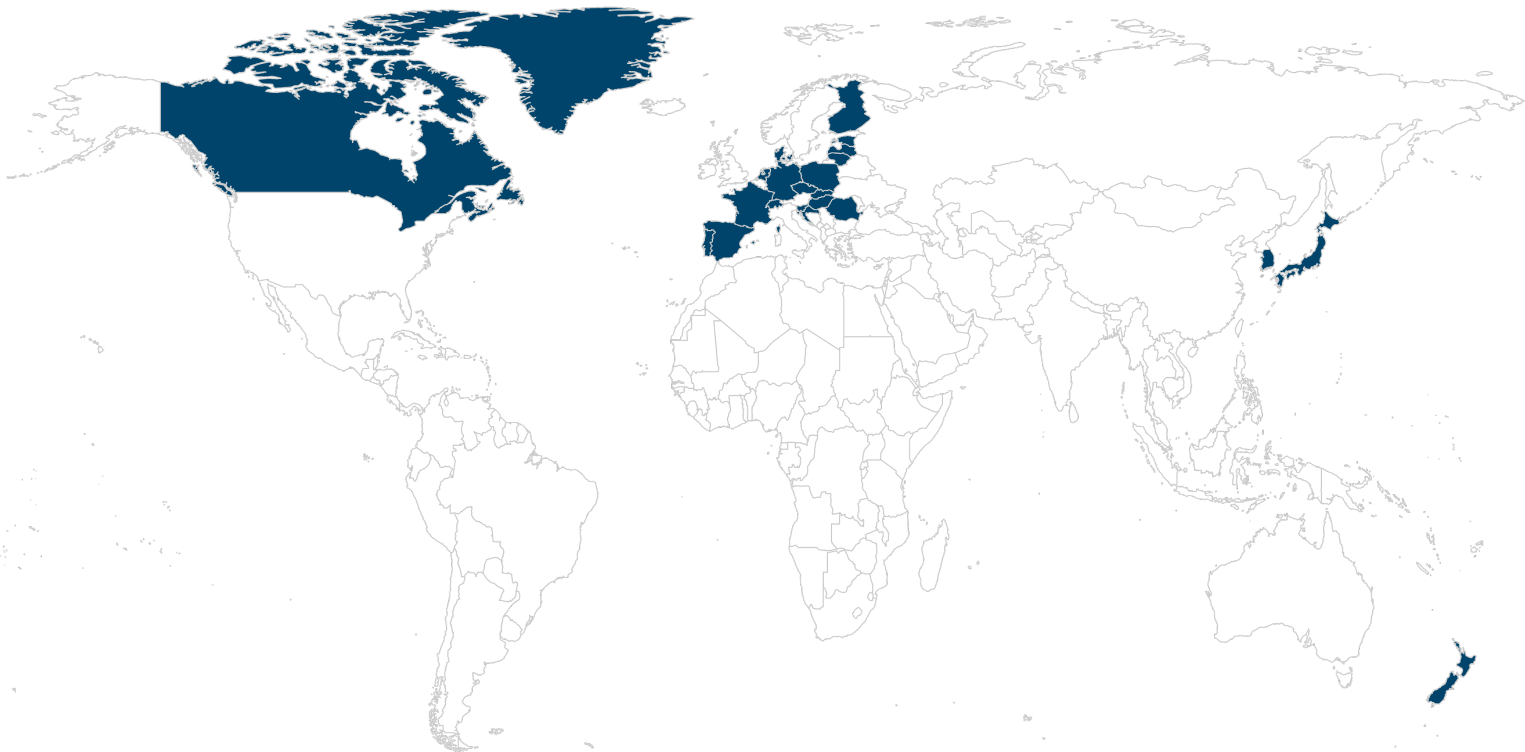
CompNet
The Competitiveness Research Network

IWH
Leibniz-Institut für Wirtschaftsforschung Halle

Firm Productivity Report

April 2025



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Introduction

As Europe navigates post-pandemic challenges amidst continuing global economic disruptions, enhancing productivity remains crucial to maintaining a competitive edge. Policymakers and economists must closely examine firm- and sector-specific factors to pinpoint vulnerabilities and identify sources of resilience, enabling the creation of policies that effectively drive productivity growth.

Using the latest vintage of our micro aggregated dataset, the 2025 CompNet Flagship Firm Productivity Report offers insights into the impact to date of the crisis on the European economy across important dimensions: firm-level productivity, competitiveness, potential output, and the reallocation of resources. We also investigate firm response to fluctuating energy prices and tighter credit constraints, as well as market concentration trends and their implications.

Why the CompNet dataset? First, it is micro-aggregated, and its underlying high-quality firm-level data improves macroeconomic analysis. We can uncover heterogeneity across sectors – and even across firms within the same sector – to pick apart the economy-wide impact of shocks. Second, the harmonized nature of CompNet data means we can compare TFP growth and respective drivers across European economies. This is especially valuable in the context of the COVID-19 crisis: those countries responded with different policies, and those policies have had widely varying economic outcomes.

Post-COVID, some firms, sectors and countries, have been resilient but not all. Discovering why this is the case helps to inform European policymaking decisions relevant for the current crisis, but also to build resilience to prepare for the next crisis.

This report is organized as follows. Chapter 1 focuses on the two-speed recovery since the coronavirus pandemic of firm-level productivity and potential output using the CompNet data, Chapter 2 introduces our latest tool, the Micro Data Infrastructure (MDI) that aims to harmonize firm-level data across countries to facilitate cross-country research. Chapter 3 uses MDI to investigate how firms respond to energy price shocks as they target Net Zero Emissions by 2030; Chapter 4 looks at how capital and labour are reallocated across sectors during expansionary and recessionary periods by firms; Chapter 5 explores Phillips curve dynamics with firm heterogeneity and resource reallocation in a New Keynesian framework. Finally, Chapter 6 presents four crucial insights using the CompNet dataset, namely, the impact of firm concentration at the regional level on the concentration at the national level (chapter 6.1), a closer examination of the manufacturing sector in Europe (chapter 6.3), an analysis of zombie firms before and after the pandemic (chapter 6.4), a look at the post Covid-19 export performance of firms (chapter 6.5), and an investigation of the EU's comparative advantage (chapter 6.6).

Executive Summary

In chapter 1, we use the latest vintage of the CompNet dataset to examine how Europe's post-COVID productivity landscape has transformed significantly, with an uneven recovery pattern where Eastern European countries now lead while some Western counterparts lag behind. Technological advancement continues to drive productivity growth, with high-technology and knowledge-intensive sectors demonstrating superior performance and resilience during the pandemic. However, a concerning productivity gap has emerged between frontier and laggard firms, exacerbated by the COVID-19 crisis, with notable variations across countries in terms of firm size, wages, and value-added ratios. Job market dynamism also varies significantly, with some economies experiencing increased job creation rates signalling entrepreneurial momentum, while others show more stable employment patterns. These divergences reflect differences in policy responses, underlying economic conditions, and industrial structures. Policymakers should prioritize strengthening laggard firms' "absorptive capacity" by expanding human and intangible capital, enhancing international market exposure, and easing financial constraints that hinder technology adoption to narrow productivity gaps and foster more balanced economic growth across Europe.

The Microdata Infrastructure (MDI), outlined in chapter 2, represents an ambitious and innovative platform designed to harmonize firm-level data across countries, simplifying and enhancing cross-country productivity research. Overcoming substantial barriers due to disparate data structures, variable classifications, and NSI access restrictions, MDI provides a standardized analytical environment. This ensures comparable and confidential data usage, enabling researchers to gain unprecedented insights into global economic dynamics. By streamlining traditionally fragmented and restrictive processes, MDI supports a range of functionalities, including data importation, harmonization, and sophisticated analytics.

Chapter 3 examines the substantial gap between EU's Net Zero Emissions targets (requiring a dramatic reduction in fossil fuel use over the next two and a half decades) and current projections (which fall far short of needed reductions). Using firm-level data from France and Portugal, we look at how energy price signalling affects this transition and evaluates the potential of environmental policies to close this gap. The findings reveal significant country differences: French firms exhibit higher elasticity between clean and dirty energy sources, allowing them to easily switch energy types without reducing overall consumption when prices increase, while Portuguese firms must reduce total energy use due to lower substitutability between sources. Additionally, using the OECD Environment Policy Stringent index as a proxy for carbon taxation, the study also demonstrates that policy stringency affects dirty-to-clean energy price ratios differently across countries — with Portuguese firms showing a much stronger price response to policy changes than French firms. These findings suggest that achieving uniform Net Zero Emissions targets across Europe will require substantially different carbon tax approaches tailored to each country's economic structure. Policymakers can leverage these insights to design targeted carbon tax approaches customized to each country's economic structure rather than implementing uniform policies across the EU.

In chapter 4, we explore how firms respond to productivity changes — a crucial factor in understanding job dynamics, investment patterns, and resource reallocation that ultimately drive economic growth and productivity trends. The research considers three key questions across Eurozone countries: how firms in different countries adjust to similar productivity shocks, whether responses differ between negative and positive shocks, and how macroeconomic conditions influence these responses. Using cross-country firm-level data from the MDI platform, the analysis examines both labour and capital adjustments, distinguishing between whether firms make adjustments (extensive margin) and the magnitude of those adjustments (intensive margin). The findings confirm that firms generally expand after positive shocks and contract after negative ones, supporting productivity-enhancing reallocation. However, firms show marked reluctance to downsize when facing negative shocks compared to their willingness to expand when experiencing positive ones. Business cycle conditions significantly impact these patterns, with firms showing muted responses during recessions, particularly in hiring decisions and capital adjustments. Cross-country analysis reveals substantial heterogeneity: Portuguese firms demonstrate stronger responses to extreme productivity shocks during economic expansions, while Dutch firms show greater flexibility in factor reallocation compared to French firms, which make more conservative adjustments even with substantial productivity changes. These findings provide policymakers with valuable insights for designing countercyclical measures that account for firm-specific adjustment behaviours and cross-country differences.

In chapter 5, we present research that examines how incorporating firm-level heterogeneity could improve monetary and fiscal policy responses to inflation surges like those following COVID-19 pandemic. While authorities responded adequately to recent inflation, a more nuanced policy toolkit could have enabled more timely and targeted interventions. The traditional Phillips Curve analysis suffers from instability in its slope parameter, limiting its practical utility. By analysing granular data on marginal costs and markups from firms with varying production technologies under different demand conditions, this chapter develops a more precise estimate of the Phillips Curve slope. The main intuition is that firms' technological capabilities significantly affect their marginal cost curves, creating varied responses to economic slack. When demand rises in an industry, prices increase less if high-productivity firms disproportionately meet that demand compared to low-productivity firms. Similarly, cost shocks have reduced aggregate impact when affecting firms with low cost pass-through. Using data from manufacturing firms in France, the Netherlands, and Slovenia, the researchers employ micro-theoretical foundations and novel clustering techniques to estimate supply curves for different firm types. Their findings demonstrate that the aggregate Phillips Curve flattens as technologically advanced firms become more numerous or satisfy larger portions of demand changes, providing a framework for better understanding how various disturbances translate into aggregate price pressures. Central banks and finance ministries can use this framework to better anticipate inflation pressures and calibrate monetary and fiscal responses based on the composition of firms in different sectors.

Chapter 6 presents varied analyses using CompNet's 10th dataset. Section 6.1 shows decreasing EU market concentration across most countries, with Switzerland experiencing the most significant reduction. Regional-national concentration patterns remained consistent, especially in capital cities. Post-COVID revenue concentration remained stable EU-wide when including France, but showed an upward trend when excluding it. Section 6.3 reveals varied post-COVID manufacturing productivity growth across European countries in 2021, with Romania, Hungary, Germany, and Poland outperforming while Switzerland lagged. Employment declined for both large and small firms from 2018, except for small German firms. While productivity growth was flat during 2013-2019, COVID created divergent patterns, with small firms growing in 2020 and large firms rebounding strongly in 2021. Chapter 6.4 examines zombie firms during COVID-19, finding an increase in financially constrained firms in 2020 but no widespread rise in zombie firms. Data suggests a delayed increase in zombie firm entries in 2022, driven by weak medium-term growth and potentially influenced by ECB monetary tightening. The findings do not support the notion that pandemic conditions boosted zombie firm entries or that support measures prevented exits. Section 6.5 shows large, productive exporters suffered most during 2020 but recovered strongly in 2021. Small exporters adjusted through the extensive margin, with many ceasing exports entirely, likely benefiting aggregate productivity. Central, Eastern, and Southeastern European countries saw surprising post-COVID export growth from low-productivity exporters through 2022. Section 6.6 addresses Europe's technological position globally using a "sufficient statistics" approach to calculate Relative State of Technology (RST). Europe maintains technological advantages across manufacturing, but only in food and non-metallic minerals does this align with export specialization.

This misalignment highlights the need for policies strengthening Europe's technological foundation in key export industries. These diverse studies provide policymakers with comprehensive insights into European business dynamics, particularly valuable for developing targeted industrial policies, competition frameworks, and innovation support mechanisms that address specific structural challenges identified across different sectors and countries.

CompNet Dataset 10th Vintage

This 2025 flagship report employs the 10th vintage of the CompNet dataset. It is an unbalanced panel dataset covering non-financial corporations from 23 countries, 19 European countries, 1 North American country, 2 Asian countries, and 1 country from Oceania.

The CompNet dataset is collected by the Competitiveness Research Network. The network is integrated withinthe Halle Institute for Economic Research and includes several partner institutions: the European Commission, the European Bank for Reconstruction and Development, the European Investment Bank, the European Stability Mechanism, France Strategie, the German Council of Economic Experts, the German Federal Ministry for Economic Affairs and Climate Action, and the Tinbergen Institute.

The CompNet dataset includes micro-aggregated indicators derived from administrative balance sheet data from 23 countries. Using the distributed micro-data approach,[1] the CompNet Team computes indicators at different levels of aggregation: country, macro-sector, macro-sector size, industry, region (NUTS2), technology/knowledge, age. For each level of aggregation there are nearly 600 variables in the dataset that can be clustered in six broad categories: finance, productivity, labour, competition, trade and others. For each of these variables the dataset includes unconditional moment of the distribution, decompositions and joint distributions. CompNet also releases transition matrices for a selected number of variables. For a comprehensive description of variables, the list of countries included, data coverage, and sources, readers should refer to the forthcoming CompNet User Guide for the 10th Vintage. It is important to note that country and sector coverage varies over time. Specifically, in 2021, data for Germany covers only the manufacturing sector. Additionally, no data is available for Germany and France in 2022 onwards. For 2023, data is limited to Croatia, Estonia, Romania, and Slovenia. The results in this report are based on the CompNet dataset that inlcudes only the European countries.

The data providers of the CompNet project are national statistical institutes and national central banks that collect administrative firm-level data covering (or representative of) the full population of firms. Indicators are computed using a single harmonized data collection protocol that ensures full cross-country comparability.[2]

The CompNet Dataset is publicly available on request for research purposes.[3]

[1] See Bartelsman et al. (2004) and Lopez-Garcia and di Mauro (2015).
[2] See Altomonte et al. (2018) for a discussion of cross-country comparability of CompNet.
[3] The application procedure is available here. See Altomonte and di Mauro (2022) for a comprehensive review of policy research applications of the dataset.

1 Contrasting Paths: European Firms' Post-COVID Revival

Author: *Ashim Dubey*

In early 2025, Europe faces renewed economic strains and geopolitical tensions, underscoring an urgent need to reinforce the continent's economic fundamentals and competitive edge. Against this backdrop, we revisit the impact of the COVID-19 crisis on firm-level productivity, using the latest CompNet dataset. A key question is whether the pandemic had a "cleansing" effect – weeding out weaker firms and boosting aggregate productivity – or if it exacerbated existing weaknesses. We examine crucial aspects of this recovery, including how productivity is converging (or diverging) across countries, the vitality of job markets, and changes in firm concentration. The evidence reveals a striking regional split: Eastern European countries are leading the productivity rebound, while some Western European economies – traditionally strong performers – are lagging behind. This chapter unpacks these trends and provides insights to guide policymakers toward a balanced and sustainable recovery. Crucially, the analysis presented in this chapter draws on micro-data, offering a far more detailed and nuanced view of productivity dynamics than traditional, average-based indicators — even at the sectoral level.

