives (managers and supervisors) and financial professionals, which together account for 58 and 67 percent of income growth of the top 1 and 0.1 percent, respectively (Bakija, Cole, and Heim, 2010). Moreover, because corporate executive pay contracts are inconsistent with

[1]The "big tradeoff" alludes to Arthur Okun's prominent book "Equality and Efficiency: The Big Tradeoff." Mankiw (2013) offers a contemporary defense of inequality and the one percent in particular.

principles of optimal contract design, there is growing evidence that executive pay, especially in recent decades, largely consists of economic rents.[2] We therefore focus on executives to gain insight into the consequences of rising inequality and the potential cost of reversing recent trends.

In both in the US and other English-speaking countries, there is a strong long-run correlation between tax cuts and top income shares (Frydman and Molloy, 2011; Piketty, Saez, and Stantcheva, 2014). Early studies advanced that the subsequent rise in top incomes was the result of increases in labor supply (Lindsey, 1987; Feldstein, 1995). However, the empirical evidence does not accord with the standard supply-side explanation (Heckman, 1993; Saez, Slemrod, and Giertz, 2012, survey the literature). In view of this evidence, an alternative explanation for the relationship between tax cuts and top income shares might be greater rents afforded to top income earners.[3]

Piketty, Saez, and Stantcheva (henceforth, "*PSS*") (2014) document empirical evidence that tax cuts also encourage rent seeking (increased "bargaining") among top income earners. The primary piece of evidence is that tax cuts are associated with higher pre-tax income shares of the top one percent, both within the United States over time and across countries. But, tax cuts are not associated with greater economic growth as standard supply-side arguments would predict. As a result, *PSS* conclude that the rent seeking response represents at least 60 percent of the total response to changes in tax

[2]That is, pay arrangements regularly fail to filter observable background noise in performance. Bebchuk and Fried (2004) show that that incentive pay fails to filter luck from performance despite quite tenable solution (e.g., indexing equity to general market or industry conditions). Bertrand and Mullainathan (2001) reach the same conclusion, finding that pay for luck is as large as pay for performance. Finally, Bebchuk and Fried (2010) point out that boards fail to limit the unwinding of equity incentives through various financial instruments.

[3]Tax avoidance, which entails a loss of economic efficiency, is another potential response (Feldstein, 1999), though a recent paper demonstrates that the efficiency loss is less than previously understood (Chetty, 2009).

policy. The second piece of evidence is that the elasticity of pre-tax income with respect to top marginal income tax rates is strongly inversely related to measures of corporate governance using cross-country variation in top tax rates.

The contribution of this paper is twofold. First, we develop a theoretical foundation that disentangles the labor-supply and rent-seeking responses using variation in the elasticity of pre-tax income with respect to changes in tax policy across measures of corporate governance. The main insight of the model is that under plausible conditions both effort and rent seeking respond to changes in tax policy. Importantly, this framework provides an interpretation of the link between the quality of corporate governance and the elasticity of income with respect to marginal tax rates.

Second, we use a unique dataset and empirical approach to quantify the rent-seeking response. Because *PSS* (2014) rely on cross-country variation in top marginal tax rates at a single point in time, the assumption that the explanatory variables are orthogonal to all unobservable country characteristics is very strong. This paper uses a panel of executives with executive fixed effects, which exploits variation in top marginal tax rates over time for a single executive. We empirically quantify a lower bound for the rent-seeking response to tax cuts, showing that it explains a large portion of the response to changes in tax policy. As a result, increasing top marginal income tax rates discourages economically wasteful activities, thereby increasing economic efficiency.

Also, while the literature finds that the elasticity of pre-tax income with respect to marginal income tax rates is essentially zero (Saez, Slemrod, and Giertz, 2012, survey the literature), we find a new result that the elasticity of pre-tax income is actually quite large for executives in firms with the worst corporate governance, where rent seeking is most prevalent. By failing to distinguish firms according to their quality of corporate governance, the existing literature has missed this important result: Rent seeking is dissuaded, at least in part, by good corporate governance.

We use executive compensation data for the top five paid executives in S&P 1500 companies from the Execucomp database for the period 1992 to 2005. We follow a similar empirical strategy as Goolsbee (2000) and Frydman and Molloy (2011) to examine the elasticity of taxable income with respect to the net-of-tax rate. We decompose the elasticity of income across various measures of corporate governance, using a well-known index of corporate governance–the so-called 'E Index' proposed by Bebchuk, Cohen, and Ferrell (2008), among several other measures. Using the framework of the model, we find that rent seeking constitutes an important component of executives' response to changes in marginal tax rates. In particular, we find that the rent-seeking response represents at least 54 percent of the total response to changes in tax policy, which is quite similar to the lower bound derived by *PSS* (2014) using cross-country regressions.

2. Model

In this section, we propose a simple model of executive compensation given both endogenous effort and rent-seeking.[4] For terminology, we refer to the opportunity cost associated with replacing the incumbent executive as "entrenchment," while "rent seeking" refers to (taxable) income afforded as a consequence of entrenchment. We refer to the additional value added to the firm by the executive (labor supply) as "effort."

[4] The model and subsequent empirical analysis abstracts from tax avoidance. Piketty, Saez, and Stantcheva (2014) find that the tax avoidance response is essentially zero, which we corroborate using the dataset herein.

Finally, we refer to the costs to the executive of imposing entrenchment and supplying effort as, simply, the cost of entrenchment and effort.

2.1 Set-up

Consider a firm comprised of a representative shareholder[5] and representative (incumbent) executive. The return to the shareholder for a given unit of time is given by

$$r = q - w + \eta \tag{1}$$

where q represents effort, w represents executive income, and η represents a random variable (noise) $\eta \sim F[\cdot]$, where $F[\cdot]$ is a cumulative distribution function. Prior to the realization of η, the executive has some leeway to choose his (*ex-ante*) level of effort, entrenchment, and compensation. However, this leeway is of course not absolute. The executive knows that he may be fired (*ex-post*) if the realized return to the shareholder plus entrenchment is less than the "outside" return, which is denoted as $\tilde{r}$. That is, the executive is fired if (*ex-post*)

$$q - w + \theta + \eta \leq \tilde{r} \tag{2}$$

where θ represents entrenchment. Therefore, the probability of the event that the incumbent executive is fired (per unit of time) can be represented as

$$P\left[\text{Firing}\right] = Pr\left[\eta \leq \tilde{r} - q + w - \theta\right] = F\left[\tilde{r} - q + w - \theta\right] \tag{3}$$

As expected, the probability that the executive is fired is decreasing in effort and entrenchment but increasing in his income. This constitutes the executive's major deterrent to increase his compensation too much.

[5]"Shareholder" is emblematic of the executive's relevant bargaining partner, which is typically assumed to be the board of directors but also includes, rival executives, acquiring companies, corporate raiders, etc.

Let's suppose, without qualification for the moment, that the cost of effort and the cost of entrenchment are represented by the functions $\hat{e}(q;\cdot)$ and $\hat{c}(\theta;\cdot)$, respectively. We assume the executive is risk-neutral, infinitely-lived, and has a pure rate of time preference, ρ. The employed executive therefore maximizes the expected present discounted value of lifetime utility given by

$$V = E\int_0^\infty \exp(-\rho t)\left[(1-\tau)\,\mathrm{w} - \hat{e}(q;\cdot) - \hat{c}(\theta;\cdot)\right]dt \tag{4}$$

where τ represents the marginal income tax rate and $(1-\tau)$ represents the so-called net-of-tax rate. We assume the utility of an unemployed executive is independent of the executive's current decisions and is represented by V^u. The expected present discounted value of utility for an employed executive over an interval $[0,t]$ is therefore given by

$$V^E(t) = t\left[(1-\tau)\,\mathrm{w} - \hat{e}(q;\cdot) - \hat{c}(\theta;\cdot)\right] + e^{-\rho t}\left(tFV^u + (1-tF)V^E\right) \tag{5}$$

Taking the limit as $t \to 0$ implies that the employed executive chooses his compensation, effort, and entrenchment to maximize the value of employment,

$$V^E = \max_{w,q,\theta}\left\{\frac{(1-\tau)\,\mathrm{w} - \hat{e}(q;\cdot) - \hat{c}(\theta;\cdot) + F[\cdot]V^u}{\rho + F[\cdot]}\right\} \tag{6}$$

