Essays on Regional Inequalities, Innovation and Global Connectivity

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consists of approximately 58,000 words excluding bibliography.

0.1 Statement of co-authored work

I confirm that chapter three was jointly co-authored with Andrés Rodríguez-Pose and chapter four with Eduardo Hernández Rodríguez and I contributed 75% in both chapters.

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Abstract

This dissertation studies how global connectivity shapes local economic development, looking at regional inequalities and innovation. It empirically contributes to our current understanding of the local distributional effects of economic globalisation and the effects of international disintegration. This dissertation comprises five chapters, with the first one introducing and motivating the overarching theme and the four remaining being self-contained empirical papers. It refers to literature from economic geography, international economics, innovation studies, and economics of inequality, exploring the regional perspective in Europe and the US.

In the first part, in Chapter 1, the overarching theme of the local distributional effects of economic globalisation is introduced. It describes the evolution of the current wave of economic globalisation, measured by trade, global value chains and the role of global companies such as multinational enterprises. While during this initial phase a stark upward trend in economic globalisation has been observed, concerns over its benefits have been increasingly voiced. In this period of "hyperglobalisation" the costs of economic globalisation have become more salient, spurring a backlash against globalisation. This dissertation provides evidence on globalisation-induced inequality at the regional level for the US and Europe and emphasises the need to address the local distributional effects. This specifically means compensating those that are adversely affected by economic globalisation, in order to avoid potential costs stemming from international disintegration.

The second part contains three empirical papers, Chapter 2, Chapter 3 and Chapter 4, which provides evidence on the local distributional effects of economic globalisation

in the US and Europe. The regional perspective regarding the effects of economic globalisation on inequality has often been neglected, which is one of the main intended contributions of this dissertation. Analysing the relationship at the regional level is particularly relevant as economic activity significantly varies across space and it can offer valuable insights that are only possible to uncover when examining at a more granular level. In this dissertation, distributional effects describe either inter-firm dynamics like innovation concentration or interpersonal income inequality.

Chapter 2 looks at the relationship between multinational enterprises and intra-regional innovation concentration within US states. While patenting concentration measured by the Gini coefficient has increased for more than three decades, we still lack evidence on the role of global firms such as multinationals. Thus, the paper analyses to what extent the presence of multinationals influences inter-firm innovation concentration, showing a positive link between the presence of domestic-owned multinationals and patenting concentration, which is more pronounced with a high share of MNEs and for non-MNEs.

Concentration between firms might also affect inequality between people. The second and third paper focus on the distribution of income, showing that engaging more in trade and global value chains is linked to higher interpersonal income inequality within European regions at the NUTS-2 level. Chapter 3 analyses how trade affects income inequality, finding a positive association between trade and regional income inequality changes, which varies based on trading partners. Chapter 4 studies the link between global value chain participation and income inequality, showing that it matters how regions participate in global value chains and in which sectors.

In the third and final part of this dissertation, in Chapter 5, I focus on the effects of international disintegration, by looking at the effect of Britain's decision to leave the European Union. It examines the effect of Brexit on the adoption of digital technologies by small and medium-sized enterprises in the UK from 2013-2019. By providing timely and detailed measures for digital technology adoption, it offers novel and deeper insights into SMEs' reactions to this shock.

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Chapter 1

Introduction

1.1 Motivation

> Doesn't free trade make us all better off — over the long run?
>
> *Rodrik (2011)*

This dissertation asks a similar question: Doesn't economic globalisation make us all better off - everywhere? While this question can hardly be fully answered within the scope of this dissertation, it focuses on a dimension that has been too often left out – the local distributional effects of economic globalisation. A major part of this dissertation looks at the effect of different forms of economic globalisation on inequality at the regional level. Globalisation, as a multi-faceted process does not only include trade, but also global value chains (GVCs) and the role of global companies such as multinational enterprises (MNEs). Does it make us all better off everywhere? And how should we measure to be "better off"? While this raises many questions, this dissertation will focus on income and innovation, looking at distributional measures in the context of Europe and the US. It will examine both the short and long run but mostly focus on the former due to data availability. However, it is important to note that looking at the effects in the short run is also crucial given that they might reflect the adjustment costs over a certain period or that they could be even indicative of the long-run effects. In addition to its distributional effects, this dissertation will also show the costs of international disintegration, by focusing on the effect of Britain's decision to leave the

European Union.

Since the 1970s, the current wave of economic globalisation has been shaping the global economy. This includes a phase of hyperglobalisation and "slowbalisation" (Antràs, 2020)[1], with the first referring to the initial phase lasting until 2008[2] and the latter to the period from then until now. The rapid decline in trade costs, the revolution in information and communication technologies as well as political developments, among others, have been named key forces in this period of hyperglobalisation (Antràs, 2020). During this phase, trade has shown a distinct upward trend, with global trade volume doubling between 1997 and 2007 and growing an astounding 32 times between 1950 and 2007 (Federico and Tena-Junguito, 2017). Trade within GVCs[3] has been accelerating starkly between 1986 and 2008, rising from around 40% to more than 50% (Borin and Mancini, 2019). Particularly since the 1980s, GVCs have deepened countries' and regions' integration into the worldwide economy (World Trade Organization, 2014; Antràs and Chor, 2022). But also the role of MNEs has intensified during this period, observing an increase in foreign affiliates' gross output (relative to global output) from around 10% in 2001 to nearly 14% in 2007 (Antràs, 2020). MNEs have taken a vital role in a profound integration of global economies. They play a pivotal role within GVCs and the global economy, constituting about a third of the global Gross Domestic Product (GDP) and half of the worldwide exports in 2014 (OECD, 2018). The profound impact of changes in these three forms of economic globalisation - trade, GVCs and MNEs - have become apparent in various forms, markedly altering the structure of economies and societies, in particular in establishing an international division of labour that allows to harvest larger gains from specialisation and economies of scale. As a result, these structural changes have left the economies worldwide more open and economically integrated (in 2007) and with benefits for its citizens that were larger than

[1]Some have also referred to it a deglobalisation, see e.g. James (2018)

[2]when international trade flows and GVC participation have seen stagnation or decline (Baldwin, 2009; Borin and Mancini, 2019)

[3]Refers to the percentage of a nation's exports that pass through a minimum of two international boundaries (Borin and Mancini, 2019).

those a century ago, as shown for the case of trade (Federico and Tena-Junguito, 2017).

At the heart of fostering economic globalisation lies its premise to spur economic development. Early theories, in particular neoclassical trade theories, have postulated that efficiency gains are brought about by countries exploiting their comparative advantage and specialising on goods in which they are most productive (Ricardo, 1891). By increasing the "extent of the market", specialisation is fostered through the division of labour and economies of scale are reinforced (Smith, 1776). Also the aspect of technological transfer has been emphasised, providing the chance for the adoption and diffusion of new technologies (Keller, 2004). From a New Economic Geography viewpoint, the agglomeration of economic activities- producers, consumers, and intermediate input - in certain areas, has the advantage of reduced transportation costs while leading to larger benefits from economies of scale (Krugman, 1991). These economies of density benefit from local capacities and gain from knowledge spillovers that are highly localised (Marshall, 1890; Jaffe and Trajtenberg, 1999; Cantwell et al., 1995).

From an empirical view, a large body of literature has emphasised that globalisation drives economic development. Trade leads to income growth (Frankel and Romer, 1999) and to welfare gains through the increase of local productivity (Melitz and Redding, 2014). Moreover, it has also been shown that the trade-induced growth has led to the alleviation of poverty, with absolute poverty being in decline in developing countries for two decades due to globalisation (Dollar and Kraay, 2004). These aggregate gains in income and welfare have been the rationale behind the continuous reinforcement of the progress of globalisation. This has led many governments in the first period of hyperglobalisation, between 1986 and 2008, to reduce trade barriers that were constructed during the interwar period, leading to a decrease in tariffs as well as trade policy uncertainty (Antràs, 2020). Also, economists strongly favor free trade, with 87.5% supporting that barriers to trade should be removed in the US (Whaples, 2006).

However, increasingly concerns are voiced whether globalisation has reached a tipping point or whether it is "at a critical conjuncture" (Martin et al., 2018). The costs of globalisation have become more salient and gaining more weight - compared to its gains - fuelling the backlash against globalisation (Rodrik, 2018). In this period of hyperglobalisation, the economic net gains are increasingly outweighed by its distributive and political consequences (Rodrik, 2011; Rodrik, 2018). The backlash against globalisation was fuelled by the globalisation-induced rises in inequality and by those who lacked sufficient compensation provided to groups who may have been adversely impacted by this advanced period of globalisation (Antràs, 2020). The challenge for the future of globalisation thus lies in addressing its distributional consequences, which are likely to widen (given as well the recent developments related to technological change).

Knowing that engaging in economic globalisation comes as well at a cost has been part of economic enquires for many decades. Early research by Stolper and Samuelson (1941) drew significant attention to the distributional consequences of international trade, revealing that trade can also have detrimental effects on certain groups of workers. Engaging in international trade transforms the structure of regional labour markets, drives business dynamics and affects technological change (Melitz, 2003; Keller, 2004; Autor, Dorn and Hanson, 2013). Recent studies have provided evidence on the rising distributive and political costs. These implications include a wide variety of consequences, including not only the decrease in employment and wages due to import competition (Autor, Dorn and Hanson, 2013; Daumal, 2013; Iammarino, Rodríguez-Pose and Storper, 2019), increasing income inequality (Heimberger, 2020) and rising technological gaps (Kemeny, 2011), but also skill polarisation (Autor et al. 2019), an increase in market power and the emergence of "superstar firms" (Autor, Dorn, Katz et al., 2020) as well as the backlash of the "places that don't matter" (Rodríguez-Pose, 2018) in the form of populism.

1.2 The Distributional Effects of Economic Globalisation

Many of these outcomes are linked to the local distributional effects of economic globalisation, which have been a main reason for discontent and the backlash against globalisation (Rodrik, 2018; Antràs, 2020). The distributional effects refer to the effects on income, in particular interpersonal income inequality, and innovation, specifically inter-firm innovation concentration, within a region.

I consider them to be central for multiple reasons. In many advanced economies, inter- and intra-regional inequality has been increasing (Rodríguez-Pose, 2012; Lindley and Machin, 2014; Lee, Sissons and Jones, 2016; Terzidis, Maarseveen and Ortega-Argiles, 2017; Iammarino, Rodríguez-Pose and Storper, 2019; Feldman, Guy and Iammarino, 2021). Because of substantial economic, social, and political implications, higher levels of economic disparity may present difficulties for regions and policy makers. Inequalities can take on many shapes, including differences in income, and unequal access to resources and opportunities. Also, more inequality might hinder economic growth (Alesina and Rodrik, 1994; Lee and Son, 2016), decelerating the economic development of regions. Higher levels of economic inequality might also increase tensions between poor and rich individuals, driving social and political instability. Previous work has shown that social unrest and civil wars is likely to occur more frequently in regions characterised with higher levels of inequality (Lessmann, 2016).

Increasingly, top income recipients have become part of the public but also scholarly discourse (Atkinson, Piketty and Saez, 2011; OECD, 2011; Alvaredo et al., 2013). In particular, incomes for some groups have observed increases in their earnings, whereas those at the tail and the middle have faced stagnation or a decline (Autor, 2019). Also, the increase in executive pay has sparked significant public debate and scholarly investigation (Gabaix and Landier, 2008). In the US, the average earnings of CEOs at the largest 350 firms have consistently risen compared to the typical worker compensation: In 1965, it was 20 times higher than the average earnings of a worker, which has increased to 278 times in 2018 (Mischel and Wolfe, 2018). Higher inequality at the top leaves higher concentration of wealth but also power in the hands of the few (Krugman, 2005; Savage, 2021). This might pose a problem for selected groups, as implemented policies could reflect a type of prioritarianism favoring certain groups.

Interpersonal income inequality might also stem from inter-firm dynamics. Inter-firm dynamics related to productivity and innovation might be substantial predictors of wages. There is increasing evidence that inequality between firms significantly drives inequality between people (Card, Heining and Kline, 2013; Barth, Bryson et al., 2014; Card, Cardoso and Kline, 2016; Song et al., 2019). This is particularly relevant given recent evidence that the gains from innovation and globalisation are becoming increasingly concentrated in a small number of superstar firms (Autor, Dorn, Katz et al., 2020) and therefore spreading less. Economic globalisation could play a crucial role by reinforcing these effects due to a considerable rise in the potential gains from innovation due to a market size effect while at the same time heightening losses due to a competition effect (Aghion, Antonin and Bunel, 2021).

The concentration observed in the US product market (De Loecker, Eeckhout and Unger, 2020; Akcigit and Ates, 2021) may be rooted in innovation dynamics between firms, which is another reason to explore innovation concentration dynamics. Recent evidence indicates that declining business dynamics and increased product market concentration in the US stem from decreasing knowledge diffusion between frontier and laggard firms (Akcigit and Ates, 2021). Falling business dynamics play a crucial role for innovative output, as competition encourages “Creative Destruction”, which is the replacement of old technologies with novel ones (Schumpeter, 1942). Many developed countries, including the US, have been facing stagnating labour productivity for more than two decades (OECD, 2015) and declining productivity in R&D investments (Bloom, Jones et al., 2020), while at the same time documenting heightened challenges in knowledge diffusion (Akcigit and Ates, 2021). Therefore, innovation concentration between firms should be explored as it is of high policy relevance given that it is likely to affect wage dynamics, innovative output, product market concentration and thus standards of living.

Thus, in short, a central argument of this dissertation is that it is key to look at the distributional effects of economic globalisation and to attempt to make it more inclusive. Interpersonal income inequality and inter-firm innovation concentration are outcomes affected by economic globalisation and are of high importance for regional development. Higher levels of economic inequality carry significant economic, social, and political implications (Alesina and Rodrik, 1994; Lessmann, 2016; Lee and Son, 2016). In particular, the political backlash has become increasingly evident these last years. Structural changes stemming from globalisation (as well as automation) have been described as major driving forces in the rise of radical-right political parties and economic nationalism in Europe and the US (Colantone and Stanig, 2019; Autor, Dorn, Hanson and Majlesi, 2016).

In turn, the globalisation-induced implications, exemplified by the political backlash, have further economic costs. A recent study has demonstrated that anti-system voting in the form of populism imposes significant economic burdens: In comparison to a non-populist counterfactual, the authors show that GDP per capita is significantly lower - by 10 percent - after 15 years, analysing 51 populist leaders, including presidents and prime ministers, between 1900 and 2020 (Funke, Schularick and Trebesch, 2023). But also international disintegration in the case of Brexit has distinct economic costs, which will make the UK economy poorer (Sampson, 2017). Given the high economic (and other) costs that follow from international disintegration and populist leaders, this dissertation argues that it is impertinent to follow another path: Addressing the globalisation-induced increases in inequality and compensate those that have been adversely affected, in an attempt to avoid these costs and (some of) the backlash.

But have the effects on those who are losing out from economic globalisation been addressed? Does it have to lead to discontent and a backlash? Some argue that this does not have to be the case, as long as individuals who suffer losses from globalisation are adequately compensated (Antràs, 2020). Compensating financially is especially relevant for individuals who have experienced a decrease in incomes or have lost their jobs. However, a substantial literature has also shown that economic factors are tightly linked to cultural factors, making a strong argument for the cultural backlash (Norris, 2019b; Margalit, 2019). Globalisation-induced shocks are also transmitted through culture and identity, affecting indirectly demand for anti-system political representation (Rodrik, 2018). Even with a financial compensation, a key component would be as well linked to respect and status, which would need to be restored (Besley, 2021). Thus, addressing the costs of economic globalisation is essential to avoid not only political, but also social and economic implications.

1.3 Dissertation Overview

This dissertation focuses on how global dynamics shape local development, looking at Europe and the United States. It studies the distributional effects - innovation concentration and income inequality - of economic globalisation in Chapter 2, 3, and 4 and the effects of international disintegration in Chapter 5. Chapter 2 studies the link between MNEs and innovation concentration between patenting firms within US states. Chapter 3 investigates how trade affects intra-regional income inequality across European region. Chapter 4 analyses the link between GVC participation and intra-regional income inequality. Chapter 5 focuses on the effect of Brexit on the adoption of digital technologies by small and medium-sized enterprises.

1.3.1 Multinationals and intra-regional Innovation Concentration

For more than three decades, the US has seen patenting concentration increase in different technology classes, measured by the Gini coefficient (Forman and Goldfarb, 2020). However, less is known about the role of MNEs regarding these developments. Their presence strongly impacts the patenting activity within regions, as they do not only produce knowledge, but they also affect existing firm dynamics, attract further MNEs and transfer knowledge by producing spillovers. However, while knowledge diffusion does not happen automatically (Blomström and Kokko, 1999), there seems increasing evidence for market concentration and knowledge concentration across firms (Feldman, Guy and Iammarino, 2021; Forman and Goldfarb, 2020).

This paper analyses to what extent the presence of MNEs influences innovation concentration between patenting firms within US states. MNEs are identified through patent data, following Crescenzi, Dyevre and Neffke (2020), requiring a firm to operate in multiple countries by producing patents across borders. I analyse the effect of the presence of domestic-owned and foreign-owned MNEs on patenting concentration, focusing on concentration between all patenting firms and non-MNEs within US states. Merging patent data and regional socioeconomic data over a period of more than three decades, Ordinary-Least-Square (OLS) and Instrumental Variable (IV) estimations show that the presence of MNEs increases patenting concentration. I first examine the effect of the presence of (domestic- and foreign-owned) MNEs on the patenting concentration of all firms and find a positive relationship that is statistically significant. This overall effect is driven by the presence of domestic-owned MNEs. Foreign-owned MNEs, in contrast, are not significantly related to higher patenting concentration. These effects differ across space: regions with a high share of domestic MNEs experience a higher increase in patenting concentration, compared to those with a low share. This effect is mostly driven by an adverse effect on patenting of non-MNEs, which are firms that tend to be less innovative, with those in the middle of the patenting distribution producing fewer patents due to the presence of domestic-owned MNEs.

These findings offer a new perspective on the drivers of innovation concentration between firms and link it to economic globalisation, which could play a crucial role by reinforcing existing effects due to a considerable rise in the potential gains from innovation while at the same time heightening losses.

1.3.2 Dissecting the Link Between Trade and Income Inequality in European Regions

Do interregional trade flows matter for changes in intra-regional income inequalities? A considerable body of research has examined income inequality through cross-country analysis (Hirte, Lessmann and Seidel, 2020; Dorn, Fuest and Potrafke, 2018; Roser and Cuaresma, 2016; Dreher and Gaston, 2008), focused on single-country studies (Barusman and Barusman, 2017; Silva and Leichenko, 2004), or linked territorial inequality within countries with international trade (Rodríguez-Pose, 2012; Rodríguez-Pose and Gill, 2006). Still, below the national level, there remains an important gap in our knowledge regarding the impact of trade on intra-regional income inequality. This is particularly the case across European regions, where a lack of specific data has further hindered this type of analysis.

Understanding the effects of trade on regional income disparities is crucial. Previous studies have failed to explore extensively the regional level across broader geographical scales, leaving open questions about how trade impacts differ based on trading partners. This paper addresses this gap by examining the complex interplay between trade and interpersonal inequality with a focus on regional disparities within Europe. Trade is measured as the inter-regional flows of intermediate and final goods, along with services (Thissen, Ivanova et al., 2019). We assess the impact of various trade types

—including domestic trade, trade within the EU, and trade with neighbouring and non-neighbouring regions— on the rise of interpersonal inequality at NUTS-2 level across the EU, using OLS and IV estimations. Our findings indicate a positive and statistically significant relationship between trade and regional income inequality, which varies significantly depending on the type of trading partners of different European regions. Trade within the EU, the same country, and with non-neighbouring regions correlates with an increase in intra-regional income inequality. By contrast, no significant effects are observed for international trade and trade outside the EU. This suggests that the impact of trade on the income distribution is nuanced and contingent on the nature and proximity of trading partners.

We leverage two novel data sets on trade and regional income inequality, incorporating inter-regional trade flow data for 2013, for the trade data, and combining the Gini coefficient data from the European Union Statistics on Income and Living Conditions and the Luxembourg Income Study, for the regional inequality data.

1.3.3 GVCs and Top Income Inequality: Evidence from European regions

This study analyses the link between GVC participation and intra-regional income inequality across European regions from 2003 to 2010. With the global economy becoming increasingly interconnected, it has become of rising importance for regions to participate in GVCs. A substantial body of literature has shown a positive relationship between GVCs and economic development, which could be through the process of technological upgrading (Giuliani, Pietrobelli and Rabellotti, 2005; Morrison, Pietrobelli and Rabellotti, 2008; Pietrobelli and Rabellotti, 2007; Pietrobelli and Rabellotti, 2011), increased productivity and higher income (Raei, Ignatenko and Mircheva, 2019; Pahl and Timmer, 2020; Jangam and Rath, 2021). However, while these economic benefits of GVC participation have been traditionally highlighted, the potential subnational disparities that can be derived from this phenomenon may have remained underexplored (Crescenzi and Harman, 2023).

Therefore, this paper studies the relationship between different indicators of GVC participation and intra-regional income inequality, with a focus on the top of the income distribution in the European context from 2003-2010. For this purpose, input-output data at the NUTS-2 level from the EUREGIO database (Thissen, Lankhuizen et al., 2018) is used to construct indicators for regional participation in GVCs. We calculate multiple GVC indicators, including total, backward, and forward participation as well as an income inequality measure, which is the share of Top 5% using data from the European Union Statistics on Income and Living Conditions.

We then empirically analyse how GVC participation and income inequality are linked, using OLS estimations. We find that there is a positive and statistically significant relationship between GVC participation and intra-regional income inequality. It is forward GVC participation that is associated with higher top income inequality. These overall effects are driven by multiple sectors, including manufacturing, transport, storage and communications, as well as real state and business activities. We then test for heterogeneity concerning the development level of the region. Indeed, lagging regions are more exposed to higher levels of top income inequality derived from GVC participation. Furthermore, this paper explores the role of institutions mediating the effects of GVC participation for regions. Results show that regional institutions matter for shaping the unequal distribution of rents derived from GVC participation. Regions with lower institutional quality are associated with higher levels of intra-regional top income inequality. Thus, institutions remain crucial to shape the benefits derived from interregional linkages.

1.3.4 Brexit and Digital Technology Adoption

This paper examines the effect of Brexit on the adoption of digital technologies by SMEs in the UK from 2013-2019. Previous research has studied the impact of Brexit on different outcomes, but leaving out the impact on SMEs and their behaviour when it comes to digital technology. SMEs are often viewed as drivers of productivity, especially those that are innovative and growth-oriented (Schneider and Veugelers, 2010). Crucially, it is this particular group that has voiced considerable concern about the effects of Brexit (Brown, J. M. Liñares-Zegarra and Wilson, 2018). Despite this, evidence is missing on how they are affected when it comes to digital technology adoption, a key component of productivity growth (Gal et al., 2019).

This study contributes to bridging this knowledge gap by developing novel measures for technology adoption, leveraging the ever-increasing volumes of data available from businesses' websites. It combines survey data from the Longitudinal Small Business Survey with novel data on digital technology adoption from firms' websites to provide detailed and timely measurements to gain deeper insights into SMEs' reactions to this shock. It uses a difference-in-differences design, with the Brexit referendum as a trade policy uncertainty shock that imposes higher potential trade costs and heightens uncertainty among exposed firms that depend on the EU. It studies how firms that trade with the EU respond and finds that they adapt by reducing digital technologies.

This chapter finds a negative effect for digital technologies that are used for e-commerce, including payment technologies, which are significantly decreased, suggesting that firms cut back in the form of trade-enhancing digital technologies. These effects are driven by multiple sectors, extending beyond those traditionally associated with the trade of goods to also include service sectors. In addition, firms exposed to the shock reduce digital technologies not directly linked to e-commerce, suggesting a wider and more substantial impact of Brexit on SMEs' technology adoption. The findings suggest that three channels have been influential: trade, investment, and strategical realignment. By looking at different digital technology categories and LSBS survey responses, support for these channels is found.

1.4 Contributions and Limitations

This dissertation intends to advance existing knowledge by providing novel insights and perspectives on the local distributional effects of economic globalisation, as well as to a lesser degree to the costs of international disintegration. Chapter 2, 3, 4 and 5 are organised as independent papers, which aim to contribute to different strands in the literature. These strands are outlined in each chapter, which include economic geography, international economics, innovation studies, and economics of inequality. Gaps in the literature are highlighted in each respective chapter, and the series of intended contributions are emphasised. This section will summarise the collective contributions and limitations.

Chapter 2, 3 and 4 have in common that they provide novel empirical evidence, and thus advance our current knowledge, on the local distributional effects of economic globalisation. They all look at the effects on regions (in the US or Europe) and emphasise that engaging in the international economy has effects on interpersonal income and inter-firm innovation concentration. Much of the previous literature has centered on the distributional effects of economic globalisation, in particular for trade, but left out its local effects. The effect for trade on income inequality has been analysed through the lenses of cross-country analyses (Hirte, Lessmann and Seidel, 2020; Dorn, Fuest and Potrafke, 2018; Roser and Cuaresma, 2016; Dreher and Gaston, 2008), single-country studies (Barusman and Barusman, 2017; Silva and Leichenko, 2004), or analyses looking at territorial inequality within countries (Rodríguez-Pose, 2012; Rodríguez-Pose and Gill, 2006). However, below the national level, a significant knowledge gap persists when it comes to the impact of trade and GVCs on intra-regional income inequality.

This is particularly the case for European regions, where a lack of specific data has further hindered this type of analysis. Gaining insight into this aspect is essential, given the potentially detrimental societal effects of income inequality.

This dissertation emphasises the importance of looking at the distributional effects of economic globalisation at the regional level. This is for several reasons. First, economic activity does not only vary across space, it is highly concentrated within certain areas. As demonstrated in Chapter 2, it is particularly those areas with a large share of MNEs that drive innovation concentration. Second, looking at the subnational level allows novel perspectives that are likely masked at the country level. For example, in Chapter 3, we assess the impact of various trade types —including domestic trade, trade within the EU, and trade with neighbouring and non-neighbouring regions— and find that it is actually national, not international trade, that is linked to income inequality. Third, the impact of economic globalisation is expected to vary depending on existing local capabilities. For example, in Chapter 4 it is shown that the effects strongly depend on the quality of local institutions and the development level. Therefore, looking at the local level is essential given that economic activity strongly varies across space, it can enable insights only possible when looking at a more granular level and the effect is likely to differ based on local capabilities.

The collective finding of all three chapters studying the distributional effects of economic globalisation is that it exerts a substantial impact. In all chapters, a positive and significant relationship is found. The distributional measures include the Gini coefficient for interpersonal income inequality and inter-firm innovation concentration, attaching more weight to the middle of the respective distribution (Atkinson et al., 1970). For interpersonal income inequality, it also applies the share of top 5% earners, focusing on the top of the income distribution. In the European context, this dissertation finds a positive link between trade integration and changes in income inequality, measured by the Gini coefficient. It dissects the link between different types of trade and income inequality, showing that it matters who you trade with. Also, participating in GVCs is positively associated to income inequality at the top, emphasising that it matters how a region engages in GVCs and in which sectors it does so. For the relationship between MNEs and innovation concentration in the US, this dissertation finds evidence for a positive relationship as well, showing that this link is particularly pronounced in states with a high share of MNEs.

This dissertation also aims to contribute to the effects, or costs, of international disintegration, focusing on the Brexit-induced firm-level effects in the UK. Evidence has been missing on this effect when it comes to digital technology adoption, a key component of productivity growth. Chapter 5 contributes to bridging this knowledge gap by developing novel measures for technology adoption and studying the effects on SMEs, which are the backbone of the economy, making up 99.9% of all private firms in the UK (ONS, 2017). It combines survey data from the Longitudinal Small Business Survey with novel data on digital technology adoption from firms' websites to provide detailed and timely measurements to gain deeper insights into SMEs' reactions to this shock. It studies how firms that trade with the EU respond and finds that they adapt by reducing digital technologies. A negative effect for digital technologies that are used for e-commerce, in multiple sectors is found, as well as in digital technologies not directly linked to e-commerce. These findings suggest a wider and more substantial impact of Brexit on SMEs' technology adoption, and thus significant costs of international disintegration.

While highlighting the contributions, the limitations of this dissertation should also be clearly stated. This includes multiple areas. The first one refers to the time horizon. When looking at inequality, trade and GVCs, which are structural variables, it would be of high value to look at the effects in the long run. Given data limitations on the trade and GVCs side, it was not possible to analyse the effect over a longer period. Despite this limitation, it is still relevant to analyse the short term effects, given that these adjustments might still significantly affect individuals' incomes and jobs and that these effects might persist in the long run. Moreover, given that the availability of the GVC data overlaps with the hyperglobalisation period and that the degree of trade integration in 2013 is likely reflecting the previously observed increases, it is a relevant period to study. Looking at the long-term effects of trade and GVC integration on interpersonal income inequality at the regional level would be a highly interesting subject for further studies.

Another limitation is that the mechanisms linked to the distributional effects of economic globalisation are not directly tested for. While theories and potential mechanisms are discussed in each chapter, it is not fully possible to pinpoint at specific mechanisms driving the overall effect. This is because all three chapters that study the distributional consequences of economic globalisation prioritise the overall relationship, focus on the macro level and are limited to the scope of a dissertation. While it is important to provide insights on these dynamics at a macro level, it would be also of high interest to zoom in, having a closer look what happens to regional actors by focusing on households and firms. This should be further explored, investigating the mechanisms driving the effect and looking more at the micro level. In order to do so, access to firm level data would be required, which would be an interesting and relevant area for further studies. In addition to these overlapping areas, every chapter will point out its own contributions and limitations.

Summing up, this dissertation highlights that economic globalisation has local distributional implications, emphasising a positive link with inter-firm innovation concentration and interpersonal income inequality. While economic globalisation has spurred economic development in the last decades, its recent backlash has steadily increased, fueled by those losing out from economic globalisation. To avoid challenges stemming from higher levels of inequality, it is of high relevance to provide evidence and address these globalisation-induced inequalities. In an attempt to address these implications, more research on the locally induced effects of economic globalisation is needed. Focusing on the regional level can reveal novel insights only possible when looking at a more granular level and is essential given that economic activity strongly varies across space. In particular, research investigating the mechanisms and the long term effects of the globalisation-induced regional inequality would be needed. In order to do so, however, more data over a longer time span and at a more granular level is needed.

When it comes to addressing the globalisation-induced increases in inequality the financial and the cultural dimension is crucial. The financial component refers to compensating those that have been adversely affected, such as in the form of lower income or job loss. However, addressing economic factors alone may prove insufficient in effectively mitigating these challenges. As economic factors are tightly linked to cultural factors, identity and status are likely also affected by these structural changes in the economy. Thus, even with a financial compensation, a key component would be to restore respect and status (Besley, 2021). Because of the high economic (and other) costs that follow from international disintegration, this dissertation argues that it is pertinent to follow another path: Providing more research on the local distributional effects of economic globalisation and addressing them by compensating those that have been adversely affected.

Chapter 2

Multinationals and intra-regional Innovation Concentration

2.1 Introduction

For more than three decades, the US has seen patenting concentration increase in different technology classes, measured by the Gini coefficient (Forman and Goldfarb, 2020). However, less is known about the role of Multinational Enterprises (MNEs) regarding these developments. Accounting for around one-third of global Gross Domestic Product (GDP) and half of global exports in 2014, Multinational Enterprises (MNEs) are considered the main actors in the global economy (OECD, 2018). Also, their innovative activities have seen an impressive surge, with the amount of international investment in Research and Development (R&D) and invested capital approximately doubling between 2003 and 2017 (Crescenzi, Dyevre and Neffke, 2020). The presence of MNEs, their foreign operations and their overall patenting activity strongly impact the patenting activity within regions, as they do not only produce knowledge, but they also affect existing firm dynamics, attract further MNEs and transfer knowledge by producing spillovers. However, while knowledge diffusion does not happen automatically (Blomström and Kokko, 1999), there seems increasingly evidence for market concentration and knowledge concentration across firms (Feldman, Guy and Iammarino, 2021; Forman and Goldfarb, 2020). With this research, I aim to explore to what extent the presence of MNEs affects innovation concentration between firms within US states from 1976 to 2010.

There are multiple reasons why we should analyse innovation concentration between firms within a region and technology class. First, the level of patent concentration or competition matters for the innovative output. Similar to the product market, a monopolist might have a lower incentive to be innovative than a firm in a competitive market, which is also called the "Arrow replacement effect" (Arrow, 1962). From this view, competition spurs innovation. Second, as pointed out by Schumpeter (1942), competition is central to creative destruction and therefore a key driver for long-run economic growth. Most importantly, these dynamics could strongly affect regional development and prosperity. Fostering innovation is seen as a key priority as it fosters regional growth and higher wages (Lee and Rodríguez-Pose, 2013), which is why this relationship should be explored. Thirdly, economic globalisation could play a role by raising the potential gains from innovation due to a market size effect while at the same time heightening losses due to a competition effect (Aghion, Antonin and Bunel, 2021). However, relatively little is known about the role of MNEs in contributing to these innovation dynamics, in particular how they contribute to the increasing patenting concentration within the US.

In this study, I analyse the effect of the presence of MNEs on patenting concentration within US states from 1976 to 2010. Using patent data from the United States Patent and Trademark Office (USPTO), I construct the Gini coefficient as a measure of patenting concentration between firms within states and calculate the share of patents by MNEs. The Gini coefficient is calculated using the patents for all firms and for firms that are not MNEs (non-MNEs). I first examine the effect of domestic- and foreign-owned MNEs on the patenting concentration of all firms and find a positive relationship that is highly statistically significant. This overall effect is driven by the presence of domestic-owned MNEs. Foreign-owned MNEs, in contrast, are not significantly related to higher patenting concentration. These effects differ across space: regions with a high and very high share of domestic MNEs experience a higher increase in patenting concentration, compared to those with a low share. Moreover, the effect on patenting concentration for non-MNEs is more pronounced than for all patenting firms. A one standard deviation increase in the domestic-owned MNE patent share is estimated to raise the Gini coefficient by 0.21 points (OLS estimates) and around 0.32 points (IV estimates). This effect is mostly driven by an adverse effect on patenting of non-MNEs, with those in the middle of the non-MNE patenting distribution producing fewer patents. To verify the robustness, further estimations are conducted that are largely consistent with these results.

This paper contributes to the literature by answering the question to what extent the presence of domestic and foreign MNEs influences the intra-regional innovation concentration, focusing on all patenting firms as well as non-MNEs. To the best of my knowledge, this question has not been answered yet. By doing so, it contributes to two main literature strands, one on internationalisation and domestic patenting dynamics and the other one on innovation concentration and its determinants. The first strand has identified a market size and competition effect but has not taken into account that it might result in increasing patenting concentration. Previous papers have found evidence for a positive market size effect, showing that (at least some) firms that internationalise become more innovative (Verhoogen, 2008; Lileeva and Trefler, 2010; Bas and Ledezma, 2010; Bernard, Redding and Schott, 2011). This also indirectly affects the domestic market through a competition effect that influences all firms by making the market more competitive (Shu and Steinwender, 2019). However, these papers have not looked at the effect of internationalisation on patenting concentration dynamics between firms, but rather looked at the effects of firm outcomes.

The second strand has not looked at the role of MNEs and their contribution to the rise in patenting concentration. Concentration of firm patenting has already been looked at in the 1940s (Edwards, 1949) but recently became increasingly the focus of academic work (Forman and Goldfarb, 2020; Akcigit and Ates, 2021). Forman and Goldfarb (2020) have analysed increasing firm concentration in patenting, proxied by the Gini coefficient, in the US and focus on the role of information technology in the rise of patenting concentration. In contrast, this paper focuses more on the role of economic globalisation by connecting it to MNEs, showing which role they play in the increase in patenting concentration. Therefore, it contributes to innovation concentration and its determinants. While it has been argued that concentration of innovative activities depends on the technology class (Malerba and Orsenigo, 1996), I find that concentration increases for nearly all classes. In addition to contributing to the academic literature, the question is also of high policy relevance, given that it might be linked to other trends currently observed, such as lower productivity and higher product market concentration.

This draft is organised in the following way: It first summarises relevant literature, then sketches out a conceptual framework and hypotheses tested in the empirical section. It describes the data and setting for this research, plots descriptive statistics and estimates the results. Further, it explores heterogeneity and reports robustness checks.

2.2 Relevant Literature and State of the Art

2.2.1 Competitive Advantage: Technological Competence and Internationalisation

From a resource-based view (Penrose, 1959), a firm's growth and competitive advantage stems from the internal resources available to a firm. The competence-based approach states that heterogeneity in firm growth is primarily rooted in differences in technological competence (Mansfield, 1962). Therefore, higher firm growth and higher market shares are the results of internal resources of the firm, in particular technological competence, which reinforces R&D investment. Firms that internationalise tend to be more productive and innovative (Melitz, 2003), and thus have higher technological competence already before participating in international markets. Firms with higher technological competence select themselves into internationalisation which allows to increase of the "extent of the market" fosters the division of labour and reinforces the realisation of economies of scale (Smith, 1776). From a transaction cost perspective (Coase, 1991; Williamson, 1965), firms can decrease costs and achieve a higher market share further by internalising R&D activities and international operations. It also enables MNEs to tap into external location specific advantages, exploiting differences in factor endowment, in particular skilled labour or technology, and access to natural resources (Hejazi and Pauly, 2003). Therefore, technological competence and internationalisation are both viewed as source of a firm's competitive advantage as they can exploit increasing returns to scale and will predict the innovativeness and the market share of the firm.

There is comprehensive literature on endogenous firm location, assessing the motivation why firms choose to locate in certain regions and rationales behind setting up operations in a foreign country (Iammarino and McCann, 2013). For each of their foreign operations' location choices, MNEs prefer particular spatial characteristics (Iammarino and McCann, 2013). For a firm to develop technological capabilities in a region, the initial technological infrastructure and human capital are key variables guiding the location decision (Siedschlag et al., 2013). The initial technological infrastructure can include several factors, such as the existing research capacities, the distance to centres of technological excellence and agglomeration economies that emerged due to foreign research activities (Siedschlag et al., 2013). Particularly when other firms are conducting research in the region, it signals to other firms that they can also successfully set up their research activities (Feldman, 2003). Other determinants of technological capabilities are the regional and national innovation system (Yang, Lee and Lin, 2012), the public investment in R&D (Amendolagine et al., 2019) and high skilled workers. The internationalisation of R&D activities is highly concentrated within a small number of locations, which are often centers of excellence (Meyer-Krahmer and Reger, 1999).