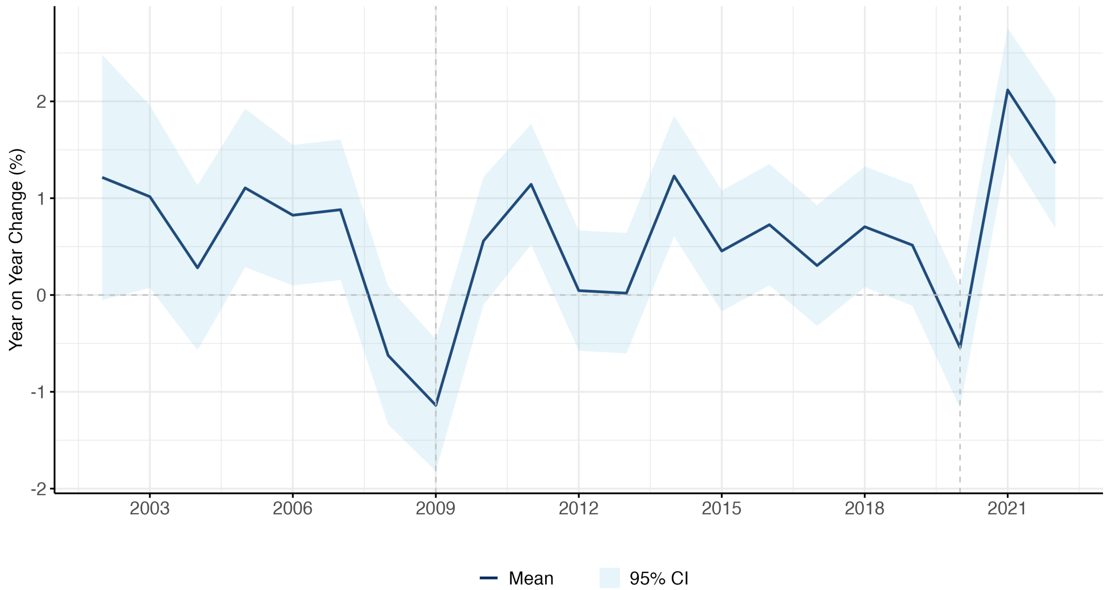
1.1 Productivity Developments

Europe's productivity landscape has transformed significantly since the pandemic. The initial shock of COVID-19 caused a drop in total factor productivity (TFP) across nearly all countries; however, this decline was milder than the one during the 2008–09 Global Financial Crisis. Moreover, the recovery that followed has been uneven and multi-speed. Different policy responses and economic structures led to distinct national trajectories: some countries rebounded vigorously, demonstrating remarkable resilience, while others continue to grapple with persistent productivity shortfalls. This disparity suggests more than just a temporary rebound effect – it points to deeper structural differences in how economies adapt and recover from shocks.

Figure 1 below illustrates Europe's average TFP growth over time, highlighting the pandemic's impact and the subsequent recovery. After a modest pre-pandemic growth, TFP fell in 2020 (though not as steeply as in 2009) and has since entered a recovery phase. By 2021, average TFP growth turned positive again, indicating that many firms managed to adapt operations or find new efficiencies despite COVID-related disruptions. This resilience in aggregate productivity suggests that, at the European level, firms learned lessons from past crises and benefitted from swift policy support during the pandemic. Still, looking at the European average alone masks the considerable variation between countries in the speed and strength of recovery.

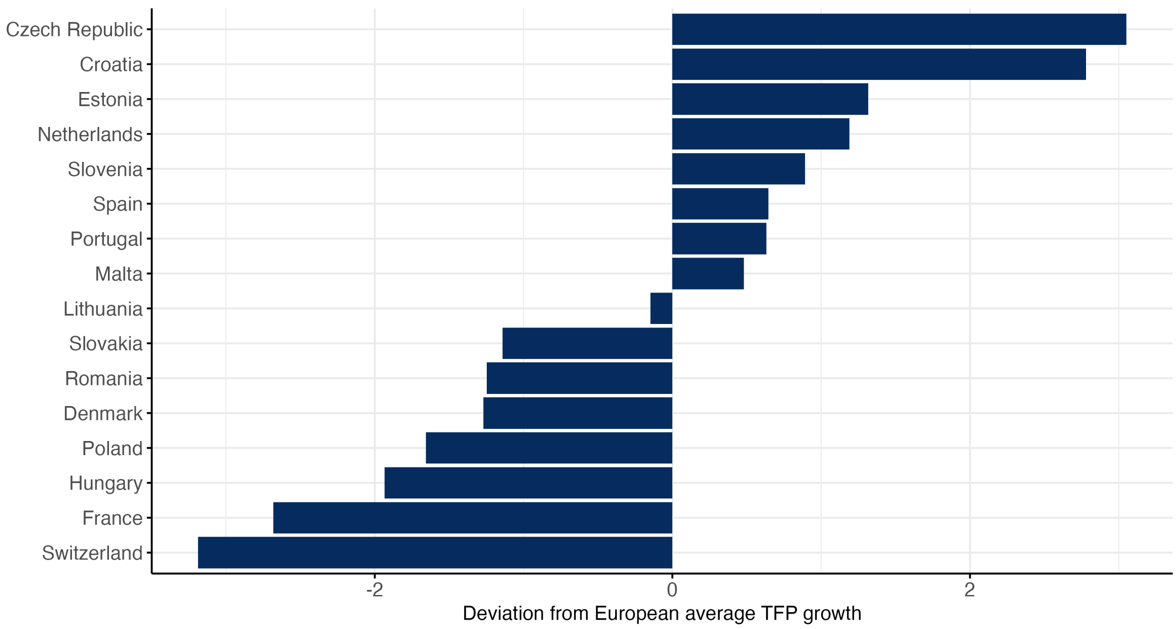
The histogram in Figure 2 provides evidence of the divergent recovery paths among European countries in 2021. This histogram shows each country's annual TFP growth relative to the European average (approximately +2.15% in 2021, excluding data-limited Germany). The chart reveals a clear two-speed recovery. Several Eastern European economies – notably the Czech Republic and Croatia – achieved TFP growth well above the European mean. Others like Estonia and Slovenia also outperformed the average, and even some tourism-dependent economies (e.g. Malta and Spain) sustained solid productivity recoveries as travel and hospitality rebounded post-lockdowns. In contrast, Western European countries such as France, the Netherlands, and Denmark registered below-average TFP growth in 2021. These sluggish outcomes in some advanced economies could be due to factors like industrial structure and crisis response: for instance, countries heavily oriented toward manufacturing or with swift, sizeable fiscal support tended to bounce back faster, whereas those with prolonged restrictions or pre-existing structural bottlenecks saw more muted productivity growth.

Figure 1: TFP Growth Trend in Europe



Note: The average predicted revenue based TFP growth (per unit of combined capital and labour input) in Europe for each year, derived from OLS regressions of the TFP growth rate on a full set of year dummies and country-industry pair dummies. Standard errors are clustered at the country-industry level. All available 2-digit industries and countries are pooled. Note that the coverage of countries and sectors changes over time.
Source: CompNet Dataset 10th Vintage; op_decomp_industry2d_20e_weighted.dta

Figure 2: TFP Deviation per Country (2021) from European Average



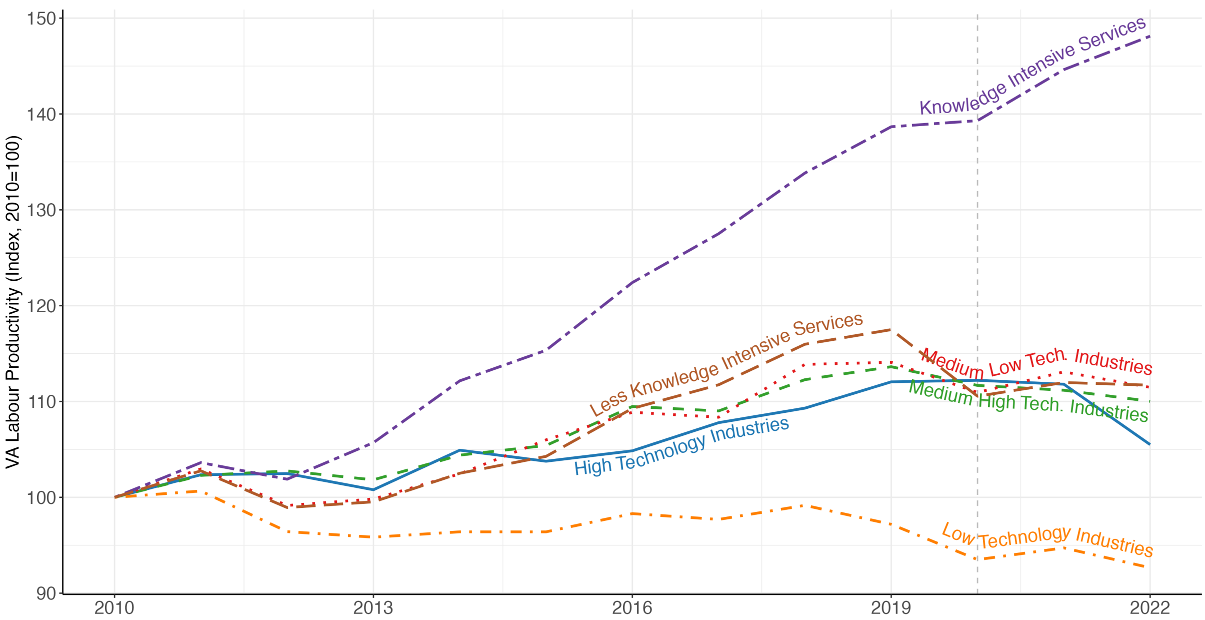
Note: This histogram shows how each country's annual TFP growth in 2021 deviated from the European average. Note that the European average excludes Switzerland.
Source: CompNet Dataset 10th Vintage; op_decomp_industry2d_20e_weighted.dta

1.2 The Role of Technology

Technology has long been a driver of productivity growth. Historically, advances in manufacturing technology and increased automation boosted labour productivity, mostly in high-tech industries. In recent years, however, the digital revolution has spread these productivity gains to services as well. The COVID-19 pandemic accelerated the adoption of digital tools and practices, particularly in sectors able to pivot to remote work and online delivery. To analyse this, we categorize industries by technology and knowledge intensity (using Eurostat's technology and knowledge-intensity classifications). This yields six groups: four levels of technological sophistication in manufacturing (from most high-tech to low-tech) and two levels of knowledge intensity in services (knowledge-intensive services and less knowledge-intensive services).

Figure 3 shows how the number of active firms has evolved in these categories over the past decade. We see robust growth in the total number of firms in high knowledge-intensive service sectors (e.g. IT, professional services). The number of firms in this sector rose steadily from 2010 to 2019 and, notably, suffered only a minor dip in 2020 during the pandemic before continuing to climb. This trend reflects how many service firms leveraged digital platforms and remote delivery to weather the crisis. In contrast, firm growth in high-technology manufacturing sectors has been more modest and flat by comparison, even before COVID-19. Lower-tech manufacturing and less knowledge-intensive services saw either stagnant or declining firm numbers in the same period. This divergence indicates a structural shift: economic activity is increasingly concentrated in tech-savvy firms and sectors, especially services that harness knowledge and digital innovation.

Figure 3: Number of Firms by Technology Intensity

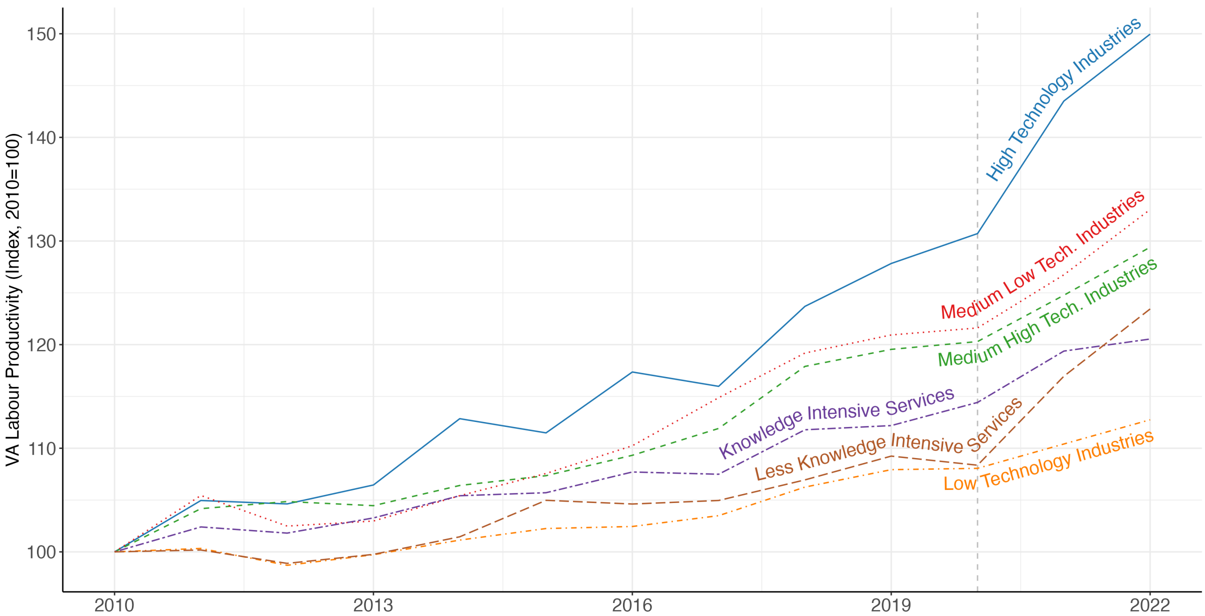


Note: Categories are based on EUROSTAT's classification of activities. The figure is based on a balanced sample of 15 countries from 2010 to 2022.
Source: CompNet Dataset 10th Vintage; unconditional_techknol_20e_weighted.dta

The productivity benefits of technology adoption are even more apparent when looking at performance outcomes. Figure 4 highlights a widening gap in labour productivity between technologically advanced sectors and less advanced ones. The lines track an index of value-added per worker (labour productivity) from 2010 to 2022 for each technology group. Firms in high-tech manufacturing and knowledge-intensive services have pulled far ahead: by 2022, the average productivity of high-tech manufacturing firms was about 50% higher than its 2010 level, outpacing all other categories. High-tech firms not only sustained productivity growth through the 2010s but actually saw accelerated gains around 2020–2021, likely by capitalizing on digital tools, automation, and robust global supply-chain links during the pandemic. In contrast, less advanced sectors (e.g. low-tech services) experienced much smaller cumulative gains. In some cases, the pandemic caused productivity in these sectors to stagnate or dip, due to factors like reduced consumer demand (e.g. tourism, hospitality) and difficulties in operating remotely.

Notably, the COVID-19 shock accentuated this productivity divide. Manufacturing firms that were already technology-intensive managed to maintain or quickly rebound in productivity, whereas service sectors, even knowledge-intensive ones like education or healthcare, faced greater disruption. One bright spot is that as economies reopened, certain low-tech service industries (like hospitality) saw a strong post-pandemic bounce-back in productivity – essentially recouping losses from 2020 – thanks to pent-up demand. But overall, the trend remains clear: the productivity frontier is being pushed outward by tech-heavy sectors, leaving others behind. This growing gap carries broader economic implications. If productivity gains (and thus income and profitability gains) concentrate in only a few sectors or regions, it can lead to widening inequality and imbalances in growth. Policymakers therefore face a dual challenge: support the continued expansion of digital, high-tech activities and ensure that the rest of the economy is not left behind. This could involve investing in widespread digital infrastructure and skills, encouraging technology diffusion to smaller firms, and helping less-digitized industries become more resilient and innovative. By broadening the base of firms that can successfully adopt new technologies, Europe can harness the digital revolution to drive inclusive productivity growth rather than one that is narrowly focused.

Figure 4: Value added Labour Productivity by Technology Intensity



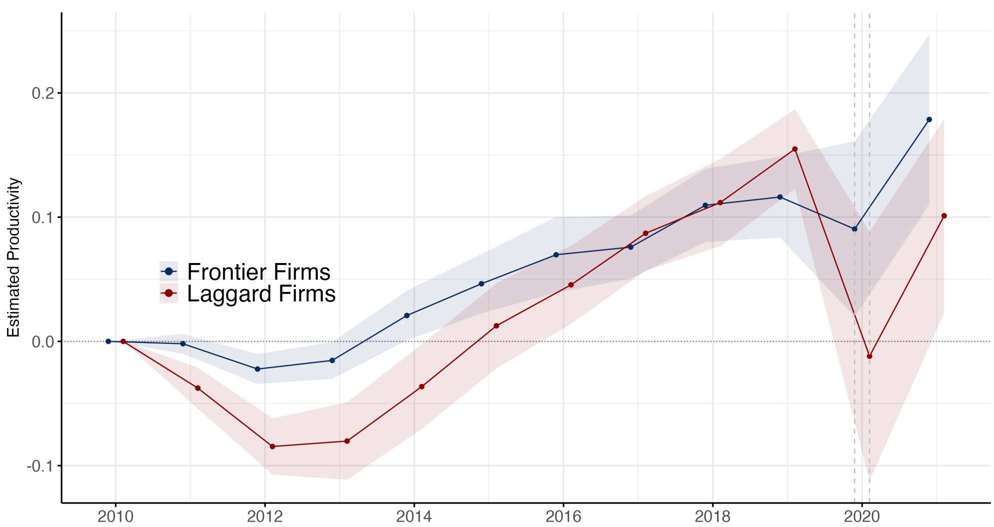
Note: Categories are based on EUROSTAT's classification of activities. The figure is based on a balanced sample of 15 countries from 2010 to 2022.
Source: CompNet Dataset 10th Vintage; unconditional_techknol_20e_weighted.dta

1.3 Productivity Convergence

Another critical aspect of Europe's productivity revival is the divide between the most productive firms and the rest. Even within the same country and industry, some firms ("frontier" firms) exhibit dramatically higher productivity than others ("laggard" firms). For clarity, frontier firms here are defined as the top 10% of firms by labour productivity in their sector, while laggard firms are the bottom 10%. Over time, a healthy economy would ideally see laggards improving and catching up to the frontier – a sign of good diffusion of innovation and best practices (i.e., productivity convergence). Conversely, a widening gap would indicate that top performers are pulling further ahead, potentially due to unique advantages or an inability of weaker firms to improve (productivity divergence).