2.2 Assumptions

Suppose effort and rent-seeking exhibit the following technologies

$$\theta \equiv A(g)\,y(\mathbf{x}) \quad \text{and} \quad q \equiv B(g)\,z(\mathbf{v}) \tag{7}$$

where $\mathbf{x}$ and $\mathbf{v}$ represent vectors of entrenchment and effort inputs, respectively.[6] The parameters $A(g)$ and $B(g)$ represent total factor productivity. The scalar g represents

[6]Because exerting effort and rent-seeking are qualitatively disparate tasks (or equivalently, employ disparate inputs), we have presumed that the cost of effort and the cost of entrenchment are independent. This assumption simplifies the analysis considerably and is a close approximation. For example, the costs associated with effort include the number of hours worked

the firm's governance. We assume the functions y and z are: ($A1$) monotonically increasing, ($A2$) twice continuously differentiable, and ($A3$) homogenous of degree less than one. Moreover, we assume the following

$$A4.\ A'(g) \leq 0 \quad A5.\ B'(g) \geq 0$$

Assumptions A1 to A3 are technical assumptions to ensure an interior solution and to facilitate comparative static derivations. We discuss assumptions A4 and A5 in more detail because they have important qualitative implications and are not standard in the literature. The quality of corporate governance (g) refers to the presence of provisions that contribute to increase the controls of shareholders on the firm's management and design of incentives to increase productivity (discussed in more detail in the subsequent section). Assumption A5 implies that a higher quality of governance has a non-positive effect on the productivity of entrenchment inputs, whereas A6 implies that quality of corporate governance has a non-negative effect on the productivity of effort inputs. Note that the assumptions do not require strict inequality. It is straightforward that higher quality of corporate governance limits the possible channels in which executives can entrench themselves, thereby reducing the productivity of entrenchment inputs. Perhaps, less straightforward is the effect of governance on the productivity of effort. However, this assumption is consistent with a number of studies demonstrating that the higher quality of corporate governance increases firm value (Gompers, Ishii, and Metrick, 2003) and productivity (Bertrand and Mullainathan, 2003).

Several implications follow (7) and A1 to A5

(foregone leisure), mental effort, and the acquisition of skills, whereas the costs associated with rent seeking include the social and legal costs associated with self-dealing, weakening shareholder rights, and transgressing social norms (Piketty and Saez, 2003).

$$R1.\,\hat{c}(\theta;\cdot) = a(g)c(\theta) \quad R2.\,\hat{e}(q;\cdot) = b(g)e(q) \quad R3.\,a'(g) \geq 0 \quad R4.\,b'(g) \leq 0$$

$$R5.\,c'(\theta) > 0 \quad R6.\,c''(\theta) > 0 \quad R7.\,e'(q) > 0 \quad R8.\,e''(q) > 0$$

where prime denotes first derivatives, and $a(g)$ and $b(g)$ are monotonically inverse transformations of $A(g)$ and $B(g)$.[7]

Furthermore, as is going to be clear below, the second order conditions to the maximization of (6) require that

$$A6.\, f'(\tilde{r} - q^* + w^* - \theta^*) > 0$$

where $f(\cdot)$ represents the probability density function of $F[\cdot]$, and $f'(\cdot)$ is evaluated at the executives optimal choice set (the marginal probability that the executive is fired is increasing at the optimal level of income, effort, and entrenchment). We emphasize that condition A6 is needed only around a neighborhood of the optimal solution and, therefore, is consistent with a broad class of probability distribution functions, including the normal distribution.[8]

2.3 Baseline Analysis

Given an interior solution, the following conditions follow from maximization of (6) (see the Appendix for a derivation).

$$(1-\tau) = f(\cdot)\left(V^E - V^u\right) \tag{8}$$

$$(1-\tau) = a(g)c'(\theta) \tag{9}$$

[7]For example, if y is a homogenous function of degree $1/\gamma < 1$ then the corresponding cost function can be represented as $C(\mathbf{p},\theta,g) = m(\mathbf{p})\left(\frac{\theta}{A(g)}\right)^{\gamma}$ where $m(\mathbf{p})$ is a per-unit cost function of a vector of factor prices $\mathbf{p}$. Thus, expressing $a(g) \equiv A(g)^{-\gamma}$ and treating factor prices as fixed yields $R1$, $R3$, $R5$, and $R6$. The other results are similar.

[8]As demonstrated below, the role of assumption A6 (as well as assumptions $A4$ and $A5$) is to ensure that the objective function is convex and therefore the optimal wage is finite.

$$(1-\tau) = b(g)e'(q) \qquad (10)$$

Condition (8) indicates that the marginal net-of-tax increase in executive wealth from wages should be equal to the expected marginal cost resulting in lost employment. The expected marginal cost resulting in lost employment is equal to the difference between employment and unemployment multiplied by the marginal increase in the probability of firing.

Conditions (9) and (10) follow from the executive's dual problem of minimizing the cost of effort and entrenchment subject to an optimal income. That is, the marginal cost of increasing effort and entrenchment should equal the marginal benefit, in terms of after tax increased wealth. The marginal benefit of increasing income is equal to $(1-\tau)$ and the marginal cost of entrenchment and effort is $a(g)c'(\theta)$ and $b(g)e'(q)$, respectively.

Result 1: The Behavioral Responses to Changes in the Net-of-Tax Rate

Both executive effort and rent-seeking are increasing in the net-of-tax rate. In particular, the behavioral responses to changes in the net-of-tax rate are described by

$$\frac{dq}{d(1-\tau)} = \frac{1}{b(g)e''(q)} > 0 \quad \text{and} \quad \frac{d\theta}{d(1-\tau)} = \frac{1}{a(g)c''(\theta)} > 0 \qquad (11)$$

Proof: Follows from conditions (9) and (10).

Equation (11) demonstrates the negative efficiency costs (or efficiency gains) of taxation associated with rent-seeking, as well as the usual efficiency costs associated with discouraging effort. The former is a consequence of the distortion engendered by diverting factors of production towards rent-seeking rather than towards creating new value. Equation (11) also demonstrates that the quality of corporate governance increases the response of effort and decreases the response of rent-seeking to changes in the net-of-tax rate.

Result 2: The Response of Income with Respect to the Net-of-Tax Rate

Executive income is determined by the net-of-tax rate and the equilibrium effort and entrenchment. Thus, the total response of income with respect to the net-of-tax rate can be decomposed into the direct effort of the net-of-tax rate and the indirect effects through effort and entrenchment responses. That is,

$$\varepsilon = -\overbrace{\frac{\left(b(g)e(q)+a(g)c(\theta)+\rho V^{u}\right)}{\Omega}}^{(-)}+\overbrace{\frac{1}{b(g)e''(q)}}^{(+)}+\overbrace{\frac{1}{a(g)c''(\theta)}}^{(+)} \tag{12}$$

Where $\Omega \equiv (\rho + F[\cdot])(1-\tau)^2 f'(\cdot)/(f(\cdot))^2 > 0$.

Proof: See the Appendix.

The first right-hand-side term correspond to the direct effect of the net-of-tax rate on income (the precaution response), reflecting that an increase in the net-of-tax rate increases the value of employment in the future, thereby increasing the opportunity cost of losing employment for *given* levels of effort and entrenchment. This effect is negative (first term). However, an increase in the net-of-tax rate also elicits greater effort and entrenchment (Result 1), which in turn increase income (second and third terms, respectively). This follows from strict convexity of the cost of effort and entrenchment and that an increase in the net-of-tax rate increases the after tax marginal benefit of income. The total effect of a change in the net-of-tax rate on income is ambiguous, and is therefore an empirical issue.

2.4. Testable Implications of Rent-seeking

While the model does not generate sharp predictions about the response of income with respect to the net-of-tax, it does generate a number of hypotheses that allow us to uncover the various responses. Towards this end, consider the following decomposition of expression (12)

$$\varepsilon(g) = -\overbrace{\frac{\rho V^u}{\Omega}}^{\equiv\sigma} + \overbrace{\frac{1}{b(g)e''(q)} - \frac{b(g)e(q)}{\Omega}}^{\equiv\varepsilon^q(g)} + \overbrace{\frac{1}{a(g)c''(\theta)} - \frac{a(g)c(\theta)}{\Omega}}^{\equiv\varepsilon^\theta(g)} \tag{13}$$

Expression (13) decomposes the response of income with respect to the net-of-tax rate into the (net) *effort response* ($\varepsilon^q(g)$) and *rent-seeking response* ($\varepsilon^\theta(g)$). Conceptually, these responses represent the partial income response to changes in taxes derived from the net behavioral and precautionary responses of effort and entrenchment.