2.2.2 The Market Size and Competition Effect

Since the mid-1970s, the world has been in an increased globalisation phase (Martin et al., 2018) that has, in combination with technological change, rearranged the geography of production and the global division of labour (Iammarino, 2018). But what happens to domestic patenting when firms internationalise? This subsection discusses how firms respond to the exposure to international markets, describing two different effects: the market size and the competition effect. The market size effect only impacts firms that internationalise, whereas all domestic firms are affected by the competition effect. A positive market size effect refers to the case when firms participating in the international market end up innovating more (Shu and Steinwender, 2019; Akcigit and Melitz, 2022). Firms select themselves into international market participation, and those who do tend to be more productive than those that operate only in the home market. Firms that operate solely in the home country are characterised by lower productivity (Helpman, Melitz and Yeaple, 2004) and have already been less productive than exporting firms before them internationalising (Bernard, Jensen and Lawrence, 1995; Melitz, 2003). Focusing on export markets, the majority of empirical evidence tends to emphasise a positive link between exporting and innovation/productivity at least for certain firms (Verhoogen, 2008; Lileeva and Trefler, 2010; Bas and Ledezma, 2010; Bernard, Redding and Schott, 2011; Iacovone, 2012; Aghion, Bergeaud et al., 2018; Munch and Schaur, 2018; Shu and Steinwender, 2019). In line with the market size effect, those firms that are initially more productive and more innovative are experiencing the highest gains due to exporting (Lileeva and Trefler, 2010; Iacovone, 2012; Aghion, Bergeaud et al., 2018). While these findings are focused on exporting, we might also expect a positive home market effect when a domestic-owned firm sets up an R&D center outside of the US. These effects might be even stronger in comparison to exporting, given that engaging in export activities can occur without any innovation-related investments. Thus, we might expect a larger positive market size effect when MNEs selectively open research labs abroad, as they can exploit location-specific regional advantages and access highly specialised human capital. It is likely also affecting the most innovative MNEs within the US more favourably. Thus, economic globalisation tends to increase the potential gains from innovation through the market size effect, in particular for innovative firms (Aghion, Antonin and Bunel, 2021).

In contrast, the direction of the competition effect tends to be ambiguous. The "Arrow replacement effect" (Arrow, 1962) describes how a monopolist might have a lower incentive for innovation than a firm in a competitive market. From this view, competition spurs innovation. This perspective is juxtaposed by the Schumpeterian view (Schumpeter, 1942), which is, that higher competition can reduce the incentive for firms due to lower rents and lower resources to invest in R&D. Aghion, Bloom et al. (2005) reconciles these findings on competition and innovation by showing evidence on the relationship resembling an inverted U-shape in the UK and how they differ for leading and laggard firms. Competition tends to foster innovation in industries that are originally characterised by a lower level of competition. In this case neck-and-neck firms innovate, which is labelled as "escape-competition effect". The Schumpeterian effect prevails for laggard firms in industries with high level of competition and large technological distance. In this case, higher competitive pressure discourages innovation for those firms further away from the technological frontier. There is empirical evidence on the Schumpeterian effect from exporting (Baldwin, Gu et al., 2009; Aghion, Bergeaud et al., 2018) and from importing (Autor, Dorn, Hanson, Pisano et al., 2020), where increased competition decreases innovation in less innovative firms.

2.2.3 How the Presence of MNEs Can Increase or Decrease Innovation Concentration

Questions related to firm patenting concentration have been already explored since the 1940s. Scholars in earlier times have pointed out concerns about the concentration of patents within large firms (Edwards, 1949) and questioned whether new innovations contribute to higher overall welfare (Anderson and Harris, 1986; Tirole, 1988). While theory has held that new innovations would increase social welfare, patents could also decrease it through defensive patenting draining all parties' resources (Kimmel, Antenucci and Hasan, 2017).

Decrease in patenting concentration due to firm entry, knowledge diffusion, and a positive competition effect

There are three main mechanisms how domestic and foreign MNEs and their patenting activity can reduce concentration of innovative activity between firms. Following the concentration definition by Hirschman (1946) "concentration of the few", which means concentration stemming from a small number of firms patenting, we would expect ceteris paribus to see patenting concentration to decrease with the increase of firm entry. MNEs can serve as anchor firms (Feldman, 2003) signalling other firms that technological capacities are present in a region, which attracts other firms, among them MNEs. Therefore, because of the anchoring effect, we would expect a concentration decreasing effect due to more firms starting patenting within the US state. Moreover, we could also observe a decrease in patenting concentration in the case of a positive competition effect. If a US domestic-owned enterprise starts investing abroad or a foreign-owned subsidiary starts producing patents within a state, this might lead to increase competitive pressure for firms. Depending on the technological distance to the firm and the technological frontier, firms could respond competing neck-and-neck for technological leadership, which might decrease innovation concentration for a innovative firms. Moreover, higher levels of competition foster riskier and novel innovation, increasing the likelihood of breakthrough outcomes (Callander, Lambert and Matouschek, 2021). However, this effect might be different for less innovative firms, but could be linked to lower concentration at some part of the patenting distribution.

Innovation concentration can also be decreased through knowledge diffusion, such as spillover effects and firm alliances. Many papers have explored the linkage between the geography of innovation and globalisation and how the diffusion process is fostered due to the latter (Crescenzi, Dyevre and Neffke, 2020; Bournakis, 2021; Greenaway, Sousa and Wakelin, 2004). The role of MNEs when entering a foreign market has been emphasised in relation to the internationalisation of knowledge as well as knowledge creation and diffusion (Cantwell and Iammarino, 2005). Proximity is viewed as one main predictor for knowledge diffusion in the form of spillover effects, as spillovers are geographically localised (Jaffe, 1989; Feldman and Kogler, 2010). R&D-related FDI has been traditionally regarded as a primary mechanism to spread out knowledge across borders (Abramovitz, 1986). With foreign-owned MNEs setting up their operations in the US, they become embedded in the local ecosystem, interact with actors within the region and transfer knowledge to the local economy. By setting up R&D-related FDI, MNEs can affect the US states by producing spillover effects and initiating collective learning (Athreye and Cantwell, 2007). These Marshallian externalities (Marshall, 1890) are seen as key benefits of agglomerations, combining spillover effects, pooled labour markets and specialised input (Krugman, 1991). Large and dense areas enable positive externalities supporting the exchange of knowledge, with density playing a key role for knowledge transfer (Duranton and Puga, 2001; Storper and Venables, 2004). Foreign intervention has also contributed to the emergence of the most significant technological hubs by linking their location to other technology clusters (Saxenian, 2007). The recent study of Crescenzi, Dyevre and Neffke (2020) provides evidence that regional innovation rates in the home market are substantially enhanced due to foreign intervention by MNEs. For these reasons, foreign MNEs are viewed as key actors in the international diffusion of knowledge when entering a foreign market, which applies to foreign-owned MNEs.

Increase in patenting concentration due to knowledge concentration, selective gains from globalisation, and a negative competition effect

However, knowledge is not necessarily always “in the air" in clusters. Fitjar and Rodríguez-Pose (2017) show that there is “much less is the air" in the Norwegian case as typically suggested by the literature. Geographical proximity is not a necessary nor sufficient condition (Boschma, 2005) for innovation to take place. Knowledge diffusion in the form of FDI spillovers and linkages to local firms do not happen automatically (Blomström and Kokko, 1999), or as described by several scholars, there is a cost-benefit trade-off between inward and outward spillovers (Myles Shaver and Flyer, 2000; Crescenzi, Dyevre and Neffke, 2020). While firms appreciate inward spillovers as they learn from other firms, they have an incentive not to share knowledge to keep and enhance their competitive edge. Sharing knowledge with competitors can come at a high cost. Indeed, Crescenzi, Dyevre and Neffke (2020) finds evidence that technological leaders produce on average fewer spillovers and form less strategic alliances with local firms compared to other less innovative MNEs. Thus, for the case of MNEs not creating outwards spillovers, but producing patents, it might be that patenting concentration within a region is rising as it becomes increasingly concentrated within large firms.

More patents can increase innovation concentration if these are increasingly produced by large firms that can better harvest the gains from internationalisation. Due to the market size effect, we expect domestic-owned MNEs that set up a foreign R&D centres to become more innovative and produce more patents than those that do not internationalise or that ceteris paribus benefit less from internationalisation. As these are likely firms that have been more productive or innovative before, we would expect an increase in patenting concentration as more innovative firms would be more able to reap the benefits from economic globalisation. For this case, we would expect an increase in patenting concentration because of a change at the top of the patenting distribution, as the most innovative MNEs are becoming more innovative. There seems to be evidence for increasingly larger firms patenting (Archibugi, Evangelista and Simonetti, 1995) and an increase in patenting concentration within the US

(Akcigit and Ates, 2021; Forman and Goldfarb, 2020).

Moreover, due to increased pressure from internationalisation, we may observe a negative competition effect. This is more likely to be the case where technological knowledge is more dispersed between firms, as is the case for countries close to the technological frontier like the US. In this case, we could expect higher competitive pressure because of domestic-owned MNEs becoming more innovative as they set up a foreign R&D facility. Less innovative firms might struggle to keep up with their competitors, discouraging them from innovating. This effect will likely depend on the distance to the technological frontier as firms strongly differ in their capacity to absorb knowledge. One crucial predictor of the firm's absorptive capacity (Cohen and Levinthal, 1990) is cognitive proximity, which refers to the knowledge gap between new knowledge and a firm's prior knowledge base. Therefore, with increased competitive pressure it is likely to become more difficult for less innovative firms to absorb knowledge, apply and reuse it in a different setting (Cohen and Levinthal, 1990). There is empirical evidence for a negative competition effect showing how over the last three decades import competition within the US has affected the patent production of the least profitable firms the most (Autor, Dorn, Hanson, Pisano et al., 2020). In case of a negative competition effect, we expect an increase in patenting concentration because of a decrease in patenting from less innovative firms.

In addition, we could see an increase in concentration if incumbent firms use strategic patenting to gain a competitive edge over other firms and block firms from innovating. In this case, a higher number of patents could impede instead of encourage innovation. Strategic patenting is more likely to occur when innovation tends to be more incremental, when the expenses to get patents are reasonably low, and the creation of a product includes multiple patentable inventions (Hunt, 2006; Bessen and Hunt, 2007). For strategic patenting, large firms use the acquisition of many patents to hold up competitors, threatening litigation (Bessen and Hunt, 2007). Innovative firms might respond with a counter-threat, by creating a defensive patent portfolio. This might end up in a cross-licensing solution of the whole portfolios, with both firms abstaining from suing each other and the firm with the weaker portfolio paying fees (Grindley and Teece, 1997). Building a thick web of patents has been referred to as "patent thickets" (Shapiro, 2001), which has been measured by patent counts (Lerner, 1995; Cockburn and MacGarvie, 2011) or patent overlap (Hall, Graevenitz and Helmers, 2021). Another option would be merger and acquisition, for example with MNEs acquiring smaller innovative firms. There is recent empirical evidence for the US on strategic patenting (Akcigit and Ates, 2021) and a decline of entrants' patent share (De Loecker, Eeckhout and Mongey, 2021; Akcigit and Ates, 2021). For the UK, scholars also find increased patent entry costs due to patent thickets (Hall, Graevenitz and Helmers, 2021). Therefore, we might expect an increased number of patents to increase intra-regional patenting concentration as it reinforces the competitive advantage of firms and the entry costs for other firms.

2.3 Hypotheses

This study answers the research question to what extent the presence of MNEs affects patenting concentration. As firms that demonstrate relatively high productivity tend to be more likely to internationalise, we would expect them to become even more innovative through the market size effect. Therefore, we expect an increase in patenting of more innovative firms, which increases patenting concentration, as the patent share of innovative firms increases compared to firms that are less innovative. In addition, a positive competition effect among more innovative firms could contribute to innovative firms patenting more if it spurs neck-and-neck competition. Based on these considerations, I form the first hypothesis:

Hypothesis 1: The level of patenting concentration between all firms is positively related to the patent share of domestic and foreign MNEs in a given technology sector and state.

To test this hypothesis, I will estimate the baseline model and regress the patenting concentration between all patenting firms, measured by the Gini coefficient, on the share of all patents by MNEs (domestic and foreign) within a technology class and state. The share of patents by MNEs describes the patents granted to MNE relative to all patents, which signifies dividing the absolute number of MNE patents by the number of overall patents in a state and technology class. However, the effect is likely to differ for the presence of domestic-owned and foreign-owned MNEs. First, domestic-owned and foreign-owned MNEs are different in characteristics such as productivity, wages and skill mix (Woodward and Nigh, 1998) and most of domestic MNEs grow organically within the US and then decide to internationalise. Second, the majority of MNEs producing patents within the US are domestic-owned, making up around 80% of all MNEs. Thus, the majority of patents are from domestic-owned MNEs as I am not capturing the patents from foreign MNEs outside the US. Third, foreign MNEs choose to locate within the US for different reasons, often to benefit from local capacities and to gain from knowledge spillover that are highly localised (Marshall, 1890; Cantwell et al., 1995). For these reasons, I anticipate that the higher share of domestic-owned MNEs, not foreign-owned MNEs, to boost innovation concentration between all firms. As I expect the positive correlation between domestic MNEs and patenting concentration between all firms to be driven by a positive market size effect and a negative competition effect, it is more likely to observe a concentration enhancing effect in states where the share of MNE patents is high. Given these considerations, I form my second hypothesis:

Hypothesis 2: The positive relationship between patenting concentration and MNEs is driven by domestic-owned MNEs and more pronounced in states with higher patent shares by domestic-owned MNEs in a given technology sector and state.

To verify this hypothesis empirically, I am testing first the difference between domestic- and foreign-owned MNEs by regressing their share in separate regressions on the Gini coefficient. If the hypothesis of the effect being driven by domestic-owned MNEs is confirmed, I am splitting the domestic-owned MNE share into quartiles and include a dummy indicating whether a state has a low, middle, high or very high MNE share per technology class.

Finally, I am also interested in testing how the effect varies for non-MNEs, as it has been shown that firms operating only in the home country are characterised by lower productivity than firms that internationalise (Helpman, Melitz and Yeaple, 2004). Multiple studies have empirically demonstrated that MNEs and foreign affiliates are bigger in size, more capital intensive, and invest more in R&D than domestic firms (OECD, 2019). Thus, firms that are not classified as MNEs tend to be less innovative, and we might expect them to respond adversely to increased pressure from internationalisation. With a negative competition effect, they might decrease their patent production due to more competitive pressure within a state and technology class. I test this in my third hypothesis:

Hypothesis 3: The level of patenting concentration of non-MNEs is positively related to the presence of domestic-owned MNEs in the same technology sector and region.

I start by testing the first hypothesis in the baseline model and investigate the impact of MNE presence on the overall intra-regional innovation concentration between firms. The results are shown in Table 3.1. The second hypothesis tests for the difference between foreign- and domestic-owned MNEs and intensity of the effect. The results for heterogeneity in the effect are shown in Table 3.2. For the third hypothesis, for a negative competition effect, I focus on firms that tend to be less innovative by regressing the Gini coefficient (non-MNEs) on the share of domestic MNEs. I am also using different percentiles of the patent distribution of non-MNEs as outcome variable identify how those firms are affected by increased competitive pressure. The results for this are shown in Table 3.4.

2.4 Data Description

I construct a yearly panel for US states from 1976 to 2010. For every state, I sum the absolute number of corporate patents and create different concentration measures at the state level and for different technology classes. The technology classes were developed by Hall, Jaffe and Trajtenberg (2001) and are referred to as the NBER classification, which distinguishes between the six different classes Computers and Communications, Drugs and Medical, Electrical and Electronics, Chemical, Mechanical and Others. Given the differences in their nature, I am conducting the analysis per technology class, considering differences linked to some technology classes to concentrate more. Previous research has looked at the patterns and the propensity to patent across technology classes and industries, finding that they differ (Scherer, 1983) with varying learning regimes as an important factor (Breschi, Malerba and Orsenigo, 2000) and when innovation is incremental (Bessen and Hunt, 2007).

The sample consists of 50 US states, after having excluded islands and other territories. I measure innovation using data from PatentsView, using patents granted by the USPTO. As the focus of this study is to examine the distribution of patents between firms, the focus is on assignees. Downloading the data from PatentsView shows that every patent is linked to one or more assignees, which might be in the same or different regions. To avoid multiple counting of multiple assignees patents, I divide each patent by the number of assignees and the number of regions. Thus, I am assigning every assignee a patent value, which is equal to one if there is only one assignee in one state. I only keep data where the assignee type is classified as private companies or corporations. This signifies excluding patents from individuals, governments, and unassigned assignee types. After this step, I still find patents assigned to organisations that are clearly not firms, such as Universities, Institutes or Foundations, which I remove as well. I am also excluding observations where there is no assignee identifier available, as it is not possible to identify the firm. I am choosing the state level due to my interest in firm dynamics. From an innovation perspective, the state captures an aggregate level. Still, if I was to choose a more granular level, such as county or metropolitan statistical area, I might end up underestimating firm concentration. Therefore, the state level appears to be a good compromise for both variables of interest and looking at the state level can provide meaningful insights for policymakers and researchers.

2.4.1 Measuring Innovation

Innovation can be measured in different ways. Earlier studies have proxied innovation by R&D activities, such as R&D expenditure or R&D laboratories, and thus focused on an input in the production of innovative activity (Feldman, 2000). Other papers have relied on the formation of new firms or start-ups (Audretsch and Vivarelli, 1994), investment related to innovative activity (Florida et al., 1994) or economic measures such as employment growth (Glaeser et al., 1992). In this study, innovation will be proxied by patents, as they are a measurable output of innovative activity.[1]

Location assignees

The USPTO patent data provides information on the location of the assignee and the inventor. Firms that produce patents only in one location within the US, the location of the inventor, assignee and the primary research location is the same. Thus, all patents will be assigned to that location. For firms producing research in different states within the US, we use the inventor's location, as this is the state where innovation is actually carried out and thus would influence other firms. In contrast, the assignee location refers to the legal headquarter, which might not reflect the innovative activities of the assignee.

I am identifying assignees based on the identification number provided by the USPTO, which is a disambiguated id number for every firm. However, the USPTO data does not account for dynamic changes in firm names and ownership structure. Arora, Belenzon and Sheer (2021) use the NBER patent database, which links US publicly listed firms and their patents, to account for dynamic changes. While they find that 40% of their sample is mismatched, this only provides a modest underestimation of the patent value. This substantial difference is explained by the mismatch between the NBER patent database and Compustat, the accounting for changes in names and better dynamic reassignment due to mergers and acquisitions. The study is relevant to assess the extent of a possible bias due to measurement error in firm

[1]Despite being an imperfect way of measuring innovation, it is commonly applied in the literature. Some authors have used patent text as data (Griliches, 1981), Hall et al., 2001), others have used it to measure the value of innovation (Blundell, Griffith and Van Reenen, 1999; Kogan et al., 2017), innovation and competition (Aghion, Bloom et al., 2005; Autor, Dorn, Hanson, Pisano et al., 2020; Bloom, Draca and Van Reenen, 2016), knowledge spillovers (Jaffe, Trajtenberg and Henderson, 1993; Moretti, 2004; Bloom, Schankerman and Van Reenen, 2013), innovation networks (Branstetter, Glennon and Jensen, 2019) and rent distribution (Kline et al., 2019). Patent data has the advantage of being a measurable output, being commonly applied in the economic literature and being publicly available over a long period, which allows the assessment of how MNEs have affected intra-regional innovation concentration from 1976 to 2010. However, on the other hand, using patent data to measure innovation has certain limitations. Not only that not all patents possess the same economic or innovative value, but also that not all innovative activities are patented (Feldman, 2000). By creating inequality measures with the patent data, every patent receives the same weight and therefore assumes the same innovative value. Therefore, by using patent count data, it is not possible to assess the quality of innovative activity, just the quantity of patented innovative activity, where every patent contributes to higher innovative activity to the same extent. Despite these limitations, patent data fit the purpose of this study well and are a measurable output of innovative activity and thus should be used.

dynamics that might not be accounted for in the USPTO database and thus apply to this study as well. Changes in firm names do not influence the results of this study, as I am not tracking firms over time but creating an outcome variable based on the patent shares of the firms in the region. In the case of merger and acquisition, when a large company acquires a small one, and patents are still separately recorded for both firms, this would lead to an underestimation of the concentration within the state.

2.4.2 Independent variable

Identification of MNEs with R&D centres

I am using patent data to identify MNEs, similar to Crescenzi, Dyevre and Neffke (2020). By producing patents in multiple countries, I can identify whether an assignee is an MNE. However, as I want to estimate the effect of MNEs that possess R&D centres, I identify an MNE only if it has at least five cross-border patents. To do so, I start by identifying which firm has engaged in cross-border research activities. I am using patent data from the USPTO, where the location in which the assignee mainly conducts research differs from where the inventor has her residential location. The assignees' headquarters will not be considered as the main research location, as it refers to the legal headquarter, and it does not necessarily reflect where most of the research is conducted. Instead, it is the country where most of the inventors for each firm are located. So, if the inventor or the primary research location of the assignee is located within the US, and the country where an assignee has its main research location is different from the one of the inventors, a patent is categorised as an MNE patent. In addition, to measure MNEs with R&D centres, I impose the restriction that an MNE has to have at least five cross-border patents. For every state, I will divide the absolute number of MNE patents by the overall number of patents within the state for every technology class, which is the MNE patent share. I can distinguish between foreign- and domestic-owned MNE due to an identifier provided by the USPTO, which allows me to construct patent shares separately for them. Foreign patents are often produced in the form of MNEs setting up research labs in foreign countries outside of the US. In this case, the inventor is based outside of the US, while the primary research location lies within the US. To measure the impact of foreign patents, I reassign the patents to the primary research location of the inventor, summarise the number of foreign patent count and divide it by the overall number of patents per state and technology class. More information on which countries the inventor is located, or which state the patents are frequently reassigned to can be found in the Appendix.

Cross-validation of MNEs using Orbis data

I use Bureau van Dijk's Orbis database to validate the identification of MNEs. Orbis provides information on more than 400 million companies worldwide, with data on the financial situation, supplier information and corporate structure. Multiple scholars have used Orbis data to construct firm networks or to verify MNEs cross-border activities given the provided ownership information (Vitali, Glattfelder and Battiston, 2011; Großkurth, 2019; Crescenzi, Dyevre and Neffke, 2020). I have access to data that includes the global ultimate owner for the entity. If a US entity or the global ultimate owner based in the US have an entity or the global ultimate owner based outside the US, I can identify the firm as MNE. The entity file I can access through Orbis historical data is naturally larger in size given that it does not only cover patenting firms. As I cannot match on patent identifiers, I am using fuzzy matching techniques based on the firm's name. I am checking whether the firm has an entity outside the US, which applies to 26.7% of all MNEs. This corresponds to 37.5% of domestic-owned MNEs and 12.9% of foreign-owned MNEs. This appears to be a reasonable percentage, given that the Orbis historical data only includes active companies and cover the years 2007-2019, which overlap only with four years of my observation period. In addition, I can only verify the MNE status based on limited ownership information.

2.4.3 Dependent variable

What does patenting concentration mean, and how can it be measured? This subsection answers these two questions and will describe different concentration indicators. I construct these based on patent counts establishing a distribution of innovation between firms. I sum up the number of patents for every firm, per region and technology class to assess how concentrated patents are between firms within a state. One limitation is that these indicators only include firms in a region that produce patents. As the measures described below are formed based on the patent data from the USPTO, they only comprise firms that have registered their patent with this patent office. Therefore, it does not construct a measure for all firms of the regions, only for those producing patents. Thus, an interesting extension of this paper would be to include all the firms not producing patents.

Measuring patenting concentration

Concentration can be measured in multiple ways. Hirschman (1946) defines it in two different forms "Control of an industry by few producers can be brought about by an inequality of distribution of the individual output shares when there are many producers or by the fact that only few producers exist." I am calculating the Gini coefficient as my main variable of interest, which is a concentration indicator measuring the inequality of distribution of the firm's patent shares. I am selecting this indicator as it could be relevant for other aggregate outcome variables if the innovative output is concentrated within a few firms. Moreover, it is among the most commonly used measures in the economic inequality literature (Giles, 2004) but has also been used as a concentration measure (Forman and Goldfarb, 2020). The Gini coefficient takes on values between 0 and 1, with 0 signifying perfect equality of patenting activity, which means that patents are completely equally distributed across firms. In contrast, a Gini coefficient with a value of 1 displays maximum concentration, with all innovative activity being concentrated in one firm.

Concentration measures for robustness checks

I construct further patenting concentration indicators to conduct robustness checks on patenting concentration. This includes the Herfindahl-Hirschman Index (HHI) (Herfindahl, 1950; Hirschman, 1946), and the four-firm concentration ratio (CR4). The first two measures are the most commonly used indicators for measuring firm concentration and market power within an industry (Pavic, Galetic and Piplica, 2016). The HHI and CR4 measure innovation concentration with a particular focus on firms with large patent shares. The HHI is commonly applied in industrial economics to measure market concentration, examines the presence of an oligopoly or a cartel (Tirole, 1988; Hannah and Kay, 1977), and measures economic diversity

(Chen, 2020) as well as specialisation (Kemeny and Storper, 2015). The CR4 describes the patents accrued by the four largest firms within an industry.

2.4.4 Control variables

I am using control variables to account for confounding factors influencing patenting concentration within state and technology class, the MNE patenting share and firm location. For this reason, I am including two types of control variables; those varying by state and technology class and those only varying at the state level. The first type refers to the number of patenting firms and the patent count per state, which are constructed using USPTO data. To do so, I count the number of patenting firms and patents of every assignee in the region and technology class. The second type are GDP, population and employment data. I am collecting GDP data from the Bureau of Economic Analysis, the Regional Economic Accounts, to control for the level of economic activity. As GDP per capita is not available, I am dividing it by population data, which I obtain from the United States Census Bureau. Employment data are added from the Business Dynamics Statistics. I am not using the overall employment level, but the employment level in Professional, Scientific, and Technical Services. Given that specialised human capital is an important factor for firm location (as described in section 2.1), I am controlling for employment in R&D-related sectors.

2.5 Model, Methods and Descriptive Evidence

2.5.1 Baseline model

The baseline model takes the form of the following equation:

$$GINI_{i,j,t} = \beta MNE_{i,j,t} + \gamma X_{i,j,t} + v_i + v_j + v_t + \varepsilon_{i,j,t} \tag{2.1}$$

where *GINI* is the Gini coefficient for every state i in technology class j in period t, *MNE* is the MNE patenting share in state i in technology class j for period t, X is a vector of controls in state i in technology class j for period t, $v_i,\ v_j\ and\ v_t$ are state, technology class and period fixed effects, and ε is the idiosyncratic error term. Period refers to three years, as I am creating three-year averages from 1976-2010. The control variables include the absolute number of patents, the absolute number of firms (both per technology class), GDP, population, and employment. The standard errors are clustered at the state level.

I include fixed effects to account for heterogeneity bias, which controls for unobserved time-invariant variation at the state, period, and technology class level. I therefore control for factors that are specific to each state that do not change over time, including geographic features such as access to a coast or harbour, level of the institutional environment or the level of the regional innovation system. Given that the observation period spans over more than 30 years, during which there have been substantial changes in the regional innovation system, I am accounting for this by using the number of patents and patenting firms as controls. In addition, as described in section 4, there are substantial differences across technology class by nature, which is why I include technology fixed effects. To account for shocks across states within a three-year period, I am adding period fixed effects.

The baseline model below estimates the correlation between the presence of MNEs and patenting concentration. Estimating a causal relationship is highly challenging in this case, as two main issues pose a challenge to estimating causal parameter estimates: selection and reverse causality. First, as described in section three, firm location is endogenous, as it is a highly selective process based on certain characteristics of a region. Second, there might be the issue of simultaneity, which refers in this study to MNE's patenting activities not only influencing the innovation concentration within the region, but also vice versa. The level of patenting concentration might influence the level of MNE patent share. To account for the selective locational decision of firms, I try to control for factors influencing this choice, such as economic potential, human capital, innovation infrastructure and business environment. I do so by controlling for GDP per capita, scientific employment, population, the absolute patent count, and the absolute number of patenting firms. However, it might be still the case of simultaneous influence of innovation concentration and the patenting activity of MNEs.

2.5.2 IV Strategy

Given these concerns, I am applying an instrumental variable (IV) approach that uses the information on the spatial networks of firms. For that, I am using two IVs that exploit variation in patenting outside the state of interest to proxy variation within the state. The first one is the share of foreign patents. Foreign patents are patents that are produced by MNEs outside of the US. I am reassigning them to the primary research location of the firm and divide by the number of patents of the state, technology class and year to get the foreign patent share. The idea is that foreign patents influence patenting concentration within a state only through domestic patenting activity and not directly. As these patents are produced outside the US and do not exert significant influence on the patenting distribution (see Table 2.8) this condition of the exclusion restriction is likely satisfied. The second one is following Moretti (2021), who constructs an IV that exploits the geographical structure of firms that have laboratories in multiple locations within the US. The idea is to predict changes within a US state from changes in other locations where the firm is present. Moretti (2021) uses the instrument to predict changes in innovative activity based on inventors, while I am using the instrument to predict its level based on patents. As I am focusing on the impact of the presence of MNEs, I am using a subsample of MNEs and predict their level of patenting within a state based on the innovative activity of laboratories of MNEs in other US states. Outside the state that I am applying the instrument to, I am excluding the patents of the MNE and sum up the patents of all other MNEs within that state and technology class, normalised by the patents of all firms within the US for the same period and technology class. The intuition is that the level of innovative activity for one state can be predicted based on the innovative activity of firms of other states where the MNE has their spatial networks.

The aim of using this IV approach is to predict MNE patenting within a state from variation that originates from outside the state, from other states where the MNE is producing patents. The innovative activity of other MNEs than the MNE itself in other states predicts the patenting activity of MNEs within a state. The rationale behind it is to isolate variation that is uncorrelated with innovation or productivity shocks within the MNE that is unobserved and varying over time within a state. The goal is therefore to deal with simultaneity. Given that the instrument is constructed based on specific and external factors, it is arguably exogenous (Moretti, 2021).

I construct the instrument as below:

$$IV_{j,t,i,f} = \sum_{s \neq j} D_{s,f,i} \frac{N_{s,f(-i)t}}{N_{ft}} \tag{2.2}$$

$D_{s,f,i}$ is a dummy variable that takes the value of 1 if MNE s has a minimum of 1 patent in state i and technology class f, $N_{s,f(-i)t}$ refers to the number of patents that an MNE j has in technology class f, year t in every state except for state t and N_{ft} is the number of nationwide patents in the technology class and year.

To satisfy that the IV is valid I am testing for relevance and exogeneity and report the results in the estimation section. To test for relevance, I run the first stage regression and report the F-statistic together with the 2SLS estimators in Table 2.4. As I have more instruments than endogenous variables, I run an overidentifying restrictions test (Sargan, 1958; L. P. Hansen, 1982) to test whether both instruments are exogenous.

2.5.3 Development over Time

This subsection explores the development of the main variables, the MNE patent share, as well as patenting concentration over time. As this research paper exploits their variation from 1976 to 2010, it aims at showing the change in both variables. It first focuses on the MNE patent share and then explores patenting concentration measured by the Gini coefficient over time.

MNE patent share

Figure 2.1 plots the average MNE patent share across US states for every technology class from 1976 to 2010. A substantial long-run upward trend can be observed, showing an increase

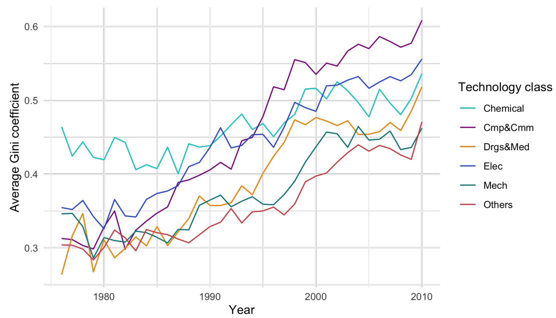

Figure 2.2: Development Gini coefficient per technology class, all patenting firms, average US states, 1976-2010

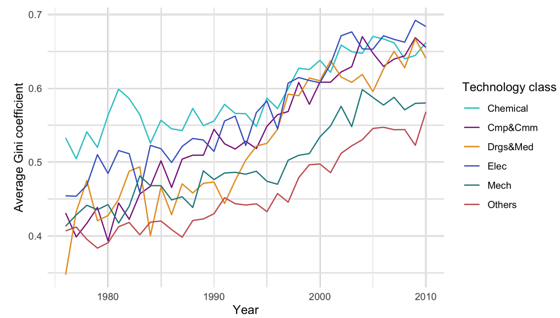

Figure 2.3: Development Gini coefficient per technology class, non-MNEs, average US states, 1976-2010

for all six technology classes. While the increase is flatter between 1976 and 1990, the slope increases from 1990 onward, particularly after 1994. The most remarkable change in patent share is for the category Drugs & Medication, where the share has been falling between 1983 and 1991, but risen from then onward for the rest of the period.

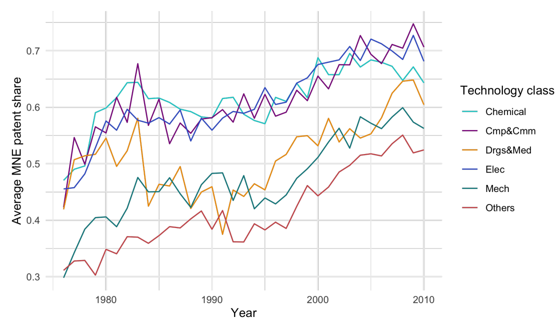

Figure 2.1: Development of MNE patent share per technology class, average across US states, 1976-2010

Patenting concentration

Figures 2.2 and 2.3 show the development of the Gini coefficient between 1976 and 2010. As the focus of this study is on the patenting concentration for all firms, as well as on non-MNEs, I am showing both plots. We can observe a substantial upward trend between 1976 and 2010, which holds for the two Gini coefficients and all six technology classes.

2.5.4 Development over Space

MNEs patenting activity

This section describes the average MNE patent share and innovation concentration between 1976 and 2010, across technology classes for every state in the US. Figure 5 below shows the geographical distribution of the MNE patent share. At first glance, it becomes clear that a large number of states have, on average, an MNE patent share between 0.4-0.6, with around 19 states falling into this category. Less frequent but still very common are average MNE patent shares between 0.2-0.4 and 0.6-0.8, while other categories occur scattered.

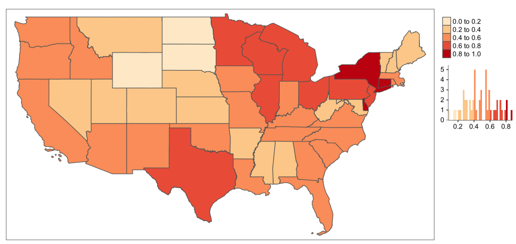

Figure 2.4: Map of MNE patent share per state, average between 1976-2010 and technology class

Intra-state Innovation Concentration

The geographical distribution of intra-state innovation concentration is shown below, measured by the Gini coefficient. It summarises the average value of the Gini coefficient for all patenting firms within state across technology classes between 1976 and 2010. Figure 2.6 does the same for the Gini coefficient for non-MNEs. While both maps depict similar patterns, with the West Coast, the Southern states and the Midwest showing high levels of concentration measured by the Gini coefficient, these dynamics become even more pronounced for the non-MNE Gini coefficient. In particular, the East Coast tends to be more concentrated for non-MNEs, as well as in the Southwest.

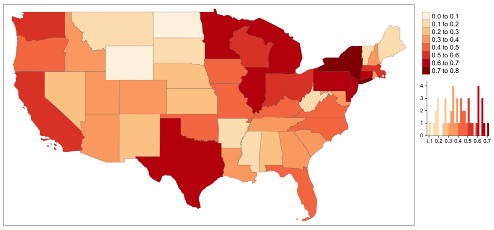

Figure 2.5: Map of Gini coefficient per state, all firms, average between 1976-2010 and technology class

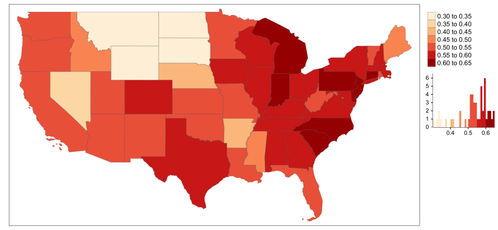

Figure 2.6: Map of Gini coefficient per state, non-MNEs, average between 1976-2010 and technology class

2.6 Results

2.6.1 Overall Results

In Table 3.1, I show the results of the overall effect, regressing the Gini coefficient on the MNE patent share. The MNE patent share comprises all MNE patents relative to the absolute patent count of the state per technology class and year, including foreign-owned and domestic-owned MNEs. I first run the three-way fixed effects model (TWFE) without any controls in the first specification. Then, I add the controls GDP per capita, population, scientific employment, number of patenting firms and absolute patent count in the second estimation. In Models 3-5, I look at different percentiles of the patent distribution of MNEs as dependent variable to understand at which part of the distribution we see the strongest effect. All models are three-way fixed effects models, including state, technology, and period fixed effects. Standard errors are clustered at the state level. The estimated coefficient of the MNE patent share is statistically significant for all specifications at the 0.1% level. I find a positive relationship between the Gini coefficient and the MNE patent share, suggesting an increase in patenting concentration linked to the MNE patent share. As expected, the association between the MNE patent share and the percentiles of MNE patent distribution is positive, with the largest coefficient size for MNEs at the top of the distribution (P75), followed by MNEs in the middle (P50) and then by MNEs at the tail of the distribution (P25).

The control variables include the number of patents and the number of firms in the region per technology class. As the distribution of these variables is highly right skewed, I use a log transformation. The two variables are highly statistically significant for all model specifications. The number of patenting firms is negatively related to the Gini coefficient. This aligns with expectations, showing that an increase in patenting firms decreases patenting concentration. For the number of patents and the Gini coefficient, we find a positive relationship. With increasing patenting activity, knowledge becomes increasingly concentrated within some firms. I also control for GDP per capita, population and scientific employment to control for market size, human capital that is specialised in R&D and the population structure. These controls are statistically insignificant.