Prior to the pandemic, there were hopeful signs of convergence. As shown in Figure 5, the productivity gap between frontier and laggard firms was at its widest around 2012 and then narrowed between 2015 and 2018, suggesting laggards were gaining ground. In this figure, the green line represents the average (within-industry) labour productivity of frontier firms and the orange line that of laggard firms, with vertical bars indicating confidence ranges. From 2010 to 2018, the two groups followed parallel upward trends, and the distance between them shrank modestly. This implies that many low-productivity firms improved their performance during the mid-2010s, perhaps aided by the economic recovery and reforms after the eurozone crisis. However, the onset of COVID-19 in 2020 abruptly reversed those gains. Figure 5 shows a sharp drop for laggard firms in 2020 – a much steeper decline than that for frontier firms – leading to a renewed increase in the productivity gap. In other words, the crisis hit weaker firms disproportionately hard. While frontier firms also suffered setbacks in 2020, their superior resilience (due to factors like better access to finance, digital readiness, or diversified markets) meant they could maintain productivity far better than the laggards. By 2021, there was some rebound for both groups, but the gap remained large – a clear indication that COVID-19 has left a lasting mark on productivity dispersion.

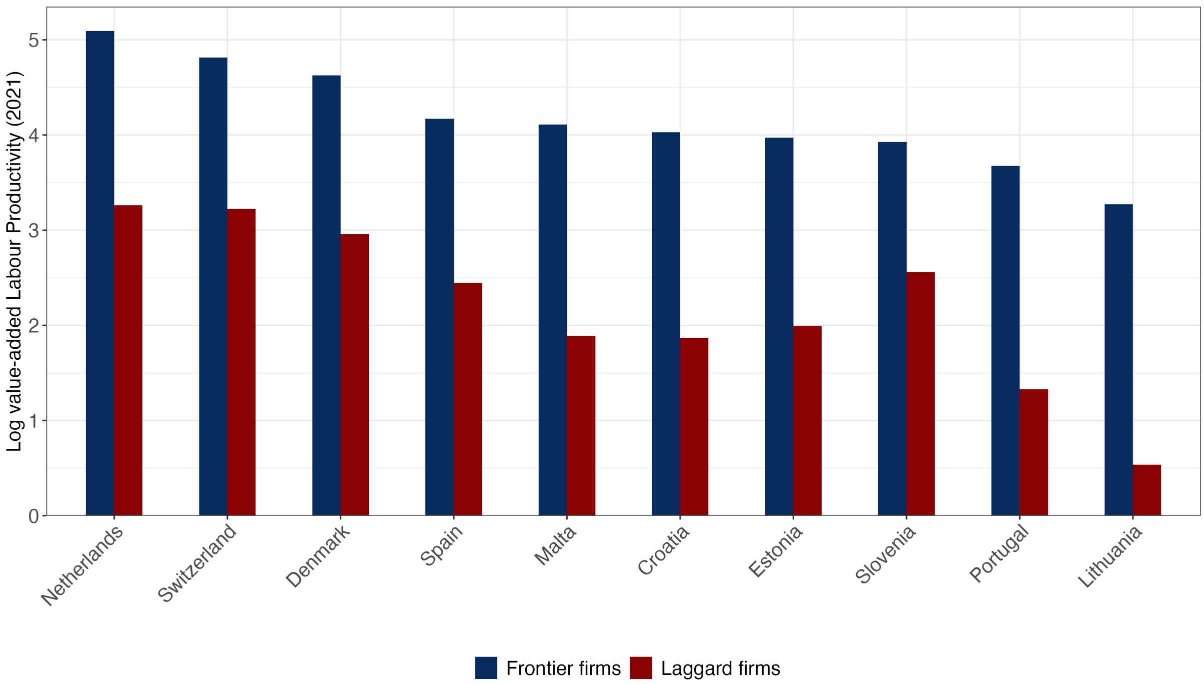
Figure 5: Frontier vs Laggard Firms Predicted Labour Productivity



Note: Frontier firms are defined as the firms in the top 10% of the log value-added labour productivity distribution in a sector for each given year while laggard firms are defined as the firms in the bottom 10% of the log value-added labour productivity distribution. The vertical axis measures estimated within-industry labor productivity growth from size-weighted regressions of labor productivity on year dummies and country-industry pair dummies for a balanced sample of 10 countries from 2010 to 2021. Standard errors are clustered at the 2-digit industry level.
Source: CompNet Dataset 10th Vintage; unconditional_industry2d_all_weighted.dta

The extent of the frontier-laggard gap is not uniform across Europe. Figure 6 illustrates the labour productivity gap in 2021 between frontier and laggard firms for selected countries. Each country's bar pair shows the average log value-added per worker for frontier firms (blue) and laggard firms (red). A larger difference between the blue and red bars means a wider productivity gap. The figure reveals that some economies exhibit an especially wide divide: for example, in Lithuania, frontier firms' productivity is vastly higher than that of laggards (reflected by one of the tallest blue-red separations), whereas in Switzerland the gap is comparatively small. We also see cases like the Netherlands, where frontier and laggard bars are closer together (indicating a narrower gap in average productivity). These variations suggest that certain national factors are at play. In countries with a wide frontier–laggard gap, frontier firms may have unique advantages – such as cutting-edge technologies, superior management, or easier access to talent and finance – that laggards struggle to obtain. Alternatively, it could reflect weaker diffusion of innovations from leaders to followers. Conversely, where the gap is narrower, it might indicate better diffusion mechanisms (for instance, strong linkages between large and small firms, effective public support for SME upgrades, or cultural factors that promote the spread of know-how).

Figure 6: Labour productivity gap in 2021 between frontier and laggard firms by country



Note: Frontier firms are defined as the firms in the top 10% of the log value-added labour productivity distribution in a sector for each given year while laggard firms are defined as the firms in the bottom 10% of the log value-added labour productivity distribution. The vertical axis measures the average log value-added labour productivity pooled across all sectors for a balanced sample of 10 countries in the year 2021.
Source: CompNet Dataset 10th Vintage; unconditional_industry2d_all_weighted.dta

In Table 1 below, we see concrete numbers highlighting how stark the frontier vs. laggard disparities can be. This table shows, for a range of countries, the ratio of frontier to laggard firms' performance in four dimensions: labour productivity, total value-added, average real wages, and firm size (employees). A value above 1 means frontier firms have a higher value of that metric than laggards, and a value below 1 would mean lower. As the table makes clear, frontier firms are typically much larger, more productive, and pay higher wages than laggard firms – but the degree differs greatly by country.

Table 1: Ratio of characteristics (frontier vs laggard firms) by country, 2021

Country	Labour Productivity	Value-added	Real Wage	Size
Croatia	3.29	79.60	2.44	3.79
Denmark	2.17	41.31	3.83	2.56
Estonia	3.14	12.55	3.15	0.97
Lithuania	8.20	16.81	1.94	0.80
Malta	4.60	56.91	3.86	1.80
Portugal	6.67	88.48	3.42	3.46
Slovenia	2.26	42.45	1.95	4.97
Spain	2.64	89.46	3.09	3.00
Switzerland	1.93	40.90	3.78	2.45
Total	3.21	33.44	3.56	1.69

Note: Frontier firms are defined as the firms in the top 10% of the log value-added labour productivity distribution in a sector for each given year while laggard firms are defined as the firms in the bottom 10% of the log value-added labour productivity distribution. Values in each cell indicate the ratio of mean firm characteristics of frontier firms compared to laggard firms in the year 2021.
Source: CompNet Dataset 10th Vintage; unconditional_industry2d_all_weighted.dta

Several insights emerge from Table 1:

- Size and Output: Frontier firms tend to be about twice as large as laggard firms in terms of employment on average (see “Size” ratio of 1.69 overall). However, in some countries the gap is far larger. For instance, in Slovenia a frontier firm has nearly 5 times the employees of a laggard firm. By contrast, in Lithuania, frontier firms are actually smaller on average than laggards (size ratio 0.80) – perhaps because many frontier firms there are nimble, high-tech startups or specialized companies, whereas laggards might include some older, larger firms with low productivity. In terms of output, frontier firms produce vastly more value-added than laggards – dozens of times more in many cases – which reflects the combined effect of higher productivity per worker and generally larger firm size. For example, Croatian frontier firms generate about 80 times the value-added of Croatian laggards on average, and in Portugal and Spain this ratio is near 90. (These extreme differences in value-added also highlight how small and unproductive the bottom tail of firms can be in some economies.)
- Productivity Levels: Looking at labour productivity (output per worker), frontier firms are on average 3.2 times more productive than laggard firms across the sample. But the gap ranges widely: in Lithuania, frontier labour productivity is over 8 times that of laggards – indicating a huge gulf in efficiency and technology within the country’s firms – whereas in Denmark it is just more than 2 times, suggesting that Danish laggard firms, while less productive, are not dramatically far from their frontier. Most countries fall in the 2–4× range for this metric.
- Wages: Frontier firms tend to pay significantly higher wages than laggard firms – roughly 3.5 times more on average (reflecting higher skill workers and greater profitability). The Netherlands shows the largest wage premium (frontier firms pay nearly 5 times what laggards do, which is consistent with its large gap in productivity and value-added). In contrast, Slovenia’s frontier firms pay only about 1.95 times laggard wages – perhaps indicating that even low-productivity firms in Slovenia pay relatively decent wages, or that labour cost differences there are compressed by institutional factors. Higher wages at frontier firms also reinforce a cycle: they attract and retain more skilled employees, further widening the capability gap.

Overall, the wide differences documented in Table 1 illustrate the diverse challenges and opportunities European countries face in boosting aggregate productivity. In places where frontier firms are dramatically ahead, the priority may be to help laggards catch up by improving their access to technology, skills, and capital. On the other hand, in countries where the gap is smaller, policies might focus on sustaining the diffusion that's already occurring and ensuring frontier firms continue to innovate.

A main reason for the persistent divide between top-performing and laggard firms is the slow diffusion of technology and best practices to the firms at the bottom. Frontier firms typically possess strong human capital (skilled workers and managers), ready access to global markets and suppliers, advanced technologies, and specialized know-how. These advantages allow them to continuously innovate and improve efficiency, even in difficult times. Laggard firms, by contrast, often lack some or all of these capabilities – they may struggle to adopt new technologies, have limited managerial expertise, or operate in local markets with less competitive pressure. As a result, many laggards fail to significantly improve productivity, and some fall further behind over time, especially when a crisis hits.

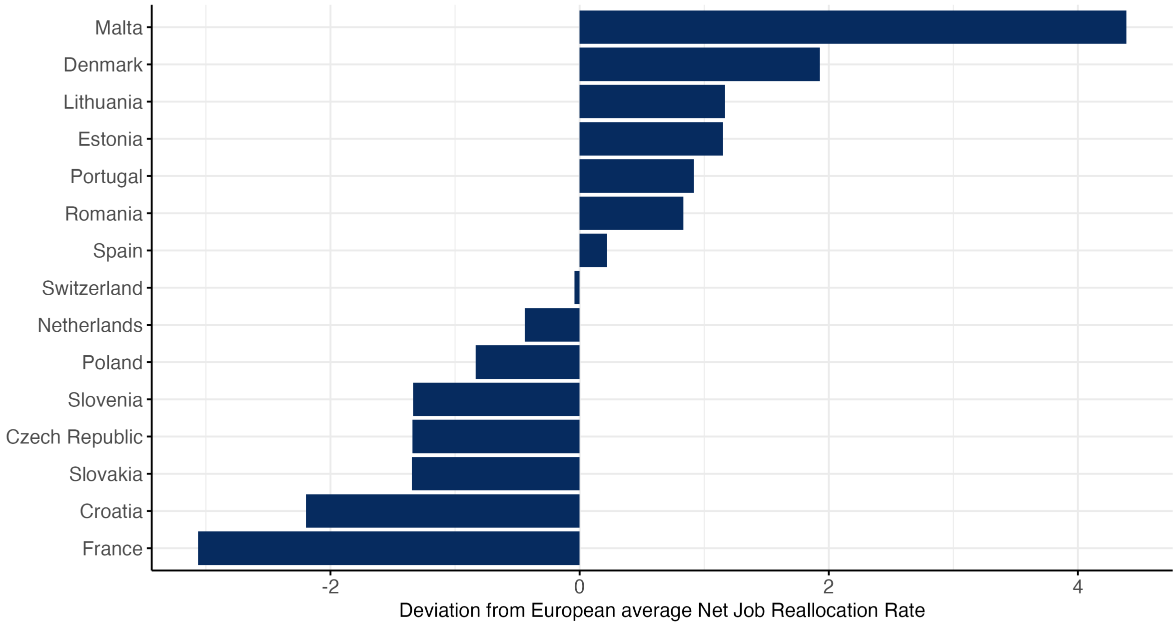
Addressing this issue requires policies aimed at strengthening the "absorptive capacity" of underperforming firms – essentially, boosting their ability to learn and incorporate new innovations. This can be done by: (1) investing in human capital and intangible assets (for example, helping small firms train workers in digital skills, or improving broadband and ICT infrastructure so that even smaller businesses can effectively use new technologies); (2) increasing exposure to international markets (through export promotion or participation in global value chains, which often forces firms to raise their game and learn from global leaders); (3) easing financial constraints that hinder firms from investing in productivity-enhancing improvements (such as upgrading equipment or software); or (4) facilitating the reallocation of resources from persistently underperforming firms to more productive ones, which can enhance overall productivity by channelling labour, capital, and other assets toward enterprises better positioned to innovate and grow. Targeted support in these areas would give laggard firms the tools and incentives to improve their performance. Over time, this should help narrow the productivity gap – as weaker firms become more efficient – and raise the overall productivity and competitiveness of the economy. For policymakers, the implication is clear: it is not enough to rely on top firms to drive growth; broad-based progress among the many smaller and less productive firms is vital for a sustainable and inclusive recovery.

1.4 Job Dynamism

Differences in firm productivity are influenced not only by technology and firm capabilities but also by the dynamism of the labour market – the processes of job creation and destruction across firms. A dynamic economy constantly reallocates resources: new firms enter and create jobs, efficient firms expand, and less productive firms shrink or exit, freeing workers to move to better opportunities. This churn boosts aggregate productivity by shifting labour from low-productivity uses to higher-productivity ones. Conversely, an economy with low job flow might see entrenched incumbents, less competition, and slower innovation diffusion.

Figure 7 illustrates the variation in net job reallocation rates across European countries in 2021, relative to the European average. Malta, Denmark, Lithuania, Estonia, and Portugal show notable positive deviations, with Malta standing out significantly above the average. These countries experienced robust dynamism characterized by substantial job churn—high rates of job creation alongside job destruction. Such high reallocation rates typically reflect active entrepreneurial environments where new firms frequently emerge, and existing businesses aggressively adjust their workforce to capitalize on new opportunities or streamline operations.

Figure 7: Deviation per Country from European Average for Job Reallocation Rates, 2021



In contrast, countries such as France, Croatia, Slovakia, Czech Republic, and Slovenia exhibited lower-than-average job dynamism. France, in particular, shows the most significant negative deviation, suggesting a relatively less dynamic labour market. This lower dynamism indicates limited job churn, where fewer new firms enter the market, and established firms tend to retain their workforce, potentially leading to entrenched market positions and slower diffusion of innovation.