Result 3: Corporate Governance and the Response of Income to Taxes

The quality of corporate governance decreases the rent-seeking response, whereas the quality of corporate governance increases the effort response. That is,

$$\frac{\partial\varepsilon^\theta}{\partial g} < 0 \quad \text{and} \quad \frac{\partial\varepsilon^q}{\partial g} > 0 \tag{14}$$

Proof: Follows from (13).

Result 3 demonstrates that, while the net effect of governance is ambiguous, the effects on the rent-seeking and effort responses are unambiguous. This generates a number of particular testable hypotheses. One particular testable hypothesis is what we refer to as the *pure efficiency hypothesis*, which is the following

The Pure Efficiency (PE) Hypothesis: Executives do not seek rents and, therefore, only effort responds to changes in the net-of-tax rate, which implies that the response of income is given by

$$\varepsilon(g) = -\sigma + \varepsilon^{q}(g) \tag{15}$$

The PE hypothesis results in sharp predictions for the relationship between firm's corporate governance and the response of income with respect to taxes.

PE Testable Implication: The response of income with respect to the net-of-tax rate is positively associated with the quality of institutions. That is,

$$\frac{\partial \varepsilon}{\partial g} = \frac{\partial \varepsilon^{q}}{\partial g} > 0 \tag{16}$$

Under the PE hypothesis, the response of income with respect to the net-of-tax is increasing in the quality of corporate governance because effort inputs are more productive. Figure 1 illustrates the PE hypothesis, where the upward-sloping "Pure Effort Response" curve represents the relationship between the response of income and the quality of corporate governance.

A *pure rent-seeking hypothesis* can also be formulated, where only rent-seeking responds to the changes in tax policy. This case would be represented by the downward-sloping "Pure Rent-seeking Response" curve. Note that we cannot, a priori, rule out a negative income response, indicated by the curves below the x-axis, but this does not impinge on generating testable hypotheses.

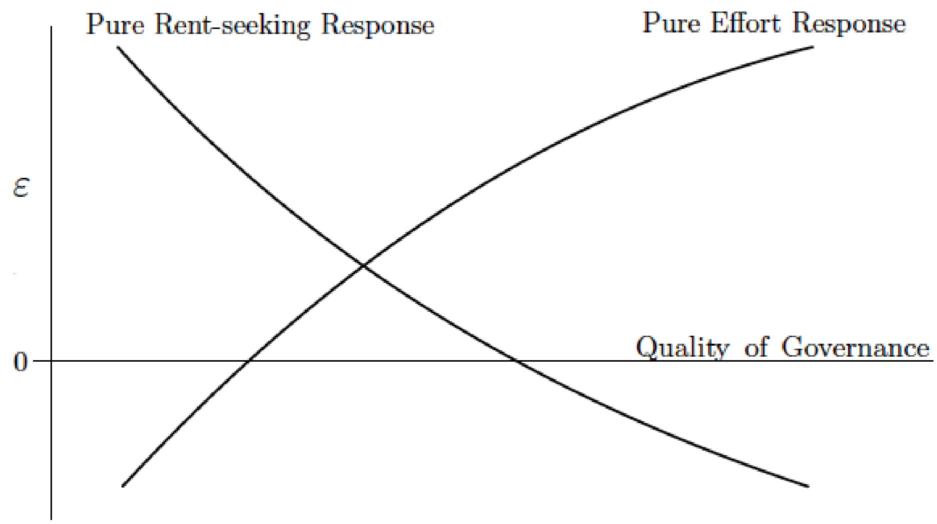

Figure 1. Pure Effort and Pure Rent-seeking Responses

A rejection of the PE hypothesis indicates that rent seeking is an important component of income. However, the hypothesis test cannot determine the quantitative significance of the rent-seeking response. Towards this end, we derive a more general framework for uncovering the rent-seeking response, which yields a lower-bound estimate.

Consider two discrete points in the quality of corporate governance continuum, $g < \overline{g}$. The following implication provides a lower bound estimate for the net rent-seeking response.

Rent-seeking Testable Implication:

$$\varepsilon^{\theta}(g) = \varepsilon^{\theta}(\overline{g}) + (\varepsilon^{q}(\overline{g}) - \varepsilon^{q}(g)) + (\varepsilon(g) - \varepsilon(\overline{g})) > \varepsilon(g) - \varepsilon(\overline{g}) \tag{17}$$

Expression (17) follows from the observation that $\varepsilon^{\theta}(\overline{g}) > 0$ and $\varepsilon^{q}(\overline{g}) - \varepsilon^{q}(g) > 0$. The rent-seeking testable implication demonstrates that if $g < \overline{g}$ implies $\varepsilon(g) > \varepsilon(\overline{g})$ then $\varepsilon^{\theta}(g) > 0$. In other words, if the response of income with respect to taxes is decreasing in the quality of corporate governance then the rent-seeking response must be strictly positive. This is satisfied whenever the observed relationship between ε and g is sloping downward (see Figure 1). Moreover, if we let $\overline{g}$ represent the minimum element of g then following expression represents a lower bound for the rent-seeking response for a given $g \leq \overline{g}$

$$\varepsilon^{\theta}(g) > \varepsilon(g) - \varepsilon(\overline{g}) \tag{18}$$

Because $\varepsilon(g) - \varepsilon(\overline{g})$ can be estimated, expression (18) can be used to estimate a lower bound rent-seeking response. If it is observed that $\varepsilon(g) \leq \varepsilon(\overline{g})$ then the rent-seeking response is either indistinguishable from zero or not sufficiently large to detect, but $\varepsilon(g) \geq \varepsilon(\overline{g})$ indicates that the rent-seeking response exceeds a strictly-positive lower bound.

3. Empirical Analysis

3.1. Data Sources

Compensation of the five highest-paid employees for the Standard and Poor's (S&P) 1500 corporations are provided by Execucomp database, spanning from 1992 to 2011. This is a panel data of executives including detailed components of compensation. Also, Compustat North America, which includes the Execucomp database, contains various firm-level financial variables.[9]

We also employ firm-level corporate governance data compiled by the Investor Responsibility Research Center (IRCC) and provided by Riskmetrics. The IRCC Takeover Defense database has been used to construct several corporate governance indicators, the most well-known being the so-called "Governance Index" (henceforth,

[9] See Goolsbee (2000) for a more detailed discussion of the data, which are used extensively.

GIM Index) by Gompers, Metrick, and Ishii (2003) and the "Entrenchment Index" (henceforth, E Index) by Bebchuk, Cohen, and Ferrell (2008), the latter refined the former twenty-four provisions composing the GIM Index to six key indicators. We focus primarily, but not exclusively, on the E Index because, as discussed by the authors, several provisions are superfluous. The data span from 1990 to 2006 for 1500 large firms, which is a slightly smaller universe than the Compustat dataset. Finally, we use the TAXSIM Model to simulate maximum marginal tax rates across states and across time, accounting for the combined effect of federal and state taxes.[10]

3.2 Tax Policy and Accounting for Tax Rates

From 1993 to 2003, a number of federal tax acts increased, and then decreased, marginal tax rates, along with changes at the state level, which can be used to identify the elasticity of taxable income. The Omnibus Budget Reconciliation Act of 1993 raised the top marginal income tax rate (for married, joint filers with taxable income greater than $250,000) from 31 percent to 39.6 percent. The Economic Growth and Tax Relief Reconciliation Act of 2001 contained a number of tax provisions that were phased in over several years. Many of the tax reductions were designed to be enacted over the course of up to 9 years; however, the Jobs and Growth Tax Relief Reconciliation Act of 2003 accelerated the reductions for 2004 and 2006, which were retroactively enacted to apply to the 2003 tax year. On July 1, 2001 and January 1, 2002, the year 2000 income rates (28, 31, 36, and 39.6 percent) were reduced by 0.5 percentage points, reducing each rate by 1 percentage point. More reductions were scheduled for the beginning of 2004 and

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[10]Table 1 defines all of the variables used and provides their respective. A more detailed discussion of the aforementioned data is available in the discussion paper, Andersen and López (2012).