	Gini	Gini	MNE P75	MNE P50	MNE P25
MNE	0.394^{***}	0.117^{***}	1.530^{***}	0.824^{***}	0.482^{***}
	(0.054)	(0.018)	(0.133)	(0.063)	(0.057)
Log(patents)		0.218^{***}	0.327^{**}	-0.039	-0.057^{***}
		(0.019)	(0.106)	(0.026)	(0.011)
Log(firms)		-0.151^{***}	-0.421^{**}	-0.078^{*}	-0.026
		(0.024)	(0.122)	(0.031)	(0.020)
GDP pc		0.219	1.375	0.977	0.754
		(0.429)	(2.977)	(1.192)	(0.927)
Log(population)		-0.036	-0.339	-0.007	0.080
		(0.027)	(0.199)	(0.086)	(0.049)
EMP SCIENT		-0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.725	0.923	0.442	0.495	0.392
Num. obs.	3222	3207	3207	3207	3207

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.1: Regression results: MNEs and patenting concentration for all firms and for different percentiles of the patenting distribution

This confirms the first hypothesis, patenting concentration between all firms is positively related to the patent share of all domestic-owned and foreign-owned MNEs in a given technology sector and state. One reason for this increase in concentration is likely that MNEs at the top of the MNE patent distribution (P75) tend to produce more patents than at the middle or the tail of distribution. However, while this is to be expected, the overall effect could be also driven by changes in the patenting distribution of non-MNEs. Moreover, it is also not clear how this effect varies for domestic-owned and foreign-owned MNEs, which is what I will look at in the next section.

2.6.2 Type of MNEs and Regional Heterogeneity

In this subsection, I am testing the second hypothesis, whether the positive relationship between the MNE patent share and patenting concentration between all firms is driven by domestic-owned or/and foreign-owned MNEs, and which states contribute most to this effect. To test for domestic-owned vs. foreign-owned MNEs, I am exploring the effect for both by running two separate regressions, with the patent share of domestic-owned and foreign-owned MNEs as regressors. As discussed in section 3, I expect to find that the domestic-owned patent share is the reason why we see the increase in the Gini coefficient, as the majority of the overall MNE patent share is ascribed to domestic-owned MNEs. The estimated coefficient in Table 3.2, model 1 confirms this that the domestic-owned MNE share is associated with a positive and highly statistically significant Gini coefficient. The coefficient for foreign-owned MNEs is also positive, but statistically insignificant. This indicates that the overall positive link is driven by domestic MNEs.

Models 3 and 4 show how the effect varies across space. I interact the MNE patent share with the absolute patent count and create a categorical variable for the MNE patent share, and categorise them as low, middle, high and very high intensity. Low intensity means a patent share between 0-0.25, middle between 0.25-0.50, high between 0.50-0.75 and very high between 0.75-1. In model 4, when interacting with the patent count, the main effect of the MNE patent share and the interaction term with patent count, is positive and statistically significant. Looking at the MNE patent share as categorical variable, I find a significant effect for the high and very high group relative to the low patent share. This suggests that the overall effect is driven by regions with a high and very high MNE patent share, with a stronger effect in regions where more patents are produced.

	(1)	(2)	(3)	(4)
Domestic MNE	0.100^{***}		0.058^{*}	
	(0.017)		(0.022)	
Foreign MNE		0.038		
		(0.025)		
Log(Nr firms)	-0.155^{***}	-0.178^{***}	-0.141^{***}	-0.164^{***}
	(0.025)	(0.025)	(0.027)	(0.028)
Log(nr patents)	0.221^{***}	0.242^{***}	0.200^{***}	0.226^{***}
	(0.020)	(0.019)	(0.023)	(0.023)
GDP pc	0.122	-0.075	0.059	0.213
	(0.412)	(0.387)	(0.427)	(0.448)
Log(population)	-0.035	-0.029	-0.033	-0.029
	(0.029)	(0.030)	(0.032)	(0.026)
Emp Scient	-0.000^{*}	-0.000	-0.000^{*}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Domestic MNE:log(nr patents)			0.022^{*}	
			(0.008)	
MNE middle				0.003
				(0.006)
MNE high				0.043^{***}
				(0.007)
MNE very high				0.059^{***}
				(0.012)
R^2	0.921	0.916	0.922	0.923
Num. obs.	3207	3207	3207	3135

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.2: Regression Results: Differences between domestic- vs. foreign-owned MNEs and patenting intensity

These findings provide support for the second hypothesis, that the increase in patenting concentration is driven by domestic-owned MNEs and is more pronounced in states with higher MNE patent shares in a given technology sector and state. Given these results, I will continue using only the patent share by domestic-owned MNEs. In addition, I test for differences between technology classes and for the effect of foreign patents, which are shown in the appendix in Table 2.8.

2.6.3 Effect on Non-MNEs

To test the third hypothesis, I am estimating the effect on the patent concentration of non-MNEs. To do so, I construct the Gini coefficient so that it only consists of firms that are not classified as MNEs and then regress it on the domestic MNE patent share. The results are presented in Table 3.4 below, with the first specification showing the effect with the same controls that we have seen in the previous table. In line with the hypothesis on a negative competition effect, the link between the MNE patent share and non-MNE patenting concentration is also positive and larger in magnitude than for all firms. A one standard deviation increase in the domestic-owned MNE patent share is estimated to raise the Gini coefficient by 0.21 points. I explain these findings based on the technological distance to the frontier and competitive pressure. Non-MNEs tend to be less innovative, and due to lower absorptive capacity and higher cognitive distance to more innovative firms, technological diffusion tends to be less common.

	Gini	Gini	P75	P50	P25
Domestic MNE	0.229^{***}	0.167^{***}	-0.748^{***}	-0.814^{***}	-0.678^{***}
	(0.026)	(0.027)	(0.059)	(0.052)	(0.067)
Log(Nr patents)		0.031^{**}	0.226^{***}	0.146^{***}	0.144^{***}
		(0.010)	(0.035)	(0.034)	(0.034)
Log(Nr firms)		0.053^{**}	-0.217^{***}	-0.125^{*}	-0.236^{***}
		(0.019)	(0.046)	(0.050)	(0.050)
GDP pc		0.632	0.783	1.163	0.648
		(0.647)	(0.478)	(2.687)	(2.034)
Log(population)		−0.094	0.019	0.096	−0.033
		(0.068)	(0.052)	(0.116)	(0.121)
Emp Scient		−0.000	0.000	−0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.619	0.685	0.519	0.654	0.615
Num. obs.	3219	3204	3207	3207	3207

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.3: Regression results: MNEs and patenting concentration for non-MNEs and different percentiles of the patenting distribution of non-MNEs.

Model 3-5 look at the effect of the presence of domestic MNEs on different parts of the non-MNE patenting distribution. It clearly shows a negative link between the patent share of domestic MNEs and the patents produced by non-MNEs at all parts of the distribution. The strongest negative effect is for non-MNEs in the middle of the distribution. Firms in the middle and the tail of the patent distribution are those the furthest away from the technological frontier, with the lowest absorptive capacity and those more affected by a negative competition effect. As the link between the MNE patent share and non-MNE patenting concentration is larger in magnitude than for all firms, it suggests that the increase in concentration is driven by the adverse effect on less innovative firms. This could provide evidence for a negative competition effect.

2.6.4 Two-Stage Least Squares Estimations

In this subsection, I am estimating the main results using 2SLS. I am evaluating the impact of the domestic MNE patent share on the patenting concentration of non-MNEs. Given simultaneity concerns, I am estimating the effects including two instrumental variables. Both IVs use variation in patenting outside the state, one of them uses it in other US states, while the other uses the foreign patents. Table 2.4 shows the results of the 2SLS estimations, including the first stage estimates, the F-statistic, and the p-value of the Sargan test. Other controls include GDP per capita, log(population) and scientific employment.

	Gini non-MNEs
Domestic MNE	0.260^{**}
	(0.090)
Log(patents)	0.006
	(0.020)
Log(firms)	0.071^{**}
First stage	
IV	3.383
Foreign patents	0.212
F-statistic	68.23
Sargan: p-value	
	0.398
Other controls	Y
R^2	0.610
Num. obs.	3122

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.4: Regression Results: Two-stage least squares estimations for the domestic-owned MNE patent share

I find a positive and statistically significant coefficient. The coefficient is larger in size compared to the OLS coefficient, which could be due to addressing simultaneity concerns. The F-statistic of 68.23 confirms relevance of the instruments and the Sargan test does not reject the null hypothesis, confirming the exogeneity of the instruments. I am running further checks to deal with simultaneity in the appendix, in Table 2.10.

2.7 Robustness Checks

To verify whether the main results are robust to different model specifications, I am running further regressions using different concentration measures and using population weighted regressions. The first robustness check is to make sure that the effects also hold for other concentration measures. I am using the HHI and the CR4, running it for all firms and non-MNEs with all MNEs and domestic MNEs as regressors. The results are presented in Table 2.5, which mostly confirm the previous findings, which is that the presence of MNEs is positively correlated with patenting concentration. I find a positive and statistically significant relationship for three out of four specifications. It is not surprising that the CR4 for non-MNEs is insignificant and negative, as the CR4 does not capture the full distribution, but only the patent shares for the four most innovative firms. As the presence of MNEs tends to mostly affect non-MNEs at the middle of the patent distribution of non-MNEs, it is not surprising that the coefficient is not statistically significant. The Gini coefficient has been criticised to be more sensitive to changes in the middle of the distribution (Atkinson et al., 1970) and the HHI also captures the whole distribution, though it focuses on the top. The second robustness check is to run population weighted regressions. The coefficients are positive, statistically significant and of similar size as the main OLS results. Thus, these checks using different concentration measures and running population weighted results confirm the main OLS results. In addition, we run the main results in first differences, which are presented in Table 2.7 (in the Appendix). The results and the size of the coefficients are similar to those of the fixed effects.

	CR4	CR4 non-MNEs	HHI	HHI non-MNEs	Gini	Gini non-MNEs
Domestic MNEs		−0.015		1286.552***		0.120***
				(314.350)		(0.023)
MNE	0.185***		861.980**		0.179***	
	(0.031)		(248.037)		(0.023)	
Log(Nr patents)	0.181***	0.060***	1127.734***	−98.780	0.224***	0.031*
	(0.037)	(0.014)	(146.865)	(101.195)	(0.020)	(0.009)
Log(Firms)	−0.360***	−0.226***	−3018.501***	−1841.039***	−0.399***	−0.000
	(0.041)	(0.017)	(228.439)	(208.918)	(0.023)	(0.019)
GDP pc	0.013	−0.226	−7939.043	−1054.754	0.677	−0.127
	(0.722)	(0.806)	(17620.751)	(17021.848)	(0.682)	(0.983)
Log(population)	−0.012	−0.024	1047.647	652.461	0.009	−0.024
	(0.057)	(0.050)	(1064.516)	(1063.195)	(0.052)	(0.045)
Emp Scient	0.000	0.000	0.004	0.005	−0.000	−0.000
	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
Pop weights	N	N	N	Y	Y	Y
R^2	0.817	0.819	0.793	0.812	0.867	0.653
Num. obs.	3211	3186	3211	3186	3211	3207

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.5: Regression Results: Robustness tests with different concentration measures and population weights

2.8 Conclusion and Discussion

For more than three decades, the US has seen patenting concentration increase in different technology classes, measured by the Gini coefficient. Yet, it is not clear what the drivers of rising innovation concentration are. For this reason, this paper analyses the effect of the presence of domestic-owned and foreign-owned MNEs on innovation concentration between all firms and non-MNEs within US states from 1976 to 2010. While there is substantial literature covering the effect of trade on domestic patenting, see, e.g., Verhoogen (2008), Aghion, Bergeaud et al. (2018) and Shu and Steinwender (2019), the effect of the presence of MNEs, and in particular on patenting concentration, remains less explored. Recent research on patenting concentration within the US (Akcigit and Ates, 2019; Forman and Goldfarb,

2020) does not cover the impact of MNEs with R&D centres on innovation concentration. Therefore, the contribution of this paper is to provide evidence to what extent the presence of domestic-owned and foreign-owned MNEs affects patenting concentration within US states and to shed light on which part of the distribution is the most affected. Using patent data from the USPTO, I construct the Gini coefficient as a measure of patenting concentration and measures of the presence of MNEs. Overall, I find evidence for a positive link of the MNE patent share and innovation concentration. This study uses OLS and IV estimates to approximate the relationship. To verify the robustness of the results, further estimations including applying more measures of patenting concentration and running a population-weighted regression.

I first examine the effect of the presence of (domestic- and foreign-owned) MNEs on the patenting concentration of all firms and find a positive relationship that is highly statistically significant. This overall effect is driven by the presence of domestic-owned MNEs. Foreign-owned MNEs, in contrast, are not significantly related to higher patenting concentration. These effects differ across space: regions with a high and very high share of domestic MNEs experience a higher increase in patenting concentration, compared to regions with only a low share. One of the key findings is that the effect on patenting concentration for non-MNEs is more pronounced than for all patenting firms. A one standard deviation increase in the domestic-owned MNE patent share is estimated to raise the Gini coefficient by 0.21 points (OLS estimates) and around 0.32 points (IV estimates). This effect is mostly driven by an adverse effect on patenting of non-MNEs, with those in the middle of the patenting distribution of non-MNEs producing fewer patents due to the presence of domestic-owned MNEs. Non-MNEs tend to be less innovative than MNEs, are further away from the technological frontier and have a lower absorptive capacity. Therefore, having a higher share of domestic-owned MNEs can be linked to non-MNEs producing fewer patents. Still, there appears to be evidence of a small number of highly innovative MNEs that become more innovative. These findings are in line with a negative competition effect and a positive market size effect that have been previously found in the literature on internationalisation and domestic patenting within the US. Economic globalisation can play a crucial role by reinforcing existing effects due to a considerable rise in the potential gains from innovation due to a market size effect while at the same time heightening losses due to a competition effect (Aghion, Antonin and Bunel, 2021). However, these findings could be also explained by other dynamics, such as merger & acquisition, strategic patenting or changes in patenting law.

There are some limitations in this study. First, I am using patent data to measure innovation. It is well known that patents are an imperfect measure of innovation and that not all innovation is patented. Therefore, I am only capturing innovation created by firms that produce patents, which likely provides an underestimation of innovation concentration between firms. Second, I am only measuring patenting concentration, which does not need to be the other coin of knowledge diffusion. It would be highly interesting to conduct a further study focusing on knowledge diffusion as outcome variable and to understand the role of domestic-owned MNEs. Third, I identify MNEs with R&D centres through patent data, which means that I only capture a subset of MNEs that produce patents internationally and have at least five cross-border patents. This also implies excluding MNEs that do not patent as well as MNEs that do not patent internationally but produce goods and services across borders. I am trying to account for this by verifying the MNE identification with Orbis data. However, this does not allow me to verify the status of all MNEs. Fourth, this study uses an aggregated measure of MNE presence, which entails a lot of heterogeneity across firms. As the goal of this research is to explore overall dynamics of the presence of MNEs, this aggregated measure is used. However, it would be highly interesting to look more into the heterogeneity across firms and gain a better understanding why this sizeable effect is observed. In general, looking more into the mechanisms of the effect could be an interesting area of future work. Despite these limitations, this paper provides an important contribution to the increasing literature on patenting concentration. It shows how the presence of domestic-owned MNEs is positively linked to an increase in patenting concentration within states and how less innovative firms are adversely affected and produce fewer patents. Given other trends such as declining knowledge diffusion (Akcigit and Ates, 2021), declining productivity in R&D investment (Bloom, Jones et al., 2020) and increasing market power (Autor, Dorn, Katz et al., 2020), it is vital to look at patenting dynamics and provide a better understanding how the distribution of innovation between firms has changed over time.

2.9 Appendix

2.9.1 Assigning foreign patents to the US states

Foreign patents are patents where the inventor is outside the US but the primary research location within the US. I reassign the patent to the primary research location which is within the US to be able to assess the effect of foreign activities on innovation concentration in the US. Figure 10 below shows the states where most patents were reassigned. It shows the top 10 states of the relative frequency distribution.

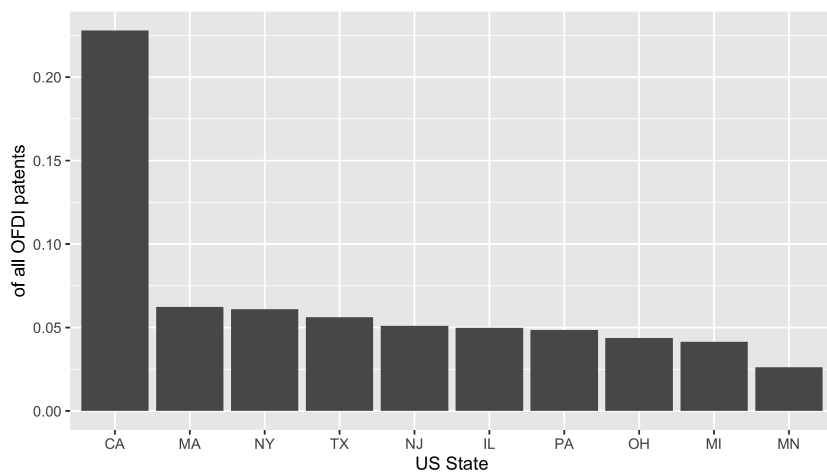

Figure 2.7: Top 10 most frequently reassigned states of foreign patents, 1976-2010

2.9.2 Descriptive Statistics

Table 1 shows the summary statistics for the relevant variables related to the patent data. The observation period is from 1976 to 2010. All variables are at the US state level, per technology class and per period. Period refers to a three-year period, which is constructed between 1976 and 2009 and takes averages for every period. Table 1 summarises the number of patenting firms, patents, MNEs and innovation concentration, based on the patent data by the USPTO, all measures are indicated in levels. The first two rows refer to the absolute patent count and absolute number of patenting firms within a state, technology class and period. The independent variable, the MNE patent measures, are displayed in the following rows. It distinguishes between MNE patents, which refers to patents by MNEs and MNE firms, both including absolute and relative measures.

Table 2.6: Summary Statistics for Patent Data, 1976-2010

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Nr Patents	3,222	146.03	365.43	0.33	10.51	45.92	150.23	9,293.99
Nr Firms	3,222	60.21	93.44	1.00	9.00	28.00	75.33	1,395.00
MNE patents								
MNE patent count	3,222	101.77	294.03	0.00	4.00	23.94	93.77	7,864.21
MNE patent share	3,222	0.540	0.229	0.000	0.380	0.561	0.715	1.000
Domestic MNE	3,222	87.63	248.56	0.00	3.28	21.04	78.11	6,261.83
Domestic MNE share	3,222	0.46	0.22	0.00	0.31	0.47	0.62	1.00
Foreign MNE	3,222	14.14	51.26	0	0.3	2.3	10.7	1,602
Foreign MNE share	3,222	0.077	0.091	0.000	0.019	0.053	0.105	1.000
MNE Firms								
Nr domestic MNE	3,222	18.65	25.65	0.00	2.67	9.00	25.00	316.00
Nr foreign MNE	3,222	5.41	10.07	0	0.3	2	6.3	160
MNE share	3,222	0.41	0.16	0.00	0.31	0.41	0.50	1.00
Concentration								
Gini coef	3,222	0.41	0.20	0.00	0.26	0.40	0.55	0.91
Gini coef no MNEs	3,219	0.52	0.17	0.00	0.45	0.56	0.64	0.89
HHI	3,222	1,884.34	2,091.58	38.16	526.72	1,080.53	2,398.04	10,000.00

All patent and firm measures are by technology class, state and three-year period.

The final rows *Concentration* refer to the dependent variables, the concentration measures. *Gini coefficient* refers to the gini coefficient created from the patenting activities of all firms within a state, period and technology class. *Gini coefficient no MNEs* only contains the patenting of those firms that are not MNEs, thus do not produce any patents internationally. The mean for *Gini coefficient* is 0.41, which is lower than *Gini coefficient no MNEs* that has a mean of 0.52, signifying that patenting is more dispersed for the overall patenting distribution. *HHI* refers to the Herfindahl-Hirschman Index constructed from the full patent distribution.

2.9.3 Main Results: First Differences

In addition to the fixed effects estimations, we run the same baseline models in first differences. The results are presented in Table 2.7, with the dependent variable in Model 1 being the Gini coefficient including the patents for all firms and Model 2 being the Gini coefficient excluding patents from MNEs. The results confirm the findings of the main model.

1

	Gini	Gini non-MNE
MNE	0.118^{***}	0.197^{***}
	(0.0182)	(0.0206)
Log(patents)	0.213^{***}	0.008
	(0.0152)	(0.0080)
Log(firms)	-0.144^{***}	0.083^{***}
	(0.0198)	(0.0141)
GDP pc	-2.994	1.857
	(0.3274)	(0.6874)
Log(popul.)	-0.127	-0.040
	(0.0342)	(0.0598)
Emp Scient	0.000^{*}	0.000
	(0.000)	(0.000)
R^2	0.830	0.439
Num. obs.	2,913	2,910

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.7: Regression Results: Overall effects, model in first differences

2.9.4 Differences Technology Classes and Foreign Research

I test for the effect of foreign patents, by adding it as a regressor as share of all patents per state and technology class. The estimated coefficient in model 1 is negative, but not statistically significant. Moreover, I test for differences across technology classes, by including an interaction term between MNE patent share and technology class. While it shows that there are significant differences between technology classes affecting patenting concentration, the effect is not significant when interacted with the MNE patent share.

	(1)	(2)
Domestic MNE patents share	0.103***	0.124***
	(0.018)	(0.030)
FRA share domestic MNEs	−0.034	
	(0.043)	
Chemical		0.053**
		(0.018)
Comp & Cmm		0.073***
		(0.014)
Drugs & Medicine		0.091***
		(0.015)
Elec		0.059*
		(0.022)
Mechanics		0.017
		(0.008)
MNE patent share*Chemical		0.008
		(0.038)
MNE patent share*Comp & Cmm		−0.044
		(0.028)
MNE patent share*Drugs & Medicine		−0.022
		(0.037)
MNE patent share*Elec		−0.051
		(0.042)
MNE patent share*Mechanics		−0.014
		(0.021)
Controls	Yes	Yes
R^2	0.921	0.922
Num. obs.	3207	3207

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level, FRA = foreign research activity

Table 2.8: Regression Results: Testing for differences technology class and foreign patents

2.9.5 Different time periods: Non-MNEs

The observation period of more than 30 years is very long considering that there have been substantial changes in the technology classes and patenting law. Thus, I split the sample in three periods, from 1976-1988, 1989-1997 and 1998-2010. I run the same regressions as model 1 in Table 3.4 and find a positive and significant effect for all three periods, with the largest coefficient from 1989-1997. This shows that the overall effect is not driven by the effect of one period, but seems to be constant, and larger in size in the two last periods.

	1976-1988	1989-1997	1998-2010
Domestic MNE	0.140^{**}	0.171^{**}	0.152^{**}
	(0.041)	(0.047)	(0.044)
Log(nr patents)	0.067^{**}	0.028	0.010
	(0.020)	(0.017)	(0.013)
Log(nr firms)	0.033	0.080^{*}	0.053
	(0.030)	(0.031)	(0.028)
GDP pc	3.111	0.831	0.533
	(2.384)	(3.241)	(0.298)
Log(population)	-0.142	-0.045	-0.186^{**}
	(0.079)	(0.165)	(0.053)
Emp Scient	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
R^2	0.672	0.694	0.648
Num. obs.	1151	879	1174

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.9: Regression results: For non-MNEs for different periods

2.9.6 Further Robustness Checks

This robustness check addresses two concerns regarding the identification of the effect. The first one is related to the dynamics in certain technology classes that have experienced a lot of change over time. Given that certain dynamics are specific to technology classes, I add an interaction between technology class and period, to address the concern that the effect might be driven by specific dynamics of certain technology classes. The results are presented below, with the MNE patent share and the domestic MNE patent share as independent variables and the Gini coefficient (including all firms) and for non-MNEs as dependent variable. The second concern is related to simultaneity. In order for the MNE patent share not to simultaneously impact the patenting concentration, I am not analysing the effect in the same period, but instead use the lead dependent variable. The results for both robustness checks are presented below in Table 2.10 and show that they are consistent with previous estimated coefficients.

	Gini all	Gini non-MNE	Lead Gini all	Lead Gini non-MNE
MNE patents share	0.117***		0.111***	
	(0.017)		(0.017)	
Domestic MNE		0.163***		0.122***
		(0.025)		(0.022)
Log(nr patents)	0.218***	0.029**	0.193***	0.030**
	(0.018)	(0.009)	(0.015)	(0.008)
Log(nr firms)	−0.149***	0.064**	−0.135***	0.029
	(0.024)	(0.019)	(0.020)	(0.015)
GDP pc	0.204	0.579	0.235	0.574
	(0.307)	(0.528)	(0.380)	(0.892)
Log(population)	−0.039	−0.104	−0.015	−0.067
	(0.028)	(0.068)	(0.039)	(0.070)
Emp Scient	−0.000*	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Technology x Period FE	Y	Y	N	N
R^2	0.925	0.692	0.859	0.649
Num. obs.	3207	3204	2913	2910

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, SE clustered at the state level

Table 2.10: Regression Results: Further robustness checks adding technology class-period fixed effects and using a lead dependent variable

Chapter 3

Dissecting the Link Between Trade and Income Inequality in European Regions

3.1 Introduction

In the last few decades, trade has driven the process of globalisation, exerting a profound influence across a wide range of societal aspects. In 2007, the volume of global trade had doubled compared to 1997, increased sixfold since 1972, and was 32 times higher compared to 1950 (Federico and Tena-Junguito, 2017). Its far-reaching impact has become evident across numerous domains, significantly reshaping the dynamics of economies everywhere and the structure of societies at large. Trade, in its expansive scope, has not only facilitated economic growth and development but has also played a critical role in shaping social and cultural interactions (Frankel and Romer, 1999; Acheson and Maule, 2006; Coyne and Williamson, 2009).

The influence trade has had on our societies extends well beyond mere economic transactions. The expansion of trade has acted as a catalyst for technological advancements, cultural change, and the dissemination of ideas, which collectively contribute to the evolving global landscape (Ben-David and Loewy, 1998; Salomon and Shaver, 2005; Acheson and Maule, 2006; Suranovic, Winthrop et al., 2005). Economies that are actively engaged in trade have often experienced accelerated growth, reduced poverty, and elevated macroeconomic productivity

(Frankel and Romer, 1999; Dollar and Kraay, 2004; Durlauf, Johnson and Temple, 2005). However, this expansion and integration into the global market often come with their own set of challenges and complexities.

In parallel, the world has witnessed a noticeable increase in both inter- and intra-regional inequality (Rodríguez-Pose, 2012; Lindley and Machin, 2014; Lee, Sissons and Jones, 2016; Terzidis, Maarseveen and Ortega-Argiles, 2017; Iammarino, Rodríguez-Pose and Storper, 2019; Feldman, Guy and Iammarino, 2021). These inequalities manifest themselves in various forms, including disparities in income, in access to resources and opportunities. As such, the rise in inequality has important economic, social, and political consequences. Studies have consistently shown that higher levels of inequality are associated with negative outcomes such as poorer health, reduced social cohesion, an increase in crime rates, and even the likelihood of conflict (Sen, 1997; Frank, 2007; Wilkinson and Pickett, 2009; Dorling, 2015).

However, to what extent are both phenomena connected? Do trade flows matter for changes in intra-regional income inequalities? Income inequality arises from a multitude of factors. Yet, globalisation, and particularly trade, are often considered a major contributing factor (Dreher and Gaston, 2008; Iammarino, Rodríguez-Pose and Storper, 2019; Heimberger, 2019). A growing body of literature, including key studies by Autor, Dorn and Hanson (2013) on the 'China syndrome', suggests that participation in trade may be instrumental in shaping regional labour markets. This type of research offers a framework for our analysis, indicating that trade can adversely affect middle classes in developed countries by escalating interpersonal inequality. Yet, the mechanisms through which trade influences income distribution are complex and multifaceted. On one hand, trade can spur economic growth, create jobs, and enhance consumer choices, potentially reducing poverty and inequality. On the other hand, it can lead to job displacement in certain sectors, wage stagnation, and a widening gap between skilled and unskilled workers, exacerbating income inequality.

Whether engaging in trade spurs rises in inequality, thus, remains a matter of controversy, particularly at the subnational level. A considerable body of research has examined income inequality through cross-country analysis (Hirte, Lessmann and Seidel, 2020; Dorn, Fuest and Potrafke, 2018; Roser and Cuaresma, 2016; Dreher and Gaston, 2008), focused on single-country studies (Barusman and Barusman, 2017; Silva and Leichenko, 2004), or linked territorial inequality within countries with international trade (Rodríguez-Pose, 2012; Rodríguez-Pose and Gill, 2006). Still, below the national level, there remains an important gap in our knowledge of the impact of trade on intra-regional income inequality. This is particularly the case across European regions, where a lack of specific data has further hindered this type of analysis. Gaining insight into this aspect is essential, given the potentially detrimental societal effects of income inequality.

This paper addresses this gap by examining the complex interplay between trade and interpersonal inequality with a focus on regional disparities within Europe[1]. We assess the impact of various trade types —including domestic trade, trade within the EU, and trade with neighbouring and non-neighbouring regions— on the rise of interpersonal inequality at a regional level across the EU. Despite recent interest in globalisation and income inequality, questions about how trade influences intra-regional income inequality at the NUTS-2 level in European regions remain unanswered. Understanding the effects of trade on regional income disparities is crucial for several reasons. Previous studies have failed to explore extensively the regional level across broader geographical scales, leaving open questions about how trade impacts differ based on trading partners. It is unclear whether trade with neighbours, non-neighbours, nationally, or internationally contributes more to intra-regional income inequality. More research is needed to comprehend these trade effects fully. For regions adversely affected, assessing the extent of this impact is vital for policy makers to address potential negative outcomes.

Our paper contributes to the literature on trade and income inequality in Europe by shedding light on which trade types affect intra-regional income inequality. This is particularly relevant for Europe, where most inter-regional trade occurs within regional borders, rather than across countries or the EU as a whole. Focusing on the regional dimension is, therefore, crucial, as

[1]Throughout the paper we refer to Europe as regions in the current 27 member states of the European Union (EU) plus the UK. For analytical purposes, when we talk of trade within the EU or with the rest of the world, we consider the UK as a member of the EU, which was the case in 2013, when the trade data is calculated.

much of the existing literature concentrates on the role of international trade outside the EU. Trade within EU and national borders has been less considered. To our knowledge, this relationship has not been previously explored. We use two novel data sets on trade and regional income inequality, incorporating inter-regional trade flow data from Thissen, Ivanova et al. (2019) for 2013, for the trade data, and combining the Gini coefficient data from the European Union Statistics on Income and Living Conditions (EU-SILC) and the Luxembourg Income Study (LIS), for the regional inequality data.

Our findings indicate a positive and statistically significant relationship between trade and regional income inequality, which varies significantly depending on the type of trading partners of different European regions. Trade within the EU, the same country, and with non-neighbouring regions correlates with an increase in intra-regional income inequality. By contrast, no significant effects are observed for international trade and trade outside the EU. Instrumental Variable (IV) estimations further confirm the positive impact of certain trade groups on income distribution changes.

The paper is organised as follows: we begin by outlining relevant literature, conceptual framework, and our paper's intended contributions. Next, we describe the data employed, including trade variables and income inequality measures. We then present descriptive statistics and detail our baseline estimation model. The paper concludes by discussing the main findings and their implications.

3.2 Does Trade shape Regional Inequality?

3.2.1 Understanding the Impact of Trade

Free trade generally drives income growth (Frankel and Romer, 1999). The more a place trades, the bigger the opportunities for growth. Yet, the intensity and distribution of trade varies enormously between territories. Factors such as geographical proximity are key in establishing trading relationships. Engaging in trade with nearby partners is advantageous in minimising transportation costs, thereby allowing for more competitively priced goods.

Numerous studies have illustrated that trade tends to occur more frequently between neighbouring countries and those sharing cultural similarities (Anderson and Van Wincoop, 2004; Disdier and Head, 2008; Klasing, 2013). Cultural affinity —which encompasses shared norms and values— significantly influences trade decisions (Tadesse and White, 2010). It builds trust and mitigates perceived risks, thus playing a fundamental role in initiating trade flows. In a similar vein, harmonious institutional frameworks are conducive to bilateral trade (De Groot et al., 2004; Álvarez et al., 2018). Therefore, trade within areas with similar institutions (e.g., the same country or within regional blocs like the European Union) tends to be more prevalent. This is partly due to lower institutional risks, the existence of established firm networks, and the objectives of entities like the EU, which aim to enhance trade among member states by eliminating trade barriers. Consequently, these types of trade are presumed to have a more pronounced impact on the division of labour, skill distribution, and, most significantly, on income distribution within these regions. Given that, as we will see below, trade is often connected with a rise in inequalities, we anticipate a positive correlation between trade conducted within a country or the EU and shifts in income inequality.

Neoclassical trade theory emphasises how regions can exploit their comparative advantage. This concept, originally put forth by Ricardo (1891), involves regions specialising in the production of goods where they are most efficient. As a result, regions typically concentrate on goods that align with their most abundant production factor. In advanced economies, this often translates in an increased demand for skilled labour while diminishing the demand for unskilled workers. The inverse trend is observed in developing countries. The rise in demand for skilled labour —assuming other factors remain constant— naturally leads to a rise in wages for these workers. Consequently, trade liberalisation will universally boost the skill premium (Burstein and Vogel, 2017). In contrast, declines in demand for unskilled labour can result not only in lower wages among the low-skilled but also trigger a significant transformation in the workforce and job market. Hence, the impact of trade is multifaceted, contingent on the trading partners involved, the specific skills and tasks in demand, and the degree to which specialisation drives workforce reallocation. As sectors become more specialised due to these trade dynamics, some expand, whereas others face decline and inequality may arise.

However, changes in the labor market are not only predicted by neoclassical trade theory. From the perspective of New Economic Geography, trade may also be a force for inequality. Krugman (1991) suggests that producers gravitate towards areas with substantial demand while simultaneously seeking to reduce transportation costs and maximise economies of scale. This economic behaviour leads to a clustering of economic activities in cities and regions with better economic conditions, often leaving other areas relatively unaffected. These clusters, predominantly in industries producing tradable goods and services, contribute to increases in total factor productivity and industry-specific growth, while other industries may stagnate or decline. This phenomenon has a differential impact on the income distributions within regions, as these dynamic economic clusters become typically highly concentrated in large agglomerations that benefit from positive externalities. The growth of such operations not only fosters new opportunities and jobs but also attracts a high-skilled workforce. However, a distinction must be made between regions focused on high-end innovative manufacturing and those engaged in routine manufacturing. High-end innovative manufacturing activities —often coupled with significant service sector growth— frequently end in already wealthy regions. In stark contrast, regions centred around routine manufacturing have witnessed employment declines and have struggled to stay competitive compared to their more innovative and productive counterparts (Iammarino, Rodríguez-Pose and Storper, 2019). Thus, looking solely at the overall level of manufacturing as a measure for agglomeration economies is insufficient, as it obscures the critical differences between routine and high-end innovative manufacturing. A more revealing approach is to consider innovation as a proxy for agglomeration economies. Innovation activity tends to cluster geographically, forming innovation hubs (Moretti, 2012). Furthermore, the role of technology in these dynamics cannot be understated, as it not only contributes to the formation of these clusters but also perpetuates the concentration of economic activities. By focusing on variables such as professional services, population dynamics, and innovative activities, a more accurate depiction of economic clusters can be achieved, suggesting that regions with these characteristics are likely to exhibit higher income inequalities.

3.2.2 Trade and Regional Income Inequality

The relationship between trade and income distribution has been at the heart of academic enquiry for many years. This interest has intensified recently with new evidence highlighting the impact of trade on labour markets (Autor, Dorn and Hanson, 2013). Early research by Stolper and Samuelson (1941) drew significant attention to the distributional consequences of international trade, revealing that while countries typically prosper with trade liberalisation, trade can also have detrimental effects on certain groups of workers. In scenarios where advanced regions trade with less developed ones, there is an expectation for an increased demand for skilled labour in advanced regions, while the demand for less skilled labour diminishes. This dynamic leads to skilled workers benefiting from higher wages due to trade, whereas the less skilled may face lower wages or job displacement.

During the current wave of economic globalisation, which began in the 1970s, studies conducted in the 1980s and 1990s suggested that trade had a limited impact on the labour markets of high-income countries (Krugman, 2008). This initial research concluded that the rise in inequality was more a result of skill-biased technical change than of economic globalisation (Katz et al., 1999; Feenstra and Hanson, 1999). However, this view has evolved with time, with a growing consensus acknowledging that increased trade, especially driven by emerging markets like China, has adversely affected the employment and wages of blue-collar workers in developed countries. Work by Autor, Dorn and Hanson (2013) on the so-called "China syndrome" has put in evidence how trade with places with a considerable comparative advantage in terms of costs can lead to job losses among the middle classes in developed countries. This shift in understanding has renewed scholarly interest in exploring the nuances of the relationship between economic globalisation and income inequality. Since then, more scholars have focused their analysis on the effect of the China shock in different geographies. This includes the US (Pierce and Schott, 2016; Feenstra and Sasahara, 2018), Germany (Dauth, Findeisen and Suedekum, 2014; Simon, 2018), Portugal (Branstetter, Kovak et al., 2019), Norway (Balsvik, Jensen and Salvanes, 2015), Europe (Barth, Finseraas et al., 2020) and Eastern Europe (Albers, 2018).

The skill-biased and routine-biased framework can explain changes in interpersonal inequalities. While evidence has shown that trade is skill-biased (in developed countries) (Burstein and Vogel, 2017), the skill-biased framework cannot account for the increase in demand for low-skilled workers and the loss of office jobs. Many countries in Europe have observed the hollowing out of jobs in the middle of the skill distribution (Goos, Manning and Salomons, 2009). To explain this phenomenon, the routine-biased technological change hypothesis (Autor, Levy and Murnane, 2003) has been suggested, which states that technological change and trade are biased towards the displacement of manual and routine tasks which affects the middle of the skill distribution. Thus, this hypothesis can partly explain the hollowing out of the middle of the income distribution and thus polarisation in the labor market in Europe (Goos, Manning and Salomons, 2009). From a skill- and routine-biased framework, we would expect groups of workers in declining industries and routine-biased tasks to obtain lower wages or to be displaced, which has been observed (Autor, Dorn and Hanson, 2013; Goos, Manning and Salomons, 2009). As a consequence, affected workers receive lower wages, have to find a new job, or move to another location. The effect of trade on interpersonal income inequality within a region is determined how persistent the effect is on wages and whether and how fast trade-displaced workers can secure new jobs.