High labour market dynamism, as evidenced in Malta and Denmark, accelerates the diffusion of innovation. New and expanding firms often introduce fresh technologies or business practices, while declining firms release resources, enabling their redeployment into more productive activities. This creative destruction process can significantly enhance overall productivity. Conversely, countries with lower dynamism, such as France or Croatia, risk locking resources into suboptimal allocations, potentially widening productivity gaps as less productive firms persist without competitive pressures.

These observed patterns highlight the importance of balanced policy interventions. Policies fostering innovation and entrepreneurship—such as reducing barriers to entry, streamlining regulations, and enhancing bankruptcy procedures—are crucial for maintaining labour market dynamism. Simultaneously, effective worker protection measures, such as active labour market programs, retraining, and reskilling initiatives, are essential for smoothing transitions and reducing social costs. European policymakers thus face the dual challenge of nurturing dynamic and innovative business environments while simultaneously ensuring that workforce adaptability and social support mechanisms facilitate rather than impede the transition to higher productivity roles. Achieving this balance is critical for turning the uneven post-COVID recovery into sustained and inclusive economic growth across Europe.

2 Microdata Infrastructure (MDI)

Authors: *Marco Miorandi, Johanna Weiß*

2.1 Overview of MDI

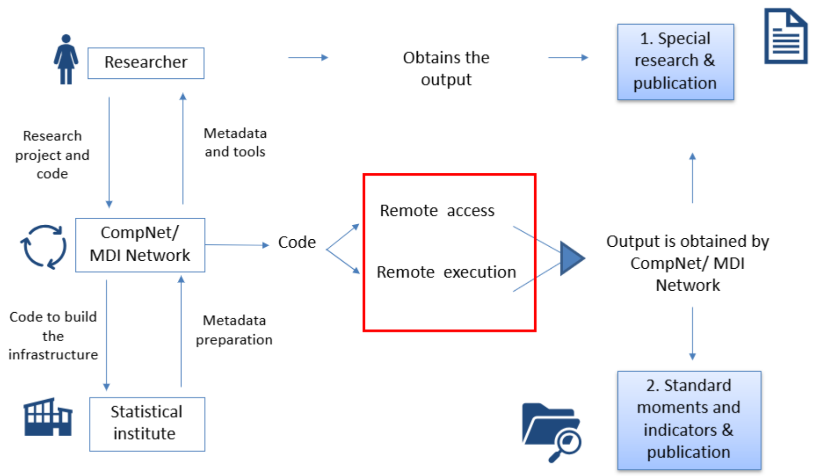
The Microdata Infrastructure (MDI) is an ambitious and innovative platform designed to tackle the complex challenge of harmonizing firm-level data across countries while simplifying cross-country research on productivity and competitiveness.

Conducting such research is notoriously difficult due to differences in data structures, variable classifications and access restrictions across National Statistical Institutes (NSIs).

MDI overcomes these barriers by providing a standardized environment where researchers can conduct identical analyses at multiple NSIs. This ensures that data is made comparable and accessible through a unified framework. The infrastructure supports a range of functionalities, including data importation, harmonization, and sophisticated analytical outputs, all while operating within a controlled environment to maintain data confidentiality.

By streamlining what is typically fragmented and restrictive process, MDI enables researchers to gain deeper insights into global economic dynamics with unprecedented ease.

Figure 8: MDI project overview



2.2 Stakeholders in the MDI Ecosystem

Several key stakeholders contribute to the functioning of MDI. NSIs and other partners play a crucial role by providing the underlying data and supporting remote execution and access to confidential firm-level data. While NSIs differ in terms of legal access rules, available data, and technical setups, they serve as the foundation of the standardized MDI research environment. Some partners may also have country-specific remote access, further enhancing the system's reach and usability.

MDI users, including productivity boards, external academic and policy researchers, and MDI thematic research staff, are responsible for developing research modules that take advantage of MDI's capabilities for cross-country data analysis. These module writers create analytical frameworks that enable meaningful insights across different datasets while ensuring methodological consistency across countries.

MDI staff play an essential role in supporting the infrastructure. This includes country specialists, thematic research personnel, and infrastructure support teams. Their responsibilities range from assisting NSIs in data preparation and documentation to supporting module writers by providing expertise on data, tools, and research themes. Their work ensures the continuous development and smooth operation of the MDI environment.

2.3 How Does the Data Harmonization Process Work?

The harmonization of the data is the step in which the NSIs' data is adjusted and transformed to ensure a consistent structure. It relies on different methods to standardize firm-level data, all of which are specified in the metadata. It involves aligning units of observation, variable definitions, and variable values to ensure consistency across datasets. This process relies on NSI metadata (i.e. metadata files on the raw data at an NSI), MD metadata (i.e. metadata about the objective MD panels), and NSI-to-MDI concordances, which serve as the foundation for standardization. The MD standard metadata is established iteratively and evolves as new countries join and as different MDI research users introduce new data requirements. The flexibility of this metadata allows for live updates to MDI data documentation through MD metadata and NSI-to-MD concordances.

A critical aspect of harmonization is mapping firms, enterprises, and legal units. This requires an in-depth understanding of NSI source data, including registers, weighted sampling, and sample designs. To ensure consistency in variable definitions and nomenclature, NSI variables are renamed, revalued, or combined.

Harmonizing classification variable values involves reclassifying values over time to align with MD standards. This requires a concordance for each NSI classification version to the MDI standard. Without proper mapping of observed classification codes from raw data to the MD classification, valuable data observations risk being lost.

Among the different classification variables, there are product codes from dataset `PRODCOM` and trade codes – the combined nomenclature – from dataset `ITGS`. Given their complex nature and their frequent changes in each year of the sample, we use a different harmonization method for the two codes. Specifically, we use a tool that standardizes the classification variables over time by tracing how the codes evolve across years and merging those with a shared final-year classification. It groups linked codes and assigns them a single, updated code, ensuring consistency and comparability across periods. By simplifying a complex web of changing classifications into a unified structure, it makes historical data clearer and easier to analyze.

For categorical variables, harmonization is achieved by recoding values based on codebooks, ensuring conformity across datasets.

Other data values, such as currency units and date formats, are also standardized using R functions. For example, if an NSI dataset expresses a variable in thousands while the MD dataset records it as a single unit, the NSI value is multiplied by 1,000. Similarly, NSI date values formatted as `%d%m%Y` can be converted to the required R date format using appropriate R functions.

3 Net Zero Emissions and Price Signalling

Author: *Marcelo Piemonte Ribeiro*

3.1 Introduction

To reach the Net Zero Emissions (NZE) targets by 2050 in the EU, the share of fossil fuel must decline from 73% to 20%. However, under existing policies, this share is projected to decline to just below 60% (Cipollone, 2024). In this chapter, we investigate how such a slow transition could possibly be related to pitfalls in the energy price signalling and we analyse the potential of environmental policies in closing this NZE gap. We do so by using novel firm level data information for France and Portugal out of our MDI project (section 3.2). In section 3.3 we first investigate how changes in energy prices affect energy demand, both of 'clean' and 'dirty' type. Secondly, we analyse how and to what extent environmental policies translate in price signals at the firm-level (Box 3.3.2). Finally, adding Austria to the data sample, Box 3.3.2 points to substantial structural differences affecting the changes in energy prices across countries, including energy demand concentration.

We find that energy demand in France is less sensitive to price changes compared to Portugal, reflecting differences in the long-run elasticity of substitution between dirty and clean energy sources we documented. In France, high elasticity allows firms to switch from dirty to clean energy easily, affecting only their energy mix, not consumption, when prices rise. Conversely, in Portugal, lower substitutability compels firms to reduce overall energy use after price spikes. The elasticities also show that while in France, clean and dirty energy are substitutes (elasticity greater than one), fostering innovation towards dirty energy, in Portugal, they are complements, encouraging innovation in clean energy.

Finally, using the OECD Environment Policy Stringent (EPS) as a proxy of carbon tax, we provide evidence on the impact of the latter in making dirty relative to clean energy prices more expensive. Our IV estimates indicate that an increase of 10% in EPS is associated with a 2.5% increase in dirty energy prices relative to clean energy among big firms in France and 15% in Portugal. Together with the elasticities documented previously, these results highlight the need for substantially different carbon taxes within Europe to meet the same NZE targets.

3.2 Data

This study leverages MDI firm-level harmonized data from multiple European countries; we present results for France and Portugal at this stage and include Austria in box 3.3.2. Our sample consists of manufacturing firms ranging from 2000 to 2020. Our key variables include energy consumption and expenditure by sources, allowing us to retrieve energy prices (by dividing expenditure over consumption) at the firm-level. We define clean energy as electricity,[4] steam, and renewable sources.

3.3 Energy elasticities

In this section, we first estimate country price elasticities of energy demand. Following a simple theoretical framework, we then compute the elasticities of substitution between clean and dirty energy and relate them to the price elasticities computed previously.

[4]Power generation has become greener over time (Fabra and Imelda, 2023) and electricity is mostly produced by renewable sources in the countries considered in this analysis (Eurostat, 2025).

3.3.1 Price elasticities of energy demand

We delve into the relationship between energy demand and its prices by adopting a log-log within-firm identification strategy, notably.

$$Y_{t,i,y} = \beta P_{t,i,y} + \theta_i + \delta_y + \epsilon_{t,i,y} \tag{1}$$

Where t represents the type of energy source (i.e., clean and dirty), i, and y, firm and year. θ_i represents firm-specific time-invariant factors influencing the outcome. γ_i stands for year fixed effects. β is likely to be endogenous due to omitted variable bias, e.g., both demand and technological shocks relate to inputs and energy prices consumed and negotiated by firms, for example via quantity discounts and input mix changes (Marin and Vona, 2021). To identify (1) we follow Fontagné et al. (2024) and build an energy price shift-share instrument that multiplies firms energy prices at t_0 (i.e., when the firm enters the sample) by the growth rate of the national average price at year t. Table 2 shows energy demand price elasticities in France and Portugal. While column 1 and 3 display OLS estimates, column 2 and 4 shows IV results. The table shows that both clean and dirty energy demand price elasticities are very similar (first and second rows), but they differ significantly among countries. While in France a 10% increase in clean energy prices induces firms to decrease their energy consumption by 1.7% (column 2), in Portugal firms reduce their consumption by about 9.7% (column 4). This can reflect the higher ability of Portuguese firms to react to energy prices (regardless the sources) by reducing consumption via improved energy efficiency. Alternatively, such differences may reflect the energy prices' markets in both countries.

Table 2: Clean and dirty energy demand price elasticity

Dependent Variable: Firm electricity demand (ln)				
	FR		PT	
Clean energy price (ln)	-0.7501***	-0.1725*	-0.9030***	-0.9691***
	(0.0432)	(0.073)	(0.0076)	(0.0469)
Obs	150,336	149,271	478,959	469,140
R2	0.946	0.944	0.937	0.936
1st stage		0.6345***		0.5178***
F-test (IV)		31,890.2		30,855.6
Dirty energy price (ln)	-0.9568***	-0.1719	–0.9129***	-0.8519***
	(0.1112)	(0.1298)	(0.0127)	(0.0759)
Obs	127,555	119,190	323,308	281,420
R2	0.92818	0.927	0.962	0.963
1st stage		0.4775***		0.1146***
F-test (IV)		12,636.8		2,736.3

Notes: Significance levels: * p<0.1; ** p<0.05; *** p<0.01.
Standard errors clustered at firm-level. Year and firm fixed effects added.

3.3.2 Dirty-clean elasticity of substitution

To examine the possible sources of the above difference in the measured energy price elasticities we compute the long-run elasticities of substitution between dirty and clean inputs[5] in these countries. A higher elasticity of substitution reflects the ability of firms to buffer price changes by shifting

[5] I.e. the extent to which the demand for such energy inputs adjusts in response to shifts in their relative prices.

their energy mix without reducing overall energy use. Next, we use the computed elasticities of substitution to illustrate the role of energy prices in directing innovation towards clean or dirty energy technology development, as highlighted by the technical change literature (Acemoglu et al., 2012, 2016; Aghion et al., 2024).

We start by characterizing the firm problem using a CES production function:

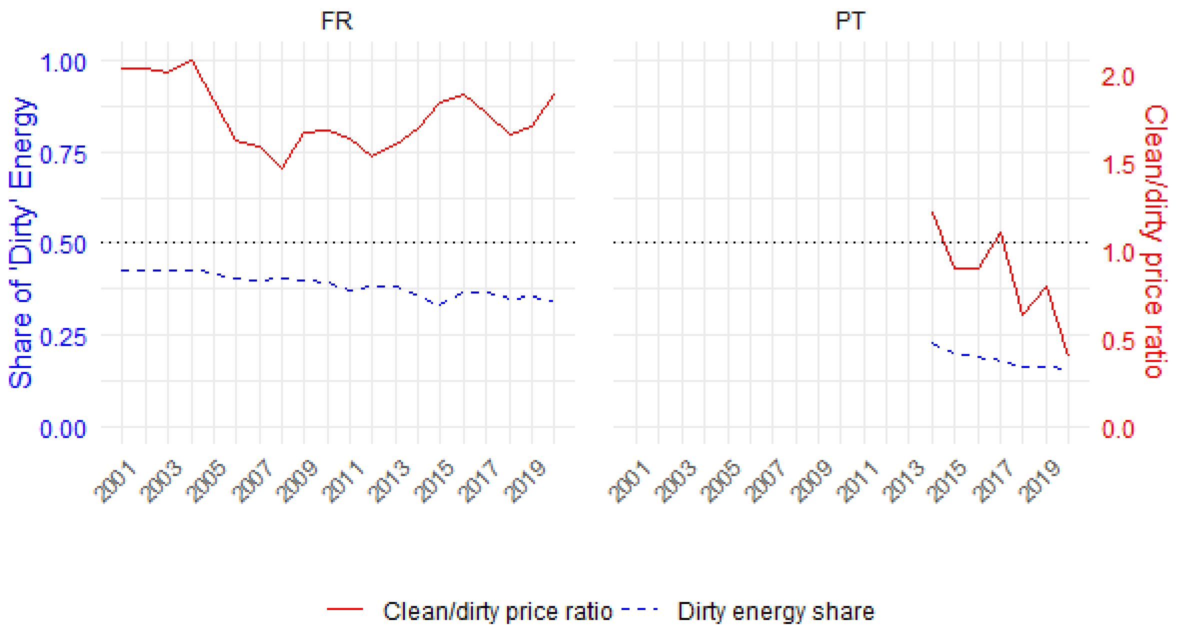
$$Y = ((A_c E_c^{\sigma}) + (A_d E_d^{\sigma}))^{\frac{1}{\alpha}} \tag{2}$$

where output (Y) is produced using clean and dirty inputs (E_c, E_d), governed by their elasticity of substitution (σ). A represents clean and dirty augmenting technologies (i.e., specific technologies improving the efficiency of clean and dirty inputs). The firm maximization problem yields the inverse relationship between price and energy consumption ratios:

$$\frac{E_d}{E_c} = \left(\frac{p_c}{p_d}\right)^{\frac{1}{\sigma}} \left(\frac{A_c}{A_d}\right)^{\frac{1}{\sigma}} \tag{3}$$

The share of dirty energy used in the economies has decreased over time (figure 9) as has the clean to dirty energy price ratio, especially in Portugal, in line with (3).

Figure 9: Dirty energy shares and clean/dirty energy price ratio (median) - Annual Trends



Note: Removed initial years from the Portuguese sample due to change in data collection methodology changes not yet addressed in the data harmonization process.

To identify the elasticity of substitution between dirty and clean energy, we follow Jo (2024) and log linearize (3), such as:

$$\ln\left(\frac{E_d}{E_c}\right) = \alpha + \sigma \ln\left(\frac{P_c}{P_d}\right) + \theta_s + \varphi_t + \epsilon_{it} \tag{4}$$

Where θ and φ are industry and time fixed effects. Omitting the firm fixed effects allows us to identify the long-run elasticity of substitution as documented in the literature (contrary, short-run substitution is obtained by adding firm fixed effects). Firms' unobservable factors (e.g., energy quantity discounts) make σ, the elasticity of substitution between clean and dirty energy, biased. To identify (4) we rely on the same price instrument used in (1).

The elasticity of substitution informs whether firms respond to price changes by altering the mix of energy inputs or by changing the total energy consumed. While high substitutability allows firms to buffer price changes by switching energy inputs, lower substitutability forces a stronger reduction in overall energy use when prices rise. Table 3 shows a higher elasticity in France. I.e., firms can easily relocate from (to) dirty to clean energy inputs following an increase in dirty (clean) energy prices without reducing overall energy consumption, which is less the case in Portugal given the lower elasticity of substitution computed.