2006, reducing the top rate by an additional 2.6 percentage points and the next three rates by an additional 2 percentage points. The 2003 tax cut accelerated these reductions, thereby, lowering the rates to 25, 28, 33, and 35 percent, which were effective for 2003 tax year. All of the reduced rates have been in effect until 2012.

One of the drawbacks of using the Execucomp database, rather than tax return data, is that we cannot observe all components of total taxable income, including capital gains income, income of the spouse, and tax deductions. We follow the conventional approach in calculating earned income, which assumes that all executives are married and file joint income tax returns, and have no household income outside the firm. While several, or even most, studies rely on variation in federal marginal tax rates (Goolsbee, 2000; Frydman and Molloy, 2011), we follow several more recent studies using variation in state tax rates, as well as federal rates (Nada and Giertz, 2006; Katuscák, 2009), using the TAXSIM Model simulator.

To circumvent the problem of endogenous tax rates for individuals around the tax bracket cutoffs, we follow previous studies (Goolsbee, 2000; Nada and Giertz, 2006) that exclude executives with permanent income below the top-bracket, where permanent income is defined as the mean income in the sample.[11] In particular, we follow Nada and Giertz (2006) and exclude executives whom have permanent income less than $400,000 (in 2006 dollars).[12]

[11]Of course, permanent income might also be endogenous and limiting the sample might bias the results. For consistency with the literature and to maintain the focus of the paper, we rely on Goolsbee (2000), who addresses these issues and finds that the results are insensitive to various cutoffs and tax rate definitions.
[12]Nada and Giertz (2006) claim to use the same cutoff (after adjusting for inflation) as Goolsbee (2000), using $376,000 in 2004$, which is roughly $399,000 in 2006$.

3.3 Executive Compensation and Firm Data

We focus on taxable income, which is comprised of the following components: salary, bonus, options exercised (ISOs and NQSOs), long-term incentive payouts (LTIP), and restricted stock grants. We also disaggregate taxable income and look at the effect of tax rates on salary and bonus and options exercised separately, as well the effect on compensation including non-taxable income. In general, all forms of taxable income are taxed at the personal earned income tax rate, except for Incentive Stock Options (ISOs), which are taxed at the capital gains rate upon sale. ISOs, unlike Nonqualified Stock Options (NQSOs), are not deductible against corporate profits and have an annual cap of $100,000 per-executive and, therefore, represent roughly 5 percent of options exercised. As conventional, we assume all options exercised are NQSOs. (See Hall and Liebman (2000) for a detailed discussion of the taxation of executive compensation.) Following Frydman and Molloy (2011), we control for firm-specific variables including market value, sales, leverage, and market-to-book ratio. To properly account for firm-level data and tax rates, it is necessary to omit firms with fiscal years straddling more than one year (i.e., firms with fiscal years not ending in December), which excludes about 40 percent of the observations.[13]

In addition to the usual set of controls employed in estimating the elasticity of taxable income, we also account for the degree in which the internal institutions of the firm favor the executive vis-à-vis shareholders–both as a determinant of taxable income and as a determinant of the elasticity of taxable income (interactive effect). This

[13]The assumptions concerning ISOs and excluding firms with fiscal years not ending in December pertain to all studies cited here. Typically, firms have fiscal years not ending in December to avoid having accounting deadlines coincide with periods of high business activity (e.g., retail sales). As far as we know, no studies have attempted to assess or remedy this shortcoming.

corresponds of course to the inverse of the variable quality of corporate governance (g) used in the theoretical analysis. We thus include the so-called E Index proposed by Bebchuk, Cohen, and Ferrell (2008), which is a categorical variable ranging, in ascending (descending) order in which the institutions of the firm favor executives (shareholders), from 0 to 6 based on the number of takeover defense provisions in place.[14] The GIM index, developed by Gompers, Ishii, and Metrick (2003), follows a similar methodology, using an additional eighteen (thus, twenty-four in total) defense provisions, which are closely related to the provisions included in the E index, but also including six state laws related to corporate governance. The GIM index and, more recently, the E index have been extensively used and it has been empirically demonstrated that shareholder rights are positively related to higher firm value, higher profits, higher sales growth, and lower capital expenditures. The role of institutions in the response of taxable income to changes in the net-of-tax rate, however, have not been explored.

3.4. Summary Statistics

Starting in 2006, the reporting of several Execucomp variables changed significantly and, starting in 2007, the variables needed to create the GIM and E index were no longer collected. Thus, we use data spanning from 1992 to 2005 (the limitation is not particularly unfavorable because there were no major changes in the federal tax code after 2004).[15] Before imposing any qualifications, the data contain 71,912 executive-year

[14]The six provisions include (1) staggered boards (directors are elected in overlapping terms, rather than simultaneously), (2) limitation on shareholders' ability to amend corporate bylaws through majority voting, (3) limitation on shareholders' ability to amend the corporate charter, (4) supermajority shareholder vote to approve a merger, (5) golden parachute (severance agreement providing benefits to executive in event of firing or change of control), and (6) poison pill (shareholder right that renders the company unattractive to a potential acquirer).

[15]The data necessary to create the GIM and E index are only available for the years 1993, 95, 98, 00, 02, 04, and 06. We use lagged variables in missing years, except for 1992 and 1997 we use 93

observations. After eliminating executives with permanent income below $400,000, at firms with fiscal years not ending in December, at firms without E Index data, or missing state residency data (therefore, we cannot assign a marginal tax rate), reduces the sample to 31,297. Executives are observed in the sample for 8 years on average, with a standard deviation of 3.7 years.

Table (2) reports summary statistics by E Index quartiles.[16] The average taxable income in the sample is $2.4 million and the median taxable income is $989,000, indicating that the distribution is highly skewed. The relationship between E Index and taxable income appears negative–the lowest E Index quartile has the highest average taxable income ($3.3 million), whereas the highest and second highest quartiles have the lowest average taxable income (approximately $2 million). Median taxable income, however, exhibits markedly less variation across E Index quartiles ($1.15 million is the maximum, whereas $0.90 is the minimum).

Table (2) also reports firm attributes by E Index quartiles. The relationship between the E Index and firm size is clearly negative–the average market value of the lowest E Index quartile is more than four times greater than the market value of the highest E Index quartile. The median values display less variation across quartiles, indicating that, similar to taxable income, the distribution of market value is highly skewed. The market-to-book ratio is also positively related to a firm's E Index, indicating

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and 98 data, respectively. The results are robust to using only non-imputed values; however, the long-run elasticity of taxable income cannot be estimated without continuous years. This is further discussedin the robustness checks.

[16]We use quartiles rather than indices because several indices have very few observations (less than 1 percent of observations have E Index equal to six). E Index quartiles correspond to E Indices 0-1 (7,712 observations), 2 (7238 observations), 3 (8957 observations), and 4-6 (7390 observations).

that firms with lower E Indices have greater growth potential than firms with higher E Indices.

3.5. Regression Analysis

To estimate the elasticity of taxable income, we use the following modified version of the standard specification[17]

$$\ln(\text{Income}_{i,t}) = \alpha_i + \sum_{E_j \in E} \beta_j (\ln(1-\tau_{i,t}) \times I\{E_{i,t} \in E_j\}) + \sum_{E_j \in E} \delta_j I\{E_{i,t} \in E_j\} + X_{i,t}\Gamma + \epsilon_{i,t} \quad (19)$$

where i indexes executives and t indexes time. The variable α_i represents executive-firm fixed effects, $X_{i,t}$ represents firm-specific variables (market value, sales, leverage, and market-to-book ratio in the previous period) and time-specific variables (time trend or year dummies) and $\epsilon_{i,t}$ represents a random component. The variable (1-$\tau_{i,t}$) represents the net-of-tax rate, where $\tau_{i,t}$ is the maximum combined federal and state marginal tax rate. $I\{E_{i,t} \in E_j\}$ is an indicator variable equal to 1 if the executive belongs to a firm with an E Index belonging to the E_j and 0 if otherwise.[18] Recall, the E Index is decreasing in the quality of corporate governance. The coefficient β_j, therefore, represents the elasticity of taxable income for an executive belonging to a firm with E Index quantile E_j. The baseline model uses E Index quartiles (identical to summary statistics).[19]

3.5.1. Regression Results

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[17] The standard specification to estimate the elasticity of taxable income takes the form: $\ln(\text{Income}_{i,t}) = \alpha_i + \beta \ln(1-\tau_{i,t}) + X_{i,t}\Gamma + \epsilon_{i,t}$

[18] We use dummy variables for E Index to account for potential non-linear relationships.