Moreover, there are other mechanisms through which trade can influence income inequality. In the United States, for instance, exporting activities and foreign direct investment have been considered a source of rising income inequality. This is primarily because such activities can significantly increase executive compensation, thereby exacerbating inequality at the upper end of the income spectrum (Keller and Olney, 2021). Importing practices can also influence earnings inequality. A study by Adão et al. (2022) in Ecuador showed that the largest economic gains from importing are concentrated at the top of the income distribution. Furthermore, changes in factor taxation driven by heightened economic integration might also play a role in income disparity. Research by Bachas et al. (2022) highlights a trend towards increasing labour taxation and a reduction in capital taxation since the 1960s, particularly in high-income countries, a development partly due to international tax competition.

An additional contributing factor to increasing wage inequality is the disparity in wages between different firms. Criscuolo et al. (2020) analysed wage inequality trends in 14 OECD countries and found that changes in the distribution of average wages between firms accounted for half of the rise in wage inequality. A significant portion of this change —two thirds— was attributed to productivity-related premia. These premia are also linked to trading activities, as firms engaged in exporting are generally more productive and tend to offer higher wages (Melitz, 2003; Bernard, Jensen, Redding et al., 2007).

Although the great majority of this research has used individual countries and the people living in them as their units of analysis, research on the relationship between economic globalisation and income inequality extends beyond individual countries. Numerous studies have examined this relationship on a global scale, using a comparative perspective (Roser and Cuaresma, 2016; Dorn, Fuest and Potrafke, 2018; Hirte, Lessmann and Seidel, 2020). A comprehensive meta-analysis conducted by Heimberger (2019) suggests that economic globalisation result in a growth —albeit a rather small one— of income inequality. This body of research provides a nuanced understanding of the complex interplay between trade policies, economic globalisation, and income distribution, highlighting the diverse effects across different regions and economic sectors.

3.2.3 The Missing Factor: Types of Trade & the Regional Perspective

Research on how the relationship between trade and interpersonal inequality pans out at the subnational level has been few and far between. This is perhaps because there has frequently been a dearth of information both about the exchanges of goods and services conducted between regions —and, especially between regions within a country— as well as about the levels of interpersonal inequality within regions. Our study aims to cover this gap in existing knowledge and to provide novel insights into the relationship between trade and income inequality at the regional level within the European context. The impact of trade on interpersonal inequality within European regions has not been explored until now. Hence, we intend to offer fresh perspectives on the significance of the intensity of trade and diversity of trading partners on interpersonal polarisation within the European communities. A major hindrance in previous research has been the lack of detailed regional data, which has impeded a comprehensive understanding of various trade forms, such as national, international, neighbouring, non-neighbouring, EU trade, and trade with the rest of the world. This study underscores the importance of regional analysis, given that the majority of observed trade flows in our data —as indicated earlier— occur within nations, within the EU, rather than with distant countries and locations.

The primary objective of this study is to discern which types of trade most significantly influence changes in intraregional income inequality and to what extent. It unveils new findings that the positive correlation between changes in income inequality within a region and the level of trade is primarily driven by national trade, trade within the EU, and trade with non-neighbouring regions. To our knowledge, the only existing analysis of trade's effect at a regional level in Europe is by Gregory, Salomons and Zierahn (2022), which concentrates on employment impacts rather than inequality. That study indirectly measures trade and is framed within a routine-replacing technological change context. Our study is the first to directly address the relationship between trade and shifts in regional income inequality across Europe at the NUTS-2 level, a task previously unattainable due to trade data limitations.

Therefore, this study not only fills a significant gap in the scientific literature but also lays a foundation for evidence-based decision-making in this crucial area. By examining the nuances of trade types and their regional impacts, it provides essential insights for policymakers and economists seeking to understand and respond to the complex dynamics of trade and income inequality within Europe.

3.3 Data

3.3.1 Trade and Regional Income Inequality

In this study, we use a novel dataset to explore inter-regional trade flows among 267 European regions at the NUTS-2 (Nomenclature of Territorial Units for Statistics, level 2) level. The data are collected to reflect trade patterns in 2013. This dataset provides a unique opportunity to measure import and export flows between each region —including exchanges of goods and services within country borders— in the 28 member states of the European Union, as well as with regions outside the EU. The dataset, derived from Thissen, Ivanova et al. (2019), estimates trade flows in intermediate and final goods, along with services. It is comprehensively disaggregated, based on input-output data supplemented by freight transport, airline, and business travel data. Having such detailed trade data at the NUTS-2 level allows for an unprecedented analysis of trade flows, not only between regions of different countries but also within individual countries, and with adjacent regions. The trade data, presented in absolute values, is normalized by dividing by the regional population to yield our primary variable of interest: trade per capita.

To measure income inequality within these regions, we turn to EU-SILC and LIS data. Our focus is on post-tax disposable labour income per person, excluding capital income. This income measure is compiled by initially calculating the pre-tax factor income, which includes employee cash income, self-employment income, and private pension. We then incorporate unemployment benefits and public pensions into each household's pre-tax national income, allocating it using the OECD equivalence scale. The final step in deriving post-tax disposable income involves deducting taxes and paid contributions (like cash transfers or wealth taxes) and adding other social benefits (such as family-related allowances, housing benefits, or social exclusion benefits). Therefore, the disposable income we consider is a measure after redistribution and taxes, inclusive of unemployment benefits and pensions. Our choice to focus on disposable income rather than pre-tax factor income is driven by the belief that disposable income more accurately reflects the actual resources available to households, a crucial factor in our analysis.

We use the Gini coefficient as our indicator of income inequality within a region. The key advantage of this indicator lies in its ability to represent the entire income distribution through a single metric. Additionally, the Gini coefficient is extensively used in academic literature, making it a widely recognised and understood measure of inequality and allowing for comparisons between our results and those conducted in different places and at different scales. However, its application is not without limitations. For instance, the Gini coefficient can remain unchanged even in the presence of opposing redistributive forces within various segments of the income distribution. It tends to concentrate more on the middle of the income distribution (Sen, 1997), and may not adequately capture the dynamics at the top of the distribution. Furthermore, a notable drawback of using survey-based income data, such as EU-SILC, is its potential underestimation of top incomes due to the often limited representation of the highest earners (Törmälehto, 2017; Ravallion, 2022). Moreover, our data does not include income from capital revenues, which for many citizens is a substantial source of income.

In those cases where EU-SILC data are not available for all countries or is only accessible at the NUTS-1 level for some, we supplement it with LIS data for the Gini coefficient. This change involves countries such as Germany, Austria, and Spain. To align the trade and inequality data, which were collected in different years, we use the NUTS 2013 classification. Due to multiple boundary changes between 2013 and 2016, regions lacking comparability are excluded from our analysis. An example of this is the Irish regions "IE01" and "IE02", which were discontinued and are thus omitted from our study. Additionally, we lack inequality data at the regional level for the Netherlands and Portugal, as neither EU-SILC nor LIS provide this information.

3.4 Descriptive Evidence

3.4.1 Geographical distribution: Trade

Figure 3.1 provides a visual representation of the logarithmic transformation of trade per capita for each region in 2013. Trade per capita is calculated by dividing the combined value of imports and exports by the region's total population in that year. The logarithmic transformation is particularly effective in normalizing data that are highly skewed, leading to an approximation that more closely resembles a normal distribution. This approach helps us to better visualise and understand the intensity of trade relative to the size of the population in each region.

In Figure 3.1, a distinct pattern emerges, highlighting the variations in trade integration across regions. Notably, regions in countries such as the Benelux countries, France, Germany, Austria, the United Kingdom, Ireland, and the three Nordic countries (Denmark, Finland, and Sweden) display higher levels of trade per capita. This could be attributed to a combination of factors such as their geographic location, industrial capacity, and economic policies that favour trade. On the other hand, countries such as Romania and Bulgaria are at the lower end of the spectrum for values for log-transformed trade per capita. These differences could be influenced by various factors, including economic lower development levels, infrastructure deficiencies, or weaker institutions that severely limit access to trade networks.

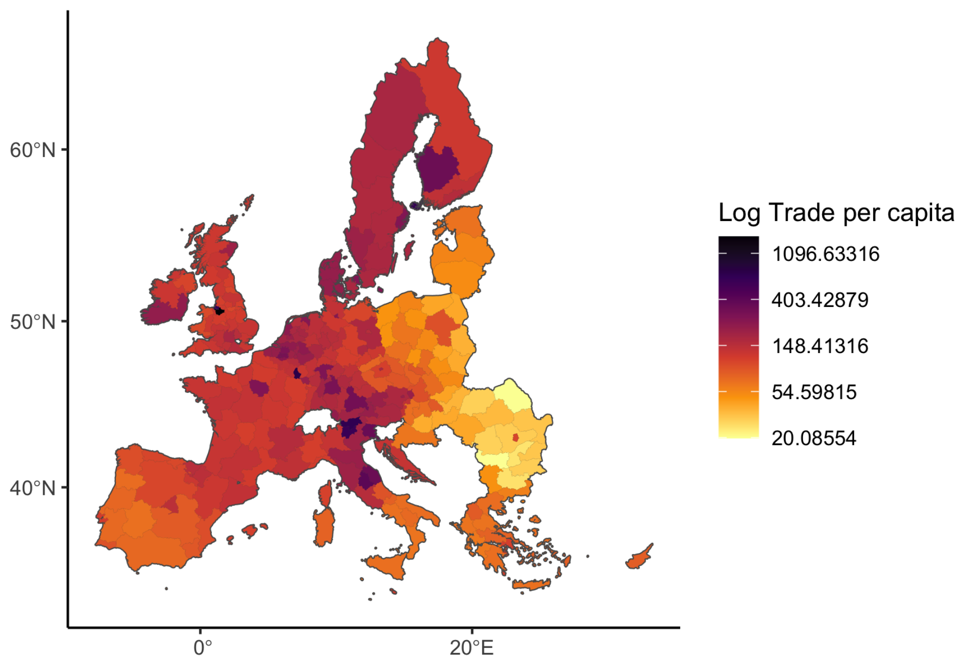

Figure 3.1: Log trade per capita, NUTS-2 regions, 2013

Types of Trade

We categorize trade into three categories and six distinct types. The first category involves a) trade within the EU vs. b) trade with the rest of the world. The second category covers c) trade with neighbouring regions vs. d) trade with non-neighbouring ones. The third and final category distinguishes between e) national trade vs. f) international trade. The first category includes trade within the EU before 2013, encompassing 266 regions. This categorization is crucial as it highlights the internal dynamics and the extent of integration within the EU's single market. Trade with the rest of the world, including Croatia (where trade data is only available at the country level), forms the second category. This distinction allows for an examination of the EU's trade relationships with non-member countries and regions.

To quantify the importance of each trade category, we calculate their respective shares in the total trade volume (in absolute values). Figure 3.3 in the appendix illustrates that trade within the EU dominates, accounting for an average of 96% of all trade in 2013. This substantial percentage is indicative of the strong internal trade ties within the EU, likely facilitated by shared regulations and reduced trade barriers. In contrast, trade with the rest of the world accounts for only 4% on average (Figure 3.4 in the appendix), indicating a more limited engagement with regions outside the EU.

For the second category, we identify neighbouring regions based on shared borders and calculate trade volumes with these and with non-neighbouring regions. The average EU region has approximately 4.5 neighbours. We then assess the proportion of trade conducted with these neighbours compared to non-neighbours. Geographical proximity and cultural similarities might suggest a propensity for regions to trade more with their neighbours. However, the limited number of neighbours and potential similarity in resources could reduce the necessity or benefit of such trade. Our data reveals that trade with neighbouring regions accounts for only around 6% of all trade, as shown in Figure 3.5 in the appendix. This finding suggests that factors other than proximity play a significant role in trade decisions. In contrast, trade with non-neighbouring regions —representing about 94% of overall trade (Figure 3.6 in the appendix)— underscores the extent to which regions engage in wider trade networks beyond their immediate geographical vicinity.

Finally, for our final category we distinguish between intra- and international trade, as this distinction can offer unique insights, especially given the absence of prior data on this aspect at the European level. We hypothesise that a major portion of trade occurs within national borders, influenced by factors such as lower transportation costs and cultural proximity. This internal trade dynamic is corroborated by data shown in Figure 3.7 in the appendix, suggesting that domestic trade forms the bulk of trade activities for most regions. In contrast, international trade comprises a smaller portion of overall trade, as depicted in Figure 3.8. This contrast highlights the different dynamics and potential barriers that influence cross-border trade compared to domestic trade within the EU[2].

3.4.2 Geographical distribution: Intra-Regional Income Inequality

Figure 3.2 below shows the changes in intra-regional income inequality across Europe, measured by the Gini coefficient, between 2013 and 2018. This change is based on data from EU-SILC, supplemented with LIS data for certain countries like Germany, Austria, and Spain. This is necessary when EU-SILC data is either unavailable or only provided at a more aggregated level. In cases where data for 2013 or 2018 is missing, we use the closest available year to ensure continuity and completeness of the dataset[3].

The geographical distribution in Figure 3.2 reveals a mix of positive and negative changes in the Gini coefficient across different regions, with many regions experiencing an increase in income inequality. Notably, regions in countries such as Italy, the United Kingdom, France, Estonia and Latvia exhibit significant increases in income inequality, as indicated by higher Gini coefficient values. Conversely, several regions in Poland, Slovakia, Hungary, and Greece show a decrease in income inequality. The analysis includes all regions where data on regional income inequality is available (excluding Portugal and the Netherlands) and where regional boundaries remained consistent during the study period, as outlined in Section 3.3.1.

[2]More information on the data can be found in the summary statistic table (Table 3.8) as well as in the correlation matrix (Table 3.9)
[3]More information in the Appendix, in Section 3.8.1

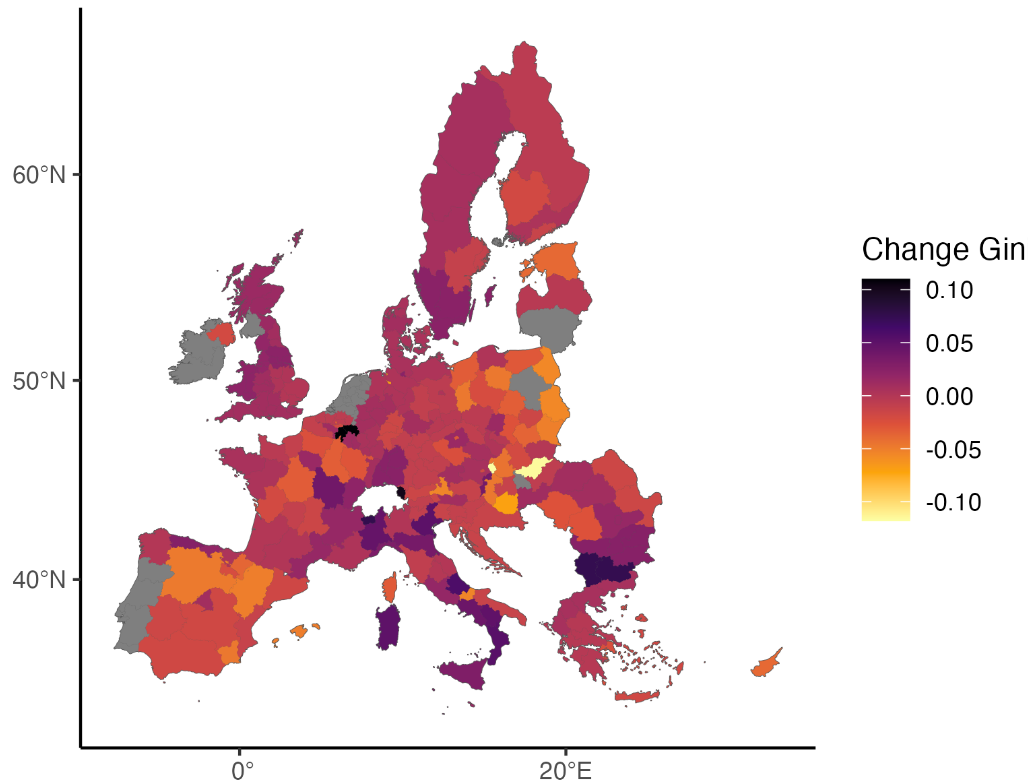

Figure 3.2: Change in Gini coefficient, EU-SILC and LIS data, 2013-2018

3.5 Methodology

Our study aims to estimate the relationship between trade and changes in intra-regional income inequality. To achieve this, we employ OLS regressions, following the equation:

$$\Delta Gini_{i,(t+5)-t} = \beta trade_{i,t} + \gamma X_{i,t} + \varepsilon_i \tag{1}$$

In this equation, $\Delta Gini$ represents the change in the Gini coefficient of region i between 2013 and 2018; *trade* refers to inter-regional trade flows per capita in 2013; and X is a vector of control variables, measured at the beginning of the period. As a result of a lack of a series for regional trade data, we assume that regional trade patterns remain fairly stable during the period of analysis. Due to the highly skewed nature of trade distribution, we employ a logarithmic scale for the trade variable. The selection of control variables is informed by existing theoretical and empirical literature. For instance, we control for GDP per capita, acknowledging that the effect of trade on income inequality can vary with the development level of a region (Stolper and Samuelson, 1941). We also consider the initial level of income inequality, hypothesising that regions with higher initial inequality are likely to experience more significant changes. Additionally, population density is included as a control variable, drawing from the New Economic Geography (NEG) and urban economics perspectives that suggest urban centres and agglomeration economies more integrated into trade networks are likely to see greater shifts in income inequality (Fujita, Krugman and Venables, 2001). The composition of skills within a region —represented by the share of tertiary education— and the industrial composition are also controlled for, considering that trade impacts income inequality through its influence on employment composition and industrial structure (Autor, Dorn and Hanson, 2013).

Moreover, we explore how different types of trade impact income inequality. This involves categorising trade and regressing the change in income inequality on each category, as per the equation:

$$\Delta Gini_{i,(t+5)-t} = \beta typetrade_{i,t} + \gamma X_{i,t} + \varepsilon_i \tag{2}$$

This equation mirrors the previous one, with *typetrade* representing the six distinct types of trade we consider in the analysis: national, international, trade with neighbouring regions, trade with non-neighbouring regions, trade within the EU, and trade with the rest of the world. All trade measures are normalized by population size and expressed on a logarithmic scale (with a small value added in cases of zero trade). The hypothesis is that the extent and type of trade a region engages in can significantly influence its income distribution. Particularly, we expect significant effects on income inequality if a region's trade volume within certain categories is substantial enough to drive specialisation and hence alter the division of labour within firms, industries, and regions. As detailed in Section 3.4.1, most trade occurs within the EU, within national boundaries, and with non-neighbouring regions. This pattern suggests that these trade groups may have a notable impact on income inequality.

In estimating these equations, we do not account for potential endogeneity issues arising from reverse causality, where changes in income inequality might also affect trade patterns, possibly through economic policy responses to heightened inequality levels. In previous studies, IV approaches have been employed to address such concerns (Autor, Dorn and Hanson, 2013; Hirte, Lessmann and Seidel, 2020; Ezcurra and Del Villar, 2021). In our analysis we address this concern by means of historical literacy rates from 1880 as an instrumental variable. For this instrument to be valid, it must be both exogenous to the model and relevant to the endogenous trade variable. We test for relevance, as evidenced by the F-statistic reported in Table 3.5, confirming the instrument's validity in certain specifications. While we cannot directly test the exogeneity of the instrument, it is improbable that variations in literacy rates across regions of Europe in 1880 would directly affect changes in income inequality in the early 21st-century. If there is a relationship between the two, it may happen from historical literacy affecting trade patterns in the past and creating a path dependency. Our use of an IV approach is aimed at yielding more robust results. However, it is important to note that our study seeks to understand the association between trade and regional income inequality, not to assert a causal relationship. To mitigate potential biases arising from omitted variables, we include multiple controls identified by empirical and theoretical literature as influencing regional income inequality dynamics. Nevertheless, since our analysis is based on cross-sectional data, there is always the possibility of unobserved variables confounding the observed effects. Our goal is to account for these factors as much as possible, but we also need to acknowledge that the study primarily captures an association between trade and income inequality, rather than a definitive causal link.

3.6 Estimation Results

3.6.1 Overall Effect

In Table 3.1, we address the main research question driving the paper and investigate the impact of overall trade on regional income inequality. The method involves regressing the change in the Gini coefficient on trade per capita, applying the logarithm of trade due to its skewed distribution. The regression begins in Model 1 with only the trade variable, and incrementally introduces control variables across subsequent models. These controls include the initial level of income inequality, GDP per capita, population density, tertiary education level, and employment shares in specific industries, notably professional, scientific, technical activities, and industry (excluding construction).

The results consistently show a significant positive relationship between trade and income inequality within the regions of Europe. This implies that regions with higher trade per capita tend to experience greater increases in income inequality. This correlation could be indicative of the economic complexities introduced by trade, such as labour market disruptions and shifts in industry demands, which disproportionately affect different segments of the population. Additionally, the positive association between the initial level of inequality and its subsequent increase suggests a compounding effect where regions already grappling with high inequality are more susceptible to further exacerbation. GDP per capita demonstrates a negative link with changes in income inequality, implying that more affluent regions may experience lower distributional changes, possibly because of more robust social safety nets or more diversified economies. This finding resonates with the Kuznets curve hypothesis, which posits an inverted-U relationship between economic development and income inequality. The positive correlation between employment in professional, scientific, and technical activities and changes in income inequality could reflect the increased demand for specialised skills in these sectors, leading to greater wage disparities.

	(1)	(2)	(3)	(4)
Log(trade pc)	0.0056^{*}	0.0084^{**}	0.0137^{**}	0.0129^{**}
	(0.0032)	(0.0033)	(0.0053)	(0.0051)
Gini		0.1275^{**}	0.1427^{**}	0.1253
		(0.0607)	(0.0690)	(0.0755)
Log(GDP pc)			-0.0088	-0.0186^{*}
			(0.0121)	(0.0101)
Log(pop density)			0.0004	-0.0010
			(0.0016)	(0.0019)
Pop tert educ			-0.0097	
			(0.0212)	
Emp prof services				0.2361^{**}
				(0.1061)
Emp ind				0.0311
				(0.0317)
R^2	0.0153	0.0394	0.0470	0.0629
F-Statistic	3.049	4.107	2.428	3.082
Num. obs.	242	242	241	240
RMSE	0.0284	0.0281	0.0282	0.0281

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level

Table 3.1: Regression Results: Overall trade and income inequality

3.6.2 National and International Trade

In terms of whether there are differences in this relationship depending on whether the trade of a region happens within national borders or outside, we calculate and regress national and international trade per capita for each region against the change in the Gini coefficient, as shown in Table 3.2. The models vary in their inclusion of controls; Models 1 and 3 are control-free, whereas Models 2 and 4 incorporate the same controls as Model 4 in Table 3.1. Controls include GDP pc, the level of inequality, population density, scientific employment and industry employment.

The findings reveal that trading with other regions within national borders significantly increases income inequality. This result suggests that internal trade within a country can be a driver of income disparities within regions. This relationship could stem from unequal regional integration into national markets, where some regions may benefit more from internal trade due to factors like better infrastructure, access to larger markets, or more developed industries. The size of the coefficient is similar to those reported in Table 3.1, indicating that the overall connection between trade and interpersonal inequality is fundamentally driven by national trade. However, we cannot find any evidence of a significant effect of international trade. International trade, however, does not show a significant effect on income inequality. This lack of association could be due to international trade being more evenly distributed or less influential in altering regional economic structures compared to national trade.

	(1)	(2)	(3)	(4)
Log(national trade pc)	0.006^{**}	0.015^{**}		
	(0.003)	(0.006)		
Log(international trade pc)			-0.001	-0.003
			(0.002)	(0.003)
Controls	N	Y	N	Y
R^2	0.021	0.072	0.000	0.047
F-Statistic	4.016	3.081	0.09881	2.539
Num. obs.	241	240	241	240
RMSE	0.028	0.028	0.029	0.028

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level

Table 3.2: Regression Results: National vs. international trade and income inequality

3.6.3 Trade within the EU vs. Rest of the World

Our analysis also explores the effect of trade within the EU compared to trade with the rest of the world (Table 3.3). Statistical models with controls include GDP pc, the level of inequality, population density, scientific employment and industry employment. We observe a positive association between trade within the EU and increases in within-region income inequality. This could be due to the intensive economic integration within the EU, leading to more pronounced effects of trade on regional economies and income distribution. However, trading with regions outside the EU does not exhibit a significant effect on income inequality changes. This difference may be attributed to the nature of trade agreements, economic integration levels, or the types of goods and services traded within the EU versus with external regions.

	(1)	(2)	(3)	(4)
Log(trade EU pc)	0.006^{*}	0.015^{**}		
	(0.003)	(0.006)		
Log(trade ROW pc)			-0.001	-0.003
			(0.002)	(0.003)
Controls	N	Y	N	Y
R^2	0.016	0.067	0.001	0.047
F-Statistic	3.07	3.117	0.1205	2.416
Num. obs.	240	238	240	238
RMSE	0.028	0.028	0.029	0.028

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level

Table 3.3: Regression Results: Trade with the EU vs. rest of the world and income inequality

3.6.4 Neighbouring and Non-Neighbouring Trade

Finally, we assess our third category of trade: the connection between trade with neighbouring versus non-neighbouring regions on income inequality (Table 3.4). Statistical models with controls include GDP pc, the level of inequality, population density, scientific employment and industry employment. Neighbour means sharing a common border, based on a contiguity matrix. Trade with neighbouring regions shows a positive but statistically insignificant effect on income inequality changes. This might indicate that trade with immediate neighbours does not substantially alter the economic landscape or income distribution within a region. In contrast, trade with non-neighbouring regions displays a significant positive coefficient on income inequality. This finding suggests that regions engaging more with distant trading partners may experience greater economic shifts, possibly due to engaging in more specialised or higher-value trade, leading to more pronounced effects on income distribution.

	(1)	(2)	(3)	(4)
Log(trade neighbours pc)	0.001	0.001		
	(0.001)	(0.001)		
Log(trade non-neighbours pc)			0.006^{*}	0.013^{**}
			(0.003)	(0.005)
Controls	N	Y	N	Y
R^2	0.004	0.051	0.017	0.065
F-Statistic	1.175	2.924	3.336	2.873
Num. obs.	239	238	239	238
RMSE	0.029	0.028	0.028	0.028

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level

Table 3.4: Regression Results: Trade with neighbours vs. non-neighbours and income inequality

These results collectively suggest that the type and scope of trade a region engages in can significantly influence its economic structure and, consequently, its income distribution. Regions tend to focus a significant portion of their trade within national boundaries, the European Union, and with non-neighbouring regions. This allocation of trade focus results in a substantial investment of resources in the production of tradable goods and services. As a consequence, certain industries within these regions experience expansion, driven by the demands of this trade orientation. As regions specialise and dynamic industries expand, income disparities may widen. Workers with the required skills and expertise benefit from higher wages and better opportunities, whereas those in sectors that are not directly benefiting from the trade may see lesser growth or even stagnation in their income. This divergence in economic fortunes contributes to increasing income inequality within these regions.

In contrast, trade with neighbouring regions, the rest of the world, or outside the country constitutes a smaller portion of overall trade. The lower volume of this type of trade results in less need for specialisation and, consequently, less reallocation of workers. Industries in regions focused on this type of trade do not experience the same level of expansion and demand for specialised skills. Therefore, the impact on income inequality is not as pronounced as in regions with high levels of national, EU, or non-neighbouring trade. These regions might maintain a more diverse or balanced economic structure, leading to a more uniform distribution of economic gains across various sectors and a less stark contrast in income levels among different worker groups.

In brief, the extent and focus of regional trade have significant implications for economic structure, industry expansion, and the demand for specific skills, all of which play crucial roles in influencing income inequality. The emphasis on certain types of trade —particularly national, within the EU, and with non-neighbouring regions— appears to be fundamental factor behind the observed variations in income inequality across different European regions.

3.6.5 IV Estimations

We address potential endogeneity concerns — and, in particular, reverse causality— by means of an instrumental variable (IV) approach. We employ historical literacy rates from 1880 as an exogenous instrument to provide variation. This choice of instrument is based on the assumption that literacy rates in the past would have influenced the development and economic characteristics of regions, thereby affecting their current trade patterns and income inequality, but would not be directly affected by contemporary trade or inequality levels.

The IV approach results, presented in Table 3.5, include the F-statistic of the first stage to demonstrate the instrument's correlation with the endogenous trade variable. For models 1, 2, 4, and 6, the instrument satisfies the relevance condition, indicated by a significant association with the endogenous variable and an F-statistic exceeding the threshold of 10, as recommended by Stock, Watson et al. (2003). This indicates a strong correlation between the historical literacy rate and current overall trade patterns, lending credibility to the use of this instrument. The same applies for national trade, trading with non-neighbours, and trading with other regions in the EU.

In these models, we observe a positive and statistically significant impact of trade on changes in income inequality. Notably, the coefficients in these IV estimates are larger than those in the OLS estimates. This difference in coefficient size could be attributed to two factors. First, the IV approach reduces the endogeneity bias, which provides a more accurate estimation of trade's impact on income inequality. Second, the analysis of a smaller sample size. We must note that our analysis using this instrument is confined to 153 regions within the EU-15, where historical literacy data are available.

For models 3, 5, and 7 — trading with regions in other countries, with immediate neighbours, and with the rest of the world—, however, the results do not point to a significant relationship between trade and income inequality. In these cases, the types of trade being considered do not have a discernible impact on income inequality, possibly because the instrument may not be as strongly correlated with the trade variable in these models.

These IV findings align with the results observed in Tables 2-5, where national trade, trade with non-neighbouring regions, and trade within the EU are shown to have a positive and significant connection with changes in income inequality. The consistency across these results reinforces the notion that certain types of trade —particularly exchanges of goods and services within national borders and EU-wide trade— are influential factors in shaping regional income disparities. The IV approach, by mitigating endogeneity concerns, provides a more robust analysis of this relationship, revealing the nuanced and significant ways in which trade dynamics can impact the economic landscape of European regions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(trade pc)	0.100*						
	(0.054)						
Log(national trade pc)		0.074**					
		(0.035)					
Log(international trade pc)			−0.299				
			(0.540)				
Log(trade non-neighbours)				0.079**			
				(0.039)			
Log(trade neighbours)					0.035		
					(0.024)		
Log(trade EU pc)						0.090*	
						(0.046)	
Log(trade ROW pc)							−0.065
							(0.042)
Gini	0.391**	0.293**	−1.814	0.322**	0.549*	0.358**	−0.152
	(0.184)	(0.131)	(3.478)	(0.141)	(0.312)	(0.164)	(0.192)
Log(GDP pc)	−0.103	−0.074*	0.403	−0.080*	−0.068	−0.092*	0.099
	(0.063)	(0.041)	(0.729)	(0.045)	(0.047)	(0.054)	(0.069)
Log(pop density)	0.005	0.006	−0.021	0.007	−0.011	0.005	0.003
	(0.005)	(0.005)	(0.042)	(0.005)	(0.011)	(0.005)	(0.005)
Emp prof services	−0.230	−0.238	1.234	−0.295	0.773	−0.199	0.050
	(0.264)	(0.266)	(2.241)	(0.296)	(0.686)	(0.243)	(0.332)
Emp ind	0.007	0.026	0.356	0.020	−0.069	0.013	0.082
	(0.066)	(0.065)	(0.751)	(0.066)	(0.074)	(0.065)	(0.116)
First stage							
F-Statistic	10.957	18.862	0.316	16.50	2.929	13.752	2.866
R^2	−0.156	−0.013	−17.764	−0.066	−2.051	−0.069	−1.440
F-Statistic	2.19	2.468	2.407	13.014	2.929	16.867	4.853
Num. obs.	153	153	153	153	153	153	153
RMSE	0.034	0.032	0.137	0.033	0.055	0.033	0.049

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level.

Table 3.5: Regression Results: IV estimations for all types of trade and income inequality

3.6.6 Sensitivity Checks

To enhance the reliability of our findings, we conduct additional robustness checks on our initial results. These checks are designed to ensure that the observed effects of trade on regional income inequality are not merely artifacts of omitted variable bias or other methodological concerns.

In the first and second models of our robustness tests, we introduce additional control variables that are potentially influential in explaining changes in regional income inequality. One such variable is institutional quality. Scholarly literature tends to highlight the significant role of institutional quality in economic development (Acemoglu, Johnson and Robinson, 2001; Ganau and Rodríguez-Pose, 2019). Barbero et al. (2021) specifically stress the importance of subnational variations in institutional quality for regional trade in Europe. The inclusion of institutional quality as a control is based on the understanding that stronger institutions may facilitate better economic outcomes, including more equitable income distribution, by enhancing the efficiency and fairness of market operations and trade practices.

Another control added in model 2 is technological change, measured using patents per capita. This inclusion is informed by previous research (Johnson, 1997; Autor, Levy and Murnane, 2003) discussing the impact of skill-biased and routine-biased technological changes on the income and earnings distribution. The rationale behind this control is that regions with higher rates of technological innovation (indicated by more patents) would experience changes in their labour markets that could affect income inequality. Technological advancements often increase the demand for skilled labour, potentially exacerbating income disparities if the benefits of these innovations are not evenly distributed.

The third robustness check involves modifying the regression weights. In model 3, we employ a population-weighted regression. This approach gives more weight to regions with larger populations, thus ensuring that our findings are not overly influenced by smaller regions that might have atypical trade patterns or income inequality dynamics.

All three regression models —with additional controls for institutional quality and technological change, as well as the population-weighted approach— consistently confirm the positive and statistically significant effect of trade on regional income inequality. The introduction of these controls and the change in regression weighting do not alter our initial conclusions. This consistency reinforces our earlier inference that trade has a tangible and significant impact on income inequality within regions. It suggests that, despite accounting for various factors such as institutional quality, technological innovation, and population size, the relationship between trade and income inequality remains robust and significant.

	(1)	(2)	(3)
Log(trade pc)	0.012^{**}	0.011^{**}	0.013^{**}
	(0.005)	(0.005)	(0.005)
Gini	0.146	0.164^{**}	0.130^{*}
	(0.091)	(0.077)	(0.067)
Log(GDP pc)	-0.018	-0.037^{**}	-0.018^{**}
	(0.013)	(0.014)	(0.007)
Log(pop density)	-0.002	-0.001	0.001
	(0.002)	(0.002)	(0.002)
Emp prof services	0.264^{**}	0.166	0.286^{**}
	(0.113)	(0.107)	(0.116)
Emp ind	0.036	0.004	0.063^{*}
	(0.034)	(0.031)	(0.035)
Inst qual	0.000		
	(0.004)		
Log (Patents)		0.007^{**}	
		(0.003)	
R^2	0.069	0.102	0.112
F-Statistic	2.631	3.623	4.34
Pop weights	N	N	Y
Num. obs.	232	239	240
RMSE	0.028	0.028	0.838

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, SE clustered at the regional level

Table 3.6: Regression Results: Sensitivity checks adding institutional quality, patents and population weights

3.7 Conclusion and Discussion

In this paper we have undertaken a comprehensive analysis of the relationship between trade and changes in intra-regional inequality across European regions at the NUTS-2 level, a perspective that has been mostly overlooked by previous research. While many analyses have focused on the national or country-wide implications of trade, this research analyses the sub-national dynamics across Europe, offering new insights into the complexities of trade and income distribution at a more granular level. By leveraging two novel datasets on trade patterns at the regional level, on the one hand, and regional interpersonal inequality in Europe, on the other, we have been able to examine the effects of not only international trade but also intra-country and regional trade dynamics.

Our findings reveal a relevant and positive association between trade and changes in regional income inequality, as measured by the Gini coefficient. European regions that engage more in trade have witnessed an increase in interpersonal inequality changes within their borders. This relationship varies depending on the trading partners: trade within the same country, with other regions in the European Union, and with non-neighbouring regions is found to increase regional income inequality. Conversely, we observe no significant impact on income inequality from international trade, trade with the rest of the world or trade with neighbouring regions. This suggests that the impact of trade on income distribution is nuanced and contingent on the nature and proximity of trading partners.

Instrumental Variable estimations reinforce the positive effect of overall trade and the types of trade signalled above on income inequality. These results are further substantiated by additional sensitivity checks, including the introduction of new controls and a population-weighted regression approach.

The study is not without limitations. One limitation is the cross-sectional nature of the trade data used. As more longitudinal trade data becomes available, further analysis in this area would be highly valuable. Additionally, the EU-SILC and LIS datasets do not cover all

NUTS-2 regions in the 28 EU countries, restricting the scope of our analysis. Future research could expand on this by incorporating data for all EU regions at various levels of aggregation. Another limitation is the aggregate nature of our data at the regional level, which precludes an assessment of firm-level dynamics, whether intra- or inter-firm, in driving the observed patterns. Future studies could explore potential mechanisms behind these findings, examine the role of different sectors, and discern the impacts of inter- versus intra-firm developments in relation to trade and regional income inequality.

Yet, despite these limitations, our research represents a significant advancement in understanding the intricate relationship between trade and intra-regional income inequality across European regions at the NUTS-2 level. It fills a critical gap in the existing literature, which has mostly concentrated on national or country-wide effects, by exploring the subnational dimensions of trade within Europe. This novel approach offers a unique perspective, contributing valuable insights into the regional impacts of trade on income distribution, a topic that deserves far more attention than it has attracted until now. Through this research, we shed light on the dynamics of how and with whom regions trade and the implications of these choices on income inequality.

Finally, our exploration into the regional dimension of trade and income inequality not only contributes to the academic discourse but also has practical implications for policy-making. Understanding the nuances of how trade affects regional economies can inform more targeted and effective economic policies that address the challenges of growing inequality within the regions of Europe.

3.8 Appendix

3.8.1 Inequality data

Due to the absence of income data for 2013 and 2018 for some countries, this study complements the observations for these years, thereby maximizing the number of available observations. To calculate the change in income inequality, we are assigning the latest available Gini coefficient to 2013 or 2018. Table 3.7 shows an overview for which regions (of a country) and year the Gini coefficient has been assigned.