The technical change literature highlights the role of market size and prices. While market size favours innovation towards more abundant and cheaper energy sources, price effects encourage innovation towards more expensive energy sources. The elasticity of substitution reveals which of these forces predominates. Table 3 shows that France' energy elasticity of substitution is above one, i.e., clean and dirty energy are substitutes, which implies that the market size dominates the price effect, signalling a technical change bias towards dirty energy (as suggested in equation 4). Conversely, in Portugal, an estimate below one implies instead a complementarity between clean and dirty inputs, reflecting the dominance of price effects.

Table 3: Long-Run Elasticity of Substitution

	Dependent Variable: ln $\left(\frac{E_{d,it}}{E_{c,it}}\right)$			
	Portugal		France	
	(OLS)	(IV)	(OLS)	(IV)
ln $\left(\frac{P_{c,it}}{P_{d,it}}\right)$	0.8822***	0.9803***	1.892***	2.767***
	(0.0029)	(0.0086)	(0.0588)	(0.1240)
Industry FE		Yes		Yes
Year FE		Yes		Yes
Observations	299,470	250,587	126,788	92,306
R2	0.74	0.88	0.24	0.31
F-test (IV only)		76,459.2		12,835.4

Notes: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard errors are clustered at the firm level.

From a policy perspective, increasing dirty relative to clean energy prices has a lower impact in France as firms can shield more easily from changes in prices. Also, it induces French firms to invest in dirty technology. Given the higher shares of clean energy in both economies, such a price increase will induce larger overall energy consumption cuts in Portugal than in France.

By extending (4), we relate the clean and dirty augmenting technology ratio[6] to energy prices ratio:

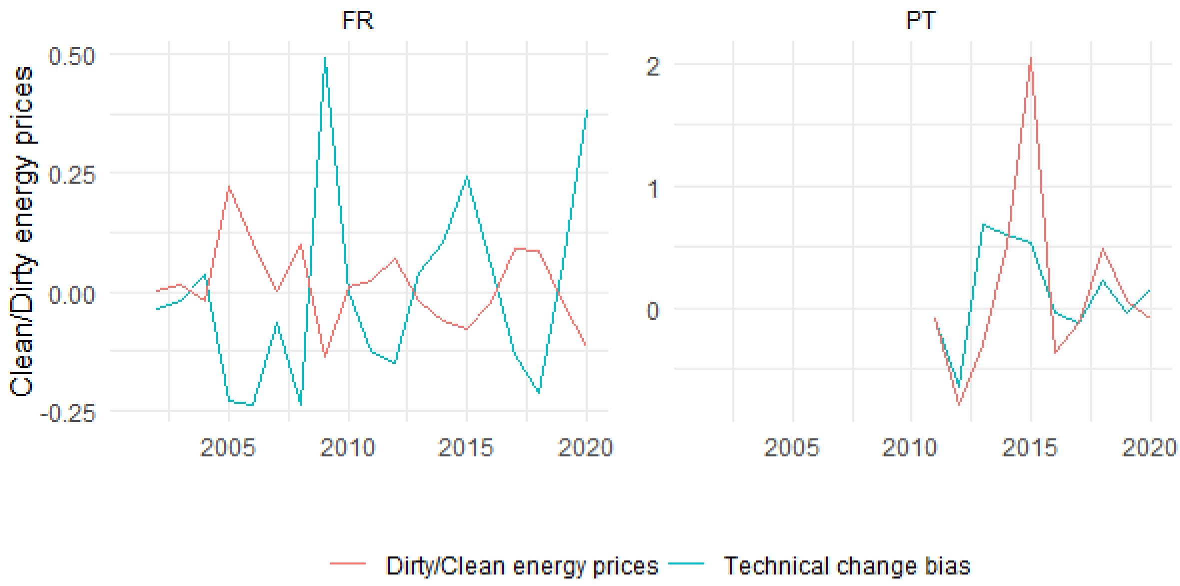
$$\ln\left(\frac{A_c}{A_d}\right) = \frac{\sigma}{1-\sigma}\ln\left(\frac{E_d}{E_c}\right) - \frac{1}{1-\sigma}\ln\left(\frac{P_c}{P_d}\right) \tag{5}$$

Using σ from the previous IV estimates, we calculate the technology ratio (LHS term). From (5), we notice that while an elasticity of substitution (σ) lower than one will make the last term multiplying

[6] A represents clean and dirty augmenting technologies. I.e., they represent technologies that augment the efficiency of dirty and clean energy use respectively.

the price ratio positive, an elasticity above one will make it negative. Figure 10 illustrates such correlation between the clean to dirty augmenting technologies ratio ($\frac{A_c}{A_d}$) and current price ratio ($\frac{P_c}{P_d}$). As expected from our previous estimates, the correlation is negative in France and positive in Portugal, which points respectively to clean and dirty inputs substitution and complementarity (technical change biased towards dirty and clean energy respectively). Our previous estimates illustrate how technical change bias can intensify or attenuate the effects of changes in relative prices on energy use.

Figure 10: Technical change bias and dirty to clean ratio. Technical change bias based on elasticity estimates



Fueling the Future: Macro-Level Impacts of Environmental Policies Through Firm-Level Responses (with Fatih Ozturk, Filiz Unsal)[a]

Despite increasingly stringent environmental policies, reflected in the upward trajectory of the OECD Environmental Policy Stringency Index (EPS), sectoral energy mixes remain stable, with considerable variations among firms. This fact suggests that energy price signals generated by environmental policies are not uniformly transmitted across all firms, potentially limiting their effectiveness in accelerating the green transition. We analyse to what extent environmental policies influence firm-level relative fuel prices.

Our initial specification includes:

$$\frac{P^d_{i,t}}{P^c_{i,t}} = \beta EPS_t \times \frac{EI^d_{i,t}}{EI^c_{i,t}} + \theta_s \times \delta_t + \epsilon_{i,t} \tag{6}$$

Where the dependent variable represents the dirty to clean energy price ratio at the firm level and EPS the index level varying at t (year) only. Unobserved variables determine firm prices, which can influence environmental policy stringency, creating simultaneity (Benatti et al., 2024). We attenuate the latter by introducing an interaction term, notably the dirty to clean energy intensiveness ratio at firm-level at time t_0 (i.e., when the firm enters our sample). The interaction term allows us to introduce firm-level ex-ante exposure to changes in environmental policies, a widely applied approach (Rajan and Zingales, 1998). When ignoring such interaction term, we find that an increase of 10% in EPS is associated with an increase of dirty relative to clean energy prices of about 1.7% in France and 4.4% in Portugal (column 1 following table). When including the interaction term (column 2), such coefficients decrease considerably.

[a] OECD

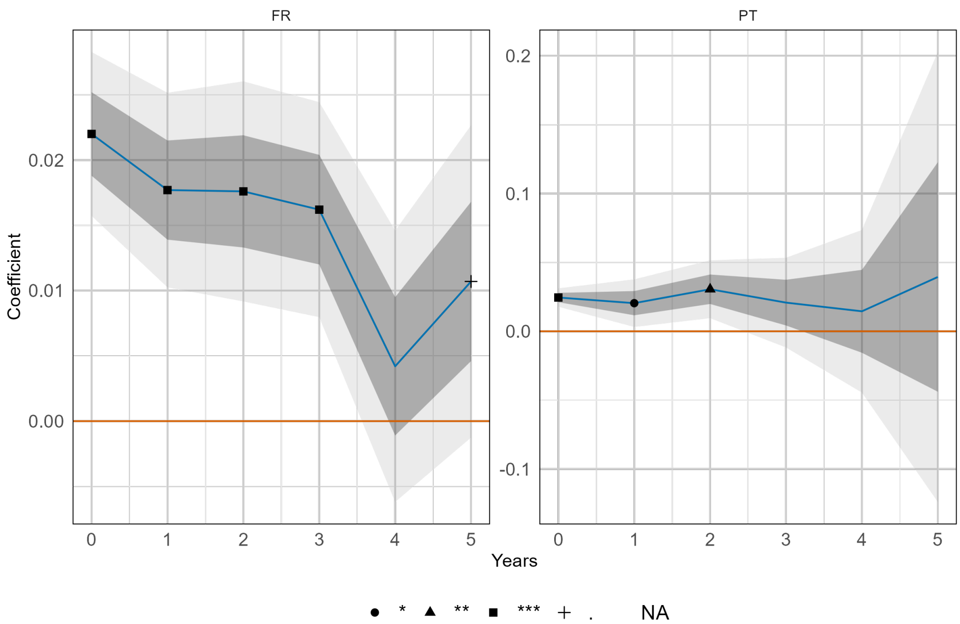
Fueling the Future: Macro-Level Impacts of Environmental Policies Through Firm-Level Responses (with Fatih Ozturk, Filiz Unsal)

	France			Portugal		
	(1)	(2)	(ln EPS)	(1)	(2)	(ln EPS)
ln EPS	0.1715***			0.4493***		
	(0.0058)			(0.0204)		
ln ($E_{intensity}$ t_0 x EPS)		0.0439**			0.3583***	
		(0.0142)			(0.0376)	
ln lag wind			-1.259***			-0.2861***
			(0.0433)			(0.0072)
Firm	Yes			Yes		
Industry	Yes		Yes	Yes		Yes
Year x Ind		Yes			Yes	
Obs	120,191	16,757	16,746	133,131	132,916	125,849
R2	0.606	0.433	0.359	0.967	0.948	0.390
F-test (IV)			952.7			663.9

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Standard errors in parentheses are clustered at the firm level.
(1) and (2) have the same dependent variable, ln $\left(\frac{P_{d,it}}{P_{c,it}}\right)$

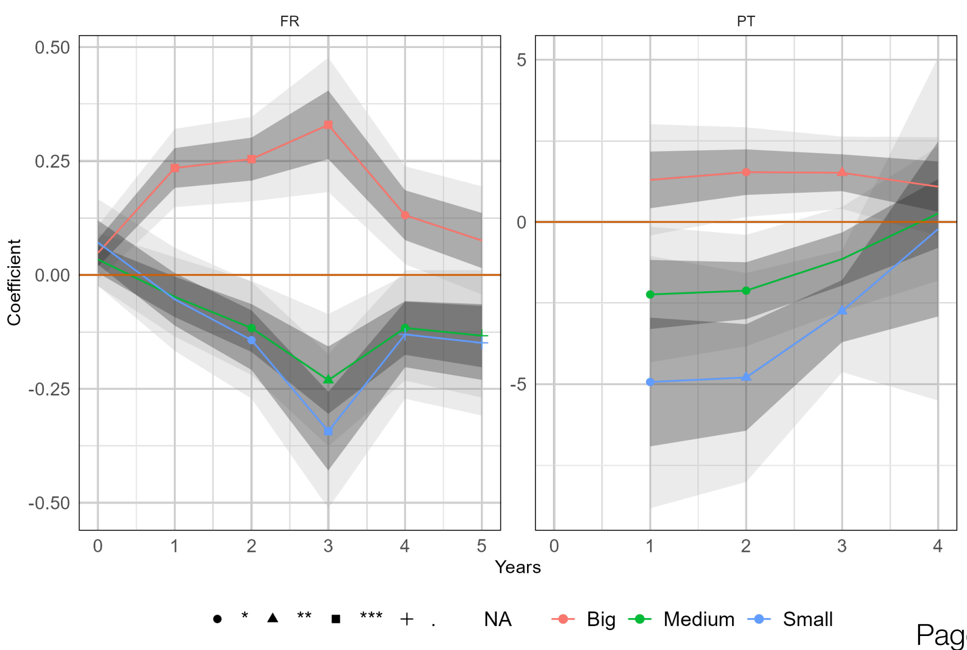
Next, we follow pollution studies (Kögel, 2024; Leroutier and Ollivier, 2022) and use wind variation as an instrument for EPS such as (Lindersten et al., 2022). We retrieve weather data from the European Centre for Medium-Term Weather Forecasting (ECMWF) ERA-5. Wind and planetary height are strongly correlated to pollution dissipation, which is correlated with environmental policies' stringency. Therefore, countries (We use capital state wind as a good proxy of the country as in (Broner et al., 2012).) with strong winds have less pollution accumulation and less policy stringency as suggested by column 3 in the previous table.

We delve into this relationship by considering firms' delayed reaction to environmental policies. Therefore, we apply a local projection approach à la Jordà (2005) with a horizon of five years. Notably, we estimate impulse response functions via regressions at each horizon. Figure 3.3.2 presents the results of our initial specification, including firms' ex-ante exposure. The coefficients are very similar in both countries (about 0.02 with a decreasing tendency in time), but they lose significance and precision, especially in Portugal. They show that a 10% increase in EPS is associated with an immediate 0.2% increase in dirty energy prices relative to clean energy, and a cumulative response of about 0.6% up to two years after the policy change.



EPS impact on Dirty/Clean energy prices ratio (log-log): Local projections

When including the IV estimates and considering firms' sizes, we compute much higher and country-distinct coefficients (Figure 3.3.2). Particularly, firms take about a year to react to EPS changes in France, but not in Portugal. An increase of 10% in EPS is associated with 2.5% among big firms only in France and 15% in Portugal, although estimates seem less precise. However, in both countries, energy prices' responses to environmental policies are concentrated among larger firms.



EPS impact on Dirty/Clean energy prices ratio (IV, log-log): Heterogeneity - firm size

Energy prices and use: decomposition and concentration (with Sellner, R., Reinstaller, A.)[a]

In this box, we characterize the energy market in different countries to assess how energy prices and environmental policies could impact firms, using data for Austria, France and Portugal.

We start by evaluating how concentrated the energy consumption is in the three countries. We calculate the share of firms consuming 90% of the total energy in their respective countries. We found that about 13.4% of firms in Austria consume 90% of the country's energy, 9.3% in Portugal, and 16% in France.

Next, we compare key characteristics of these 'mega-consumer' firms relative to the rest of the economy (Table 53.3.2). They pay lower energy prices (e.g., French mega-consumers pay about 33% less in energy, column 4), have more employees, turnover, and energy costs, and are much more energy efficient. These features suggest the need for careful environmental policy designs, as rigid rules could hamper their productivity or be passed on to consumers (Ganapati et al., 2020).

Firms consuming 90% of country energy vs rest firms - comparison

group	Country	% firms	E Price	Empl	Turnover	E costs	L costs	Clean eff	Dirty eff
E	FR	0.23	0.67	5.13	6.2	2.86	0.76	4.25	6.87
E	PT	0.08	0.4	7.3	7.26	1.86	1.2	18.04	7.26
E_{clean}	FR	0.26	0.75	5.27	6.39	2.42	0.77	4.56	3.72
E_{clean}	PT	0.1	0.52	6.09	6.41	1.36	1.26	16.5	2.3
E_{dirty}	FR	0.2	0.75	4.25	4.92	2.83	0.78	2.97	8.07
E_{dirty}	PT	0.11	0.02	8.47	9.69	1.75	1.18	3.53	6.4

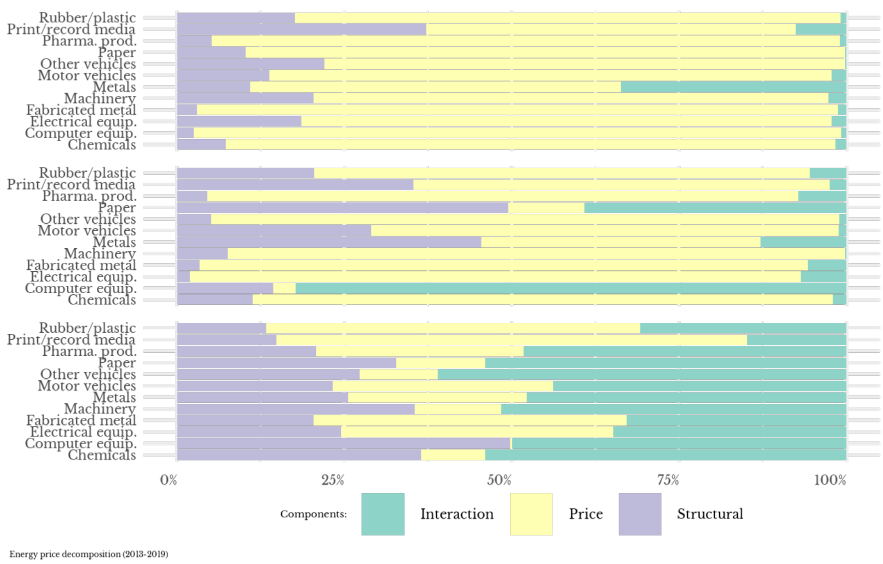
Finally, we investigate energy price markets in these countries. Particularly, we apply a Log Mean Divisia Index (LMDI) approach to understand firm-level price dynamics in the three countries. Particularly, we decompose year-on-year aggregate changes in energy price in each country at time t ($\Delta EPI_{c,t}$) into changes of the value-added share of a sector s, $w_{c,s,t}$ (structural change) and changes in energy prices of each sector as follows:

$$\Delta EPI_{c,t} = \sum_s p_{c,s,t-1} \times \Delta w_{c,s,t} + \sum_s \Delta EPI_{c,s,t} \times w_{c,s,t-1} + \sum_s \Delta EPI_{c,s,t} \times \Delta w_{c,s,t} \qquad (7)$$

The first term captures the aggregate effects of sectoral change, the second captures changes in energy prices, and the third simultaneous changes in value-added shares and sector energy prices.