[19] That is, $E_j \in E \equiv \{\{0,1\}, 2, 3, \{4,5,6\}\}$

Table (3) reports the regression results for estimating the elasticity of various forms of compensation with respect to the net-of-tax rate. Henceforth, "specification" refers to empirical specifications corresponding to columns in the tables (not equation numbers). Specification (1) estimates the standard specification, without controlling for E Index quartiles. The estimated (short-run) elasticity of taxable income for the entire sample is significant at the 1 percent significance level. Specification (2) indicates that the elasticity of income greatly varies significantly across E Index quartiles. Moreover, the relationship between the elasticity of taxable income and E Index quartiles appears to be monotonically increasing. A Wald-type test rejects the null hypothesis that the elasticities among each pair of quartiles are equal.[20]

The elasticity of other forms of compensation follow a similar pattern as taxable income, although varying in magnitude as expected. In particular, the dependent variable Total Pay, which includes taxable income and other (non-taxable) compensation, are similar to the estimates for the elasticity of taxable income. As expected, the elasticity of Salary and Bonus (Cash) compensation is relatively small compared to the elasticity of exercised stock options (Options), which is quite large. As mentioned, non-performance-based compensation (including Salary and Bonus) in excess of $1 million cannot be deducted from corporate profits, thus marginal increases in compensation are typically incentive-based pay (predominately options), reflecting their relative tax advantage.

As pointed out by Goolsbee (2000) and Hall and Liebman (2000), contemporaneous or short run responses to the net-of-tax rate may represent income shifting over time rather than "permanent" responses. Using the contemporaneous and future net-of-tax rate is the standard approach to allowing individuals to anticipate as well as react to tax changes.[21] If anticipation is important then the forward net-of-tax rate should be negatively related to current taxable income; that is, future tax increases should increase current taxable income. The sum of the short-run (contemporaneous) and the anticipation elasticity represents the long-run (or at least non-transitory) response to changes in the net-of-tax rate. Certainly this is an important consideration to explore here–it may be that pro-executive institutions (higher E Index) only afford greater discretion in the timing, rather than level, response to changes in the net-of-tax rate.

Specification (7) indicates that the anticipatory responses are remarkably similar for all quartiles; however, the contemporaneous elasticities remain larger for higher quartiles. The long-run elasticity of taxable income to changes in the net-of-tax rate for all executives is approximately 0.5 (specification 6), which is within the range of estimates in the literature, and ranges between 0.04 for executives with the lowest E Index and 0.8 for executives with the highest E Index. While the average elasticity is relatively low and in fact almost negligible for executives in firms with good corporate governance, it is quite large for executives in firms with the worst corporate governance, reaching a value that is 20 times larger than the elasticity in firms with good corporate governance. This is an important result so far ignored in the literature. A Wald-type test rejects the null hypothesis that the long-run elasticities among each pair of quartiles are equal.

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[21]Using the forward net-of-tax rate is problematic for a number of reasons; however, we follow the conventional approach because remedying these problems is beyond the scope of this paper. The primary objective is not necessarily to determine precise long-run estimates, but to show that the differences in the short-run elasticities (which are measured more precisely) are not merely a reflection of differences in timing.

These results are even more pronounced when we employ the federal, rather than state-specific, net-of-tax rates, which are reported in specification (8).[22]

3.6 Testing Alternative Measures of Governance

To corroborate the results in the previous section, this section employs alternative measures of corporate governance. First, we use executive equity at stake, which is a common measure of governance in the literature as it measures the degree in which the incentives of managers and shareholders are aligned. As pointed out by Jensen and Murphy (1990), there are many mechanisms through which value-adding incentives can be achieved; however, the primary mechanisms are ownership of stock and stock options. Following Baker and Hall (2004), we calculate the (equivalent) shares owned from the number of shares and unexercised stock options held by the executive. We refer to the change in executive wealth from all stocks and unexercised stock options held from a $1000 change in firm value as the Jensen-Murphy statistic (JMS). Similarly, we refer to the change in executive's wealth from all stocks and unexercised stock options held from a 1 percent change in firm value as Equity-at-stake (EAS).[23] Table (2) summarizes the JMS and EAS by E Index quartile. For all E Index quartiles, the value of stocks and stock options increases by $9.58 on average whenever the value of the firm increases by $1000, whereas the median value increases by $2.35. Similarly, the average EAS is $0.20 and the median is $0.05. The median summary statistics for the JMS and EAS by E Index quartiles indicate that there appears to be little relationship between wealth sensitivity and

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[22]Using federal tax rates entails losing fewer variables and overcomes possible endogeneity resulting in executives moving across state borders.

[23]Whether the Jensen-Murphy Statistic or Equity-at-stake is more important for value-adding incentives depends on whether the marginal product of effort is constant across firm size or increasing with firm size, thus we include both (the former (latter) implies the Jensen-Murphy statistic (Equity-at-stake) is more important).

E Index quartiles, and certainly variation within quartiles are more important than variation between quartiles, which suggests that the two testable hypothesis are more or less independent.

We also employ measures of the presence of large institutional investors and the equity ownership of the board of directors as alternative measures of the institutions of the firm. In particular, following Gillian, Hartzell, and Starks (2003), we use the Herfindahl-Hirschman Index of institutional ownership concentration, and following Bertrand and Mullainathan (2001), we use the average percentage of shares owned by the board of directors.[24] Table (2) reports the average percentage of shares owned by the board of directors (%Board Ownership) and the Herfindahl-Hirschman Index of institutional ownership concentration (Ownership Concentration). The average percent of shares owned by the board of directors is 0.72 percent and the median is 0.2 percent, and is negatively related to E Index quartiles. Similarly, institutional ownership concentration is inversely related to the E Index, although the relationship is quite tenuous using median values.

Similar to (22), we estimate the elasticity of taxable income allowing the elasticity of income, as well as the level of income, to depend on the Jensen-Murphy statistic, Equity-at-stake, %Board Ownership, and Ownership Concentration. Because the variables are continuous, we use both the level and quartiles of each. The generic specification takes the following form[25]

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[24]Bertrand and Mullainathan (2001) use a slightly different variable–the number of blocks of at least 5 percent, which is not readily available in our dataset.

[25]Rather than introduce superfluous notation, we import the notation used in (22). Keep in mind we are abusing notation because the estimated coefficients are obviously not identical across model specifications.

$$\ln(\text{Income}_{i,t}) = \alpha_i + \sum_{j=1}^{4} \beta_j (\ln(1-\tau_{i,t}) \times I\{Q_{i,t} \in Q_j\}) + \sum_{j=1}^{4} \delta_j I\{Q_{i,t} \in Q_j\} + X_{i,t}\Gamma + \epsilon_{i,t} \quad (20)$$

where Q_j represents quartile dummies (e.g., $\mathrm{I}\{Q_{i,t} \in Q_1\}$ if the variable for individual i at time t is less than the first quartile of the distribution).

Table (4) reports the results of estimating (20). The dependent variable is taxable income (Income) in all specifications. Specifications (1) and (3) control for the JMS and EAS, respectively, using the variables as continuous indices. Recall that greater equity at stake is positively associated with the quality of corporate governance. Both specifications indicate that the executive's equity-at-stake is inversely related to the elasticity of taxable income. A one standard deviation increase in the JMS and EAS correspond to a decrease in the elasticity of taxable income by 0.28 and 0.34, respectively. Specifications (2) and (4) control for the JMS and EAS using quartile dummies. Specifications (2) and (4) corroborate that an executive's equity-at-stake is inversely related to the elasticity of taxable income. Executives with the least equity-at-stake respond the most to changes in the net-of-tax rate, whereas executives with the most equity-at-stake respond very little, if at all. Using equity at stake is therefore consistent with the results in the theoretical section--the elasticity of income with respect to changes in marginal tax rates is inversely related to the quality of corporate governance.