Country code	Year missing	Year available
BE	2018	2017
CZ	2018	2016
EL	2018	2016
DK	2018	2016
HU	2013	2012
HU	2018	2015
IT	2013	2010
IT	2018	2016
SI	2013	2012
SI	2018	2015
FI	2018	2016

Table 3.7: Complementing observations for the Gini coefficient

Statistic	N	Mean	St. Dev.	Min	Max
Change Gini	242	−0.0004	0.029	−0.118	0.110
Gini	242	0.289	0.037	0.204	0.383
Trade pc	261	144.158	129.392	19.854	1,575.465
Trade national pc	261	129.038	109.727	17.918	1,346.525
Trade international pc	261	23.176	34.895	1.516	405.561
Trade neighbours pc	259	10.425	16.187	0.000	156.738
Trade non-neighbours pc	259	134.097	117.571	15.995	1,418.727
Trade EU pc	259	137.117	116.742	18.764	1,398.845
Trade ROW pc	259	7.405	13.852	0.257	176.620
Popdensity	266	476.662	1,644.133	2.632	20,703.640
GDP pc	266	26.046	14.820	7.634	204.662
Emp prof services	264	0.086	0.029	0.021	0.204
Emp ind	263	0.173	0.072	0.032	0.377

Table 3.8: Summary Statistics for inequality, trade and control variables

3.8.2 Summary Statistics

3.8.3 Types of Trade

EU Trade vs. with the rest of the world

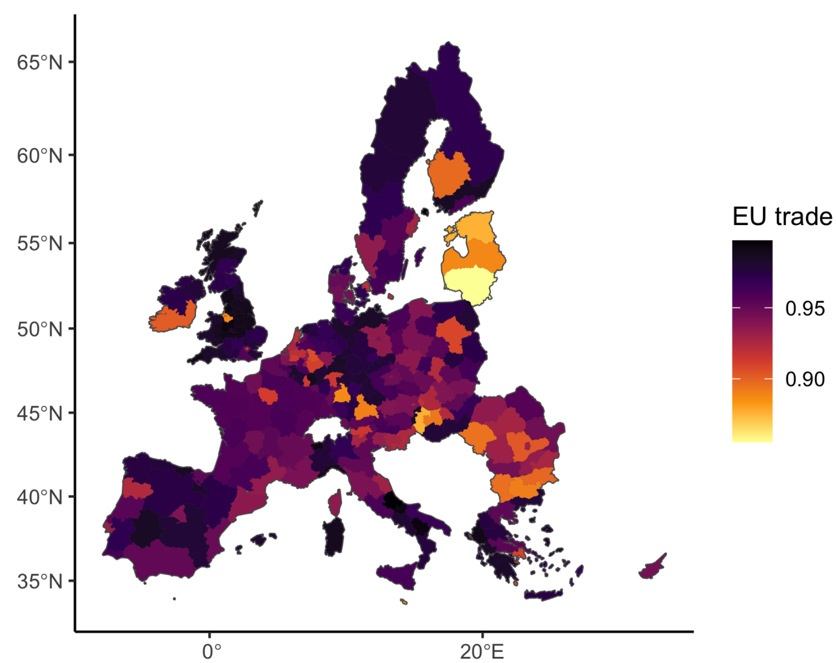

Figure 3.3: EU Trade as percentage of all trade, per NUTS-2 region in 2013

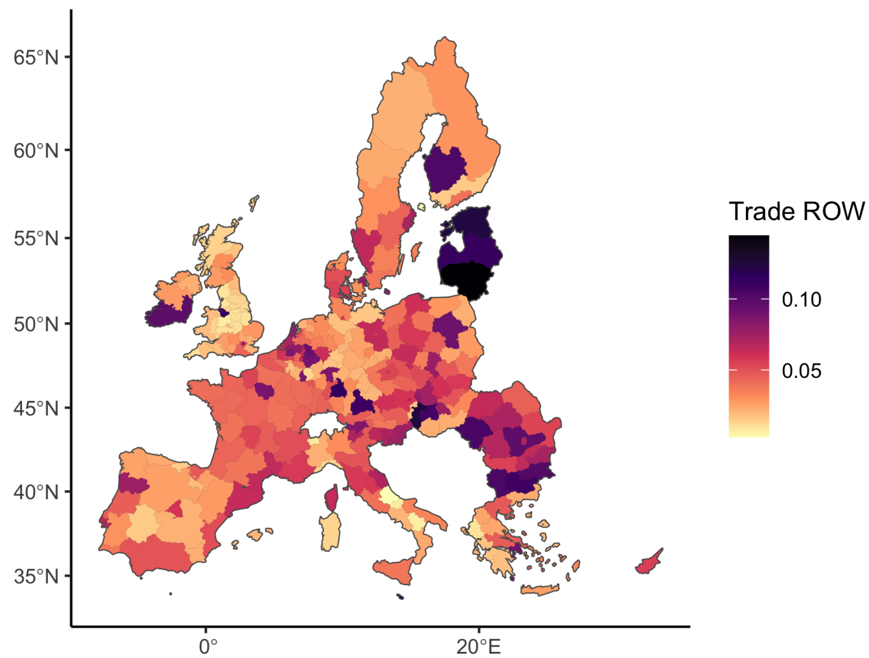

Figure 3.4: Trade with the Rest of the World of all trade, per NUTS-2 region in 2013

Trade with neighbouring regions vs. non-neighbouring regions

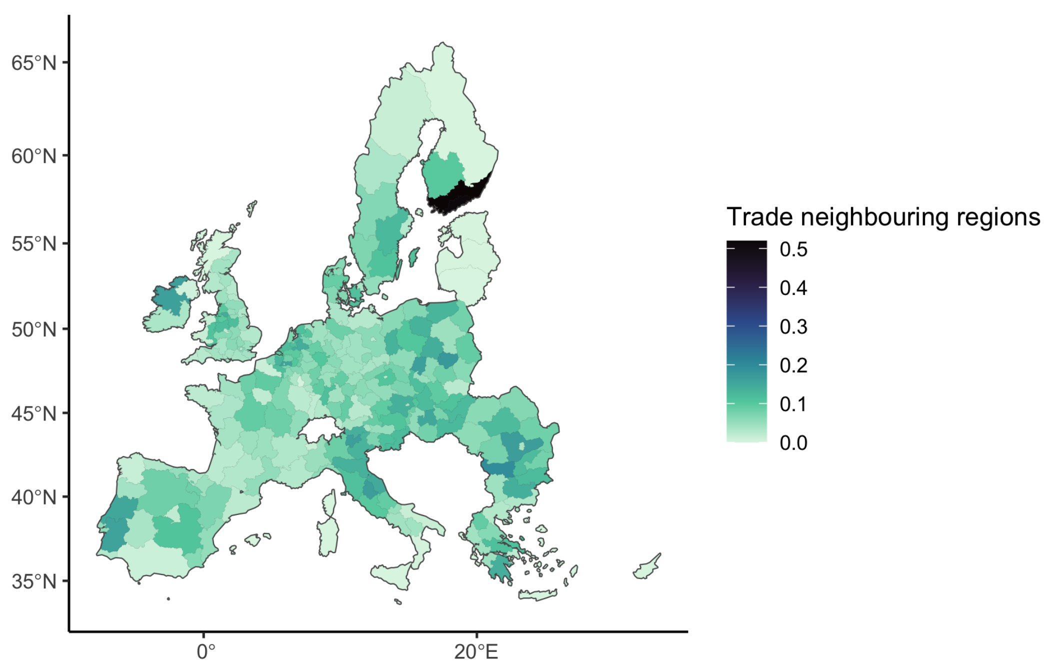

Figure 3.5: Neighbour Trade as percentage of all trade, per NUTS-2 region in 2013

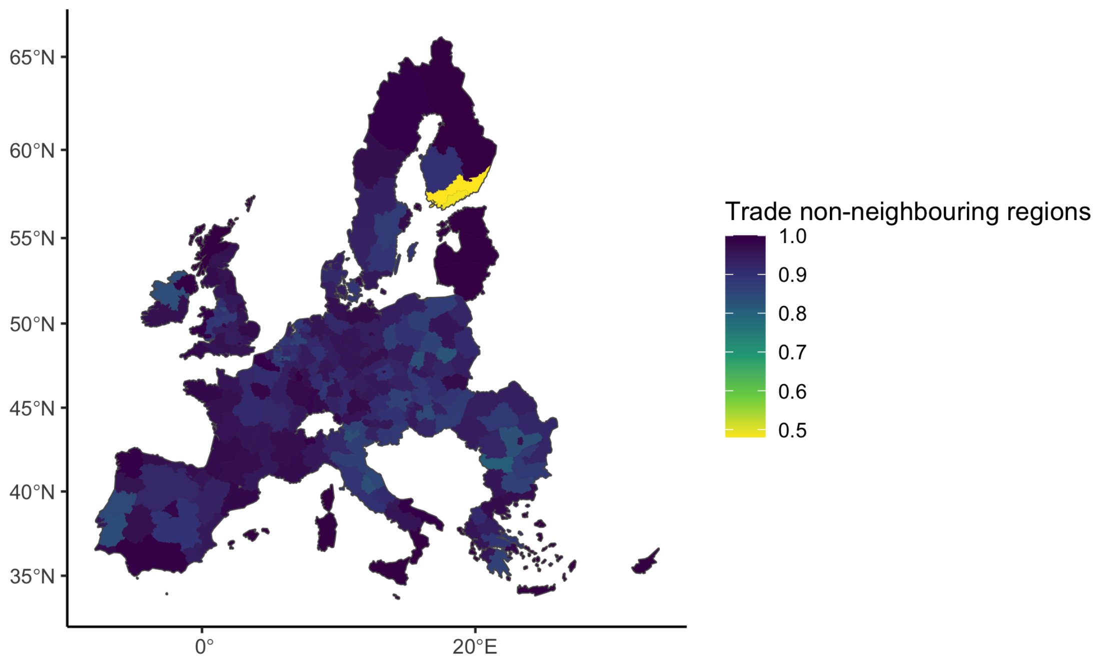

Figure 3.6: Non-neighbour Trade as percentage of all trade, per NUTS-2 region in 2013

National trade vs. international trade

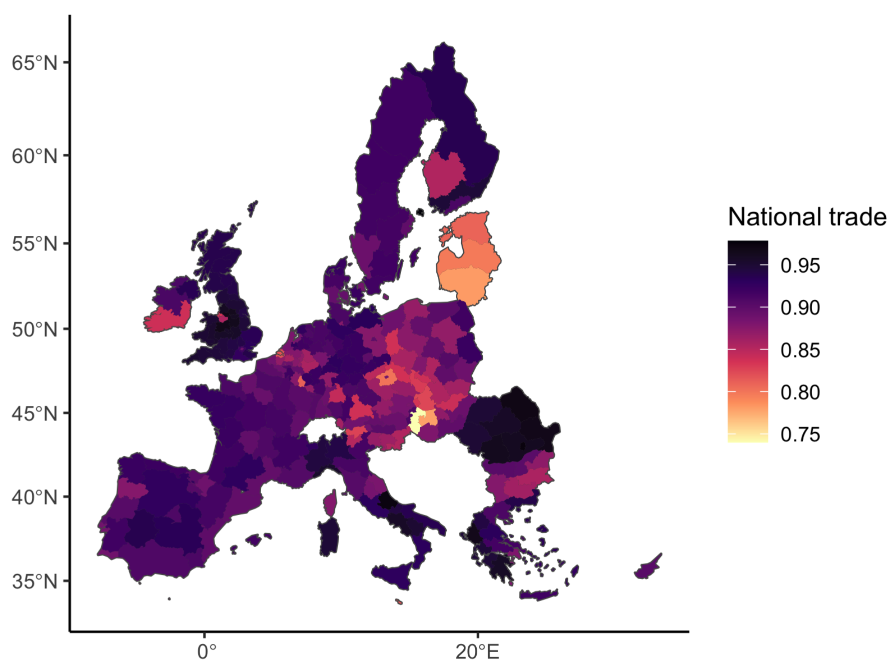

Figure 3.7: National Trade as percentage of all trade, per NUTS-2 region in 2013

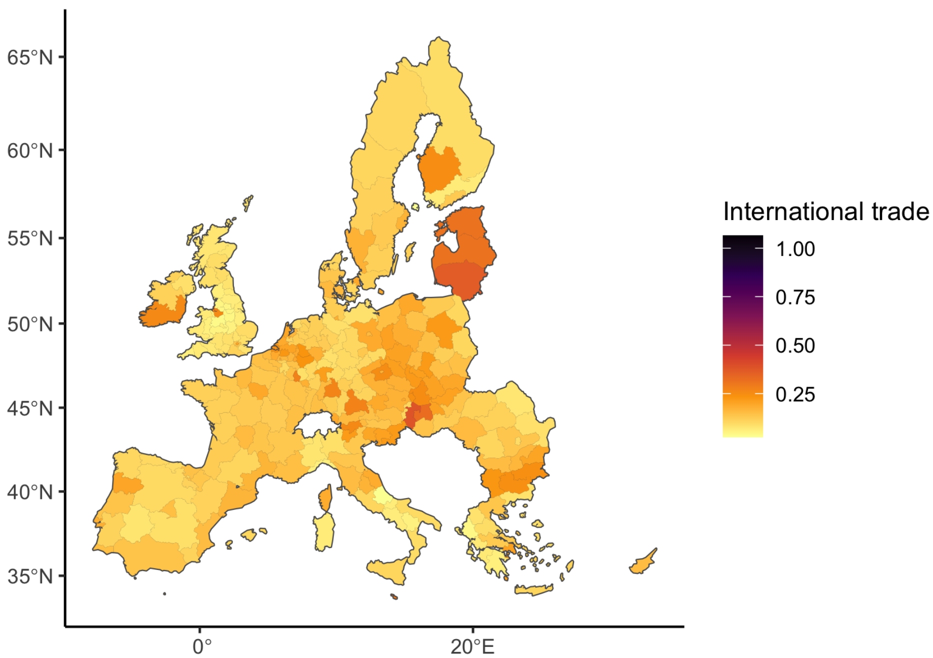

Figure 3.8: International Trade as percentage of all trade, per NUTS-2 region in 2013

3.8.4 Correlation Matrix

	ΔGini	Gini	Trade pc	Popden.	GDP pc	Emp prof services	Emp ind
ΔGini	1.00	0.10	0.09	0.00	0.04	0.17	-0.08
Gini	0.10	1.00	-0.20	0.20	-0.02	0.07	-0.26
Trade pc	0.09	-0.20	1.00	0.13	0.39	0.38	-0.14
Popden.	0.00	0.20	0.13	1.00	0.79	0.45	-0.28
GDP pc	0.04	-0.02	0.39	0.79	1.00	0.62	-0.25
Emp prof services	0.17	0.07	0.38	0.45	0.62	1.00	-0.53
Emp ind	-0.08	-0.26	-0.14	-0.28	-0.25	-0.53	1.00

Table 3.9: Correlation Matrix for inequality, trade and control variables

Chapter 4

GVCs and Top Income Inequality: Evidence from European regions

4.1 Introduction

With the global economy becoming increasingly interconnected, it has become of rising importance for regions to participate in Global Value Chains (GVCs). A substantial body of literature has shown a positive relationship between GVCs and economic development, which could be through the process of technological upgrading (Giuliani, Pietrobelli and Rabellotti, 2005; Morrison, Pietrobelli and Rabellotti, 2008; Pietrobelli and Rabellotti, 2007; Pietrobelli and Rabellotti, 2011), increased productivity and higher income (Raei, Ignatenko and Mircheva, 2019; Pahl and Timmer, 2020; Jangam and Rath, 2021). Thus, through GVC participation regions can develop their existing skills and capabilities and diversify technologically, bringing about novel innovative opportunities and economic growth (Crescenzi, Pietrobelli and Rabellotti, 2014; Iammarino, 2018; Crescenzi and Harman, 2023).

However, while these economic benefits of GVC participation have been traditionally highlighted, the potential sub-national disparities that can be derived from this phenomenon may have remained underexplored (Crescenzi and Iammarino, 2017). While some scholars have pointed toward a significant link between GVCs and income inequality at the national level (Gonzalez, Kowalski and Achard, 2015; Aguiar de Medeiros and Trebat, 2017; Carpa and Martínez-Zarzoso, 2022), the regional dimension remains understudied. This calls for a better understanding of the dark side of GVC participation at the regional level (Yeung, 2021; Boschma, 2022). With higher participation in global value chains and regional income inequality on the rise, it becomes indispensable to have an enhanced understanding of the link between these two factors at the sub-national level (Crescenzi and Iammarino, 2017; Boschma, 2022).

In particular, scholars have emphasised that GVC participation is affecting the income distribution measured by the Gini coefficient (Gonzalez, Kowalski and Achard, 2015), but have not explored the effect on the top of the income distribution. Moreover, while the theoretical link between the uneven distribution of rents derived from GVC participation and the benefits for top earners has been pointed out (Kaplinsky, 2019), we are still lacking empirical evidence within regions in the European context. The development of several institutional factors may have ensured rent protection across territories (De Rassenfosse et al., 2022), benefiting the top of the rent distribution. Therefore, the role of regional institutions may be crucial to understand which regions and groups may benefit more, from such as interconnected global economy (Rodríguez-Pose, 2013; Rodríguez-Pose, 2021). Furthermore, the role of regional institutions may also mediate the effect of GVC participation depending on the regional level of development (Rodríguez-Pose, 2012; Boschma, 2022). In the development process, inequality tends to rise until a tipping point (Kuznets, 1955). In this vein, lagging regions may be more exposed to the negative unintended consequences of globalisation forces, which may be reinforced by having lower institutional quality.

Therefore, this paper studies the relationship between different indicators of GVC participation and intra-regional income inequality, with a focus on the top of the income distribution in the European context. For this purpose, input-output data at the NUTS-2 level from the EUREGIO database (Thissen, Lankhuizen et al., 2018) is used to construct indicators for regional participation in GVCs. We conduct our analysis for the period 2003-2010 as income data is available from 2003 onward and input-output data ends in 2010. We calculate multiple GVC indicators, including total, backward, and forward participation as well as an income inequality measure, which is the share of Top 5% using data from the European Union Statistics on Income and Living Conditions (EU-SILC). Relying on EU-SILC data we expect to get a conservative estimate of top income inequality levels, given that only labour income is included, and capital income is left out, as well as top incomes tend to be underreported (Groves, 2006; Ravallion, 2022). We then empirically analyse how GVC participation and income inequality are linked, exploring the short-term effects of this relationship. We focus on different forms of GVC participation, differences by sector and regional heterogeneity, such as development level and institutional quality.

We find that there is a positive and statistically significant relationship between GVC participation and intra-regional income inequality. It is forward GVC participation which is associated with top income inequality. These overall effects are driven by multiple sectors, including manufacturing, transport, storage and communications, as well as real state and business activities. We then test for heterogeneity concerning the development level of the region. Indeed, lagging regions are more exposed to higher levels of top income inequality derived from GVC participation. Furthermore, this paper explores the role of institutions, specifically measured by the control of corruption, in mediating the effects of GVC participation for regions. Results show that regional institutions matter in shaping the unequal distribution of rents derived from GVC participation. Regions with lower institutional quality are associated with higher levels of intra-regional top income inequality. Thus, institutions remain crucial to shape the benefits derived from interregional linkages. Moreover, we also run robustness checks that add new control variables and exclude the period of the economic and financial crisis, which validate the previous findings. They show not only that the results are not driven by changes to income inequality stemming from the economic and financial crisis, but that it is in particular the years between 2003-2007 that play a crucial role in shaping the relationship between GVC participation and income inequality.

Finally, the contributions of this paper are several. First, it explores how different ways of GVC participation may impact income inequality at the regional level. Results show that while backward participation has no effect on income inequality, forward participation is associated with higher income inequality at the top. Second, the level of economic development of regions matters for the exposure towards top income inequality derived from GVC participation. Lagging regions are more likely than developed regions to have higher levels of top income inequality derived from forward GVC participation. Third, it shows how regional institutions may shape this relationship between forward GVC participation and top income inequality. Thus, regions with lower institutional quality suffered more from the unequal distribution of rents derived from forward GVC participation. Fourth, this paper contributes to the current debate between GVCs and evolutionary economic geography strands of literature, focusing not on the bright, but on the dark side of interregional linkages. While there is a growing number of papers studying the benefits of non-local linkages for regions, there is still a need to understand what the potential unintended consequences of this interconnectedness might be.

The remainder of this paper is organised in the following way. In Section 2, it first summarises the existing literature related to GVC participation, income inequality, and their intersection. In Section 3, it then presents the data and indicators of interest, and plots some of the measures. In Section 4, it continues by describing the method used to estimate this relationship. In Section 5, it shows the main results. Finally, in Section 6, it concludes with the discussion, policy recommendations, and venues for future research.

4.2 Literature Review

4.2.1 Regions and the unintended consequences of GVCs

The rise of global value chains has brought several opportunities for regional economic development (Crescenzi and Iammarino, 2017; Crescenzi and Harman, 2023). In this sense, regions may leverage on non-local sources of knowledge to acquire new technological capabilities and spur innovation processes (Giuliani, Pietrobelli and Rabellotti, 2005; Morrison, Pietrobelli and Rabellotti, 2008; Pietrobelli and Rabellotti, 2007; Pietrobelli and Rabellotti, 2011; Crescenzi, Pietrobelli and Rabellotti, 2014). Along this technological upgrading, other economic benefits may be triggered such as productivity gains, and higher wages and income per capita

(Shepherd, 2013; Raei, Ignatenko and Mircheva, 2019; Pahl and Timmer, 2020; Jangam and Rath, 2021).

However, the literature has mainly focused on the benefits of GVC participation (Gereffi, 1999; Gereffi, Humphrey and Sturgeon, 2005). For instance, the notion of downgrading has received much less attention in the literature than upgrading (Blažek, 2016; Gereffi, 2019). Despite this tendency, there is a growing literature studying the potential unintended negative consequences of GVC participation. In this vein, at the national level some contributions have been recently made. For example, López-Villavicencio and Mignon (2021) explored the role of GVC participation on national account balances finding that backward GVC participation is associated with negative contributions. Tukamuhabwa et al. (2015) studied issues related to supply chain resilience and potential trade disruption that may arise from GVCs. In this regard, there is an emerging literature focusing on the intersection between GVCs disruptions and inflation dynamics (Di Giovanni et al., 2022). In addition, it is important to acknowledge that while the literature focusing on downgrading and the negative consequences of GVCs mainly focused on economic downgrading, there is a growing number of papers highlighting other forms of downgrading such as social and environmental downgrading (De Marchi, Maria and Micelli, 2013; Barrientos, Gereffi and Pickles, 2016; Krishnan, De Marchi and Ponte, 2022; De Marchi and Gereffi, 2023).

Nevertheless, the large majority of the empirical evidence on both the bright and the dark sides of GVC participation remains at the national level. Traditionally, the lack of data at the sub-national level deterred scholars from addressing these issues at the regional level (Los, Timmer and De Vries, 2015; Pahl and Timmer, 2019; Timmer, Miroudot and Vries, 2019). This lack of GVC data at the regional level did not, however, prevent the literature to emphasise how important the sub-national dimension remains to understand globalisation dynamics such as GVCs (Iammarino, 2018). In this vein, Kano, Tsang and Yeung (2020) and Yeung (2021) have called for integrating interregional linkages such as GVCs in evolutionary frameworks of regional economic development. The inclusion of non-local capabilities in such frameworks is a long-standing debate in fields like evolutionary economic geography

(Boschma, 2017; Trippl, Grillitsch and Isaksen, 2018; Balland and Boschma, 2021), which is also in line with the research agenda recently provided by Boschma (2022). Furthermore, the role of regional institutions remains central in the debate on the crossroads between regional economic development and GVCs (Rodríguez-Pose, 2021; Frenken, Neffke and Dam, 2023).

However, the recent publication of new sources of data has spurred the creation of state-of-the art work on the role of regional linkages. In particular, the EUREGIO interregional input-output tables and the use of alternative data to proxy GVCs such as FDI and MNEs, fostered the empirical evidence regarding the regional consequences of GVC participation (Crescenzi, Pietrobelli and Rabellotti, 2014; Thissen, Lankhuizen et al., 2018; Cortinovis, Crescenzi and Van Oort, 2020). Thus, more recently, Tsekeris (2021) analysed the EU global value network considering both, direct and indirect linkages. Colozza et al. (2021) studied the relationship between GVC participation and regional economic upgrading proxied using economic complexity metrics. Bolea et al. (2022) found that neighbouring regions affect regional participation and positioning in GVCs. Hernandez-Rodriguez et al. (2023) provided an evolutionary framework to approach both functional upgrading and downgrading at the regional level. Their findings highlight that EU regions are more (less) likely to upgrade (downgrade) in GVCs when they are specialised in related production functions. Finally, Duan et al. (2023) explored the relationship between Chinese exports and regional income inequality from a GVC perspective, differentiating between processing and ordinary export activities.

Therefore, the role of regions in GVCs remains crucial to understand the spatial disparities that may arise from these phenomena. Particularly, the different ways in which regions participate in GVCs poses certain issues. Since production processes have been spatially splitted across territories, different regions may be specialised in different production functions (Hymer, 1982; Massey, 1984; Grossman and Rossi-Hansberg, 2008; Iammarino and McCann, 2013; Crescenzi, Pietrobelli and Rabellotti, 2014). The ways regions participate in GVCs, for example regions at the beginning vs. regions at the end of GVCs and regions at the buying vs. regions at the seller sides of the GVCs, may relate to spatial disparities in value added generation and appropriation (Kaplinsky, 2019), fostered by unequal market power (Kaplinsky, Tijaja and Terheggen, 2010). At the same time, these dynamics may be mediated by other aspects such as regional institutions (Rodríguez-Pose, 2021; Frenken, Neffke and Dam, 2023) and IPRs (De Rassenfosse et al., 2022).

4.2.2 Income Inequality

In many advanced economies, inter- and intra-regional inequality has been increasing (Iammarino, Rodríguez-Pose and Storper, 2019; Feldman, Guy and Iammarino, 2021). Higher levels of economic inequality might pose challenges to regions and policy-makers for multiple reasons. First, more inequality might hinder economic growth (Alesina and Rodrik, 1994; Lee and Son, 2016), decelerating the economic development of regions. Second, higher levels of economic inequality might increase tension between poor and rich individuals, driving social and political instability. Previous work has pointed out that social unrest and civil wars tend to occur more frequently in regions characterised by higher levels of inequality (Lessmann, 2016). Third, higher inequality at the top leaves higher concentration of wealth but also power in the hands of the few (Krugman, 2005; Savage, 2021). This might pose a problem for selected groups, as implemented policies could reflect a type of prioritarianism favoring certain groups.

Generally, the drivers of regional income inequality can be described with the framework from Breau (2015), who classifies the variables in economic, spatial, social and demographic terms as well as institutional and policy variables. When conducting research in this area, it is important to take into account the influence that each of these variables has. Social and democratic factors refer among others to education or race, spatial contains population size or density and economic variables include for example the level of economic development or the industry mix. The relationship between economic development, proxied by income, and inequality has been described as inverted U-shaped (Kuznets, 1955), describing that inequality tends to increase when a region develops, until a certain point, when it tends to fall again. Thus, we would expect inequality to be lower for those regions at a higher development stage. Also, the quality of institutions is vital for the development of regions (Rodríguez-Pose, 2013), in particular shaping the distribution of resources such as income. We follow the definition of North (p.477 1990), defining institutions as "the rules of the game in a society; (and) more formally, (as) the humanly devised constraints that shape human interaction". In areas with already well-established formal but also informal institutions, institutional intervention is more likely to succeed; with high levels of autonomy and participation, minimised transaction costs, containment of moral hazard due to transparent and specific information as well as control of rent-seeking due to competition, with firms regularly entering and exiting the market (Rodríguez-Pose, 2013). Institutions play a crucial role for rent-seeking (Feldman, Guy and Iammarino, 2021), creating incentives and costs in economic transactions. Rents are described as abnormal profits stemming from the establishment of artificial monopolies, information asymmetries, interventions in the market by the government that favour particular groups and short-term frictions (Stiglitz, 1996). Thus, rent-seeking could be measured in the form of abnormal profits, stemming from the "pursuit of earnings primarily through redistribution in one's own favour, rather than in return for any productive accomplishment" (p.11 Baumol, 2004) and has been recently mapped into three categories good, bad and grey (Mazzucato, Ryan-Collins and Gouzoulis, 2023).

Increasingly, top income recipients have become part of the public but also scholarly discourse (Atkinson, Piketty and Saez, 2011; OECD, 2011; Alvaredo et al., 2013). But who are the top income recipients in Europe? An answer for this is provided by Denk (2015) coming from a large employer-based survey covering 10 million employees in 18 European countries. It shows that workers in the top 1% are likely to be male senior managers between 40 and 60 years old, possessing tertiary education and working in the field of manufacturing or finance. These results are based on the largest harmonised source available at the time (Denk, 2015), covering only employed workers. But not only in terms of their income level, but also in terms of income growth experienced, some groups have done relatively better than others. Looking at EU-SILC data between 2005 and 2017 at the national level, managers saw an increase in real pay of 24% while only seeing a 4.4% growth in the pay of service and sales workers (Rabensteiner and Guschanski, 2022). Also, often high labour income goes hand in hand with high capital income (M. N. Hansen, 2014). Thus, the top labour income earners tend to have capital income stemming from self-employment (Rehm et al., 2016). Additionally, market power can play a role in the compensation (Bao, De Loecker and Eeckhout, 2022), which also shapes regional dynamics. Feldman, Guy and Iammarino (2021) have emphasised the intertwined role of market power of corporations and financial sector in shaping regional income inequality the US.

However, at the regional level, empirical papers have often overlooked the role of income inequality at the top. One potential reason is related to measurement issues, referring to the problem of the “missing rich", which tends to be even more pronounced in survey data at the regional compared to the national level (Emmenegger and Muennich, 2023). Many regionally focused studies have looked at the middle of the distribution, proxied by the Gini coefficient (Rodríguez-Pose, 2012; Lee and Rodríguez-Pose, 2013; Sujarwoto and Tampubolon, 2016; Lessmann, 2016). Fewer spatial studies have focused on top income inequality (Moser and Schnetzer, 2017; Feldman, Guy and Iammarino, 2021), with even fewer studies doing so on income inequality within regions.

4.2.3 GVC participation and income inequality

There is a large literature on the determinants of income inequality, with economic globalisation identified as one main driver among others (Iammarino, Rodríguez-Pose and Storper, 2019; Heimberger, 2019). Studying the effects of economic globalisation on the income distribution has a long tradition in economic-related disciplines, with some of the early and well known work by Stolper and Samuelson (1941) drawing substantial scholarly interest to the topic. Since then, researchers have focused on the impact of trade on the income and wage distribution, with some recent scholarly examples (Rodríguez-Pose, 2012; Roser and Cuaresma, 2016; Dorn, Fuest and Potrafke, 2018; Hirte, Lessmann and Seidel, 2020). However, there is substantially less evidence analysing the link between GVCs and income inequality, even less so at the regional level. This is for two reasons. First, although the rise of global value chains dates back in time, systematic approaches to study their configuration were provided during the last decades, receiving increasing attention by scholars since then (Gereffi, 1999; Humphrey and Schmitz, 2002; Gereffi, Humphrey and Sturgeon, 2005; De Marchi, Di Maria et al., 2020). Second, due to the lack of data in particular at the regional level it was barely possible to conduct research on the role of global value chains at the sub-national level in the European context, which has been improved with the recent provision of the data from the EUREGIO database (Thissen, Lankhuizen et al., 2018).

Previous literature analysing the link between GVCs and inequality have shown that the impact of GVCs on wage inequality is determined by multiple factors. It depends on the development level, the sector and the tasks performed (Costinot, Vogel and Wang, 2012; Ndubuisi and Owusu, 2022; Gonzalez, Kowalski and Achard, 2015), the time horizon (Carpa and Martínez-Zarzoso, 2022) and how regions participate in global value chains. Traditionally, GVC participation has been split into backward and forward participation (Wang et al., 2017). There is an extensive literature covering the consequences for both, but when it comes to income inequality the emphasis has been put on backward participation. In this vein, Gonzalez, Kowalski and Achard (2015) analysed how GVC backward participation at the national level is associated with reductions in wage inequality. This effect is small, stems from receiving goods and services that are complementary to low-skilled tasks and thus are linked to a decrease in wage disparities. They explain their finding as the wage gap between low-skilled and high-skilled workers narrows because the earnings of low-skilled workers increase at a faster rate compared to high-skilled workers. However, it depends on the nature of GVC that is determining the effect on wages, for high-skilled tasks it is expected to enhance the productivity of high-skilled labor compared to their low-skilled counterparts. This is expected to widen the wage gap between low and high-skilled workers (Gonzalez, Kowalski and Achard, 2015). For backward participation, two mechanisms are at play: boosting the productivity through specialisation on tasks where they are most efficient and a heightened demand for labour as with the increase in the productivity of firms relying more on low vs. high-skilled labour, they are boosting the demand for—and thus wages of low or high-skilled labour. Similarly, Carpa and Martínez-Zarzoso (2022) also found that backward participation is associated with a reduction in inequality in developing countries in the long run. Most of these papers have found significant links with backward participation, and inequality measures that focus on the middle of the income distribution. Evidence is missing in the link of forward participation and inequality, which is why this paper shifts the discussion towards the other side of the coin.

GVC participation plays an important role for firms and regions for economic upgrading (Kummritz, Taglioni and Winkler, 2017; Crescenzi and Harman, 2023). Whether upgrading takes place through backward or forward participation depends on the development level, with backward participation providing increased possibilities for developing countries and forward participation doing so for developed ones (Tian, Dietzenbacher and Jong-A-Pin, 2022). As discussed above, many of the wage effects discussed above have been found for developing countries. In contrast, for European countries, forward participation tends to provide more opportunities for regions to upgrade. Forward participation in GVCs raises domestic value added particularly at the selling side in high income countries (Kummritz, Taglioni and Winkler, 2017). Empirical works has shown that participation in GVCs and the resulting specialisation is linked to higher wages being paid in developed countries (Shepherd, 2013; Ndubuisi and Owusu, 2022), which likely stems from increased demand for skilled workers. Thus, GVC participation benefits the skilled labour and the capital owners who are paid a skill premium in developed countries, it exacerbates the income gap in developed countries (Dollar, Inomata et al., 2017).

Moreover, scholars have argued that GVCs can influence the top of the income distribution, by broadening existing gaps to other parts of the distribution, such as the middle or tail of the distribution. One potential way would be through monopoly prices stemming from natural scarcity or artificially-created scarcity through anti-competitive behaviour, providing the chance to set prices higher than the actual cost of production (Aguiar de Medeiros and Trebat, 2017). In particular when it comes to forward participation, which is usually referred to the seller GVC side, it allows to set prices above the production costs. One potential channel affecting income inequality through incomplete pass through of costs savings and rent extraction (Bao, De Loecker and Eeckhout, 2022). Firms that start exporting tend to be more productive (Melitz, 2003), with internationalisation extending the market size and increasing returns to scale (Smith, 1776), which further increases productivity for some firms. Yet, because of the incomplete transmission of cost reductions, increases in productivity are not passed on to customers, leading to higher markups as well as higher profits (Bao, De Loecker and Eeckhout, 2022). Scholars find a general trend towards product market concentration that has been observed in developed countries since the 1980s and find evidence for higher markups in the US and in Europe as a consequence for growing global market power (De Loecker, Eeckhout and Unger, 2020; Autor, Dorn, Katz et al., 2020). Globalisation is among the forces driving sales of the most productive firms of their industry, increasing markups and market concentration, resulting in “superstar firms" (Autor, Dorn, Katz et al., 2020). Consequently, there are fewer buyers and sellers becoming increasingly reliant on a selected few. This is particularly the case for suppliers, who possess the power to conduct opportunistic renegotiations (Asmussen et al., 2023). An increase in inequality within a region might be observed when rents are extracted from customers or competitors to managers or firm owners, which is more likely to stem from the seller side in the form of forward participation,

Depending on whose income increases by how much relative to other groups, we would expect to see an increase or decrease in income inequality. In the European context, it might likely be the wages of skilled workers, who are benefiting by earning a wage premium due to higher demand for skilled workers. This would be mirrored in an increase of the wages in the middle to the upper part of the income distribution. It might be that managers mostly gain from the participation in global value chains, seeing an increase in their incomes. This change is likely to be mirrored at the top of the income distribution, as top earners mostly include senior managers with tertiary education in the field of manufacturing or finance (see Section 4.2.2). If this is the case, we would expect to see a significant relationship between global value chain participation and top income inequality, particularly related to certain sectors.

How the participation in global value chains affects income inequality is also likely shaped by the quality of local institutions. Global value chains, which include a wide set of actors who are intertwined with institutions (Coe, Dicken and Hess, 2008), could affect the regional income distribution through multiple mechanisms. The first one could be through intra-regional coordination, as complex global value chains include a wide set of intertwined actors including governments, suppliers, financial organisations, competitors, universities, among others. The interaction with local institutions in the coordination process can shape the impact on income inequality. Second, and more general, with institutions setting the rules of the game in a society, they determine moral hazards, the provision of transparent information and rules, transaction costs and opportunism (Rodríguez-Pose, 2013). With weak institutions, it is less likely that interventions will bring about expected results.

4.2.4 Contributions

The contributions of this paper are several. First, it sheds light on how regional participation in global value chains is linked with intra-regional top income inequality. While there is an extensive literature covering the opportunities for regional economic development brought by GVCs, much less is known about the unintended regional disparities that may arise from GVC participation.

Therefore, this paper builds different metrics for capturing regional GVC participation, namely total, backward, and forward GVC participation. Since regions may engage in GVCs in different ways, these indicators offer different perspectives on the regional engagement in GVCs. Particularly, this paper highlights the role of forward GVC participation. Traditionally, the literature in the field has focused on the consequences of backward participation over forward participation. However, although both capture GVC participation, they may have different implications for the economic development of regions. Thus, this paper contributes to a better understanding of the different roles backward and forward GVC participation play for regional economic development.

Moreover, it adds a new perspective on the link between GVCs and top income inequality. Previous literature has barely covered the link between GVC participation and top income inequality, but focused instead of the middle of the income distribution measured by the Gini coefficient (Gonzalez, Kowalski and Achard, 2015). Looking at this link remains important because of an increasing debate around top income earners and their determinants, as well as on the winners and losers of economic globalisation. In order to create place-based policies, it is essential to have an evidence-based understanding of who benefits and who loses from global value chain participation. Understanding in which regions we observe this link and what characteristics of regions are relevant is crucial in mitigating potential negative consequences stemming from global value chain participation.