[a] Austrian Productivity Board (OeNB)

Figure 3.3.2 summarizes the results by illustrating the participation of each of the specification's components in changes in energy prices. While in Austria and in France to a lesser extent much of the aggregate change in energy prices is driven by firms' specific factors (the yellow part of the histograms), this is much less the case in Portugal. In the latter, energy price changes appear to be driven mainly by structural factors and the interaction between changes in prices and in the share of the sector. One could possibly investigate whether such peculiarity is not somehow connected with the sharp difference we found in the measured energy demand elasticities between Portugal and France in Section 3.3.



3.4 Discussion

In this chapter, we analyse the strength of price signalling in shaping the green transition. Our energy demand price elasticities highlight the role of energy prices in reducing energy consumption. The elasticities in Portugal are much higher than in France. Section 3.3.2 helps us to elucidate such a difference. In France, higher energy elasticity of substitution allows firms to relocate from dirty to clean energy more easily, so price increases mainly cause shifts in energy mix within firms rather than reductions in total energy consumption. In contrast, the lower elasticities of substitution in Portugal illustrate firms' need to cut overall energy use to keep production constant. The long-run elasticities also inform us of the direction of innovation; while in France firms invest in dirty energy following changes in dirty-clean energy price ratio changes, Portuguese firms invest in clean energy. Given that clean energy shares are relatively high in these countries' energy mixes (about 60% in France and 80% in Portugal), investments in clean energy following changes in dirty-clean energy price ratio changes will lead to higher overall reductions in energy consumption than investments in dirty energy.

The computed elasticities highlight the need for higher levels of carbon taxes in France to achieve

NZE targets relative to Portugal. This becomes especially true as environmental policies increase the dirty-clean relative prices more in Portugal than in France (box 3.3.2). Given the countries' differences in price dynamics and energy consumption concentration (box 3.3.2), target policies are essential to bridge the gap between countries, but they should be carefully designed to avoid negative impacts competitiveness in view of the 'mega-consumers' firms' characteristics.

4 Firm Responsiveness over the Business Cycle: New Evidence from Europe

Authors: *Alberto Ferreira*[*], *Javier Miranda*[†], *Chengzi Yi*[*]

4.1 Introduction

Understanding how firms respond to changes in productivity is crucial to unpacking the rich dynamics of job creation and destruction, those of aggregate investment, and, more broadly, the magnitude and pace of resource reallocation in the economy. These processes are ultimately central to determining long-term growth and aggregate productivity trends.

In this chapter, we investigate how firm responsiveness to idiosyncratic shocks varies across countries and over the business cycle. Within a set of Eurozone countries, we pose three main questions: (1) how do comparable firms in different countries adjust to identical firm-specific productivity shocks? (2) how different are their responses to adverse *vs* positive shocks? (3) how do aggregate macroeconomic conditions - being in a boom or a recession - affect these firm-level responses?

We leverage cross-country firm-level data accessible through a new microdata infrastructure platform (MDI)[1], to focus our analysis on both labour and capital adjustments (responses), providing a deeper understanding of resource reallocation during different phases of the business cycle. The study also disentangles firm responsiveness into extensive margins (whether firms make lumpy adjustments) and intensive margins (the magnitude of adjustment when firms do adjust), motivated by the literature on adjustment costs to production inputs.[2] These costs can significantly constrain firms' ability to respond to shocks, thus preventing resource reallocation from less productive to more productive firms, which is vital for improving aggregate productivity.

We find patterns of responsiveness that are consistent with productivity-enhancing reallocation for the economies under analysis; that is, firms that experience positive shocks tend to expand, while those that experience negative shocks tend to contract. However, our findings reveal distinct patterns across countries over business cycle phases. In general, when faced with negative productivity shocks, firms show a clear reluctance to downsize: they're much more willing to hire or invest when experiencing positive shocks than they are to fire workers or sell off capital when hit by negative shocks of similar size. Once firms decide to adjust, the magnitude typically increases proportionally with shock size.

Business cycle conditions substantially influence adjustment patterns. During recessions, firm responses are noticeably muted compared to expansionary periods, with this effect particularly pronounced for labour along the extensive margin and capital along the intensive margin. Firms are significantly less likely to hire in response to positive shocks during downturns, while irreversibilities

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[†]This report builds upon the foundation established by Leonardo Indraccolo and Elliott Weder in previous iterations. We also thank Orlando Roman for his valuable contribution to the visualization of results in this report.

[1]All results have been reviewed to ensure no confidential information is disclosed in accordance with the requirements of country-specific legal frameworks as applied by each of the National Statistical Offices we partner with. We access the confidential micro data under the auspices of the Technical Support Instrument TSI-2022-MULTIMSPROD-IBA, and TSI-2023-MULTIMSPROD-IBA, Project Numbers 101101853, and 101140673, Enhancing the Micro Foundation of the Research Output of National Productivity Boards. These projects are funded by the European Union. We thank the European Commission for their support.

[2]Examples from this literature include Caballero and Engel (2003); Cooper et al. (1999); Cooper and Willis (2003); Cooper and Haltiwanger (2006). The presence of adjustment costs can be motivated based on legal, bureaucratic, or market frictions such as stringent labour regulations –translated into high firing and hiring costs and resale price discounts on capital –making it costlier to divest from a firm's capital stock.

in capital adjustment appear more binding during recessions, with adverse shocks significantly less likely to trigger divestment decisions.

Our cross-country analysis reveals striking heterogeneity in adjustment behaviours. Portugal stands out for showing strong convexity in labour-extensive margin responses during expansions, indicating Portuguese firms are more likely to adjust employment when facing extreme productivity shocks in either direction. The Netherlands and France represent opposite ends of the spectrum regarding intensive margin adjustments: Dutch firms display the steepest response slopes for both labour and capital, suggesting greater flexibility in factor reallocation when they do adjust, while French firms exhibit the flattest slopes, indicating more conservative adjustments even when productivity shocks are substantial. These patterns hold across business cycles and for both production factors, suggesting fundamentally different adjustment cost structures across European economies that persist through different macroeconomic conditions. Such results suggest that the framework conditions potentially play an important role, which we will explore further in our future work.

4.2 Data and Methodology

This study relies on rich firm-level data from multiple European countries; we present results for NL, FR, PT and SI.[3] Our sample consists of an unbalanced panel of firms [4] operating in the manufacturing sectors from 2010 to 2020. The dataset was constructed under the Microdata Infrastructure (MDI) framework and incorporates information from National Business Registers and Business Statistics.[5] Key variables include capital stock, number of persons employed, gross output, and raw material expenditures. The data harmonisation across countries ensures consistency in variable definitions and facilitates robust cross-country analysis.

Our research question requires defining a variable for country-specific business cycles. Naturally, synchronization of the business cycles across the EU economies means that there is a large common component in this dating. However, to assess country-specific macroeconomic features, we define a recessionary year at the country level as one where the real GDP of that country experiences a negative growth rate (as per the measure made available by AMECO, from the European Commission)[6]. Hence, in any given year, we observe some countries in recession and others not[7].

4.2.1 Estimation of Productivity Shocks

To estimate firm-level productivity, we employ the approach of Ackerberg et al. (2015), where production functions are estimated at the two-digit manufacturing sector level. We assume a Cobb-Douglas production function:

$$Y = AL^{\alpha}K^{\beta} \tag{8}$$

Since direct observations of prices are unavailable, output Y is measured using value-added data,

[3]We expect to be able to extend results to Austria, and Finland soon with Germany and the United Kingdom later this year.

[4]At this stage, our results focus on *continuing* firms within the unbalanced panel; hence, they do not reflect the responsiveness patterns of entrants and exiters.

[5]See Bartelsman and MDI-Team (2025a)

[6]While the sample period may not contain dramatic boom-bust cycles, our binary classification effectively captures meaningful differences between favorable and adverse macroeconomic conditions at the country level, including asymmetric impacts of the European Sovereign Debt Crisis.

[7]Future work would test the current results against different business cycle definitions - such as that put forward by the Euro Area Business Cycle Dating Committee or the country-specific business cycle committees.

while labour L and capital K inputs are proxied by the number of employees and tangible fixed asset values, respectively. All monetary variables, including gross output, capital stock, and raw material expenditures, are converted into real terms using appropriate deflators: GDP deflator for output, capital goods price index for capital stock, and producer price index for intermediate goods.

Revenue productivity (TFPR) is assumed to follow an autoregressive process:

$$a_{it} = \rho a_{i,t-1} + \eta_{it}, \quad \eta_{it} \sim N(0, \sigma_\eta) \tag{9}$$

where a_{it} denotes the log value of A. The productivity shock corresponds to the unpredictable component of firm-level TFPR, specifically the innovation term η_{it} in the AR(1) process. Given the absence of firm-level price controls, TFPR should be interpreted as a composite term that incorporates both technical efficiency and demand shocks.

4.2.2 Responsiveness Regressions

We analyse firm responsiveness to productivity shocks by running regressions as in Decker et al. (2020) and Cooper et al. (2024). We estimate two types of regressions that capture both extensive and intensive margins of adjustment. We measure labour and capital adjustment by the yearly change in the log of the number of employees and tangible fixed assets, respectively.

The extensive margin regression examines the probability that a firm adjusts its labour or capital stock in response to productivity shocks, modelled as a binary outcome. An adjustment is defined as a change exceeding 2.5

This separation helps disentangle the fixed and variable costs associated with firm adjustments. If firms face high fixed adjustment costs, they are expected to adjust infrequently but by a large magnitude when they do. Conversely, frequent but small adjustments suggest the presence of lower fixed costs but higher variable adjustment costs.

The probability of adjustment is modelled as a function of the lagged productivity shock $\eta_{i,t-1}$, allowing for potential convexities in firm responsiveness by including quadratic terms. Implicitly, this amounts to assuming a one-period time-to-build in both inputs, i.e. the notion that firms take some time to adjust capital or labour. Additionally, a recession indicator D_t captures differences in firm behaviour across business cycle phases, enabling us to assess whether firms adjust more or less during recessions. The extensive margin regression is specified as follows:

$$Pr(1^{adj} = 1) = c + \beta_1^{ext}\eta_{i,t-1} + \beta_2^{ext}\eta_{i,t-1}D_t + \beta_3^{ext}D_t + \alpha_1^{ext}\eta_{i,t-1}^2 + \alpha_2^{ext}\eta_{i,t-1}^2 D_t + X_{i,t}'\Theta + \nu_{i,t} \tag{10}$$

where $Pr(1^{adj} = 1)$ represents the probability of adjustment, $\eta_{i,t-1}$ is the lagged productivity shock, and D_t is a dummy variable indicating recessionary periods. The vector $X_{i,t}'$ includes additional firm-level controls, such as sector dummies, past employment and past capital stock. The coefficient β_1^{ext} captures the direct effect of productivity shocks, while β_3^{ext} measures how responsiveness changes during recessions. Additionally, α_1^{ext} and α_2^{ext} allow for non-linearity in firm responsiveness.

The intensive margin regression follows a similar structure but estimates the magnitude of the employment or capital adjustment $g_{i,t}$ rather than the probability of adjustment. We run this regression for the subset of firms that adjust in a given year. The intensive margin regression is specified as follows:

$$g_{i,t} = c + \beta_1^{int}\eta_{i,t-1} + \beta_2^{int}\eta_{i,t-1}D_t + \beta_3^{int}D_t + \alpha_1^{int}\eta_{i,t-1}^2 + \alpha_2^{int}\eta_{i,t-1}^2 D_t + X_{i,t}'\Theta + \nu_{i,t} \tag{11}$$

where $g_{i,t}$ represents the growth rate in employment or capital between years $t-1$ and t for firms that adjust.

4.3 Cross-Country Results

Leveraging the properties of our main regression specifications, we are able to study firms' responsiveness to idiosyncratic productivity shocks along four dimensions: (1) labour and capital adjustments; (2) along the extensive and intensive margins; (3) during recession *vs* expansion years; and - as allowed by our unique dataset - (4) across EU countries. We present our results for labour and capital separately - uncovering novel cross-country and business cycle features of firms' responses -and conclude with some remarks on the comparative labour *vs* capital adjustment dynamics.

Our comparisons throughout, mostly visual for ease of exposition, rely on plotting the coefficient of interest of our main regression specifications. Namely, to study the business cycle features of *extensive* margin adjustments (of either input), we compare $\beta_1^{ext}\eta + \alpha_1^{ext}\eta^2$ (for expansion years) with $(\beta_1^{ext} + \beta_2^{ext})\eta + (\alpha_1^{ext} + \alpha_2^{ext})\eta^2$ (for recession years). For these, the outcome variable we compare is the *relative probability of adjustment* - i.e. the probability that firms hit by a given productivity shock adjust labour or capital *relative* to firms that, *all else equal*, were not hit by a shock. Conversely, to analyze the business cycle properties of *intensive* margin adjustments (of either input) we compare $\beta_1^{int}\eta + \alpha_1^{int}\eta^2$ (for expansion years) with $(\beta_1^{int} + \beta_2^{int})\eta + (\alpha_1^{int} + \alpha_2^{int})\eta^2$ (for recession years). In this case, the outcome variable of interest is the *relative growth rate* of labour or capital, i.e. the input's year-on-year growth rate accounted for by the idiosyncratic productivity shock, everything else held constant.

A few important points should be made regarding the interpretability of the coefficients. First of all, since we are ultimately interested in *relative* cross-country differences in *responsiveness* to a given (comparable) productivity shock, we do not consider any constants (c) in our analysis - since these reflect baseline (absolute) cross-country differences in adjustment patterns.[8] Secondly, we only study intensive margin responsiveness (i.e. the extent of adjustments) for the subset of firms that, in a given year, adjust the input in question (i.e. outside the bands of inaction). Therefore, the population of firms analysed for extensive and intensive margin analysis differs by construction. Thirdly, the unit of analysis differs slightly across countries - while for FR and PT we observe firm-level responses, for NL and SI we observe enterprise-level responses (i.e. potentially a collection of firms). We expect the granularity of the unit of analysis to impact the responsiveness patterns, with potential nonlinearities at the plant or firm level being smoothed out at the enterprise level.

4.3.1 Hiring and Firing: Labour Responsiveness over the Business Cycle

Along the extensive margin, we observe clear patterns in how firms adjust their workforce in response to productivity shocks. In general, firms show asymmetric responses: the probability of adjusting (i.e., hiring) increases with the size of positive shocks, while negative shocks of higher magnitude are associated with decreasing probabilities of adjustment (i.e., less likely lay-offs).

By comparing figure 11a and figure 11b, a key business cycle feature stands out: while the probability of hiring increases with positive shock magnitude, this relationship is steeper during booms

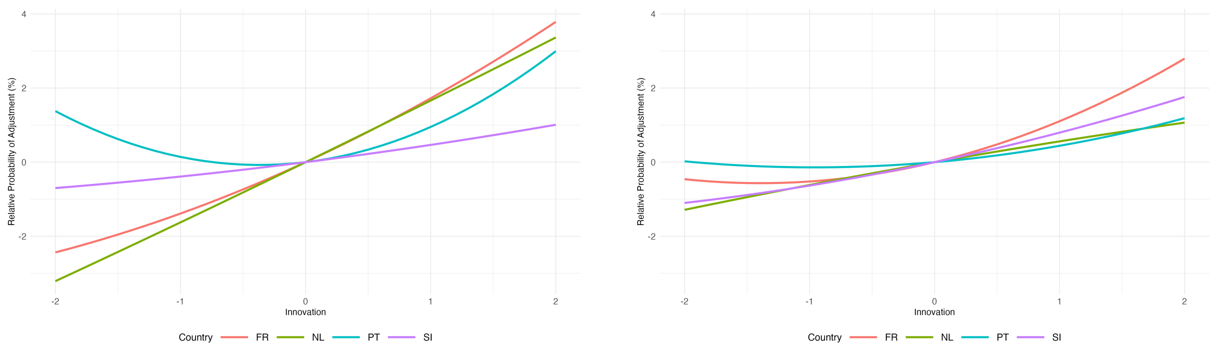
[8] As such, all results should be interpreted relative to the firms of that country-industry peer group not hit by a shock.

than recessions. In other words, a very positive shock to firms' productivity is more likely to lead to hiring in a boom than in a recession, *ceteris paribus*.