Similar specifications are employed for analyzing the role of the average percent of shares owned by the board of directors (%Board Ownership) and the Herfindahl-Hirschman Index of institutional ownership concentration (Ownership Concentration). Specification (5) indicates that the percent of shares owned by the board of directors is negatively associated with the elasticity of taxable income and is significant at all significance levels. The elasticity of taxable income at the median percent of shares owned decreases by 0.7 for a one standard deviation increase in the percent of shares owned. Similarly, specification (7) indicates that institutional ownership concentration is negatively associated with the elasticity of taxable income and is significant at the 5 percent significance level. The elasticity of taxable income at the median concentration index decreases by 0.19 for a one standard deviation increase in ownership concentration. Using quartiles results in estimates similar to the baseline model.

3.7 Robustness Checks

Next, we demonstrate that the results are robust with respect to particular modeling assumptions using obvious variations to the baseline model. First we show that the results are not sensitive to using various quantile groups, besides the four quartiles used in the baseline model.[26] Table (5) demonstrates that the elasticity of taxable income is monotonically increasing in E Indices using various quantile groups. That is, variation within quartiles are consistent with variation between quartiles. Specification (4) indicates that, using six quantiles, the income of the lowest sextile does not exhibit an elasticity significantly different from zero, whereas the income of the highest sextile exhibits a markedly elastic response.

Second, we show that the results are consistent using the GIM index. We employ the GIM index using both quartiles (specification 5) and as a continuous index (specification 6). Similar to the baseline model, the estimates for the second and third

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[26]The partitions were chosen to form the most balanced blocks that are collectively exhaustive and mutually exclusive. 2-Groups represents the partition $\{\{0,1,2\},\{3,4,5,6\}\}$, 3-Groups represents $\{\{0,1,2\},3,\{4,5,6\}\}$ 5-Groups represents $\{\{0,1\},2,3,4,\{5,6\}\}$ and 6-Groups represents $\{0,1,2,3,4,\{5,6\}\}$. We do not use the 7 groups because less than one percent of the sample has E index equal to six.

quartiles are not statistically different from each other, but we can reject that the elasticity of the first and fourth quartiles are equal at all conventional significance levels (p-value=0.000). Specification (6) indicates that a one point increase in the GIM Index corresponds to an increase in the elasticity of income by approximately 0.3 (similarly a one standard deviation increase in the GIM Index corresponds to an increase of in elasticity by approximately 0.8).

Table (6) performs a number of further robustness checks. Specification (2) uses a quadratic polynomial time trend.[27] Specification (2) controls for year fixed effects, which eliminates all variation in federal tax rates and is, therefore, typically not employed in related studies.[28] Nevertheless, the results still show consistent variation across E Index quartiles. Specification (3) uses only non-imputed E Indices and specification (4) uses only executives with four or more years of data.[29] Specification (5) uses a similar set of firm-controls as Goolsbee (2000), which includes return on assets and market value. Specification (6) uses the baseline model firm controls, the Goolsbee (2000) firm controls, and return on equity. We also allow for the slopes of the firm-specific control variables to depend on E Index quartiles by interacting all of the firm-specific controls with E Index quartile dummies (not reported). All of the results presented in Table (6) corroborate that the elasticity of taxable income is positively related to the internal institutions of the firm.

3.8 Result Highlights

[27]The results are robust using a cubic polynomial as well (not reported).

[28]All other studies use a linear time trend and do not control for year fixed effects, except where it is possible to identify variation in the tax rate within years (e.g., comparing the top tax bracket with the second highest tax bracket). But that is not possible here because almost all of the sample is in top bracket.

[29]Excluding executives with limited years of data possibly introduces a survivorship bias as opposed to an attrition bias.

The results indicate that the elasticity of taxable income with respect to the net-of-tax rate is negatively related to the quality of the firm's governance regardless of the indicator of governance used. Thus, we reject the *pure efficiency hypothesis*. As indicated by significant variation in the elasticity of income with respect to taxes, the rent-seeking response appears to be large and statistically significant. Using the lower bound estimate derived in the conceptual model (Equation 18) and the estimated coefficients from Table 3 specification (2), the rent-seeking response represents 54 percent of the total response of income with respect to taxes for the highest E Index quartile. Similarly, the lower bound estimates for the second and third quartiles are 26 percent and 30 percent, respectively. These estimates are lower bounds because we cannot disentangle the rent-seeking response for the lowest E Index quartile. Actual rent seeking responses are therefore likely to be even larger than those reported above. Thus the rent-seeking response appears to represent a significant share of the overall response to changes in tax policy.

4. Conclusion

This paper develops a theoretical framework that distinguishes between the effort and rent-seeking responses to changes in marginal income tax rates. The model provides a framework in which variation in the elasticity of income with respect to changes in tax policy can be interpreted in terms of effort and rent-seeking responses. Moreover, the model sheds light on a lower-bound estimate of the rent-seeking response. Using a unique dataset of corporate executive compensation and firm corporate governance and empirical approach, we find that rent seeking constitutes a quantitatively and statistically significant response to changes in tax policy, which is consistent with Piketty, Saez, and

Stantcheva (2014). Moreover, we add to the literature by showing that good corporate governance appears to put the brake on the rent-seeking response.

While the empirical results are consistent with the predictions of the theoretical model, we are cautious to rule out all alternative interpretations. That is, it is possible that explanations precluding rent seeking, or at least precluding a rent-seeking response to tax policy, might generate similar predictions. To gain further insight, future studies should investigate the actual behavioral responses to changes in tax policy, not just the response of income, or explore further indirect testing. Another indirect test might entail investigating the performance of firms corresponding to changes in tax policy.

Given the high levels of public debt in advanced nations and growing public support for higher taxation on the rich, or at least curtailing the rise in after-tax income inequality, it is likely that many countries, including the United States, will significantly raise top income tax rates. However, as pointed out by Hall and Liebman (2000), executives manage assets worth billions of dollars and the incentives that the executives face, which are shaped by tax policy, are of substantial importance to economic performance as well as government revenue. Understanding whether tax policy influences rent seeking is, therefore, crucial to understand the efficiency costs associated with reducing income inequality and public debt.

Mathematical Appendix

First order conditions

Optimality implies $\{w, q, \theta\}$ satisfies the following

$$\{w, q, \theta\} \in \operatorname{argmax}\left\{\frac{(1-\tau)\,\mathrm{w} - b(g)e(q) - a(g)c(\theta) + F[\cdot]V^u}{\rho + F[\cdot]}\right\} \tag{A1}$$

This implies the Karush-Kuhn-Tucker conditions (along with complementary slackness condition for non-negativity constraints).

$$V^E - \max_{q,\theta}\left\{\frac{\left((1-\tau) + f(\cdot)V^u\right)}{f(\cdot)}\right\} \leq 0 \tag{A2}$$

$$V^E - \max_{w,\theta}\left\{\frac{\left(b(g)e'(q) + f(\cdot)V^u\right)}{f(\cdot)}\right\} \leq 0 \tag{A3}$$

$$V^E - \max_{w,q}\left\{\frac{\left(a(g)c'(\theta) + f(\cdot)V^u\right)}{f(\cdot)}\right\} \leq 0 \tag{A4}$$

Equations (A2) to (A4) hold with equality for interior solutions of w, q, and θ respectively. The optimality conditions follow from inspection.

Result 2

Using (8) and the envelope theorem implies

$$\frac{\partial w}{\partial(1-\tau)} = \frac{(1-\tau) - f(\cdot)\frac{\partial V^E}{\partial(1-\tau)}}{f'(\cdot)\left(V^E - V^u\right)} \tag{A5}$$

Using that $(1-\tau) = f(\cdot)(V^E - V^u)$ and

$$\frac{\partial V^E}{\partial(1-\tau)} = \left(\frac{1}{1-\tau}\right)\left(V^E + \frac{b(g)e(q) + a(g)c(\theta) - F[\cdot]V^u}{\rho + F[\cdot]}\right) \tag{A6}$$

implies the desired result after rearranging terms.