Therefore, with this paper we then contribute to the literature on GVCs and income inequality at the subnational level. As described in the previous section, there are already multiple papers covering the relationship between GVCs and income inequality at the country level. However, the regional perspective has been largely neglected due to missing data. We fill this gap by exploiting a novel data set on GVC participation and link it to intra-regional income inequality measures based on EU-SILC data. Adopting a regional perspective for these questions is highly relevant, given that regions behave economically differently than countries, and in particularly with regards to their industrial specialisation and the trade that they engage in (Isard, 1951; Miller and Blair, 2009). Thus, it is our goal to contribute to the existing scholarly debate between GVC, inequality and economic geography literatures by adding a regional perspective, and look at regional specifics, such as industrial specialisation and regional characteristics (Rodríguez-Pose, 2021; Yeung, 2021; Boschma, 2022).

Furthermore, this paper investigates relevant heterogeneities in the overall results. First, as regional GVC participation differs across industries, it may have different implications for top income inequality. Thus, industries such as manufacturing of fuels and chemical products, transport storage, and communications, and real state, renting and business activities are found to be driving the relationship between forward GVC participation and intra-regional top income inequality, among others. Second, it shows how the level of economic development of regions also mediates this relationship. It is found that less developed regions are more prone to have higher top income inequality derived from forward GVC participation. This highlights the relevance of exploring regional characteristics such as industrial structures and levels of economic development when analysing globalisation dynamics at the subnational level.

Finally, this paper also contributes to the literature in regional institutions. The empirical analysis incorporates the role of regional institutions mediating the relationship between forward GVC participation and intra-regional top income inequality. The results show how regions with weaker institutions are associated with higher top income inequality derived from forward GVC participation. This is in line with the existing literature in the field, stating that regional institutions remain crucial to understand the uneven spatial consequences of globalisation dynamics such as GVC participation (Rodríguez-Pose, 2013; Rodríguez-Pose, 2021).

4.3 Data

4.3.1 Regional GVC indicators

In order to map regions along and across GVCs, interregional input-output tables are required. In this sense, while there is a substantial lack of this kind of data at the sub-national level (Los, Timmer and De Vries, 2015), the EUREGIO database provides, to the best of our knowledge, the best coverage for European regions (Thissen, Lankhuizen et al., 2018). EUREGIO contains information on input-output flows for 249 regions from 24 European countries, 16 non-EU countries, rest of the world, and 14 industries, between the years 2000 and 2010. The 14 industries are based on the 2-digit NACE Rev.1 definition that include agriculture, mining, quarrying and energy supply, food, beverages and tobacco, textiles and leather, coke, refined petroleum, nuclear fuel and chemicals, electrical, optical and transport equipment, other manufacturing, construction, distribution, hotels and restaurants, transport, storage and communications, financial intermediation, real estate, renting and business activities, and non-market services.

Following Aslam, Novta and Rodrigues-Bastos (2017), and based on the seminal work of Hummels, Ishii and Yi (2001) and Koopman, Wang and Wei (2014), it is possible to compute an indicator for assessing regional participation in GVCs. In this vein, using EUREGIO, the total regional participation in GVCs is computed as follows:

$$TotalGVCParticipation_{it} = \frac{ForeignVA_{it}}{GrossExports_{it}} + \frac{DomesticVA_{it}}{GrossExports_{it}} \tag{4.1}$$

Therefore, the total GVC participation is computed as the sum of the backward and forward GVC participation. Indeed, the total GVC participation can be decomposed depending on the origin of the value added embedded in the exports (Kowalski et al., 2015). On the one hand, backward GVC participation is defined as the ratio between foreign imported value added and domestic gross exports. On the other hand, forward participation is defined as the ratio between domestic value added used in third regions' exports and domestic gross exports. Thus, while both backward and forward participation are two sides of the same coin, the total GVC participation, they may capture different ways of GVC engagement.

In this sense, while backward GVC participation captures the buyer or demand GVC side, forward GVC participation measures the seller or supply GVC side (Gonzalez, Kowalski and Achard, 2015). While regions with high backward GVC participation largely rely on foreign value added in order to produce their own exports, regions with high forward GVC participation mainly produce domestic value added to be used in other regions' exports. Thus, characterised by different combinations of backward and forward GVC participation, regions can be identified as having different roles in GVCs. For example, regions with a high backward GVC participation and low forward participation may be predominantly specialised in assembling and exporting final products. On the contrary, regions with low backward participation and high forward participation may be supplying intermediates to assembler regions (Kowalski et al., 2015).

4.3.2 Intra-Regional Income Inequality

We use income data from the European Union Statistics on Income and Living Conditions (EU-SILC). Income always refers to disposable post-tax labour income, which is then used to construct the top income measure, indicating how income is distributed between households within a region. We get disposable income following the steps of getting first the pre-tax factor income by summing the employee cash income, private pensions, and self-employment income. We then get pre-tax national income by adding unemployment benefits and public pensions to the factor income. To get the post-tax disposable income per household we subtract taxes as well as other contributions that were paid, such as cash transfers, and include benefits, such as for housing and unemployment. We chose disposable income as it describes the income that is actually available to households, which we argue to be an important indicator. Using the pre-tax factor income instead would have increased the level of the inequality indicators due to progressive taxation in EU countries.

We focus on the top of the income distribution, by creating the following measure: the share of the top 5%. It describes the share of top 5% income recipients in the region, relative to the country. An increase in this share signifies that the top 5% earners in the region have more disposable income compared to the rest of the country. We interpret an increase in this share as a rise in income inequality, given that the top earners in the country earn *even more* compared to the rest of the country, widening existing gaps in incomes to middle and low earners. This measure is likely to proxy wealth, as the top labour income earners tend to possess high capital income as well (M. N. Hansen, 2014), which is often linked to higher wealth. However, we will refer to it as income inequality, given that we use the data for income. Measuring income inequality at the top using top income shares has been increasingly done since the influential work by Piketty (2003) and Piketty and Saez (2003). Measures such as the Gini coefficient, in contrast, focus on the whole distribution and are more sensitive to the middle of the income distribution. For this reason, the Gini coefficient is not a proxy for what is happening at the top, thus we use the share of top income earners, relative to the rest of the country, instead.

One limitation of EU-SILC data is that region does not always refer to the NUTS-2 level. Depending on the country, the data might be available at NUTS-1 or NUTS-2 level. One example is Austria, where the data is only available at NUTS-1 level. In addition, when measuring inequality at the top using EU-SILC data, we are likely underestimating the level of inequality. The first reason is the underreporting of top incomes. As shown by multiple scholars, survey data tends to miss top income recipients, due to nonresponse bias stemming from rich households (Groves, 2006; Ravallion, 2022). Second, EU-SILC income data does not include capital income, thus disposable income only refers to labour income. Global value chain participation is likely to influence labour and capital income. However, we can only measure the effect on labour income using EU-SILC data. If we were to include capital income as well, we would expect the measures of income inequality to be higher. Thus, due to nonresponse bias from richer households, as well as using only labour income we are likely to underestimate the effect of GVC participation on top income inequality.

4.3.3 Control variables

In addition to the EU-SILC and EUREGIO data, we also get data from other data sources for the control variables. These are variables on the regional level, including Gross Domestic Product (GDP), quality of government, population and patents. We get data on GDP and population from Eurostat and regional quality of government indicators from Rodríguez-Pose and Di Cataldo (2015). Institutional quality is a multi-dimensional concept, including the quality of public services, control of corruption, and impartiality. For this paper, institutional quality will refer to control of corruption, given that this could be one particular dimension affecting how inequality is affected.

4.3.4 Descriptive evidence

Average annual change in total, forward and backward participation

Figure 4.1 below describes the average annual regional change in total GVC participation over the period 2000-2010. It includes all regions of the GVC data except for the region “Comunidad Valenciana" (ES52), which is an outlier and is thus marked in grey. It shows a clear pattern with the highest average increase in GVC participation in Western and Central Europe, in particular in France, Germany, Austria, Southern Italy or the Netherlands. Most regions in Spain, Portugal, in the UK, Poland and Czech Republic show on average an increase in total GVC participation. However, some regions in Greece, Bulgaria, Estonia, and Latvia depict a decline in total GVC participation. As a next step, we look at the change in forward and backward GVC participation.

Figure 4.2 shows the average yearly change per region in forward participation from 2000-2010. It shows more variation, but a similar pattern to total participation. Those regions

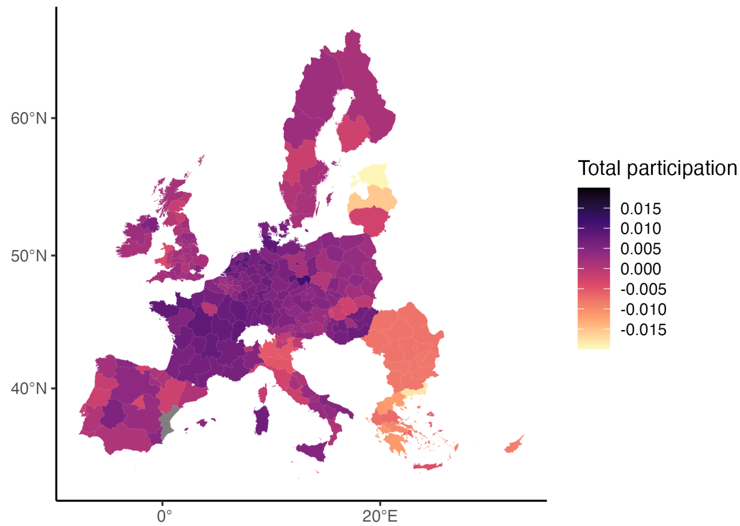

Figure 4.1: Average yearly change in total participation per region, 2000-2010

with the highest increase forward GVC participation are located in Germany, France and Southern Italy. Regions in Spain, Portugal, in the UK and Austria have seen an increase in forward GVC participation. Others, in Greece, Bulgaria, Estonia and Latvia have experienced a decline.

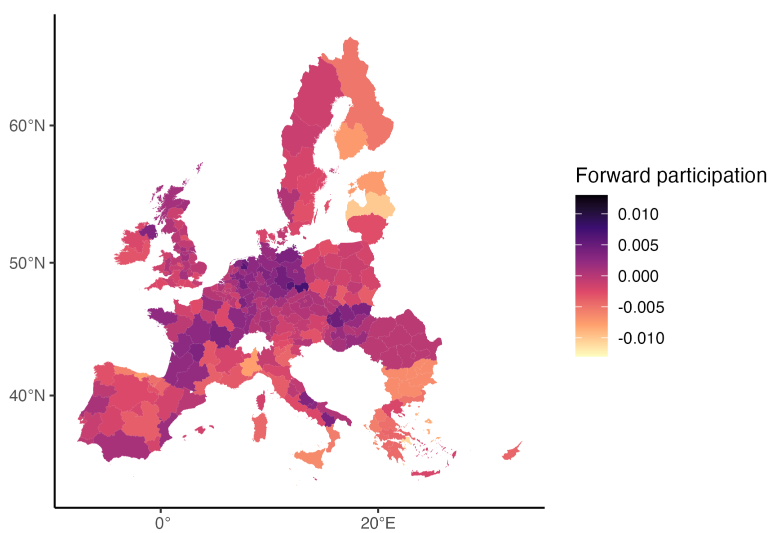

Figure 4.2: Average yearly change in forward participation per region, 2000-2010

Figure 4.3 shows the average yearly regional change in GVC backward participation from 2000-2010. It shows substantially less variation over space, but is described by a similar spatial pattern as total and forward participation. Regions in Western and Central Europe show the highest rise in backward participation, while those in in Greece, Bulgaria, Estonia and Latvia the lowest changes, experiencing a decline.

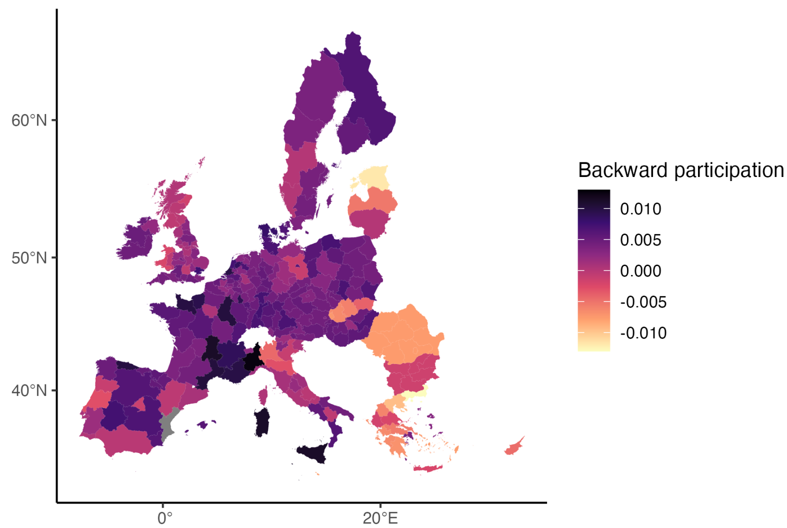

Figure 4.3: Average yearly change in backward participation per region, 2000-2010

4.4 Methodology

In the results section, we estimate the following standard two-way fixed effects model:

$$INEQ_{it} = \beta GVC_{it} + \gamma X_{it} + v_i + v_t + \varepsilon_{it} \tag{4.2}$$

where $INEQ_{it}$ describes the share of the top 5 in region i in year t, GVC_{it} refers to an indicator of global value chain participation in region i in year t, X_{it} is a vector of control variables, v_i are region fixed effects and v_t are year fixed effect. Including region fixed effects allows us to control for time-invariant region-specific characteristics shaping the relationship between global value chains and income inequality. Year fixed effects account for specific trends in every year. The selection of control variables aims at taking into account relevant variation that changes over time that affects income inequality, as well as participation in global value chains. To do so, we include GDP, population density, institutional quality and education. To account for serial correlation, we cluster the standard errors at the regional level. With the model specification, we capture a correlation between global value chain participation and income inequality, given that we do not control for potential omitted variables or account for other endogeneity concerns.

In addition, we run the models at the sectoral level, with the independent variable GVC participation being measured for 14 different industries. The empirical specification takes the following form:

$$INEQ_{it} = \beta GVC_{ijt} + \gamma X_{it} + v_i + v_t + \varepsilon_{it} \tag{4.3}$$

The specification is similar to above, with the difference of GVC_{ijt} referring to an indicator of global value chain participation in region i in year t and industry j. Otherwise, we include the same dependent variable, control variables and fixed effects. The industries include (1) agriculture, (2) Mining, quarrying and energy supply, (3) food, beverages and tobacco, (4) textiles and leather, (5) coke, refined petroleum, nuclear fuel and chemicals etc., (6) electrical, optical and transport equipment, (7) other manufacturing, (8) construction, (9) distribution, (10) hotels and restaurants, (11) transport, storage and communications, (12) financial intermediation, (13) real estate, renting and business activities and (14) non-market services.

It is important to note that we do not take into account potential endogeneity concerns. In particular, we might be concerned about omitted variable bias and reverse causality. We aim to avoid potential bias stemming from leaving out relevant variables by controlling for variables that have been identified previously by the literature. These variables are described in Section 4.2.2. However, it might still be the case that we have failed to include a relevant variable. Moreover, reverse causality might also pose a problem to causal interpretation. It can be that not only GVC participation affects top incomes, but also that GVC participation is also influenced by the presence of top earners. For these reasons, it is vital to acknowledge that potential endogeneity concerns are not addressed, which means that this study captures a correlation between GVC participation and the share of the top 5, instead of a causal relationship.

4.5 Results

4.5.1 Different GVC measures

We regress the share of the top 5 on different GVCs measures, including total, forward and backward participation. As described in Section 4.2.3 the effect is likely to differ depending on how regions participate in global value chains, as it affects which activities are carried out within a region. All models include region- and year-fixed effects, with standard errors clustered at the regional level. The observations include all regions where data is available except for the "Comunidad Valenciana" (ES52), which is an outlier[1]. We find a statistically significant effect for total and forward participation, depicting a positive link between these two types of GVC participation and income inequality at the top. The effect of total participation becomes insignificant when adding control variables (see Section 4.6 in the appendix), thus we focus on forward participation in the following results.

[1]The results shown in the table below are consistent to those when including Valencia in the sample.

Table 4.1: Regression Results: Different GVC measures and income inequality

Dependent Variable:	Top 5			
Model:	(1)	(2)	(3)	(4)
Total part	0.0594**			
	(0.0235)			
Forward part		0.1221***		0.1271***
		(0.0397)		(0.0401)
Backward part			0.0143	0.0268
			(0.0225)	(0.0238)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,258	1,258	1,258	1,258
R^2	0.81492	0.81622	0.81310	0.81650
Within R^2	0.01015	0.01711	0.00044	0.01864

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

There are multiple reasons why we observe these results. First, participation in GVCs and the resulting specialisation are linked to higher wages being paid in developed countries (Shepherd, 2013; Ndubuisi and Owusu, 2022). Thus, on average, firms that participate in GVCs tend to pay higher wages than their counterparts. Second, forward participation refers to the seller GVC side, which allows to set prices above the production costs. Incomplete pass-through of cost savings and rent extraction could affect the distribution of income (Bao, De Loecker and Eeckhout, 2022). An increase in inequality at the top within a region might be observed when rents are extracted from customers or competitors to managers or firm owners (Bao, De Loecker and Eeckhout, 2022). Given that the top earners in Europe tend to be managers, who have seen higher wage growth than other groups between 2005 and 2017 (Denk, 2015; Rabensteiner and Guschanski, 2022), it could be that their income has increased unproportionally due to forward participation. Third, an explanation why no significant effect for backward participation is found could be that the middle of the income distribution would be mostly affected as well as the effect being heterogeneous across European regions. Previous research has focused on the Gini coefficient instead of the top of the income distribution and has shown that the effect for backward participation depends on whether the demand for high vs. low-skilled workers is increased. Given that skill levels highly differ across European regions, establishing an overall relationship could be challenging.

4.5.2 Forward participation

To test whether the relationship between forward GVC participation and inequality is robust, we include different fixed effects and control variables. We first start with a simple one-way fixed effects model, including only region-fixed effects. Then we add year-fixed effects in the next model, which slightly increases the estimated coefficient. In model 3, we add the control variables GDP and institutional quality, as they are the economic and institutional factors likely to influence income inequality and global value chain participation. In model 4, we add further controls, including population density to control for spatial factors such as potential agglomeration effects and education to account for social and demographic factors.

Table 4.2: Regression Results: Forward participation and income inequality

Dependent Variable:	Top 5				
Model:	(1)	(2)	(3)	(4)	(5)
Forward part	0.1048***	0.1221***	0.1018***	0.1046***	0.1039***
	(0.0332)	(0.0397)	(0.0372)	(0.0383)	(0.0385)
Log(GDP pps)			-0.0358***	-0.0343***	-0.0296***
			(0.0115)	(0.0117)	(0.0100)
Inst			0.0113***	0.0127***	0.0120***
			(0.0036)	(0.0034)	(0.0030)
Secondary educ				0.0005**	0.0005**
				(0.0002)	(0.0003)
Log(popdensity)					-0.0598
					(0.0478)
Fixed-effects					
Region	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Fit statistics					
Observations	1,258	1,258	1,199	1,192	1,192
R^2	0.80813	0.81622	0.81702	0.81446	0.81595
Within R^2	0.01624	0.01711	0.04983	0.05825	0.06584

Clustered (region) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Overall, we show that the estimated coefficients are consistent using different fixed effects and control variables, and barely change size, remaining around 0.1. It increases when including year-fixed effect and then decreases again slightly when adding the different control variables described above.

4.5.3 By Sector

The effect likely depends on the sector in which regions participate in global value chains. For this reason, we create subsets for every of the 14 sectors following the 2-digit NACE Rev.1 classification. We then regress global value chain integration in each sector on our top income inequality measure and find statistically significant results for some sectors, which are shown below. These sectors are manufacturing in coke refined petroleum nuclear fuel and chemicals, transport storage and communication, hotels and restaurants, real estate renting and business activities, food, beverages and tobacco, and electrical, optical and transport equipment. The effects for other sectors are insignificant but are shown in the appendix for completeness (see Section 4.8.4).

For all sectors where forward participation is significantly associated with inequality, we find a positive link except for food, beverages and tobacco. For those that are significant at the 5% level, we find the largest effect size for transport storage and communication, followed by manufacturing of coke refined petroleum nuclear fuel and chemicals. The effect for real estate renting and business activities only shows a small estimated coefficient but is significant at the 1% level. The sectors electrical, optical and transport equipment as well as food, beverages and tobacco are only significant at the 10% level.

There are multiple explanations for why we observe these effects. It is highly likely that in these sectors where we find a positive link, the top earners are concentrated. One example would be manufacturing. As discussed in Section 4.2, the top earners in Europe include managers in the field of manufacturing. It might be that their income rises unproportionally due to domestic production that is exported later. Moreover, these sectors might be more likely to have high fixed costs and thus a tendency towards natural monopoly (such as petroleum, chemicals and electrical equipment), information asymmetries, benefit from economies of scale and rely more on forward participation.

Table 4.3: Regression Results: Forward participation by sector and income inequality

Dependent Variable:	Top 5					
Model:	Manufac.	Transp. & Comm.	Busin.	Hotels	Elec. equip.	Food & tobacco
Forward part	0.0354***	0.0757**	0.0093**	0.0003***	0.0472*	-0.0673*
	(0.0103)	(0.0311)	(0.0045)	(0.0000)	(0.0272)	(0.0381)
Log(GDP pps)	-0.0290***	-0.0261***	-0.0318***	-0.0309***	-0.0327***	-0.0319***
	(0.0102)	(0.0099)	(0.0106)	(0.0104)	(0.0107)	(0.0107)
Inst	0.0117***	0.0104***	0.0138***	0.0132***	0.0131***	0.0131***
	(0.0031)	(0.0030)	(0.0033)	(0.0032)	(0.0032)	(0.0033)
Secondary educ	0.0006**	0.0005**	0.0005**	0.0005*	0.0005*	0.0005**
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(popdensity)	-0.0593	-0.0164	-0.0585	-0.0559	-0.0612	-0.0594
	(0.0476)	(0.0567)	(0.0467)	(0.0487)	(0.0478)	(0.0470)
Fixed-effects						
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,192	1,192	1,192	1,192	1,192	1,192
R^2	0.81586	0.82209	0.81448	0.81668	0.81443	0.81427
Within R^2	0.06535	0.09697	0.05835	0.06950	0.05810	0.05730

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.5.4 Heterogeneity: development level and institutions

How does the effect differ across regions? In which regions is the effect more pronounced? This subsection explores heterogeneities across regions, focusing on the development level and institutions. We select these variables as previous research has pointed out that these are likely to play a role in shaping the relationship between GVC participation and inequality, as described in Section 4.2. We do so by understanding whether there are significant differences between groups and their link to forward participation.

First, to look at how the effect varies by development level, we create four groups and interact it with forward participation. The four groups are constructed using quartiles of the whole GDP distribution, with every region being assigned to one of the groups based on their average GDP value across all periods, showing the relative position of one region to others in terms of their GDP. The four groups that are created are GDP “low", “low-mid", “mid-high" and “high". The results are shown in model 1, demonstrating that the link between global value chain participation and top income inequality is less pronounced in highly developed regions. Compared to the regions in the “low" GDP category, which is the baseline category, the regions in the categories “mid-high" as well as “high" tend to experience a significantly lower effect of forward participation on top incomes. These findings are in line with theoretical predictions such as the Kuznets curve.

Second, we look at regional differences in institutional quality, measured by the variable control of corruption stemming from Rodríguez-Pose and Di Cataldo (2015). Similarly to GDP, we form four groups based on institutional quality across regions, describing for each group how high their control of corruption is. Using the whole distribution of regional values of institutional quality, we assign each region based on their average value to one of the quartiles “low", “low-mid", “mid-high" and “high". We then interact forward GVC participation with these groups for institutional quality. In model 2, we find that the effect tends to be more pronounced in regions with lower institutional quality. The regions in the group ‘low-mid" tends to drive the highest increase in top incomes linked to forward participation. These findings are in line with expectations, given that institutions set the rules in a society, create incentives and costs in economic transactions and contain moral hazard due to transparent and specific information as well as control of rent-seeking. With lower institutional quality, less control for corruption, we would expect higher inequality linked to participation in global value chains.

Table 4.4: Regression Results: Heterogeneity by development level and institutions, forward participation and income inequality

Dependent Variable:	Top 5	
Model:	(1)	(2)
Forward part	0.2616***	0.0641**
	(0.0819)	(0.0276)
Inst	0.0083***	
	(0.0024)	
Secondary educ	0.0006**	0.0005*
	(0.0002)	(0.0003)
Log(popdensity)	-0.0813	-0.0517
	(0.0496)	(0.0532)
Forward part × GDP low-mid	-0.1145	
	(0.1049)	
Forward part × GDP mid-high	-0.1993**	
	(0.0825)	
Forward part × GDP high	-0.2730***	
	(0.0900)	
Log(GDP pps)		-0.0148*
		(0.0081)
Forward part × Inst low-mid		0.2168**
		(0.1012)
Forward part × Inst mid-high		0.0767
		(0.0931)
Forward part × Inst high		-0.0289
		(0.0698)
Fixed-effects		
Region	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	1,192	1,192
R^2	0.81652	0.81434
Within R^2	0.06870	0.05765

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.6 Sensitivity checks

To make sure that the results are not driven by changes to income inequality stemming from the economic and financial crisis, we exclude the period between 2008 and 2010, with our sample now covering the period from 2003 to 2007. We first run the two-way fixed effects model without any controls and then add them in model 2. The results are positive and statistically significant at the 1% level and the coefficient is larger in size than those of the base models. This suggests that our results are not driven by the changes in income inequality due to the economic and financial crisis. Instead, it shows that in particular the years between 2003-2007 have been the main driver when it comes to the relationship of forward participation and top income inequality. One limitation of this robustness check is that we lose some observations due to a lower number of observations in the inequality variable in the earlier years. Less countries participated in EU-SILC in 2003, with many of them starting at a later stage. However, to make sure that the overall effects are not driven by the financial crisis and to show that in particular the earlier years are essentially driving the effect, we are showing the results in model 1 and 2.

The second sensitivity check we conduct concerns the institutional measure. Given that it is a multi-dimensional measure, we include another measure for institutional capacity in model 3. As there are no other institutional indicators available at the regional level, we are relying on the same dataset, but different measures of institutional capacity. We now include the measure for institutional quality, instead of the control for corruption. Compared to the baseline model the coefficient remains similar in size and is still significant at the 1% level. Therefore, we conclude that using a different measure of regional institutions does not change the findings concerning the relationship between forward GVC participation and top inequality. As a third robustness check, we are taking into account the role of technology. As scholars have pointed out the role of technology in shaping the relationship between global value chains and labour markets, we include the proxy patents per capita. This is to make sure our results do not exhibit potential omitted variable bias stemming from leaving out technological capacity shaping this relationship. Thus, model 4 adds patents per capita in a logarithmic form as a control. However, the estimated coefficient for patents is not significant and forward participation remains overall significant, while decreasing in size. This reduction in estimated coefficient size and significant level might stem from controlling for a relevant variable (which is insignificant) or from a reduction in sample size coming from the patent measure not being available for all observations.

Table 4.5: Regression Results: Sensitivity checks for forward participation by sector and income inequality

Dependent Variable:	Top 5			
Model:	(1)	(2)	(3)	(4)
Variables				
Forward part	0.2526***	0.2032***	0.1004***	0.0660**
	(0.0771)	(0.0683)	(0.0370)	(0.0287)
Log(GDP pps)		-0.0750***	-0.0324***	-0.0219**
		(0.0246)	(0.0097)	(0.0088)
Inst cor		0.0134***		0.0103***
		(0.0047)		(0.0030)
Secondary educ		0.0009*	0.0007***	0.0005*
		(0.0005)	(0.0002)	(0.0003)
Log(popdensity)		-0.2322**	-0.0376	-0.0730
		(0.0985)	(0.0455)	(0.0510)
Inst qual			0.0161***	
			(0.0034)	
Log(patents pc)				-0.0009
				(0.0009)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	567	546	1,192	1,176
R^2	0.84256	0.86126	0.82323	0.83543
Within R^2	0.04424	0.17421	0.10280	0.05545

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.7 Conclusion

As the global economy grows more intertwined, the participation of regions in global value chains has become increasingly crucial for regional development. While the literature has emphasised how regions can benefit from GVCs in terms of technological upgrading, knowledge spillovers, productivity gains, and higher incomes, fewer is known about how these benefits are shared within regional economies.

Therefore, this paper studies the relationship between regional GVC participation and income inequality for European NUTS-2 regions between 2003 and 2010. The results show that the effect depends on how regions participate in GVCs. Forward GVC participation is on average linked to higher inequality at the top of the income distribution. On the contrary, backward GVC participation is not found to be associated with intra-regional income inequality. These results point towards the fact that regions on the seller side, those with higher forward participation, are associated with higher top income inequality. This effect is not found for regions on the buyer side, thus with higher backward participation.

Furthermore, the empirical analysis uncovered some regional disparities underpinning these findings. In the first place, certain sectors, such as manufacturing in coke refined petroleum nuclear fuel and chemicals or transport storage and communication, are found to be the main drivers behind the relationship between forward GVC participation and intra-regional top income inequality. There could be multiple reasons for it, with one of them being economic rents stemming from information asymmetries, a tendency towards natural monopoly or economies of scale. In the second place, this relationship is stronger in less developed regions. This suggests that lagging regions may suffer more from an unequal distribution of the benefits derived from GVC participation. In the third place, the results show how regional institutions shape this relationship. In fact, regions with weaker institutions are more prone to have a stronger association between GVC participation and intra-regional top income inequality.

Therefore, these findings present a fresh viewpoint on how global value chain integration affects intra-regional inequality within the European context, with forward participation playing a significant role for income inequality at the top. However, this paper is not without limitations. First, although the input-output data used in the empirical analysis provides, to the best of our knowledge, the best coverage for European regions it has several shortcomings. For example, the period of analysis is restricted to the years 2003-2010. While structural changes such as regional GVC participation may require long periods, the EUREGIO data can just capture a limited variation in such dynamics. This period is also characterized by the global economic crisis, which is why some robustness checks are carried out and the results remain the same. Also, the industrial classifications used in EUREGIO remain quite aggregated. More granularity at the sectoral level will allow to better disentangle differences across industries, particularly in manufacturing sectors. Second, the EU-SILC data may suffer from underreported information at the top of the income distribution. While this does not hamper the results, since the analysis would report a conservative estimate, it may not provide the exact picture of the income distribution of European regions. Third, due to the existence of endogeneity concerns, particularly omitted variable bias and reverse causality, this paper provides a rather descriptive study on the link between regional global value chain participation and top income inequality. Despite these limitations, we argue that it is still of high interest to observe what happens in the short run, and what determining factors are, such as the development level and the institutional quality, in shaping this relationship.

In addition, a crucial challenge for this paper is to derive policy implications. Due to the above-mentioned limitations, no direct policy recommendations are stated. However, the link between global value chain participation and income inequality remains of high relevance for policymakers. The distributional outcomes of costs and benefits derived from regional GVC participation still needs to be incorporated into policies such as Smart Specialisation Strategies. While these policies have focused on the intra-regional dynamics, much less attention has been drawn to the interregional dimension, in which GVCs remain crucial (Radosevic et al., 2017; Iacobucci and Guzzini, 2016; Sorvik et al., 2016; Uyarra, Marzocchi and Sorvik, 2018; Barzotto et al., 2019; Santoalha, 2019). Particularly, since GVCs may also come with a cost, issues such as inequality or environmental performance in GVCs need to be addressed to mitigate further territorial disparities, social polarisation and political discontent (Rodríguez-

Pose, 2018; Rodríguez-Pose, 2021; Diemer et al., 2022; Rodríguez-Pose and Bartalucci, 2023).

Finally, this paper also opens new venues for future research. While this paper focuses on intra-regional inequality derived from GVC participation, nothing has been said regarding interregional dynamics. Thus, more research is needed to understand the interregional consequences in terms of inequalities that may come from regional GVC participation. Particularly, within the ongoing debate on regional convergence and the increasing social and political divides across regions, the interregional income disparities that may be derived from GVC engagement should be further studied (Rodríguez-Pose, 2018). This is particularly relevant when it comes to neighboring regions and the differences in the ways regions engage in GVCs (Bolea et al., 2022; Capello, Dellisanti and Perucca, 2023). In this vein, it remains understudied how the interplay between neighbouring regions and between regions from the same country is. The role of regional institutions mediating these dynamics also requires a more in-depth analysis. The identification of particular regional institutions that help to mitigate income disparities derived from GVCs represents a challenge for the scholar and policy debate (Rodríguez-Pose, 2021).

In this vein, to uncover the exact mechanism driving the relationship between GVC participation and income inequality, the use of firm-level data remains crucial. While we provide evidence with this paper for an overarching link, there is much to uncover at the micro level. This kind of data may provide insights about the distributional dimension of income between different firms and occupations. To understand how income disparities between different occupations (blue vs. white collars, routine vs. non-routine) may be associated with GVC participation at the regional level, firm-level data should be exploit. This is also of high relevance for understanding how the functional specialization of regions along GVCs may have implications for their development trajectories and upgrading dynamics (Ponte and Ewert, 2009; Crescenzi, Pietrobelli and Rabellotti, 2014; Timmer, Miroudot and Vries, 2019; Bontadini et al., 2024). This is extremely important since the GVC approach may be different from previous studies studying income inequality and trade with import-export data (Rodríguez-Pose, 2012; Timmer, Erumban et al., 2014).

4.8 Appendix

4.8.1 Correlation Matrix

	Top 5	GDP	Inst	Total part	For. part	Back. part	Sec. educ	Popdensity
Top 5	1.00	0.34	0.14	0.01	0.06	-0.03	-0.05	0.36
GDP	0.34	1.00	0.03	-0.06	0.30	-0.30	-0.17	0.09
Inst	0.14	0.03	1.00	0.06	0.20	-0.08	-0.12	0.03
Total part	0.01	-0.06	0.06	1.00	0.56	0.78	0.14	-0.08
For. part	0.06	0.30	0.20	0.56	1.00	-0.09	0.12	0.04
Back. part	-0.03	-0.30	-0.08	0.78	-0.09	1.00	0.07	-0.12
Sec. educ	-0.05	-0.17	-0.12	0.14	0.12	0.07	1.00	-0.15
Popdensity	0.36	0.09	0.03	-0.08	0.04	-0.12	-0.15	1.00

4.8.2 Summary statistics

Below we show a table of the most relevant summary statistics for the variables: top 5, forward participation, backward participation, total participation, GDP, institutional quality, population density and secondary education. Relevant summary statistics include the number of observations N, the mean, the standard deviation, the minimum and the maximum. It shows the different number of observations of the variables, with the inequality measure showing the lowest number of 1,258. This stems from the availability of EU-SILC data, which starts in 2003 for some countries, compared to GVC data which covers the whole period.

Statistic	N	Mean	St. Dev.	Min	Max
Top 5	1,258	0.046	0.021	0.000	0.186
Forward part	2,072	0.265	0.059	0.068	0.472
Backward part	2,072	0.374	0.080	0.136	0.608
Total part	2,072	0.638	0.087	0.320	0.863
GDP	1,888	45,205.310	50,763.220	838	545,520
Popdensity	1,888	352.650	755.466	3.330	6,805.858
Secondary Educ	1,880	46.590	15.351	6.900	80.300
Inst	1,840	0.337	0.889	−2.509	2.761

4.8.3 Results for total participation with controls

Table 4.6: Regression Results: Total participation and income inequality

Dependent Variable:	Top 5
Model:	(1)
Variables	
Total part	0.0270
	(0.0208)
Log(GDP pps)	-0.0297***
	(0.0100)
Inst	0.0124***
	(0.0030)
Secondary educ	0.0005**
	(0.0002)
Log(popdensity)	-0.0542
	(0.0464)
Fixed-effects	
Region	Yes
Year	Yes
Fit statistics	
Observations	1,200
R^2	0.81366
Within R^2	0.05441

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.8.4 All Sectoral Results

In addition to the results of the six sectors depicted in Section 4.5, we show the results for the remaining eight sectors in the tables below. As discussed before, we do not find any significant results for the link between this sectoral value chain participation and income inequality. However, for completeness, we show these tables for these sectors as well. These eight sectors are agriculture, mining, quarrying and energy supply, textiles and leather, other manufacturing, construction, distribution, financial intermediation, and non-market services.

Table 4.7: Regression Results: Forward participation other sectors and income inequality

Dependent Variable:	Top 5			
Model:	Agriculture	Mining	Textiles	Other Manufacturing
Variables				
Forward part	-0.0032	0.0048	0.0399	-0.0175
	(0.0115)	(0.0035)	(0.0426)	(0.0272)
Log(GDP pps)	-0.0317***	-0.0320***	-0.0303***	-0.0318***
	(0.0105)	(0.0105)	(0.0101)	(0.0106)
Inst	0.0138***	0.0129***	0.0128***	0.0142***
	(0.0033)	(0.0031)	(0.0031)	(0.0034)
Secondary educ	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Log(popdensity)	-0.0612	-0.0581	-0.0525	-0.0595
	(0.0476)	(0.0468)	(0.0501)	(0.0467)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,192	1,192	1,192	1,192
R^2	0.81381	0.81463	0.81419	0.81389
Within R^2	0.05498	0.05911	0.05687	0.05539

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4.8: Regression Results: Forward participation further sectors and income inequality

Dependent Variable:	Top 5			
Model:	Construction	Distribution	Financial intermed.	Non-market service
Variables				
Forward part	0.0054	0.0010	-0.0059	0.0047
	(0.0101)	(0.0019)	(0.0057)	(0.0100)
Log(GDP pps)	-0.0323***	-0.0309***	-0.0328***	-0.0302***
	(0.0107)	(0.0106)	(0.0106)	(0.0109)
Inst	0.0140***	0.0134***	0.0143***	0.0133***
	(0.0034)	(0.0033)	(0.0033)	(0.0033)
Secondary educ	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(popdensity)	-0.0618	-0.0605	-0.0600	-0.0605
	(0.0478)	(0.0477)	(0.0473)	(0.0474)
Fixed-effects				
Region	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,192	1,192	1,192	1,192
R^2	0.81384	0.81389	0.81407	0.81390
Within R^2	0.05511	0.05538	0.05625	0.05543

Clustered region standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Chapter 5

Brexit and Digital Technology Adoption

5.1 Introduction

On June 23rd, 2016, the United Kingdom (UK) voted to leave the European Union (EU), a decision that drastically shifted expectations for the UK's future relationship with the EU. The resulting significant trade barriers have led to a decrease in trade for UK firms in both imports (Kren and Lawless, 2022) and exports (Crowley, Exton and Han, 2018). The Brexit referendum has led to a decline in investment and productivity for larger firms (Bloom, Bunn et al., 2019), but little is known about the effect of this shock through impacts on innovation among Small and Medium Enterprises (SMEs) in the UK. SMEs are the backbone of the economy, making up 99.9% of all private firms in the UK (ONS, 2017) and providing 60% of all jobs (BEIS, 2021). This is even more the case for local economies in South West England and Wales, where their employment makes up 70% of employment in the private sector (Department for Business Energy and Industrial Strategy, 2021). This paper exploits the Brexit referendum as a trade policy uncertainty shock, studying how SMEs that trade with the EU adjust their digital technology adoption and compare it to firms that do not have trade linkages with the EU. In addition, it uses the inter-regional variation in the Brexit referendum, measured by the regional share of the actual Brexit vote, to estimate the local effect on firm-level performance. It also applies novel data sources on digital technology adoption to provide detailed measures to explore differences in how SMEs respond to this trade policy uncertainty shock.