Looking at adverse shocks across the business cycle, we find the relationship between shock magnitude and adjustment probability is more pronounced during expansions, with most firms demonstrating greater reluctance to implement lay-offs (with the Netherlands exhibiting this pattern most strongly, while Portugal presents a notable exception). During recessions, however, this pattern weakens substantially as firms exhibit higher relative probabilities of downward labour adjustments across most countries in our sample.

Conditional on labour adjustment taking place, we focus on firms' responsiveness along the intensive margin (i.e., by how much to grow/shrink the workforce in response to productivity shocks). Unlike the extensive margin, intensive margin responses typically exhibit a more linear and upward-sloping pattern, with the magnitude of adjustment increasing proportionally with the size of the productivity shock.

Figure 11: Cross-country comparison of labour extensive margin responsiveness

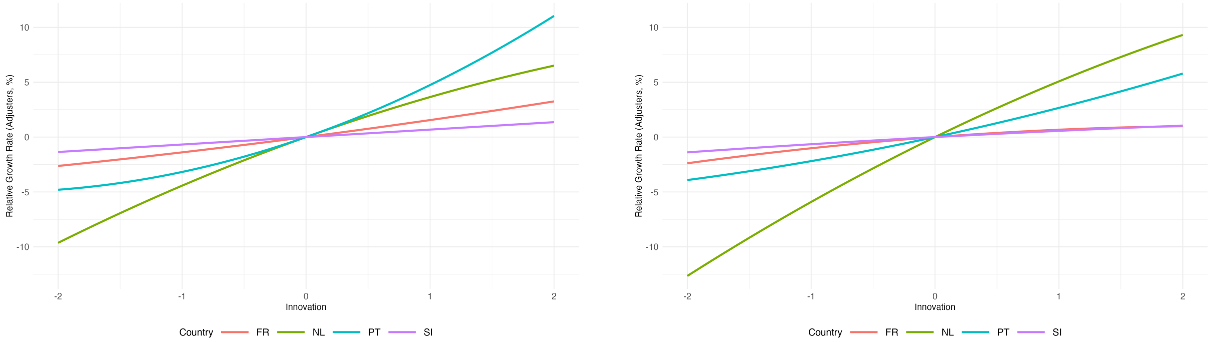


(a) Expansionary periods **(b)** Recessionary periods

Note: These figures plot the relative probability of labour adjustment as a function of idiosyncratic productivity shocks (horizontal axis). The lines represent the estimated coefficients $\beta_1^{ext}\eta + \alpha_1^{ext}\eta^2$ for expansions (panel (a)) and $(\beta_1^{ext} + \beta_2^{ext})\eta + (\alpha_1^{ext} + \alpha_2^{ext})\eta^2$ for recessions (panel (b)), showing how firms in different countries adjust their workforce in response to productivity shocks of varying magnitudes.

Across countries, we find striking contrasts between FR/SI and NL in their intensive margin labour adjustments. Dutch firms display the steepest response slopes, suggesting that when they do adjust, they do so with greater magnitude. This pattern holds across business cycles and points toward a more flexible factor reallocation environment. French and Slovenian firms exhibit the flattest slopes in intensive margin adjustments, remaining notably unresponsive to idiosyncratic productivity shocks for either upward or downward labour adjustments in booms or recessions.

Figure 12: Cross-country comparison of labour-intensive margin responsiveness (adjusters only)



(a) Expansionary periods

(b) Recessionary periods

Note: These figures plot the relative growth rate of labour as a function of idiosyncratic productivity shocks (horizontal axis). The lines represent the estimated coefficients $\beta_1^{int}\eta + \alpha_1^{int}\eta^2$ for expansions (panel (a)) and $(\beta_1^{int} + \beta_2^{int})\eta + (\alpha_1^{int} + \alpha_2^{int})\eta^2$ for recessions (panel (b)), showing how firms in different countries adjust the magnitude of their workforce changes in response to productivity shocks of varying magnitudes.

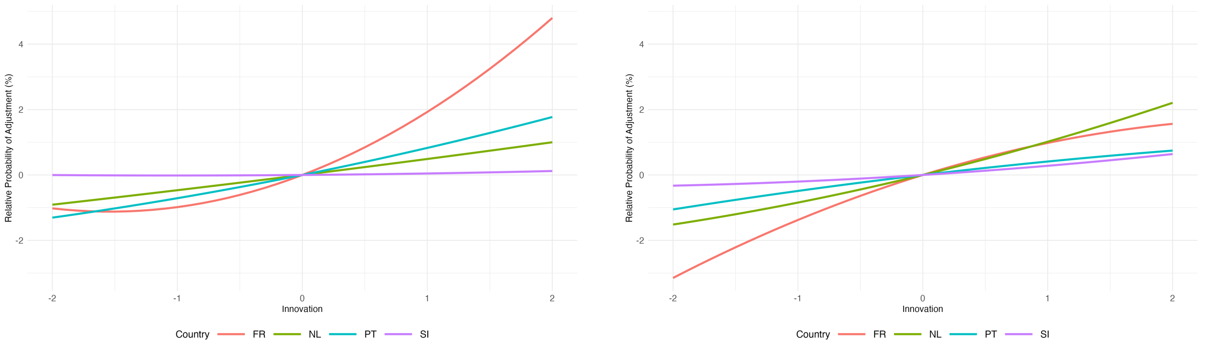
4.3.2 Investing and Divesting: Capital Responsiveness over the Business Cycle

Focusing on the extensive margin of capital adjustment, there are pervasive asymmetries in firms' responses to productivity shocks. In general, firms show asymmetric responses: they are less likely to respond to negative productivity shocks than to positive shocks of similar magnitude.

A key business cycle feature emerges similar to labour: capital adjustment probabilities are higher in expansions than in recessions. However, capital-specific patterns diverge from labour in an important way. While labour becomes more flexible during downturns (with higher firing probabilities), capital appears to become more rigid - during recessions, large negative idiosyncratic shocks are significantly less likely to trigger divestment than during booms. This suggests that irreversibilities in capital adjustment (i.e., low resale value) become particularly binding during economic downturns, deterring firms from uninstalling or reselling capital despite negative productivity signals.

At the cross-country level, French firms exhibit striking business cycle sensitivity: in recessions, they show the lowest relative probability of capital adjustment when facing negative shocks, suggesting particularly binding irreversibilities or high fixed costs of capital reduction. Conversely, in expansionary periods, they show the highest probability of capital adjustment in response to positive shocks among all countries studied. This pronounced swing in responsiveness suggests a cyclical fixed cost scheme. Slovenia, in contrast, shows relatively muted responsiveness on the capital extensive margin across all shock sizes and business cycle phases.

Figure 13: Cross-country comparison of capital extensive margin responsiveness

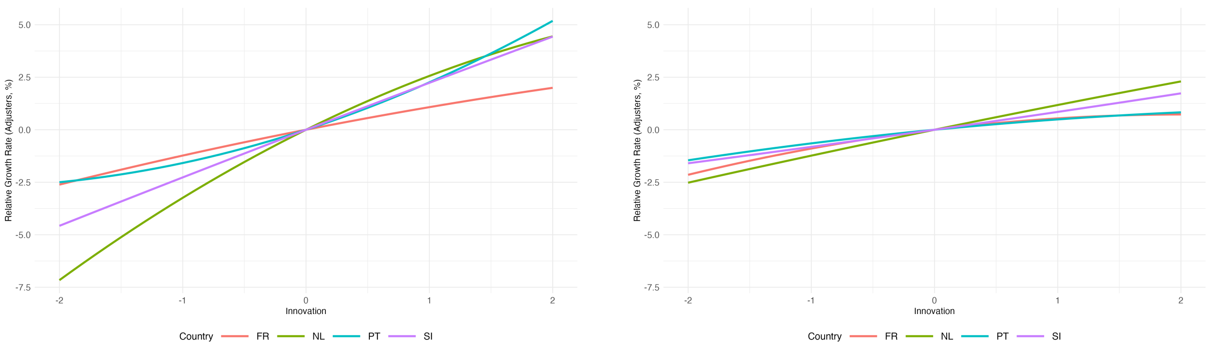


(a) Expansionary periods

(b) Recessionary periods

Note: These figures plot the relative probability of capital adjustment as a function of idiosyncratic productivity shocks (horizontal axis). The lines represent the estimated coefficients $\beta_1^{ext}\eta + \alpha_1^{ext}\eta^2$ for expansions (panel (a)) and $(\beta_1^{ext} + \beta_2^{ext})\eta + (\alpha_1^{ext} + \alpha_2^{ext})\eta^2$ for recessions (panel (b)), showing how firms in different countries adjust their capital stock in response to productivity shocks of varying magnitudes.

Figure 14: Cross-country comparison of capital-intensive margin responsiveness (adjusters only)



(a) Expansionary periods

(b) Recessionary periods

Note: These figures plot the relative growth rate of capital as a function of idiosyncratic productivity shocks (horizontal axis). The lines represent the estimated coefficients $\beta_1^{int}\eta + \alpha_1^{int}\eta^2$ for expansions (panel (a)) and $(\beta_1^{int} + \beta_2^{int})\eta + (\alpha_1^{int} + \alpha_2^{int})\eta^2$ for recessions (panel (b)), showing how firms in different countries adjust the magnitude of their capital stock changes in response to productivity shocks of varying magnitudes.

For the intensive margin of capital adjustment, recessions severely dampen firms' investment and divestment magnitudes in response to shocks compared to expansions, a more pronounced effect than observed for labour. Nevertheless, even during downturns, firms in all four countries maintain slightly upward-sloping responsiveness regardless of the business cycle phase.

Cross-country comparisons reveal the same pattern observed for labour: French firms exhibit the flattest slopes in their capital adjustment responses to shocks, while Dutch firms display the steepest. Dutch companies adjust their capital stocks more proportionately to shock magnitudes, suggesting lower variable costs of capital adjustment compared to their French counterparts. This consistent positioning of countries across both labour and capital adjustments points to fundamental differences in factor adjustment cost structures that persist across production factors and business cycle phases.

4.4 Conclusion

Our analysis examines firm responsiveness to productivity shocks across the business cycle, focusing on labour and capital adjustments along the extensive and intensive margins in four European countries - the Netherlands, Portugal, Slovenia, and France.

4.4.1 Business Cycle Effects: Expansions vs. Recessions

The business cycle plays an important role in determining firm responsiveness patterns. During recessions, responses to positive shocks are noticeably muted compared to expansionary periods. For labour, the extensive margin shows particularly dampened responses in recessions. Firms are significantly less likely to hire in response to positive shocks. In contrast, they are less reluctant to fire when facing adverse shocks. This suggests that economic downturns may simultaneously inhibit workforce increases while also weakening firms' ability to retain workers.

For capital, the intensive margin becomes especially subdued during recessions. While firms may still make the decision to adjust capital (extensive margin), the magnitude of investment or divestment (intensive margin) is markedly reduced compared to expansionary periods. On the extensive margin, firms show lower overall probabilities of capital adjustment during recessions compared to expansions. Particularly notable is how firms respond to negative shocks: in recessions, large adverse productivity shocks are significantly less likely to trigger divestment decisions than during boom periods. These patterns suggest that during economic downturns, firms face higher effective costs of downsizing their capital stock, which limits both the probability of adjustment and the scale of capital adjustments even when they do occur. In this regard, policies that induce countercyclical costs of capital adjustment might improve reallocation - especially during downturns.

4.4.2 Adverse vs Positive Shocks

We document clear asymmetries in the extensive margin of adjustment: firms are generally less likely to respond to negative productivity shocks than to positive shocks of similar magnitude. For labour, the probability of hiring in response to positive shocks consistently exceeds the probability of firing in response to negative shocks across most countries. For capital adjustments, this asymmetry is even stronger, suggesting higher fixed costs associated with capital divestment than with investment.

In contrast, intensive margin responses exhibit a more linear and upward-sloping pattern. Once firms decide to adjust, the magnitude of adjustment typically increases proportionally with the size of the productivity shock.

4.4.3 Cross-Country Heterogeneity

Our analysis reveals striking cross-country differences in adjustment patterns. Portugal stands out for showing strong convexity in labour-extensive margin responses during expansions, indicating that Portuguese firms are more likely than their European counterparts to adjust employment when facing extreme productivity shocks in either direction, especially when the shocks are negative.

The Netherlands and France represent opposite ends of the spectrum regarding intensive margin adjustments for both capital and labour. Dutch firms display the steepest response slopes, suggesting that when they do adjust, they do so with greater magnitude in response to productivity shocks - both positive and negative. In this regard, the Dutch economy exhibits significantly higher degrees of productivity-enhancing worker reallocation as workers move towards firms that exhibit increasing productivity. This pattern holds across business cycles and for both labour and capital, pointing toward a more flexible factor reallocation environment. Conversely, French (and Slovenian) firms exhibit the flattest slopes in intensive margin adjustments, especially during booms, indicating that even when they decide to adjust, they do so more conservatively than their European peers. The weak responsiveness suggests the average firm in these economies experiences little productivity-enhancing reallocation - a process where resources flow towards more productive firms from less productive firms. In future work, we plan to explore the role of framework conditions in explaining these cross-country differences, which could provide insights for policymakers to enhance framework conditions that facilitate productive reallocation.

5 Heterogeneous Technology and the Phillips Curve

Authors: *Daniele Aglio*, *Eric Bartelsman*

5.1 Introduction

Monetary and fiscal authorities have responded well to the recent surge in inflation that followed the large sectoral and aggregate shocks during Covid-19, the post-covid run-up in aggregate demand, and the sharp rise in energy costs and other supply disruptions in 2022. Nonetheless, the policy response may have been more timely and targeted with a better policy toolkit. The traditional macroeconomic Phillips Curve (PC) analysis attempts to quantify the link between inflation and labour and product market tightness, conditional on expected inflation. As a practical tool, however, it falls short owing to the instability of the "slope" parameter. More granular data allows us to study how aggregate inflation depends on the response of heterogeneous firms to a variety of shocks. This chapter provides evidence on marginal costs and mark-ups of firms with different production technology under different demand conditions, allowing more precise and timely estimates of the aggregate PC slope parameter. The analysis is based on Aglio and Bartelsman (2025), extending the analysis presented in the Productivity Report of CompNet (2023).

The main intuition of our results is that the level and slope of a firm's marginal cost curve varies with its technology, resulting in different slopes of the economic slack-inflation relationship. Productivity and costs are inversely related: if demand for an industry's output rises, and this demand is disproportionately supplied by the highest productivity (lowest cost) firms, industry-level prices may rise less than if the demand is met by low-productivity firms, ceteris paribus. Similarly, cost shocks will have less aggregate impact if they hit firms with low cost pass-through. Taking a firm-level perspective for tracking shocks and output/price response will thus enhance the information available to macro policy makers to understand the impact of economic disturbances and determine the required policy response.

This chapter analyses data from manufacturing firms in France, the Netherlands, and Slovenia, with information on firms' output, inputs, prices, and production capacity. Using micro-theoretical foundations and a novel statistical technique to cluster firms according to technology and demand characteristics, we estimate supply curves and PC slopes for heterogeneous clusters of firms. Together, this work can form a theoretical and empirical framework to better understand how different demand and supply disturbances can lead to aggregate price pressure.

The results show that the aggregate Phillips curve will become flatter with an increase in the number of technologically advanced firms or with a larger share of demand changes met by these firms.

5.2 Data and Methodology

Confidential firm-level data in each country are accessed using the newly built Micro Data infrastructure (MDI)\footnote{For more details, see Bartelsman and MDI-Team (2025b). The MDI provides access to annual data on production, labour input, payroll, intermediate input, and capital stock for each firm sourced from the merged Balance Sheet (BS) and Structural Business Statistics (SBS) files. Data on value and unit value of firm shipments at an 8-digit product level of detail, sourced from the Prodcom files, are used to compute firm-level price indexes. Finally, annual indicators of exogenous demand shocks by 2-digit NACE industry and 6-digit HS product level are computed using the OECD input-output tables and the Comtrade export data, respectively, and are merged into the firm-level panel data. Availability of output prices from Prodcom and the product-level exports from Comtrade limit the analysis to the manufacturing sector.

Using the MDI, the program code is run in each country to cluster firms into groups endogenously based on similarity in estimated demand and supply characteristics. In particular, the relevant estimated characteristics are the level and slope of the marginal cost curve and the elasticity and curvature of the demand curve facing the firm (see the technical box below for the estimated functions). When a firm is hit with an exogenous shock to demand for its products, its profit-maximizing response to output or price (i.e., cost markup) depends on the demand and supply characteristics. Given the demand curve, a firm with a flat marginal cost curve will respond more in output than price to a demand shock. Given a supply curve, a firm with more curvature in demand will see a higher increase (or lower decrease) in markup following a positive demand shock. Similarly, the optimal pass-through of an exogenous shock to costs, say a rise in the price of imported energy, depends on these characteristics, with higher curvature leading to higher markups and, thus, cost pass-through.