Table 1: Variable Descriptions

Variable	Description	Source
Total Pay	Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised + All Other Compensation	Execucomp
Income	Total taxable income: Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised	Execucomp
Cash	Salary + Bonus	Execucomp
Options	Value of options exercised	Execucomp
Other Compensation	Compensation not counted elsewhere and is predominately non-taxable (Goolsbee, 2000), including severance payments, signing bonuses, 401K contributions, among others.	Execucomp
Jensen-Murphy Statistic	Change in the value of the executive's portfolio of stocks and stock options from a \$1000 change in firm value. The value of the executive's portfolio is calculated by adding the number of shares owned and the number of (exercisable and unexercisable) unexercised, in-the-money options, the latter multiplied by 0.7 following Baker and Hall (2004) to convert options to share-equivalents.	Execucomp
Equity-at-stake	Change in the value of the executive's portfolio of stocks and stock options from a 1% change in firm value (see above for calculation of portfolio value).	Execucomp
Market Value	Price-Annual Close × Outstanding Shares	Compustat
Sales	Sales	Compustat
Leverage	Total Liabilities / Assets	Compustat
Market-to-Book	Price-Annual Close / Book Value per share	Compustat
Return on Assets	Net Income before extra. items and disc. operations / Total Assets	Compustat
%Board Ownership	Average number of shares owned by board directors as a percent of all shares outstanding.	RiskMetrics
Ownership Conc.	Herfandal Index of institutional investor ownership concentration.	Thomas Reuters
E Index	Categorical index of firm "Entrenchment", ranging from 0 to 6, in descending order of shareholder rights (ascending order of executive power). See section (3.3) for more details.	Lucian Bebchuk[a]
GIM Index	Categorical index of firm "Governance" constructed by Gompers, Ishii, and Metrick (2003), ranging from 0-24, in descending order of shareholder rights. See section (3.3) for more details.	RiskMetrics
Net-of-tax rate (1-τ)	Maximum tax rate (total federal and state) for an additional \$1000 of income on an initial \$1,500,000 of wage income. The taxpayer is assumed to be married and filing jointly. A mortgage interest deduction of \$150,000 and the calculated state income tax are present as personal deductions.	TAXSIM[b]

[a]Bebchuk and Ferrell (2008). Data hosted at www.law.harvard.edu/faculty/bebchuk/data.shtml.
[b]Feenberg, Daniel Richard, and Elizabeth Coutts, 1993 See www.nber.org/∼taxsim/state-rates for a description of the simulation used.

Table 2: Summary Statistics by E Index Quartiles (1992-2005): mean (top row) and median (bottom row) values

E Index Quartile	All	1	2	3	4
# Observations	31,297	7,712	7,238	8,957	7,390
	Executive Compensation				
Total Pay (x1000)	2,938	3,984	2,973	2,411	2,453
	1,217	1,428	1,238	1,129	1,153
Income (x1000)	2,442	3,342	2,456	1,991	2,034
	989	1,151	1,015	903	950
Cash (x1000)	1,050	1,278	1,051	929	957
	722	829	735	673	693
Options Exercised (x1000)	1,365	2,054	1,394	1,026	1,027
	96	111	102	90	88
Other Compensation (x1000)	169	208	165	145	160
	32	32	30	32	35
	Executive Wealth Sensitivity				
Jensen-Murphy Statistic	9.58	12.17	9.78	7.80	8.90
	2.35	2.13	2.43	2.30	2.48
Equity-at-stake	0.203	0.257	0.207	0.165	0.188
	0.051	0.047	0.053	0.051	0.054
	Firm Financials				
Market value (x1mil)	13,823	28,721	12,694	8,145	6,269
	3,750	5,626	3,710	3,619	2,966
Market-to-Book	3.17	3.65	3.39	2.87	2.80
	2.40	2.55	2.57	2.38	2.22
Leverage	0.63	0.62	0.61	0.61	0.66
	0.63	0.63	0.61	0.62	0.66
Return on Assets	4.35	3.87	4.27	4.84	4.35
	4.10	3.66	4.51	4.26	3.89
	Firm Governance				
%Board Ownership	0.72	1.06	0.81	0.51	0.57
	0.20	0.27	0.23	0.20	0.17
Ownership Concentration	0.057	0.071	0.055	0.052	0.049
	0.044	0.046	0.042	0.044	0.043
Governance (GIM index)	9.57	6.88	8.78	10.55	11.96

Note: See Table 1 for a description of variables. Sample includes executives with permanent income greater than $400,000 in 2006 US$ and at firms with fiscal years ending in December. All prices deflated by the Consumer Price Index in 2006$.

Table 3: Elasticity of various forms of compensation with respect to the net-of-tax rate.

Variables	(1) Income	(2) Income	(3) Total Pay	(4) Cash	(5) Options	(6) Income	(7) Income	(8) Income
(1-τ_t)	2.550***					3.235***		
	(0.262)					(0.329)		
(1-τ_{t+1})						-2.727***		
						(0.343)		
(1-τ_t)×I{E ∈ E_1}		1.525***	1.724***	0.195	3.954***		2.904***	2.815***
		(0.407)	(0.371)	(0.268)	(1.022)		(0.495)	(0.493)
(1-τ_t)×I{E ∈ E_2}		2.373***	2.547***	0.775***	6.428***		3.212***	3.095
		(0.381)	(0.348)	(0.251)	(0.957)		(0.463)	(0.468)
(1-τ_t)×I{E ∈ E_3}		2.514***	2.849***	0.950***	7.993***		3.325***	3.624***
		(0.351)	(0.320)	(0.231)	(0.875)		(0.430)	(0.424)
(1-τ_t)×I{E ∈ E_4}		3.316***	3.614***	1.363***	7.169***		3.661***	4.003***
		(0.376)	(0.343)	(0.248)	(0.940)		(0.457)	(0.444)
(1-τ_{t+1})×I{E ∈ E_1}							-2.865***	-3.082***
							(0.347)	(0.315)
(1-τ_{t+1})×I{E ∈ E_2}							-2.854***	-3.076***
							(0.347)	(0.315)
(1-τ_{t+1})×I{E ∈ E_3}							-2.861***	-3.076***
							(0.348)	(0.315)
(1-τ_{t+1})×I{E ∈ E_4}							-2.853***	-3.072***
							(0.348)	(0.315)
I{E ∈ E_2}		-3.378*	-3.268**	-2.295**	-9.909**		-1.209	-1.104
		(1.760)	(1.607)	(1.160)	(4.423)		(2.071)	(2.414)
I{E ∈ E_3}		-3.897**	-4.426***	-3.007**	-16.05***		-1.593	-3.177
		(1.822)	(1.663)	(1.201)	(4.563)		(2.149)	(2.307)
I{E ∈ E_4}		-7.073***	-7.470***	-4.692***	-12.59***		-2.875	-4.672*
		(1.947)	(1.776)	(1.284)	(4.878)		(2.289)	(2.381)
Market Value	0.398***	0.399***	0.329***	0.0737***	0.751***	0.343***	0.355***	0.343***
	(0.014)	(0.014)	(0.013)	(0.009)	(0.035)	(0.016)	(0.016)	(0.014)
+Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Federal Tax Rates	No	No	No	No	No	No	No	Yes
Observations	26,727	26,727	26,736	26,713	25,999	20,896	20,559	26,044
# of Executives	6,063	6,063	6,063	6,063	5,993	5,365	5,302	7,004
R-squared	0.208	0.209	0.251	0.131	0.149	0.195	0.197	0.120

Note: The sample in each regression pertains to 1992-2005, prices in 2006 constant dollars. All estimations control for executive-firm fixed effects and a linear time trend. Income represents total taxable income and includes: Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised. Total pay includes Income + Other compensation (non-taxable). Cash represents Salary + Bonus. Options refers to the value of options exercised. All specifications control for the combined federal and state net-of-tax rate, except specification (8) uses only federal rates. I{E∈E_j} is an indicator variable equal to 1 if the executive-firm's E index belongs to the j quartile and 0 if otherwise. +Firm Controls includes: Sales, Market-to-Book value, and Leverage in the previous year. All non-ratio-scale variables, including all forms of compensation, the net-of-tax rate, Market Value, and Sales, are in log form. Sample includes executives with permanent income greater than $400,000 in 2006 US$. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: Elasticity of taxable income with respect to the net-of-tax rate (dep var: Income).