A large body of literature has reported a strong link between digital technology adoption and productivity gains at the country and firm level (Draca, Sadun and Van Reenen, 2009; Van Reenen et al., 2010; Bloom, Sadun and Reenen, 2012). In light of the UK's productivity growth already lagging behind comparable nations since the global economic and financial crises (Financial Times, 2018), the economic downturn and productivity slowdown catalysed by Brexit (Sampson, 2017; Bloom, Bunn et al., 2019) underscores the necessity to understand the response of the largest group of private firms to such a major shock. SMEs are often viewed as drivers of productivity, especially those that are innovative and growth-oriented (Schneider and Veugelers, 2010). Crucially, it's this particular group that has voiced considerable concern about the effects of Brexit (Brown, J. M. Liñares-Zegarra and Wilson, 2018). Despite this, evidence is missing on how they are affected when it comes to digital technology adoption, a key component of productivity growth (Gal et al., 2019). I seek to fill this knowledge gap, providing insights into which firms and digital technologies have been most impacted by Brexit. Such findings should prove useful for policymakers, empowering them with the information needed to design and implement effective measures that mitigate some of the detrimental effects on firms. This is of paramount importance, particularly in the long run, as alleviating some of the negative effects of Brexit on UK firms is intrinsically tied to overcoming the ongoing productivity decline affecting UK living standards and SMEs' growth potential.

This paper studies the effect of the Brexit referendum on the digital technology adoption of UK SMEs from 2013-2019. It combines survey data from the Longitudinal Small Business Survey (LSBS) with novel data on digital technology adoption from firms' websites to provide detailed and timely measurements to gain deeper insights into SMEs' reactions to this shock. It uses a difference-in-differences design, with the Brexit referendum as a trade policy uncertainty shock that imposes higher potential trade costs and heightens uncertainty among exposed firms that depend on the EU. I study how firms that trade with the EU respond and find that they adapt by reducing digital technologies. I find a negative effect for digital technologies that are used for e-commerce, including payment technologies, which are significantly decreased, suggesting that firms cut back in the form of trade-enhancing digital technologies. These effects are driven by multiple sectors, extending beyond those traditionally associated with the trade of goods to also include service sectors. In addition, firms exposed to the shock reduce digital technologies not directly linked to e-commerce, suggesting a wider and more substantial impact of Brexit on SMEs' technology adoption. The findings suggest that three channels have been influential: trade, investment, and strategical realignment. By looking at different digital technology categories and LSBS survey responses, support for these channels is found.

This study contributes to three different types of literature. First, it links to the growing literature on how Brexit affects firm-level outcomes. The Brexit referendum changed expectations about future UK-EU relations and business expectations, leading firms to reduce trade with the EU (Crowley, Exton and Han, 2018) as well as decreasing investment and innovation (Brown, J. M. Liñares-Zegarra and Wilson, 2018). It contributes to this strand by complementing existing literature on the response through innovation, by looking at SMEs and their digital behaviour, showing that SMEs exposed to this shock experienced, on average, a reduction in their digital technologies compared to before the Brexit referendum.

Second, it relates to the literature on trade policy reforms and uncertainty. While a large number of studies have demonstrated that trade liberalisation is linked to higher growth (Pavcnik, 2002; Melitz, 2003; Amiti and Konings, 2007; Bloom, Draca and Van Reenen, 2016; Handley and Limão, 2017), Brexit can be seen through the lens of reverse trade reform. These growth- increasing effects of trade liberalisation reforms materialise through improved productivity and allocation and higher innovation. It has been shown that trade policy uncertainty negatively affects firms' export investments, particularly when high sunk costs in trade are involved (Handley and Limao, 2015). Thus, with high trade policy uncertainty, negative effects on growth through lower trade, investment and innovation would be expected.

Third, this study explores the evolution of digital technology adoption metrics, facilitated by the linking of existing survey data with novel online data sources. It develops novel measures for technology adoption by leveraging ever-increasing volumes of data available from businesses' websites. Matching these novel measures to existing data sources allows us to create more detailed and timely estimates on technology adoption and SMEs' digital behaviour. These can be used to have a more accurate picture of adjustments made by firms in their technology portfolios over time.

This paper is organised as follows: it first summarises relevant literature, focusing on the effect of Brexit on UK firms, particularly SMEs. It then describes the data for this study, consisting of LSBS data and digital technologies based on firms' website data. It shows some descriptive statistics linked to Brexit and trends in digital technologies and explains in the methodology section how the effect of Brexit on SMEs' technology adoption is identified. Finally, the results for different technology groups are estimated, the findings and mechanisms are discussed in the last sections.

5.2 Related Literature

This section first summarises relevant literature, pointing out the state of the art regarding the effect of Brexit on UK firms, focusing on SMEs. I then show how there is a gap regarding the impact of Brexit on SMEs' digital technology adoption and discuss how this study can provide novel insights. This paper contributes to the growing literature by creating detailed measures of digital technologies at the firm level and then estimating the effect of Brexit. There is substantial research on the impact of Brexit on the UK economy (Dhingra, Fry et al., 2022; Du, Beyza and Shepotylo, 2022; Hantzsche, Kara and Young, 2019; Van Reenen, 2016), with the overall conclusion that Brexit will make the UK economy poorer than it would have been otherwise due to barriers to trade and migration (Sampson, 2017). The decision to leave the EU has had a large negative impact on the UK economy from 2016 to 2019, including a decline in investment, higher import, and consumer prices, as well as a decreased growth in GDP and real wages (Dhingra and Sampson, 2022).

Looking at regional and firm-level outcomes, previous research has also studied the impact of Brexit on regional productivity, governance response and competitiveness (Fingleton et al., 2022; Thissen, Oort et al., 2020; Billing, McCann and Ortega-Argilés, 2019), the trade exposure of UK regions (Chen et al., 2018), consumer prices (Bakker et al., 2022), firm size and age (Uddin, Chowdhury and Wood, 2022), firm investment (Górnicka, 2018; Bloom, Bunn et al., 2019), turnover, sales and trade in the textile and apparel industry (Casadei and Iammarino, 2021), the potential impact on SMEs (Brown, J. Liñares-Zegarra and Wilson, 2019) and the strategic intentions of SMEs (Brown, Kalafsky et al., 2020).

5.2.1 Brexit as a trade policy uncertainty shock

With the decision to leave the single market in 2016, the Brexit referendum created increased trade friction between the UK and the EU market. With the expectations of rising trade barriers linked to the largest trade partner of the UK, firms become more pessimistic regarding their outlook on the future and the business environment. Firms are likely to anticipate higher costs from importing, lower profits and increased administrative work and thus respond with reduced trade with the EU. This has already been observed, with the potential future trade barriers leading to a fall in trade with the EU (Brown, J. Liñares-Zegarra and Wilson, 2019; Crowley, Exton and Han, 2018) and a decrease in investment (Górnicka, 2018; Bloom, Bunn et al., 2019). Trade is generally linked with productivity increases, with the literature showing that the liberalisation of trade is linked to growth in income, innovation, and employment (Frankel and Romer, 1999; Pavcnik, 2002; Amiti and Konings, 2007; Bloom, Draca and Van Reenen, 2016; Handley and Limão, 2017). This effect could be due to productivity changes stemming from an improved allocation between firms (Pavcnik, 2002) or within-firm adjustments linked to trade. Thus, from an aggregated perspective, a reverse trade liberalisation shock to decrease productivity and innovation is expected.

In addition to being a trade policy shock, the Brexit referendum created uncertainty for firms that trade with the EU. The Brexit referendum was not only a trade policy shock but a trade policy uncertainty shock. There is substantial literature on uncertainty, the business cycle, output, and investment (Bernanke, 1983; Bloom, 2009; Basu and Bundick, 2017; Fernández-Villaverde and Guerrón-Quintana, 2020), showing that an increase in uncertainty about the future leads to a decrease in output, investment, and consumption. The effects of an uncertainty shock tend to be larger when tightly linked to political uncertainty (Redl, 2017), as is the case for Brexit.

Directly after the referendum, uncertainty was induced and high, as shown in Figure 5.14 in the appendix. It increased until September 2018 when the EU rejected the UK's proposal at the Salzburg summit, which raised the likelihood of a Brexit without an agreement and increased potential future trade costs. In November 2018, a withdrawal agreement between the UK and the EU was reached but was later refused by the UK parliament. With uncertainty still at a high level, it kept increasing until March 2019, when it was originally planned for the UK to leave the European Union. Uncertainty began to decrease once Brexit was delayed until October 31, 2019, while it was still high in July 2019 and greater than it had been in the initial two years following the referendum (Bloom, Bunn et al., 2019).

The Brexit referendum was a trade uncertainty shock that persisted for more than three years. Given the lack of clarity regarding how and when the UK would leave the EU, what conditions would follow afterward and the extent to which the UK economy would be impacted by it, it was more up to the firm's expectations how to adapt to this novel situation than actual knowledge about how it would develop. Related research has shown that firms are likely to act more cautiously, reducing their investment and innovation (Górnicka, 2018; Brown, J. Liñares-Zegarra and Wilson, 2019). This might happen instantly or with a slower response. Hassan et al. (2020) find an immediate effect of Brexit with the largest marginal effect on international firm investment in 2017. In contrast, Bloom, Bunn et al. (2019) find a gradual effect for UK firms. One explanation might be a "cautionary effect" induced by uncertainty (Guiso and Parigi, 1999) describing how firms slowly adapt their behaviour, implying that an effect a few years after the referendum would be observed.

5.2.2 The effect of Brexit on UK firms

Multiple papers have looked at the effect of Brexit on UK firms. This includes the effect on investment and productivity (Bloom, Bunn et al., 2019; Górnicka, 2018), on the stock market (Shahzad et al., 2019), on UK exports (Crowley, Exton and Han, 2018; Brown, J. Liñares-Zegarra and Wilson, 2019), the potential impact on SMEs (Brown, J. Liñares-

Zegarra and Wilson, 2019; Brown, Kalafsky et al., 2020), but also global firms (Hassan et al., 2020). Bloom, Bunn et al. (2019) estimate the effect of the anticipation of Brexit three years after the referendum, finding a substantial effect on firm investment and UK productivity, with Brexit decreasing investment by approximately 11% and UK productivity by around 2% to 5%. Their findings are representative of larger UK firms, as they use the Bureau van Dijk FAME database, with their sampling being based on UK businesses that have more than ten employees. They also find that firms more heavily exposed to the EU are more affected by Brexit, which is similar to the findings of other studies, such as Davies and Studnicka (2018) pointing out that a firm's global value chain position plays a major role, with those with higher EU exposure being more impacted. Evaluating the effect of Brexit on exporting behaviour of UK firms, Crowley, Exton and Han (2018) find that a substantial amount of firms have exported less and/or exited from exporting to the EU.

The number of studies focusing on the effect of Brexit on SMEs is limited, in particular, lacking evidence on the actual impact of Brexit. Brown, J. Liñares-Zegarra and Wilson (2019) focus on the potential impact of Brexit by looking at the expectations of SMEs after the Brexit referendum (2016-2017), stemming from extra questions in the LSBS about whether and why Brexit is perceived as a major obstacle. They find heterogeneity in their results, with more knowledge-intensive, larger, and internationally oriented businesses more concerned about the potential impact of Brexit (Brown, J. Liñares-Zegarra and Wilson, 2019). Another study focusing on SMEs uses a mixed-methods approach for the case of Scotland, combining survey data and interviews to show that a large part of SMEs was struggling operationally and strategically to deal with the uncertainty created by Brexit (Brown, Kalafsky et al., 2020).

5.2.3 The Geography of Discontent

A large number of studies has looked at the determinants of Brexit, emphasising the critical role of economic factors and geography. Other drivers have also been pointed out, in particular demographic and cultural factors. The economic hypothesis has found popularity given that economically left behind regions are those with a majority voting to leave (Norris and Inglehart, 2018). These regions include Yorkshire, Eastern England, and the Midlands, where more voters tend to be older, white, and less educated. Particularly those regions that have been historically reliant on mills and mining industries, with poorer households, higher unemployment, and lower educational attainment, have been showing their discontent with the status quo. Lacking opportunities and poor future prospects have led these “places that don’t matter” to revolt using the ballot box (Rodríguez-Pose, 2018). Indeed, the Brexit vote varies substantially across space, as shown in Figure 5.13 in the appendix.

Looking at the district level shows that the education levels of the population, low wages, high unemployment, and past reliance on manufacturing jobs are major predictors of voting in favour of Brexit (Becker, Fetzer and Novy, 2017). The gap between those benefiting and losing from economic globalisation has been found to be crucial for the vote (Hobolt, 2016), but also a growing gap between the internationalisation of local firms and their employees’ “localistic” viewpoints (Crescenzi, Di Cataldo and Faggian, 2018). Others point out the role of austerity, arguing that it has fuelled support for UKIP, transformed the political landscape and is the reason why the votes towards “Leave” outweigh the “Remain” ones (Fetzer, 2019). Zooming in on geography, a close link between geographic voting behaviour and spatial productivity has been pointed out in the case of Brexit by scholars. Differences in characteristics across spaces being reflected in the populist voting pattern is referred to as the “Geography of Discontent“ (Dijkstra, Poelman and Rodríguez-Pose, 2020; McCann and Ortega-Argilés, 2021). I am also interested in the spatiality of the effect, assessing how SMEs’ digital technology adoption has been differently affected, and whether those with higher Brexit votes have seen larger effects.

Which regions have been bearing potentially detrimental consequences of the “Geography of Discontent"? Which regions have been more affected by Brexit? Are those the regions that have voted for Brexit? These questions have been looked at by scholars. Studies have found mixed results, indicating that regions voting for Brexit have been hit harder (Los, McCann et al., 2017), which stands in contrast to the findings of Winters (2016) and Dhingra, Machin and Overman (2017). The study by Los, McCann et al. (2017) creates a measure determining the extent a region is dependent on EU trade and concludes that locations with higher Brexit votes have a higher EU dependency. Thus, regions with a higher vote share towards Brexit are more exposed. Dhingra, Machin and Overman (2017) find different results as they consider the substitutability for EU imports as well as the sectoral differences linked to the expected level of trade barriers arising upon the UK's leaving the EU.

5.2.4 Gap in the Literature and Contribution

Despite this evidence, less is known about how different SMEs respond to this trade policy uncertainty shock in terms of digital technologies. There is a substantial gap in the literature on quantifying the actual impact of the Brexit referendum since its withdrawal in 2020 on SMEs and their ability to innovate. To the best of my knowledge, no study has yet assessed SMEs' digital performance. Given the relevance of new technologies in reducing costs and enabling productivity gains, having a better understanding of the differential impact of this productivity shock on SMEs and their adoption of innovative technologies is vital, as SMEs play a central role in shaping regional economic outcomes. This study contributes to the existing literature by employing web scraping tools to identify technologies used in SMEs' website source code. This information can be used to track shifts in technology adoption that result from the Brexit vote, with a focus on different technologies and industries affected. Therefore, their conclusion differs, stating that locations with higher pro-Brexit votes will be more impacted by Brexit, such as London or the South East.

5.3 SMEs' potential digital response to the Brexit referendum

This section discusses SMEs' potential response in terms of digital technologies and how they are expected to adjust their behaviour after the Brexit referendum. The Brexit referendum is conceptualised as a trade policy uncertainty shock that led to higher potential future trade costs and, thus, more negative expectations about the business environment for firms trading with the EU. Given higher future costs linked with uncertainty, SMEs are expected to respond in multiple ways. First, they would likely reduce trade and innovation, which has already been shown by (Brown, J. Liñares-Zegarra and Wilson, 2019). This response is likely to be also reflected in digital technologies by observing a reduction of technologies linked to e-commerce, such as payment or shipping technology. This could be related to digital technologies that are free of charge or premium. Despite SMEs trading less than larger firms, previous research has shown that because of constrained resources and lacking resilience, SMEs tend to be disproportionately affected when it comes to higher uncertainty stemming from an unanticipated shock, in particular, linked to investment irreversibility (Ghosal and Ye, 2015). Thus, following the Brexit referendum, exposed firms are likely to respond by reducing e-commerce related digital technologies.

Second, firms have reduced capital investment, including investment in R&D and likely also related to digital technologies due to higher uncertainty about the future. Existing evidence shows that Brexit has led UK firms to cut investment (Górnicka, 2018; Bloom, Bunn et al., 2019), including SMEs reducing investment in innovation (Brown, J. Liñares-Zegarra and Wilson, 2019). Therefore, it is likely that SMEs would also cut costs on digital technologies, decreasing, in particular, the amount spent on cost-intensive technologies and digital technologies less relevant to the core business.

Third, in addition to SMEs reducing digital technologies related to e-commerce and cutting investment, a third channel is discussed, which is through a change in SMEs' strategic intentions. In this case, the direction of their strategic planning changes, given the unexpected trade uncertainty shock. Instead of planning growth-related activities, the management of the SMEs will spend more time conducting an assessment of how Brexit will affect the firm and devising strategies on how to respond to this shock. The time on expansion is replaced by Brexit planning. Bloom, Bunn et al. (2019) show that this is the case for UK firms, being one of the main channels why firms become less productive after the Brexit referendum. I expect firms to spend less time searching and learning how to adopt a free or premium technology for this channel. Thus, I could also expect to see a decrease in free digital technologies on firms' websites. For all three channels, a large number of SMEs trading with the EU is expected to be affected, given that the EU is their major trade partner of UK firms.

5.4 Data

5.4.1 Longitudinal Small Business Survey

The Longitudinal Small Business Survey is compiled by the UK Department for Business, Energy, and Industrial Strategy (BEIS) and is available yearly from 2015-2021 as a cross-sectional and longitudinal survey. It is a large-scale telephone survey that covers around 0.1% of the UK SME population, with approximately between 6,500 and 16,000 SMEs participating every year (UK Data Service, 2019). Every year, the LSBS surveys businesses with less than 250 employees, with the majority of questions being repeated every year. The sample is stratified by UK region, sector, and size, covering information on performance measures of SMEs, including employment, innovation, exporting and turnover (UK Data Service, 2019).

The LSBS was chosen to study the effect on SMEs for multiple reasons. First, it covers a large population of firms. Second, it includes rich information on firm-level characteristics. Information on sector, region, turnover, trade, and innovation allows us to classify firms according to relevant groups. Third, it includes specific questions on Brexit, making it possible to understand firms' perceptions towards Brexit. The survey is conducted in the second half of each year, with the perception of Brexit being asked after the referendum in 2016. The surveys in 2017 and 2018 were carried out during a time of high uncertainty created by Brexit, and in 2019 the fieldwork was completed before the start of the Coronavirus pandemic (BEIS, 2019).

One limitation is that we cannot observe variables from the LSBS over the observation period, which is from 2013-2019. As the LSBS has only started in 2015 and some SMEs have only participated once or twice in the survey, it is not possible to assess how certain variables have developed over time, for example how employment has evolved. However, we can use information that has not changed, such as sector. For variables like trading with the EU, a firm is assigned to do so if it has done so at least once. We use relevant information from the LSBS and complement it with measures of the firm's partial technology stack. Another limitation is that we cannot distinguish between business-to-business or business-to-consumer trade as we do not know whether SMEs are selling goods or services to consumers or firms or both, as the LSBS does not include this information. The previous version, the Small Business Survey, has done so in 2015 showing that firms that do not export have on average 38% of business as their main customers, which means that the larger part of their customers are consumers (BEIS, 2016). It is estimated that of those business that SMEs are supplying to, 29% are exporters (BEIS, 2016). Thus, it is likely that SMEs' main customers are both, firms and consumers. However, as information in the LSBS about the individual firms is lacking, the information on business-to-business or business-to-consumers trade cannot be used in the analysis.

5.4.2 Existing vs. novel measures of firm-level technology adoption

A considerable amount of literature has been published using measures of technology adoption. At the firm level, this includes patents (Jaffe and Trajtenberg, 1999; Forman and Zeebroeck, 2019), Research and Development (R&D) expenditures (Stoneman and Kwon, 1996; Bessen, 2002) as well as survey-based measures (Cirera et al., 2021). As patents are more likely to be filed and approved for larger firms, they do not seem an appropriate measure focusing on SMEs (Succurro and Costanzo, 2019). Survey-based measures within the UK, such as the LSBS, include questions on innovation within the firm but ask only very broadly whether a new process or product innovation has been adopted within the last three years.

Most surveys lack information on detailed measures of technology adoption, particularly on digital technologies for SMEs. For the US, the 2018 Annual Business Survey has included a new survey model covering technologies linked to the Fourth Industrial Revolution. Analysing the findings of the survey, Zolas et al. (2021) found that while some technologies, such as cloud computing, appear to be widely adopted, others, such as artificial intelligence, tend to be highly skewed, with only very productive firms having adopted them. For the UK, measuring innovation and technology adoption across firms in the UK is commonly done using the UK Innovation Survey (Battisti and Stoneman, 2010; D'Este et al., 2008; Crescenzi, Gagliardi and Iammarino, 2015), which is part of the wider Community Innovation Survey and covers the topic of innovation in detail. However, the UK Innovation Survey is focused on larger firms, containing only firms with more than ten employees, leaving out a majority of firms within the UK. For smaller firms, selected surveys on digital technologies have been implemented, such as by Stankovska, Josimovski and Edwards (2016). They surveyed 66 SMEs in the UK, documenting the high usage of SMEs for some digital channels, particularly social media. To get information on a large sample of SMEs, the LSBS can be used. The LSBS questions cover a large spectrum of SMEs' characteristics, with innovation being one aspect of many. Therefore, the information on which technologies were adopted is broad, which is why the LSBS data is complemented with novel measures on digital technologies.

5.4.3 Novel measures of firm-level technology adoption

Accessing data from business websites provides novel insights on firm-level digital technology adoption. Digital technologies refer to the illustration of information in bits (Goldfarb and Tucker, 2019). The rationale behind many firms adopting digital technologies is to reduce costs, with the costs consisting of tracking, search costs, reproduction, verification and transportation and benefit from productivity gains (Goldfarb and Tucker, 2019). This paper complements the LSBS data with data from business websites using BuiltWith, which scrapes the websites getting data from the page body, cookies, and server headers. For every SME with a website, I get detailed information for 33 different technology categories and when they have been observed for the first time. This can, in contrast, provide more detailed information than surveys, allowing an understanding of the process of technology adoption at a more granular level. Having more information to complement existing measures of technology adoption provides a better evidence-based foundation for policymakers to adjust their existing policies, given that fostering digitalisation is at the centre of many policymakers aiming to foster economic growth. The goal is to provide a more accurate measurement of drivers of productivity and which technologies have a larger contribution to this, particularly in the wake of Brexit. This study is not the first to use data on technology adoption of firms using information from their website and leveraging the platform BuiltWith. Among others, Ragoussis and Timmis

(2022) use it to analyse the digital response of firms during the COVID-19 pandemic, and Koning, Hasan and Chatterji (2022) test how experimentation affects start-up performance.

5.4.4 Linking LSBS data and business' website data

The LSBS data includes the firm name and address if firms have agreed to data linkage, which is the case for 32,139 SMEs out of 39,177, making it possible to search for their website. To find and verify company homepages, a multistage process is used involving online searches on DuckDuckGo and fuzzy string matching. Initially, a search is conducted using the keywords "company name" and "UK company". If the company name highly matches one of the resulting URLs, it is considered the homepage. If unsuccessful, a secondary search extends the search by adding the company's address to the keywords. Upon finding a suitable URL in either stage, a verification step checks the company's LSBS provided address presence on the alleged homepage. If the address is found, the homepage is classified as "verified". 9,685 homepages are found, out of which 4,423 are verified. For the analysis, only the 4,423 SMEs where the homepage is classified as verified are used. I construct a balanced panel dataset following these firms for seven years, constructing a sample of 30,961 observations. One limitation from linking LSBS data and business websites is that only time-invariant characteristics from the LSBS questionnaire can be observed, for example industry. As some firms participate in the LSBS in only one year, it is not possible to track changes stemming from the LSBS data over time.

5.4.5 Measuring technology adoption using data from business websites

As soon as we obtain the right URL of the business website, I can get the information about technology adoption from their website. I do this by using the tool BuiltWith, which is a database covering a large number of web technologies that enable us to determine which technologies a firm's website is using. Whenever a website is built with a certain technology, I assume that this firm has adopted this technology. For example, if I find the technology Shopify on a firm's website, I assume that a firm has adopted one technology in the e-commerce category. I can follow firms over time, as BuiltWith detects when a firm uses a technology for the first and the last time, providing information from 2000 onwards. With this information, I can create the partial tech stack of a firm, showing for each of the 33 categories the count of technologies.

Digital technologies related to e-commerce

Given that Brexit is a trade policy uncertainty shock, I am interested in technologies linked to e-commerce, with some of them more closely related than others, describing technologies that are trade-enhancing. This includes eight technology categories, including payment, javascript, secure sockets layer, language, analytics, shipping, e-commerce and content delivery network. Each category contains multiple specific technologies, and I count the number of technologies for each category by firm and year. Payment describes any technology that enables online payment, such as Visa or Mastercard. Javascript is used for interactive elements often linked to e-commerce, such as shopping carts or login information. A secure sockets layer is adopted for secure payment, enabling encrypted communication. Different languages are relevant for trading internationally, as well as shipping and e-commerce. In addition, analytic technologies are likely more relevant for firms that rely on their turnover mostly generated from their website. A content delivery network is also often adopted by firms using e-commerce, given that it is used for scaling up.

Limitations using technology adoption data based on business websites

One main limitation of using indicators relying on web scraping business websites is the selection of firms into technology adoption. There are major differences across firms regarding whether they actually have a website and how advanced their website will be. Many firms do not have a website but only a Facebook page or other online representations of their business. Firms self-select into technology adoption, signifying that the sample will not be representative of the overall SME population but will rather over-represent firms that tend to adopt technology quicker and that are more productive, with a low or missing representation of less innovative firms. Moreover, I can only observe when a technology has been detected for the first and the last time. If a firm frequently removes and adopts a technology, I cannot observe it. However, it is not likely that firms will adopt and remove a technology frequently, given that this is an investment in capital or time. For a major shock like Brexit, I expect, though, that firms would reconsider the use of certain technologies. Additionally, I cannot observe whether the website was built internally or outsourced. For this paper, even if the development and maintenance of the website were outsourced, it would still be interesting to observe what happens after a major shock like Brexit. Since firms are likely to cut investment, this might also include reducing spending on website maintenance. Finally, the information how much firms spend on each digital technology would be of high interest, in particular whether there are high sunk costs involved, as well as how high the costs of maintenance are. This information is not provided by BuiltWith, thus it will not be included in the analysis.

5.4.6 The Brexit vote

This paper is also interested in how the effect on firms varies across space, thus data linked to Brexit is obtained. This is the Brexit vote from the referendum on June 23rd, 2016. I get the data from Norris (2019a), covering the calculated percentage of voters supporting the decision to leave the European Union at the constituency level. The vote share for “Leave" is aggregated to the NUTS-3 level.

5.5 Descriptives

5.5.1 Brexit as a major obstacle for SMEs

The aim is to show whether Brexit was perceived by SMEs as a major obstacle and to what extent. To get a general picture that is representative of the SME population, I use the cross-section for the specific questions introduced to the LSBS questionnaire in 2016 inquiring whether the UK leaving the EU is seen as a major concern. I calculate the percentage of firms indicating that Brexit is a major obstacle relative to all SMEs in the respective year and weigh it with cross-sectional weights. I show the extent and development of Brexit being perceived as an obstacle, for all SMEs and exporters over time, which are shown in Figure 5.1 and 5.2. In general, it can be observed that the percentage of SMEs being concerned about Brexit tends to be around 20% for all years. Thus, while around $\frac{1}{5}$ of SMEs is concerned about Brexit, a large part has indicated otherwise. SMEs are definitely more likely to indicate that Brexit is a major obstacle if they think they are affected by it. This finding is relevant for the construction of the control group, indicating clearly that a large part of SMEs tends to see Brexit not as an obstacle as they expect not to be affected by it. The majority of these SMEs have not exported in the last year or innovated within the last three years. Smaller firms being more likely to be underrepresented in international trade, given less resources available to cover higher costs usually linked to entering foreign markets (OECD, 2019).

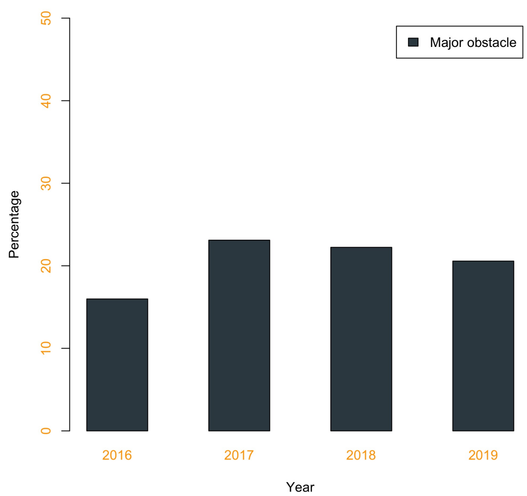

Figure 5.1: Percentage of SMEs that perceive Brexit as major obstacle, weighted, 2016-2019

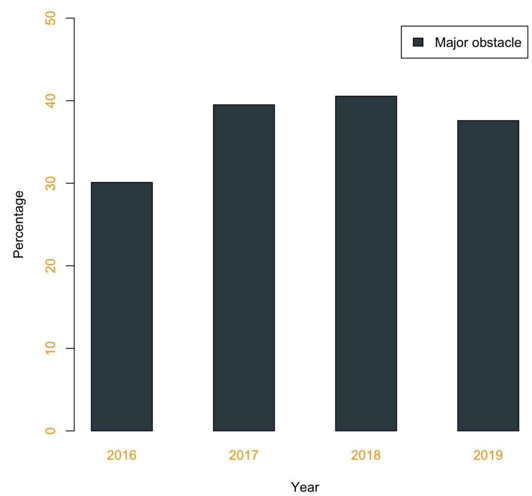

Figure 5.2: Percentage of Exporters that perceive Brexit as major obstacle, weighted, 2016-2019

It also shows that the percentage of firms perceiving Brexit as a major obstacle increased over the observation period, reaching its peak in 2017. In 2016 the concern tends to be the lowest with a substantial rise in 2017. In 2018 and 2019 the concern for Brexit as a major obstacle slightly declines, remaining at a higher level than in 2016. The figure for exporting SMEs, Figure 5.2, shows a similar trend, but at an elevated level, clearly pointing out that the concern of exporters towards Brexit as a major obstacle is substantially higher.

5.5.2 Types of Brexit-related Obstacles

The Brexit referendum affects SMEs in multiple ways, but mostly through trade with the EU and uncertainty. In 2017, SMEs participating in the LSBS were surveyed about their views on Brexit as a significant hindrance. If they responded affirmatively, they were further asked about the specific factors they considered obstacles. Figure 1 shows the percentage of SMEs concerned about each relevant factor as a percentage of all SMEs that perceived Brexit as a major hurdle in 2017. Uncertainty related to the EU market, uncertainty linked to regulation and an increase in import costs are most commonly viewed as the major obstacles related to Brexit, with more than 50% indicating so. The results of the survey support empirically that trade policy uncertainty compiles the major shock for SMEs.

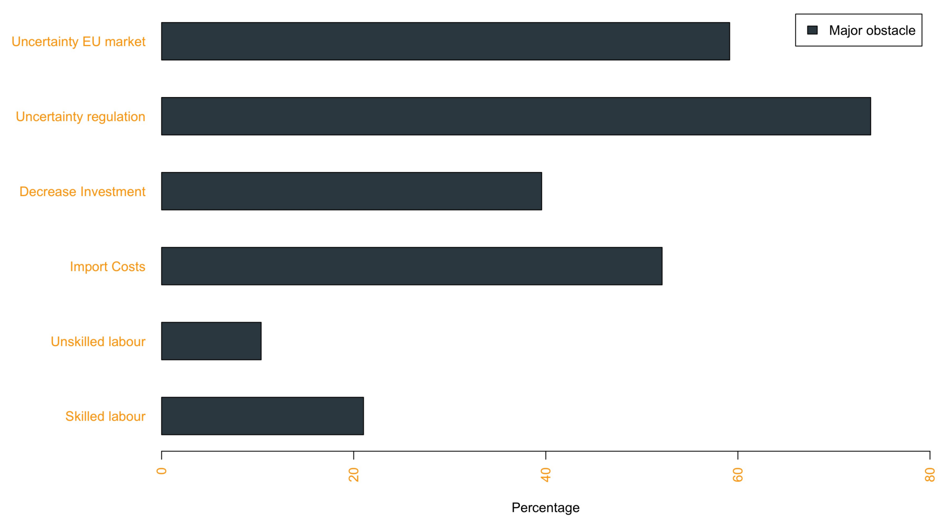

Figure 5.3: Type of Brexit-related obstacles, weighted, 2017

5.5.3 Development of Digital Technology Adoption Levels over Time

This subsection also plots how different digital technology levels develop over the observation period, from 2013-2019. It shows an increase in the average count of most digital technologies. Figure 5.4 plots the development for e-commerce related technologies, showing an increase in the technologies javascript, analytics, content delivery networks, secure layer, payment and shop. No changes for shipping or language are shown, where the average count of technologies is close to 0. Given the lack of change and low levels of these digital technologies I cannot include them in the analyisis. For these eight categories, javascript is the most used, with an SMEs on average possessing 1 in 2013 and more than 4 in 2019. For analytics, content delivery networks and secure layer SMEs tend to have on average 1 of these digital technologies. In Figure 5.5 the development of further technologies, including content management (mgmt), framework, hosting, media, mobile and web server is shown. All technologies are increasing over time.

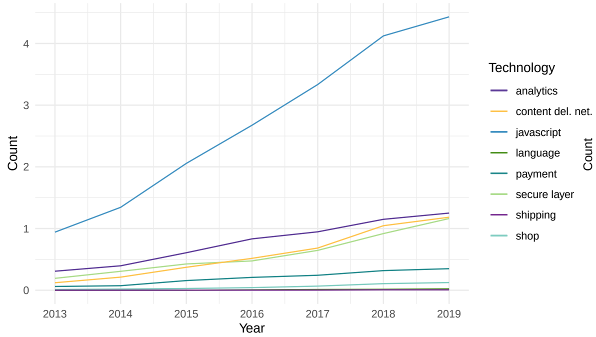

Figure 5.4: Development of e-commerce related technologies, 2013-2019

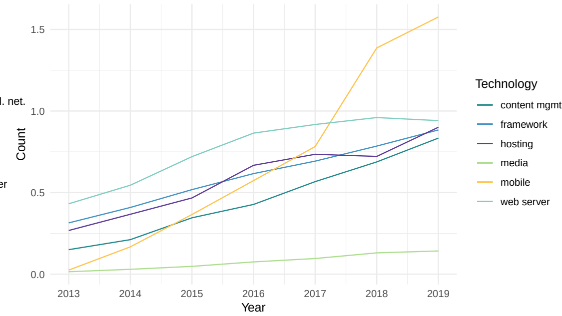

Figure 5.5: Development of other technologies, 2013-2019

5.5.4 Changes in digital technologies by group

For e-commerce related technologies this subsection plots the average changes per group between 2013 and 2019. The treatment group consists of SMEs that have indicated trading with the EU at least once, which applies to 1,286 firms. The control group makes up 2,921 SMEs. So, if firms in the sample have participated in the LSBS twice and indicated trading with the EU only in one year, they will be assigned to the treatment group. SMEs that have never indicated to trade with the EU, in contrast, are assigned to the control group. I have excluded shipping and language, given that only a very small number of SMEs possess these, substantially reducing the sample in the analysis to a few hundred observations. For e-commerce, I come to the conclusion that the parallel trends assumption does not hold, as shown in Figure 5.16 in the appendix. For the other five technologies - payment, secure sockets layer, analytics, javascript and content delivery system - I find that before the treatment, the trends appear to move in parallel. 2013 is used as the first year, given that in the previous years the mean and the change have been centred around 0. For e-commerce, in contrast, a drop in the adoption from 2014-2015 in the treatment group is found, whereas the control group observes an increase. For this reason, it cannot be assumed that the parallel trends assumption is met and thus it will be excluded from the following analysis. For most of the five digital e-commerce related technologies, an immediate drop after the treatment, in 2017, is observed. While before 2016, the average change in the treatment group was mostly above that of the control group, it dropped below its comparison for the first time after the Brexit referendum.

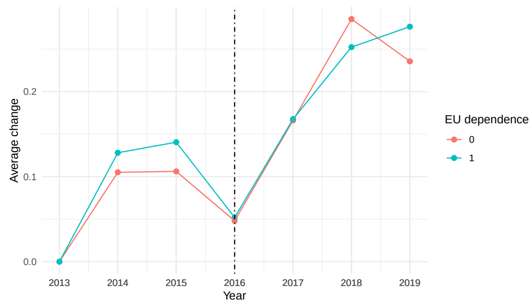

Figure 5.6: Average trends secure socket layer by group, 2013-2019

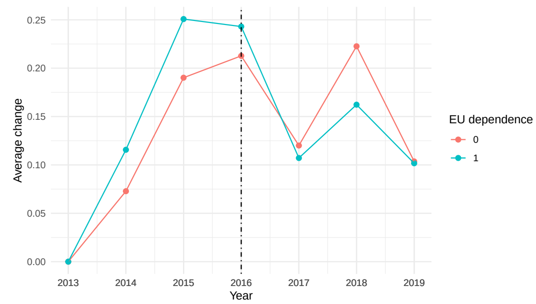

Figure 5.7: Average trends analytics by group, 2013-2019

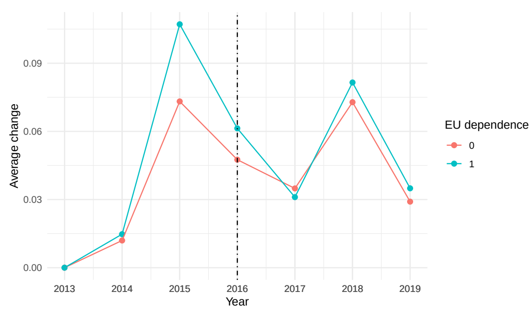

Figure 5.8: Average trends payment by group, 2013-2019

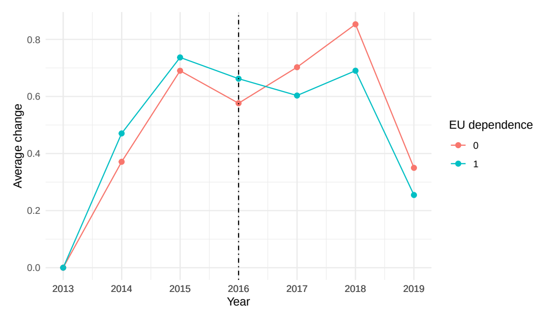

Figure 5.9: Average trends javascript by group, 2013-2019

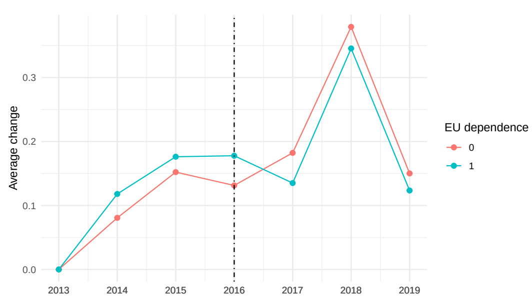

Figure 5.10: Average trends content delivery network by
group, 2013-2019

5.6 Methodology: Difference-in-Differences

This paper studies the effect of Brexit on firm-level performance, focusing on how digital technology adoption has been affected. It does so by exploiting the Brexit referendum as a trade policy uncertainty shock to firms that trade with the EU, compared to all SMEs that do not trade with the EU.

5.6.1 EU Dependence: Trade with the EU

Previous papers have used a difference-in-differences approach to estimate the effect of Brexit on different outcome measures. The effect on trade has been studied, among others, by Crowley, Exton and Han (2018), Kren and Lawless (2022) and Freeman et al. (2022). I study the effect of Brexit on firm-level performance, focusing on how digital technology adoption has been affected. I exploit the Brexit referendum as a trade policy uncertainty shock to firms that trade with the EU, compared to those that do not trade with the EU or do not trade at all. I use a standard 2x2 difference-in-differences equation in the following form:

$$y_{it} = \beta(EU_i * Post_t) + v_i + v_t + \varepsilon_{it} \tag{5.1}$$

where y_{it} describes the count for the digital technology i in year t related to e-commerce, EU_i is a dummy for firms that take the value one if they trade with the EU and 0 otherwise, $Post_t$ a time dummy taking the value 1 for all years after 2015, v_i are firm fixed effects, v_t are year fixed and ε_{it} the error term. I use the technologies related to e-commerce described in section 5.4.5 where parallel trends hold, as described in the previous section. Firm fixed effects control for time-invariant heterogeneity including sector, age and size, which all are major predictors for the adoption of technology. As the dependent variable is a count variable, a Poisson model is used to estimate the effects and cluster the standard errors at the firm level.

5.6.2 Identification Assumptions

Given the difference-in-differences approach, causal identification relies on the parallel trends assumptions. Thus, in the absence of treatment, the outcome of the treatment group and the control group would have moved in parallel. In this case, the average changes in digital technology adoption of the group of SMEs that trade with the EU have moved in parallel with the average change of the control group. In section 5.5.4, we plot the average outcome changes per group between 2013 and 2019 to show that the changes of both have been moving in the same direction before the treatment. In addition, we plot the dynamic treatment effects in Figure 5.17 in the appendix, including the pre- and post-treatment periods. It shows that none of the pre-treatment coefficients is significantly different from 0, which further supports that there are no differences in the trend for the two groups prior to the treatment and that no anticipation effects are present.

A challenge to causal identification could stem from other shocks affecting technology adoption, which might lead to the identification of another shock or an interaction with it. One of these shocks could be the Covid-19 pandemic. Previous research by Riom and Valero (2020) has shown that Covid-19 has impacted many firms to adopt remote work and has accelerated digital tech adoption for more than 60% of the UK firms surveyed. To disentangle the effect of Brexit, we exclude the last year of the transition period before the UK–EU Trade and Cooperation Agreement was signed. Thus, the post-treatment period lasts from 2017-2019, excluding the period from 2020 onward due to Covid-19.

Moreover, I address concerns regarding the timing of assignment to the treatment and control group, potential responses of the treatment group and contamination of the control group. First, firms cannot be assigned to treatment before Brexit in all cases, as I do not have the information before 2016 in all cases as it depends on when firms participated in the LSBS (see Section 5.4.1). However, it is not likely that firms started trading with the EU for the first time as a response to Brexit as (1) firms have responded with a decrease in trade after Brexit, (2) trading with firms in other foreign markets is costly as well as risky and (3) uncertainty was high. Thus, it appears unlikely that Brexit caused firms to trade with the EU for the first time. In a similar vein, it is also not likely that SMEs have started trading with other countries, such as the US, given that it contains higher risks and costs, which are avoided in a highly uncertain period such as after the Brexit referendum. Third, a potential concern about the control group might be that it is also affected by Brexit. Around 80% of the representative

SME population indicated that Brexit is not a major concern (see Figure 5.1) and thus they are likely not affected. However, there might be still cases when SMEs are affected by Brexit despite not trading with the EU. One example would be if the SME is a supplier to another firm that trades with the EU. Unfortunately, we do not have any information on supply chains or how many of the SMEs' employees are from the EU, but we know whether firms are concerned about Brexit. SMEs that have indirect linkages to EU trade or have more EU employees are more likely to be concerned. Thus, I add a robustness check in Section 5.9 to avoid contamination of the control group. For these both cases, we would anticipate to have a conservative estimate, given that for the two case mentioned we would expect control firms to reduce their digital technology adoption as well.

5.6.3 The Local Economic Effects

This study also estimates how differences in regional voting patterns affect SMEs' digital technology adoption. This strategy thus exploits the inter-regional differences in the actual Brexit vote share, and identifies the effect of Brexit on firm-level performance between regions. I estimate a difference in-differences equation of the following form:

$$y_{ijt} = \beta(BrexitVote_j * Post_t) + v_i + v_t + v_j + \varepsilon_{ijt} \tag{5.2}$$

with y_{ijt} being the count for the digital technology i in year t related to e-commerce, $BrexitVote_j$ is the Brexit vote share per region j at NUTS-3 level, $Post_t$ is a dummy that takes the value of 0 before 2016 and 1 after. v_i are firm fixed effects, v_j are region fixed effects and v_t are year fixed effects.

5.7 Results

5.7.1 Main Results: e-commerce related digital technologies

Table 5.1 shows that SMEs which trade with the EU experienced, on average, a decline in all five e-commerce related digital technologies compared to the comparison group and before the Brexit referendum. For payment, secure sockets layer, analytics and javascript, the decline is significant at the 5% level. The coefficient of the content delivery network is negative but not statistically significant. The dynamic treatment effects for all five digital technology groups are shown in Figure 5.17, showing that the pre-treatment coefficients are insignificant and most of the post-treatment coefficients are significant, with an increasing trend until 2019. The effect intensifies until 2019, suggesting a gradual response by SMEs adjusting to the shock. In addition, we run negative binomial regression models, the results are shown in Table 5.6 and confirm the findings of this section.

Table 5.1: Regression Results: The effect of Brexit on digital technologies related to e-commerce

Dependent Variables:	Payment	Secure Layer	Analytics	Javascript	Content Del. Net.
Model:	(1)	(2)	(3)	(4)	(5)
Post × EU trade	-0.165**	-0.135**	-0.199***	-0.154***	-0.068
	(0.076)	(0.053)	(0.042)	(0.041)	(0.061)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	8,540	20,594	15,820	21,301	17,080
Squared Correlation	0.60438	0.44457	0.59391	0.65514	0.63701
Pseudo R^2	0.25204	0.22088	0.24086	0.40801	0.33278

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes have been removed.

These findings align with other studies showing that firms have reduced exports (Crowley, Exton and Han, 2018; Brown, J. Liñares-Zegarra and Wilson, 2019) after the Brexit referendum, which is likely also reflected in e-commerce related digital technologies. Given that SMEs reduce trade in general or just for particular goods or services, they are likely to respond by also removing or reducing technologies that are needed to trade. The response intensifies over time, which can be explained by trade policy uncertainty remaining high for firms until 2019, leaving firms adjust their digital behaviour three years after the Brexit referendum. Until then, it was not clear whether there would be a "hard" or "soft" Brexit, leaving firms in trade policy uncertainty. The results suggest that SMEs have responded to this trade uncertainty shock by reducing trade-enhancing technologies over these three years after the Brexit referendum, compared to SMEs that do not have any direct links to the EU.

5.7.2 Results by Sector: digital technologies related to e-commerce

Table 5.2 below looks at the effect by industry (SIC1DIG), demonstrating that multiple sectors drive the overall effects. This is the case for all technology groups, where different sectors are relevant for explaining the overall decline. These include typical sectors for the trade of goods, such as manufacturing or retail, but also for the trade of services, like professional and scientific as well as other services. For the category payment, the results show a significant decline in the primary sector, other services as well as wholesale and retail, with the largest coefficient in other services. Regarding secure sockets layer, I find that in the sectors education, manufacturing, wholesale and retail, as well as information and communication a significant decline can be observed, with the largest changes observed in the education sector. For analytics, I find a significant decrease in the primary sector, in administrative, and support services, in manufacturing, wholesale and retail as well as professional and scientific services, with the largest change in the primary sector. The overall decline in javascript is driven by the primary sector, manufacturing, transport and storage, information, and communication as well as professional and scientific, also showing the largest decline in the primary sector. For the content delivery network category, I find that the overall decline stems from the sectors education, accommodation and food as well as professional and scientific services, with the largest decline in the education sector. Thus, the significant reduction in e-commerce related digital technologies stems from the decline of technologies in multiple sectors, which vary by technology class and in magnitude, with the education, service, information and communication as well as the primary sector playing a major role.

Table 5.2: Regression Results: The effects of Brexit on digital technologies by Sector

Dependent Variables:	Payment	Secure Layer	Analytics	Javascript	Content Del. Net.
Model:	(1)	(2)	(3)	(4)	(5)
Treat × Primary	-0.658**	0.109	-0.499**	-0.498*	-0.195
	(0.320)	(0.360)	(0.253)	(0.276)	(0.311)
Treat × Admin./Support	-0.272	-0.193	-0.284**	0.023	-0.139
	(0.192)	(0.176)	(0.135)	(0.131)	(0.161)
Treat × Education	0.088	-0.500*	0.608	0.250	-0.603**
	(0.454)	(0.283)	(0.434)	(0.302)	(0.300)
Treat × Health/Social Work	-0.390	-0.119	0.326	0.153	-0.076
	(0.404)	(0.398)	(0.396)	(0.269)	(0.288)
Treat × Arts/Enter.	-0.333	-0.172	-0.185	0.149	-0.387
	(0.311)	(0.266)	(0.253)	(0.380)	(0.336)
Treat × Other service	-0.738**	-0.087	-0.195	0.073	0.104
	(0.358)	(0.451)	(0.218)	(0.215)	(0.184)
Treat × Manufacturing	-0.129	-0.223**	-0.213***	-0.186**	0.056
	(0.137)	(0.089)	(0.064)	(0.072)	(0.133)
Treat × Construction	-0.090	0.141	0.142	0.076	0.432
	(0.334)	(0.250)	(0.216)	(0.191)	(0.334)
Treat × Wholes./Retail	-0.206*	-0.177*	-0.141**	-0.114	-0.104
	(0.112)	(0.091)	(0.070)	(0.077)	(0.115)
Treat × Transp./Storage	0.459	-0.139	-0.079	-0.235	-0.030
	(0.581)	(0.177)	(0.174)	(0.144)	(0.171)
Treat × Accomm./Food	0.243	-0.014	-0.187	0.009	-0.386**
	(0.398)	(0.239)	(0.164)	(0.145)	(0.191)
Treat × Inform./Comm.	-0.368	-0.274**	-0.265**	-0.269**	0.076
	(0.287)	(0.121)	(0.125)	(0.132)	(0.244)
Treat × Financial/Real Est.	-0.158	0.559	-0.250	-0.294	0.018
	(0.414)	(0.473)	(0.191)	(0.204)	(0.262)
Treat × Profess./Scient.	0.060	0.024	-0.220**	-0.227**	-0.287**
	(0.183)	(0.142)	(0.094)	(0.101)	(0.127)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	7,560	18,319	14,140	18,879	15,141
Squared Correlation	0.611	0.447	0.591	0.658	0.643
Pseudo R^2	0.253	0.220	0.235	0.406	0.336

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes were removed.

5.7.3 Local Economic Effects

This section looks at how the effect varies across space, whether regions with higher Brexit vote shares are more likely to bear a higher burden in the form of lower technology adoption. Studies have found mixed results on which locations will be hit harder. Some have indicated that regions voting for Brexit have been hit harder (Los, McCann et al., 2017), while others have found the opposite (Winters, 2016; Dhingra, Machin and Overman, 2017). To test whether regions that voted for Brexit are more affected, the regional Brexit vote share is interacted with the post dummy and the results are shown in Table 5.3. It shows that regions with a higher vote share tend to observe higher adoption of all e-commerce related digital technologies. Thus, regions that have not voted for Brexit are more affected, in the form of lower adoption of new technologies.

Table 5.3: Regression Results: The effect of Brexit on digital technologies in “Leave" compared to “Remain" areas

Dependent Variables:	Payment	Secure Layer	Analytics	Javascript	Content Del. Net.
Model:	(1)	(2)	(3)	(4)	(5)
Post × Brexit Vote	0.010***	0.004*	0.006***	0.005**	0.007**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	8,792	20,853	15,953	21,427	17,185
Squared Correlation	0.602	0.442	0.592	0.658	0.632
Pseudo R^2	0.251	0.219	0.238	0.409	0.330

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes have been removed.

5.7.4 Other technologies

In addition to the effect on trade-enhancing technologies, this section also looks at other technologies that may have been significantly impacted by the Brexit referendum. This is highly relevant to understand whether SMEs are not only responding through the trade channel but whether this trade policy uncertainty shock has had a wider impact beyond trade. The results suggest that this is the case, as shown in Figure 5.11 (and in Table 5.7, in the appendix), where I show seven digital categories where I find a significant effect. For all seven technologies, the results are statistically significant at the 5% level, indicating a negative effect for technologies that are not classified as e-commerce. In response to the trade policy shock, SMEs reduce or adopt fewer multiple digital technologies, including media, content management systems, framework, hosting, mobile, web server and name server. The coefficients vary in size, with the largest coefficient in media, followed by name server and mobile.

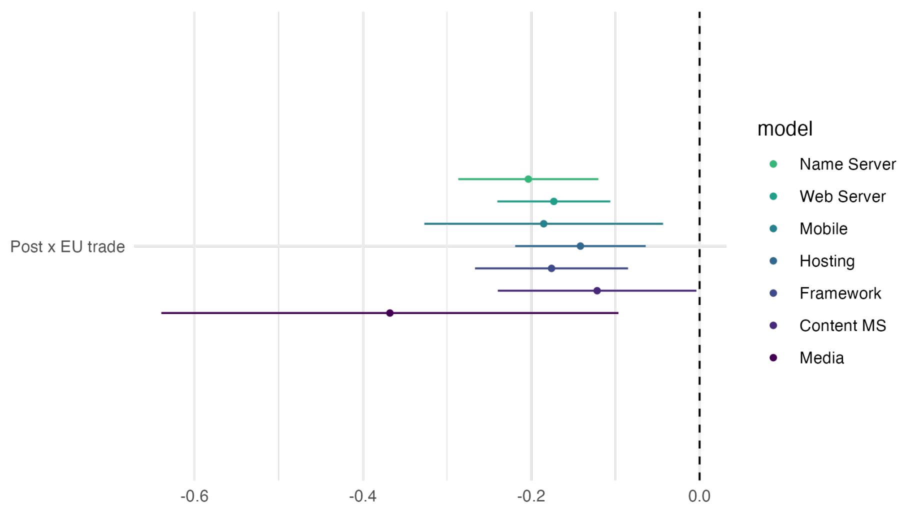

Figure 5.11: Coefficient plot: The effect of Brexit on other technologies that are not e-commerce related

Some of these technologies can be regarded as basic technologies, suggesting that SMEs are removing basic technologies that are needed for the functioning of the website. One example would be name server; websites would only be useful if they can be found using a human-readable name, not via the IP address. SMEs might remove these technologies or adopt them less as they stop using them temporarily, compared to before the Brexit referendum. Therefore, the results suggest that Brexit has had a major impact beyond the trade channel, removing basic technologies needed for the functioning of a website. These results are also in line with what was found in previous literature. Given that the Brexit referendum has had a major impact not only on trade but also on investment, productivity, and overall innovation, I would expect firms to be affected to a larger extent.

5.8 Mechanisms

There could be multiple explanations why firms that trade with the EU are scaling back digital technology adoption. These channels are reduced trade, lower investment and strategical realignment. By looking at different dependent variables and LSBS survey responses, I find support for these channels.

5.8.1 Plans of SMEs affected by the Brexit referendum

In addition to asking how SMEs perceive Brexit, they are also asked what plans have been affected. From 2017 onwards, SMEs of cohort B in the LSBS were surveyed about whether their plans for the next three years have been affected by Brexit. In the survey, the following question is posed: "Have any of these plans been affected by the UK exit from the EU? IF YES: Which plans?" and a set of answers is provided. The answers are coded as a binary variable. I use the first year where the question is asked in 2017 to provide an overview of how SMEs have been affected. In Figure 5.12, the percentage of those SMEs that indicated that their plans had been affected by Brexit for different relevant answers are shown. It shows that "increasing export sales or begin selling to new overseas markets" is the most commonly indicated, with around 35% of SMEs whose plans have been affected related to exporting and selling overseas. Launching a new product and services (15.2%), capital investment (14.7%) and investing in R&D (14.4%) are the most frequent plans disrupted due to Brexit after exporting. Increasing skills (10.9%) and new working practices (10.9%), in contrast, are the least indicated by those SMEs whose plans have been affected.

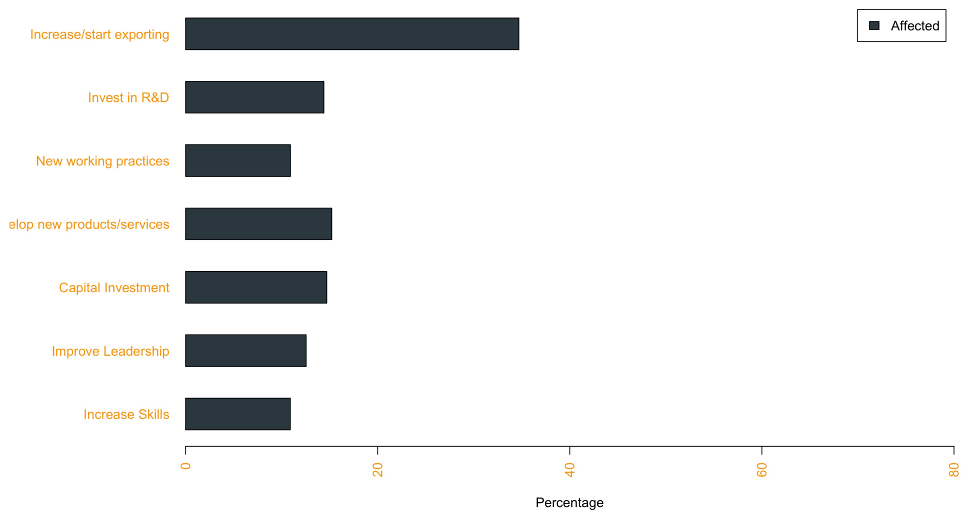

Figure 5.12: Type of plans affected by Brexit, weighted, 2017

First, the Brexit referendum changed firms' expectations towards higher trade costs and administrative burdens, thus they were likely to reduce trade with the EU. A substantial amount of SMEs have voiced their concern over import costs and uncertainty about the EU market (see Figure 5.3) and SMEs' most frequently disrupted plans are linked to exporting (see Figure 5.12). Combined with the main results - a decline in e-commerce related technologies - it is reasonable to conclude that trade is an important channel. Second, looking at investment, I find supporting evidence that it plays a role. First, I do not only find evidence for a decline in technologies that are linked to e-commerce/trade, but also for other technologies. This suggests a broader impact than only through only the trade channel. Moreover, SMEs have been highly concerned about uncertainty, which is often linked to lower investment. This is also shown by the responses of SMEs indicating that their plans concerning investment in R&D and capital investment has been affected. Finally, there is also support for the strategic realignment channel, which means that SMEs spend less time on planning future-growth but instead adjust their strategies. The LSBS survey responses show that SMEs have also changed the introduction of new working practices or put on halt improving leadership, which is likely to suggest some strategic reorientation after the Brexit referendum. Finally, there might be also that the Brexit referendum affects employment (for example EU workers to leave the UK). There is less evidence in the survey responses, but it might still play a role as SMEs indicated being affected concerning skills (see Figure 5.3 and Figure 5.12).

5.9 Robustness

This section conducts further robustness tests to verify that the control group has not been affected by Brexit. As discussed in Section 5.6.2, there might be a concern that the control group could be affected indirectly, for example through supply chains with SMEs being dependent on EU trade or by having many EU employees. As the LSBS lacks information on these two specific cases, I use the information whether firms regard Brexit as a major obstacle. It is likely that firms that have indirect linkages to the EU are concerned about Brexit. Thus, as an additional check, observations in the control group that have indicated at least once that they are concerned about Brexit are removed. In these both cases where the control group might have been affected, a conservative estimate is expected (as in Table 5.1), as control firms have likely reduced their digital technology adoption as well. Thus, in this robustness check, the effect size is expected to be larger. This is the case in Table 5.4, which might be because of the initial control group being affected or because of a substantially smaller sample size being analysed.

Table 5.4: Regression Results: Robustness check of the effect of Brexit on digital technologies related to e-commerce - different control group

Dependent Variables:	Payment	Secure Layer	Analytics	Javascript	Content Del. Net.
Model:	(1)	(2)	(3)	(4)	(5)
Post × EU trade	-0.191	-0.352***	-0.264***	-0.225***	-0.197*
	(0.143)	(0.088)	(0.071)	(0.070)	(0.101)
Fixed-effects					
serial	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,723	6,993	5,502	7,280	5,915
Squared Correlation	0.610	0.457	0.590	0.660	0.657
Pseudo R^2	0.257	0.218	0.238	0.405	0.340
BIC	7,572.9	22,253.5	20,131.1	38,100.8	18,721.7

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes have been removed.

5.10 Conclusion

This study analyses the impact of the Brexit referendum on the digital technology adoption of UK SMEs from 2013-2019. The Brexit referendum as a trade policy uncertainty shock is exploited, using a difference-in-differences estimation to examine the response of SMEs engaged in trade with the EU. The Brexit referendum increases potential future trade costs and casts uncertainty over firms that depend on the EU for import and export activities. I link existing survey measures to novel data sources on digital technology adoption from firms' websites. This integrated approach provides more detailed and timely measures to better understand how SMEs respond to a severe policy shock. Given that SMEs are the largest group of private firms and recognising the positive correlation between digital technology adoption and productivity gains, it is essential to understand the response to such a major shock. However, evidence is missing on this effect when it comes to digital technology adoption, a key component of productivity growth. This study contributes to bridging this knowledge gap by developing novel measures for technology adoption, leveraging the ever-increasing volumes of data available from businesses' websites.

The results show that SMEs react to this shock by decreasing their use of e-commerce related technologies, as well as other digital technologies. In light of the uncertainty shock imposing higher future trade costs, SMEs appear to decrease e-commerce technology from the following groups: payment, secure sockets layer, analytics and javascript. The effects are observed across sectors, including those typically linked to the trade of goods but also those of services: the primary sector, education, other services, manufacturing, administrative and support, wholesale and retail, accommodation and food, professional services, as well as information and communication. In addition, this study also finds a significant decrease in other technologies that are not classified as e-commerce related, with some of them being basic technologies for the functioning and quality of a website. This is in line with previous research, showing that the Brexit referendum has had a substantial impact on UK firms, who respond by decreasing investment in technology and innovation, leading to declines in exports and productivity. This research supplements the existing literature by shedding light on how Brexit has influenced SMEs' adoption and use of productivity-enhancing digital technologies. The analysis identifies a pervasive effect and points out the likely mechanisms at play which extend beyond trade channels, including investment and strategic realignment.

There are multiple limitations linked to this study. First, while currently existing measures of digital technologies are enhanced, the full tech stack SMEs cannot be measured, relying instead on the technologies that can be observed in firms' websites. One area for future research would be to expand in this direction by gathering further data sources and using supervised learning approaches to estimate full technology stacks firms may use over time.

Second, due to the onset of the Covid-19 pandemic, the scope of this analysis ends in 2019, implicitly limiting the ability to observe the fallout of the actual outcome of Brexit. It would be of high interest to see what happens after 2020, when the UK actually has left the European Union. Despite these limitations, this study fills the knowledge gap by providing insights into which firms and digital technologies have been most impacted by the Brexit referendum. These findings should prove useful for policymakers, empowering them with the information needed to design and implement effective measures that mitigate some of the detrimental effects on firms.

5.11 Appendix

5.11.1 Spatial dimension of the Brexit vote

I also show the map of the spatial differences in the Brexit vote at the regional level. It clearly shows a gap between voting patterns, with constituencies in Scotland and London being clearly more in favour of remaining part of the EU, whereas the East Midlands and the South West of England voting for the UK leaving.

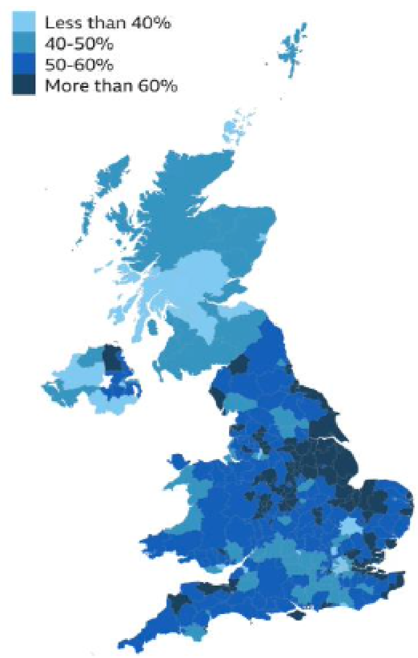

Figure 5.13: Brexit vote towards "Leave"
Source: BBC News (2016)

5.11.2 Uncertainty Index

Figure 5.14 plots the uncertainty index from 2016-2019, measured from survey data stemming from UK firms (Bloom, Bunn et al., 2019). It shows that uncertainty remained high until three years after the Brexit referendum and increased substantially at the time that the UK was supposed to leave the EU and before it actually left.

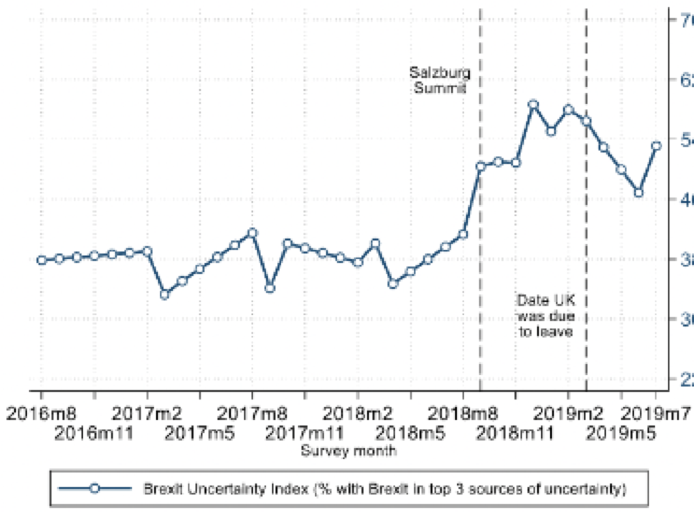

Figure 5.14: Development of the Brexit Uncertainty Index
Source: Bloom, Bunn et al. (2019)

5.11.3 Brexit-related questions in the LSBS

The LSBS asks firms about their main obstacles every year, with Brexit as one of them. In the survey questionnaires from 2016 onward, questions about Brexit have been included. These range from very general questions such as whether Brexit is perceived as a major obstacle, to more specific elements, like what aspects of Brexit they are concerned about and how their plans have been affected. Not all of these questions were already asked in 2016; some have been introduced in 2017, such as whether their plans have been affected, and some are only available in 2017, for example whether they feel prepared for Brexit. Also, not all questions have been asked to all firms, some of them have only been asked certain cohorts, such as whether their plans have been affected. A short overview of information on Brexit is shown in Table 5.5 below.

Table 5.5: Overview of Brexit-related questions in the LSBS

Identifier	Question	Years asked
G2	Which of the following would you say are major obstacles to the success of your business in general?: UK exit from the EU	2016-2021
R9	Overall, how beneficial or detrimental would UK exit from the EU be to your business? (scale 1-5)	2016-2021
G8	Which of these, if any, are the obstacles that you firm faces because of the UK's forthcoming exit from the EU?	2017-2021
R8a	Have any of these plans been affected by the UK exit from the EU? IF YES: Which plans?	2017-2021
R8b	How has the scale of these plans been affected by UK exit from the EU? For each that I read out, please tell me whether they have been scaled down or scaled up, or do they remain at the same level?	2017-2021
R8c	How has the timing of these plans been affected? For each that I read out, please tell me whether they have been brought forward, pushed back or is the timing unaffected?	2017-2021
R10	How prepared do you feel your [ANSWER AT A-2] is currently for the UK's exit from the EU? (scale 1-5)	2017

5.11.4 Summary statistics

I compare the sample analysed to the representative SME population. I find that the sample tends to include more SMEs that are larger in size and are more likely to export. Looking at employment as a firm size indicator, it becomes clear that the sample consists of larger firms. I use four categories, including no employees, micro (1-9 employees), small (10-49 employees), and medium (50-249). In the sample, most firms fall into the category of micro and small, making up around 36% and 33% respectively. Firms with no employees account for 17% and medium enterprises for 14%. The sample includes a substantially smaller percentage of firms with no employees. In 2015, firms without any employees were making up 76% (Department for Business Energy and Industrial Strategy, 2016).

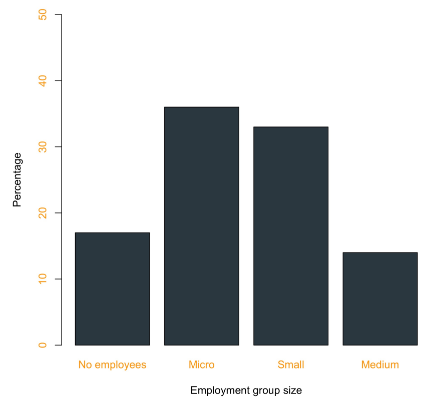

Figure 5.15: Percentage of firms by employment size, whole sample

5.11.5 Average trends in e-commerce

I also show the average changes by group for e-commerce technologies over time. In contrast to the other five technologies, I do not find that trends before the treatment are moving in parallel. Thus, I have excluded e-commerce as technology from the main analysis.

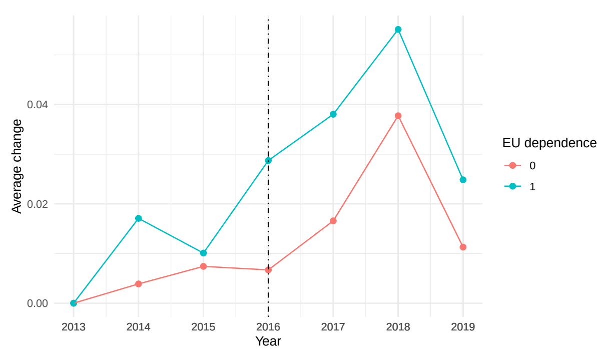

Figure 5.16: Trends in e-commerce by group, 2013-2019

5.11.6 Main results: Dynamic treatment effects

The coefficient plot below shows the dynamic treatment effect for all five dependent variables relative to one year before the treatment. It shows the pre-treatment coefficients, which are all not statistically significant, and the post-treatment coefficients, which are gradually increasing in magnitude. While in 2016 most of the coefficients are not statistically significantly different from 0, I see that the effect size increases with every year, becoming significant for nearly all e-commerce related technologies in 2019. This speaks for the effect intensifying over time which is likely stemming from the uncertainty that remained high until the end of 2019.

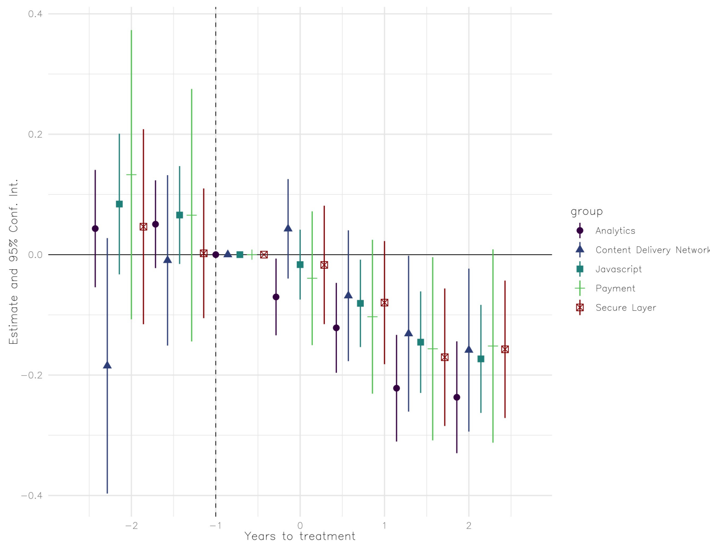

Figure 5.17: Dynamic treatment effects for e-commerce related technologies, 2013-2019

5.11.7 Main results: Negative Binomial Regression Models

Table 5.6: Regression Results: The effect of Brexit on other technologies that are e-commerce related - Negative Binomial

Dependent Variables:	Payment	Secure Layer	Analytics	Javascript	Content Del. Net.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Post × EU Trade	-0.221**	-0.134**	-0.276***	-0.231***	-0.102
	(0.090)	(0.053)	(0.049)	(0.046)	(0.063)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,560	21,042	23,450	31,080	24,890
Squared Correlation	0.576	0.444	0.602	0.558	0.680
Pseudo R^2	0.312	0.219	0.296	0.256	0.387
Over-dispersion	10,000	10,000	10,000	3.86	10,000

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes have been removed.

5.11.8 Table other technologies

In addition to plotting the results in Section 5.7.4, I also show the results in Table 5.7, including the coefficient size as well as fit statistics. The table demonstrate that firms trading with the EU also observe a decline in other digital technologies that are not e-commerce related. For all seven technologies, the results are statistically significant at the 5% level.

Table 5.7: Regression Results: The effect of Brexit on other technologies that are not e-commerce related

Dep. Var.:	Media	Content MS	Framew.	Hosting	Mobile	Web Serv.	Name Serv.
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Post × EU trade	-0.368***	-0.122**	-0.176***	-0.142***	-0.185**	-0.173***	-0.203***
	(0.139)	(0.060)	(0.046)	(0.040)	(0.072)	(0.034)	(0.042)
Fixed-effects							
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	6,560	22,300	26,240	26,144	26,660	29,286	19,024
Sq. Corr.	0.548	0.564	0.567	0.528	0.711	0.586	0.501
Pseudo R^2	0.315	0.334	0.298	0.234	0.479	0.265	0.182

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered firm standard-errors in parentheses. Different numbers of observations are explained by the exclusion of firms that never adopt a given technology as those with only 0 in the outcomes have been removed.

5.11.9 Robustness: dynamic treatment effects

In addition to the results in Table 5.4, I also show the dynamic effect treatment effect in Figure 5.18. The model is the same as in the main results, using a different control group that excludes firms that have voiced concern over Brexit. The findings are very similar to those in the main results, it shows no significant differences in the pre-treatment coefficients, as well as a gradual decline in the post-treatment coefficients.

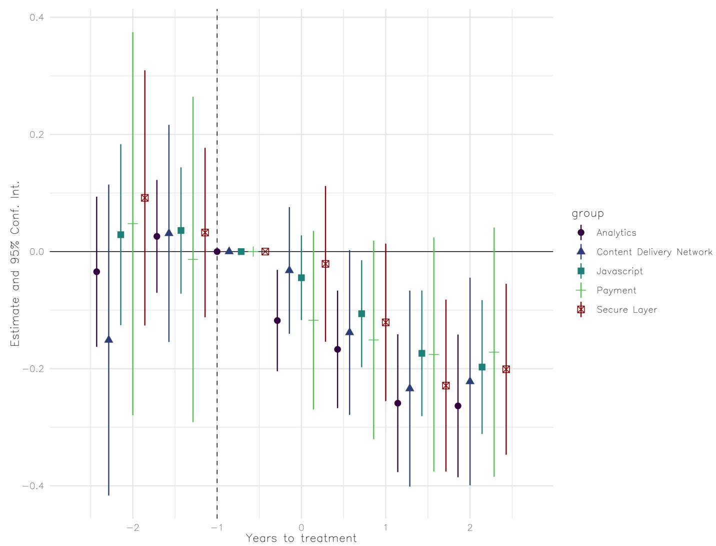

Figure 5.18: Dynamic treatment effects for e-commerce related technologies, robustness check, 2013-2019

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