	Jensen-Murphy		Equity-at-stake		%Board Ownership		Ownership Concentration	
Independent	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Index	Quartiles	Index	Quartiles	Index	Quartiles	Index	Quartiles
(1-τ_t)	1.593***		1.626***		2.364***		1.935***	
	(0.004)		(0.237)		(0.361)		(0.249)	
Index $\times$(1-τ_t)	-0.009***		-0.531***		-0.370***		-3.206**	
	(3.439)		(0.171)		(0.085)		(1.527)	
Index	0.0382***		2.195***		1.496***		12.56**	
	(0.014)		(0.691)		(0.344)		(6.167)	
(1-τ_t)$\times$I$\{Q \in Q_1\}$		2.603***		2.703***		3.592***		2.070***
		(0.355)		(0.357)		(0.428)		(0.285)
(1-τ_t)$\times$I$\{Q \in Q_2\}$		1.950***		2.041***		2.035***		1.434**
		(0.310)		(0.311)		(0.427)		(0.274)
(1-τ_t)$\times$I$\{Q \in Q_3\}$		1.415***		1.440***		0.997**		0.734**
		(0.301)		(0.300)		(0.440)		(0.304)
(1-τ_t)$\times$I$\{Q \in Q_4\}$		0.134		0.216		1.013		1.572***
		(0.323)		(0.320)		(0.494)		(0.368)
I$\{Q \in Q_2\}$		2.650*		2.701*		6.327***		2.458**
		(1.388)		(1.395)		(1.574)		(1.093)
I$\{Q \in Q_3\}$		4.764***		5.085***		10.42***		5.193***
		(1.518)		(1.519)		(1.747)		(1.240)
I$\{Q \in Q_4\}$		9.925***		10.04***		10.25***		1.782
		(1.618)		(1.618)		(1.995)		(1.494)
+Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,876	34,876	34,876	34,875	20,893	20,893	33,982	33,982
# of Executives	8,195	8,195	8,195	8,195	8,451	8,451	7,358	7,358
R-squared	0.183	0.182	0.183	0.185	0.148	0.148	0.205	0.199

Note: The sample in each regression pertains to 1992-2005, prices in 2006 constant dollars. All estimations control for executive-firm fixed effects and a linear time trend. The dependent variable is total taxable income, which includes: Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised. The variable Index indicates that the independent variables are considered continuous and I$\{Q \in Q_j\}$ is an indicator variable equal to 1 if the index is in the j quartile of the distribution and 0 otherwise. The Jensen-Murphy Index is the change in executive wealth from all stocks and unexercised stock options held from a \$1000 change in firm value. The Equity-at-stake Index is the change in executive wealth from a change of 1% change in firm value. %Board Ownership is the average percent of shares owned by the board of directors. Ownership concentration refers to the Herfandal Index of institutional investor ownership concentration. +Firm Controls includes: Market Value, Sales, Market-to-Book value, and Leverage. All non-ratio-scale variables, including all forms of compensation, the net-of-tax rate $(1-\tau)$, Market Value, and Sales, are in log form. Sample includes executives with permanent income greater than \$400,000 in 2006 US\$. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: Elasticity of Taxable Income with respect to the net-of-tax rate using various E Index quantiles and the GIM Index

Variables	(1) 2-Groups	(2) 3-Groups	(3) 5-Groups	(4) 6-Groups	(5) G Index	(6) G quantiles
$(1-\tau_t)\times$ I{E $\in$ E$_1$}	2.070***	2.052***	1.528***	0.543		
	(0.326)	(0.326)	(0.407)	(0.583)		
$(1-\tau_t)\times$I{E $\in$ E$_2$}	2.877***	2.496***	2.367***	1.854***		
	(0.295)	(0.350)	(0.381)	(0.450)		
$(1-\tau_t)\times$I{E $\in$ E$_3$}		3.298***	2.469***	2.421***		
		(0.376)	(0.350)	(0.381)		
$(1-\tau_t)\times$I{E $\in$ E$_4$}			2.573***	2.506***		
			(0.404)	(0.351)		
$(1-\tau_t)\times$I{E $\in$ E$_5$}			6.552***	2.610***		
			(0.720)	(0.405)		
$(1-\tau_t)\times$I{E $\in$ E$_6$}				6.582***		
				(0.720)		
$(1-\tau_t)\times$ I{ G $\in$ G$_1$}					1.547***	
					(0.377)	
$(1-\tau_t)\times$ I{G $\in$ G$_2$}					2.405***	
					(0.340)	
$(1-\tau_t)\times$ I{G $\in$ G$_3$}					2.049***	
					(0.344)	
$(1-\tau_t)\times$ I{G $\in$ G$_4$}					3.603***	
					(0.399)	
$(1-\tau_t)$						-0.452
						(0.633)
$(1-\tau_t)\times$(GIM Index)						0.294***
						(0.0610)
GIM Index						-1.181***
						(0.246)
+Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,727	26,727	26,727	26,727	29,167	29,167
# of Executives	6,063	6,063	6,063	6,063	6,560	6,560
R-squared	0.208	0.208	0.210	0.210	0.200	0.200

Note: The sample in each regression pertains to 1992-2005, prices in 2006 constant dollars. All estimations control for executive-firm fixed effects and a linear time trend. The dependent variable is taxable income, which includes: Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised. I{E$\in$E$_j$} is an indicator variable equal to 1 if the executive-firm's E index belongs to j quantile and 0 if otherwise. 2-Groups represents E index medians, 3-Groups represents E index terciles, and so forth. Similarly, I{G$\in$G$_j$} is an indicator variable equal to 1 if the executive-firm's GIM index belongs to the j quartile. GIM Index uses the index as a continuous-type variable. +Firm Controls includes: market value, sales, market-to-book ratio, and leverage. All non-ratio-scale variables, including all forms of compensation, the net-of-tax rate, market value, and sales, are in log form. Sample includes executives with permanent income greater than $400,000 in 2006 US$. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: Elasticity of taxable income with respect to the net-of-tax rate robustness checks (dep var: Income).

	(1)	(2)	(3)	(4)	(5)	(6)
	+Trend^2	Year Dummies	Restricted Sample[a]	Restricted Sample[b]	Goolsbee Controls[c]	All Firm Controls
$(1\text{-}\tau_t)\times$I{E=0-1}	0.946**	1.835	1.153	1.470***	1.695***	1.853***
	(0.468)	(1.579)	(0.710)	(0.411)	(0.406)	(0.397)
$(1\text{-}\tau_t)\times$I{E=2}	1.787***	2.617*	2.973***	2.350***	2.555***	2.828***
	(0.447)	(1.578)	(0.656)	(0.385)	(0.381)	(0.373)
$(1\text{-}\tau_t)\times$I{E=3}	1.919***	2.802*	3.101***	2.462***	2.650***	2.870***
	(0.423)	(1.564)	(0.603)	(0.354)	(0.350)	(0.342)
$(1\text{-}\tau_t)\times$I{E=4-6}	2.720***	3.584**	4.465***	3.353***	3.561***	3.393***
	(0.445)	(1.570)	(0.647)	(0.380)	(0.391)	(0.368)
Market Value	0.397***	0.382***	0.471***	0.405***	0.300***	0.397***
	(0.0137)	(0.0141)	(0.0256)	(0.0140)	(0.0118)	(0.0149)
Return on Assets					0.00280***	0.0035***
					(0.0006)	(0.0009)
Return on Equity						-2.35e-05
						(0.0002)
Linear Trend	Yes	n.a.	Yes	Yes	Yes	Yes
Quadratic Trend	Yes	n.a.	No	No	No	No
Year Dummies	No	Yes	No	No	No	No
+Firm Controls	Yes	Yes	Yes	Yes	No	Yes
Observations	26,727	26,727	11,904	24,935	26,810	26,276
# of Executives	6,063	5,063	5486	5,834	6,066	5,992
R-squared	0.209	0.219	0.226	0.206	0.203	0.216

Note: The sample in each regression pertains to 1992-2005, prices in 2006 constant dollars. All estimations control for executive-firm fixed effects and a linear time trend. The dependent variable is total taxable income, which includes: Salary + Bonus + Restricted Stock Grants + LTIP Payouts + Value of Options Exercised. [a]Specification 3 employs only the actual (non-imputed) E Index data. [b]Specification 4 restricts the sample to executives with at least 4 observation years. [c]Goolsbee Controls refers to identical firm controls employed in Goolsbee (2000), which includes return on assets and market value. Specification (6) controls for the baseline firm controls, the Goolsbee controls, and return on equity. +Firm Controls includes: market value, sales, market-to-book ratio, and leverage. All non-ratio-scale variables, including all forms of compensation, the net-of-tax rate, market value, and sales, are in log form. Sample includes executives with permanent income greater than $400,000 in 2006 US$ and at firms with fiscal years ending in December. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

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