We estimate the demand and supply parameters in turn, relying on the exogenous firm-level demand shocks and the implied exogenous shifts in costs. Our algorithm iterates between estimation of supply and demand for given firms in a cluster and the reassignment of firms to supply and demand clusters based on similarity of parameter estimates, until a minimum residual sum of squares is found.

We assume there are five supply and three demand clusters[9]. Starting with equal sized initial clusters from the observed distributions of labour productivity and price-cost ratios, we estimate firm productivity and output elasticities for each supply cluster, given the prices pass-through from the demand side. We then estimate price pass-through for each demand cluster given the level and slope of marginal costs from the supply side. Based on estimation from the final clusters, firms with higher productivity (lower marginal cost) also have flatter marginal cost curves.

Once the firms are clustered according to production technology and demand characteristics, we can estimate the slope of the Phillips curve for each technology cluster, controlling for strategic interaction across firms (for derivation, see Aglio and Bartelsman (2025)) using:

$$dp_{it} = \beta_1 dy_{it} * C + \beta_2 dp_{it}^{comp} * C + \beta_4 dp_{it-1} + \delta_{st} + \epsilon_{it}$$

where dp_{it}, dy_{it}, and dp_{it}^{comp} are log change in prices, log change in real output (instrumented with demand shocks), and log change in competitors' price (defined at the 4-digit NACE industry level); C indicates the interaction with each cluster. The parameter of interest, β_1 for each cluster, gives the effect of exogenous shifts in demand on firm pricing changes, controlling for heterogeneous demand and strategic interaction across firms.

[9] The choice of the number of clusters allows us to differentiate between different parts of the distributions. For this, we eyeballed the empirical distributions of labour productivity and price divided by unit labour cost for firms in France. For Slovenia, we assume only two demand and two supply clusters, owing to the small number of firms in the sample.

Technical box on clustering estimation

For the supply side estimation, given demand clusters, we estimate a Cobb-Douglas production function, using the exogenous demand instruments to control for endogeneity of variable inputs.

$$y_{it} = \alpha + \gamma_k k_{it} + \gamma_l l_{it} + \gamma_m m_{it} + \delta_t + \epsilon_{it}$$

where y_{it}, k_{it}, l_{it}, and m_{it} are logs of real output (revenue deflated with the price index from Prodcom), real capital, full-time equivalent labour, and real material, respectively, for firm i in year t, and δ_t are time fixed effects.
For the demand estimation, given the production technology clusters, we follow Mrazova and Neary (2017), who show that the cost pass-through is a function of demand elasticity and convexity in monopolistic competitive markets. Therefore, we cluster firms according to the estimate of price pass-through, β_{mc}, from the following equation with time fixed effects:

$$dp_{it} = \beta_0 + \beta_{mc} dmc_{it} + \delta_t + \nu_{it}$$

where dp_{it} and dmc_{it} are the log change in price and the log change in marginal costs, respectively, for firm i in year t. Marginal costs are measured by average unit variable costs (wages and intermediate goods and services costs per unit of real output), and the change is the residual change in marginal costs after regressing marginal costs on the exogenous demand shift.

5.3 Cross-Country Results

Table 5 shows the parameter estimates and other characteristics of firms for each technology cluster. As can be seen, the clusters show increasing total factor productivity, labour productivity, and increasing size, as well as decreasing marginal costs. The slope of the marginal cost curve depends inversely on the sum of the output elasticities which becomes higher for the higher technology clusters. On average, markups also increase with technology. The patterns by technology cluster are very similar across countries[10].

Table 6 gives information for each demand cluster. In all cases, the estimated cost pass-through, β_{mc}, is less than 1, implying a less-than-proportional increase in prices when marginal costs rise. The majority of firms in France are characterized by high pass-through, suggesting a relatively more rigid residual demand faced by these firms. Dutch firms are concentrated in demand clusters with lower cost pass-through, hence more elastic demand. The same is true for Slovenia.

Figure 15 summarizes the result for each technology cluster. The lines reflect the estimated marginal cost curves, where the slope depends inversely on the sum of the output elasticities, controlling for the differences in demand facing the firms in each technology cluster. The axis labels show the average marginal cost level and average sales for firms in each technology cluster.

[10] Average firm-size (reported in millions euros), differs across countries because sampling for the merged SBS-Prodcom dataset varies across countries.

Table 5: Firms' characteristics by technology cluster

France							
Technology cluster	N° firms	TFP	$\gamma_k + \gamma_l + \gamma_m$	Labour productivity	Size	Markup$_m$	Marginal costs
1	4593	1.47	0.91	90.0	8.3	1.20	2.39
2	14397	1.39	0.92	162.4	12.8	1.25	1.05
3	8442	1.68	0.94	219.2	19.7	1.38	0.73
4	3428	1.74	0.99	361.4	22.7	1.43	0.55
5	1371	2.32	1.05	812.4	24.9	1.82	0.27
Netherlands							
Technology cluster	N° firms	TFP	$\gamma_k + \gamma_l + \gamma_m$	Labour productivity	Size	Markup$_m$	Marginal costs
1	791	1.03	0.89	139.7	36.8	1.22	1.75
2	2634	1.43	0.90	244.7	47.2	1.15	0.99
3	988	1.72	0.87	387.6	47.5	1.31	0.74
4	416	1.80	0.93	411.62	47.8	1.60	0.62
5	286	1.74	1.04	1164.4	77.6	1.45	0.34
Slovenia							
Technology cluster	N° firms	TFP	$\gamma_k + \gamma_l + \gamma_m$	Labour productivity	Size	Markup$_m$	Marginal costs
1	773	1.33	1.02	70.8	4.6	1.08	1.15
2	594	1.65	1.04	116.7	4.9	1.25	0.77

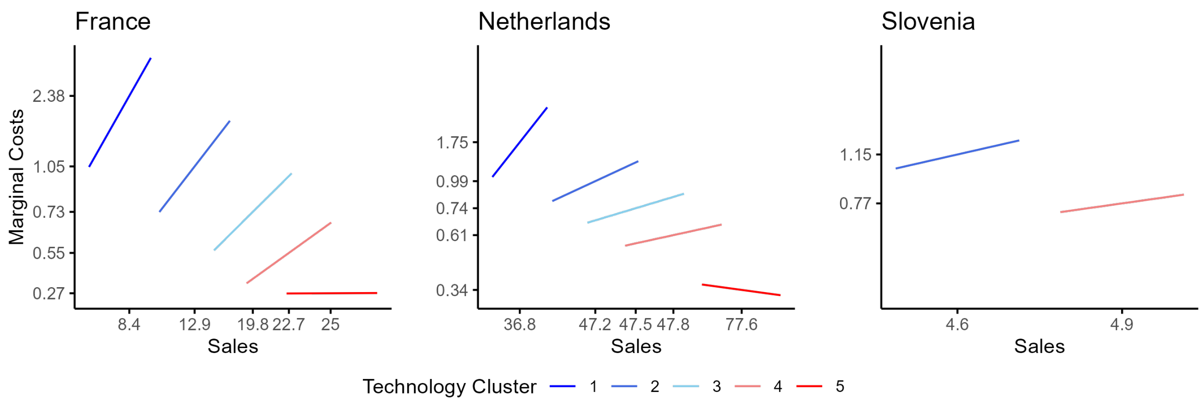
Note: *TFP* (α) and the γ parameters result from the production technology estimation; *Labour productivity* is real output in thousand 2010 euros per employee (fte);*Size* is nominal revenue in thousand euros; Markup$_m$ is price - intermediate input costs markup computed as in Loecker and Warzynski (2012); *Marginal costs* are calculated as unit variable costs.

Table 6: Cost pass-through by demand cluster

France		
Demand cluster	N° firms	β_{mc}
1	7895	0.17
2	3169	0.83
3	21167	0.91
Netherlands		
Demand cluster	N° firms	β_{mc}
1	2004	0.11
2	2594	0.89
3	517	0.94
Slovenia		
Demand cluster	N° firms	β_{mc}
1	822	0.13
2	545	0.94

Note: β_{mc} is the cost pass-through coefficient from the demand clustering equation.

Figure 15: Supply curves by technology cluster

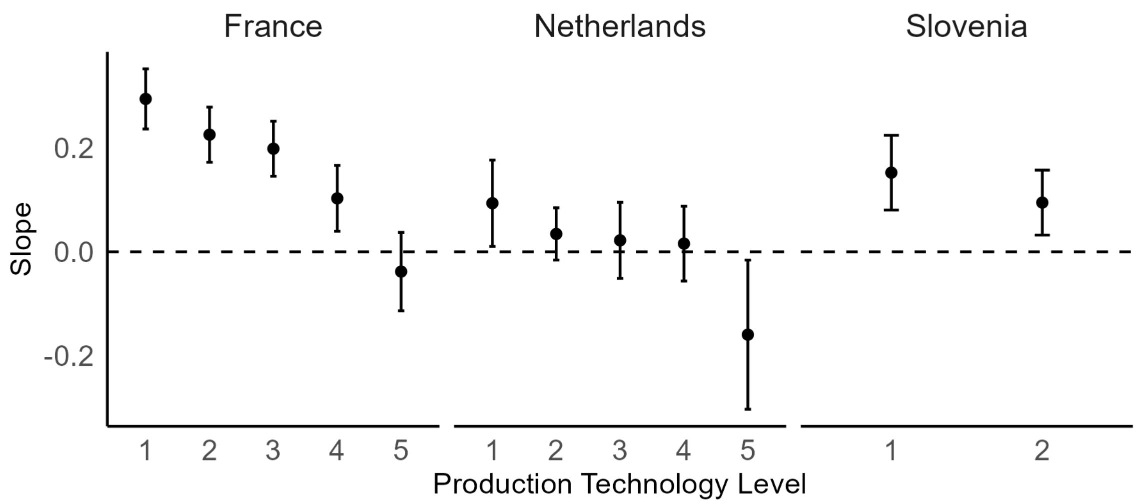


Note: Marginal costs and sales are data from table 5, while slopes are average sum of output elasticities, controlling for demand and strategic interaction estimated from the pricing equations.

Next, we show in Figure 16 the resulting slope parameters of the Phillips curve by technology cluster, controlling for demand characteristics and competitors' price behaviour. Firms with higher output elasticity (lower slope of marginal cost curve) and higher productivity (lower marginal costs) feature lower price increases when faced with exogenous demand shocks.

The slope of the aggregate Phillips curve will depend on the slopes of the individual technology clusters. An increase in the number of technologically advanced firms or a larger share of demand changes met by these firms will flatten the aggregate Phillips curve.

Figure 16: The slope of the Phillips curve by technology cluster



Source: MDI
Note: 95% confidence intervals.

5.4 Conclusion

Traditional macroeconomic frameworks, such as the Phillips Curve, can be derived using micro theory but are generally estimated using macroeconomic time series. In this chapter, we show that there is considerable heterogeneity in the parameters at the micro level which could result in unstable macro estimates. Our clustering method provides a flexible way to capture the heterogeneity while aggregating the micro data into a limited number of sub-aggregates. Having estimates of how such heterogeneous clusters respond to shocks, together with information on the nature of shocks faced by each of the clusters, can lead to better and more timely macro forecasts.

6 Exploring Other Perspectives of the CompNet Dataset

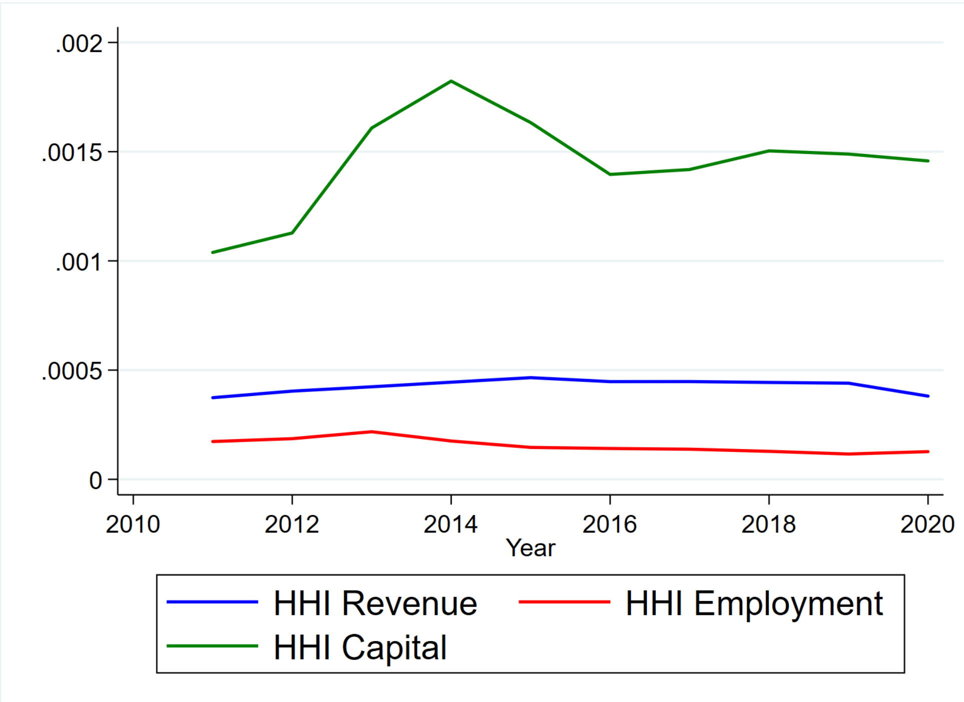
6.1 The Impact of Regional Concentration on Country-Level Concentration

Author: *Hoang Duy*

This section examines the development of national concentration and its correlation with regional concentration. Our regional data is collected using the NUTS 2 classification.

Using the method developed by Bighelli et al. (2023), we aggregated the contribution of individual countries and regions into total EU concentration. Our proxy for market concentration is the Hirschman-Herfindahl index (HHI), constructed for three indicators: revenue, employment, and capital.

Figure 17: Concentration, EU NUTS 2 regional aggregated, 2011-2020

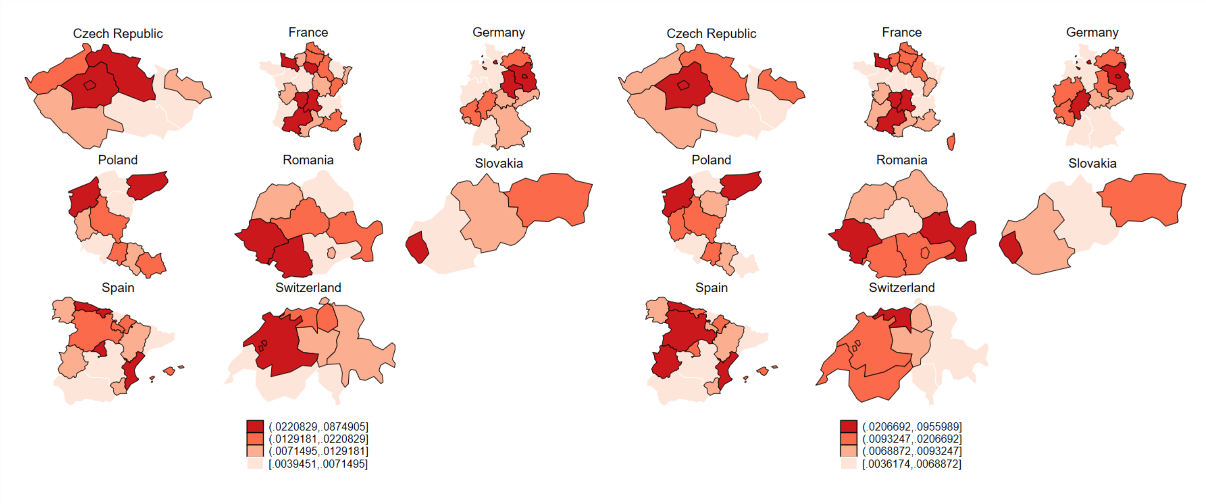


Source: author's calculation using CompNet 10th Vintage (unconditional_nuts2_20e_weighted). Countries are CH, CZ, DE, ES, FR, PL, RO, SK.

Between 2011 and 2020, capital emerged as the primary driver of EU concentration. HHI for capital increased by 39.82% (Figure 17), with the most significant rise occurring between 2012 and 2014. After peaking in 2014, HHI for capital declined and stabilized from 2016 onward. In contrast, HHI for revenue and employment remained relatively stable. Given these trends, we focus on capital HHI for our regional-national correlation analysis.

Figure 18 illustrates the distribution of capital HHI across NUTS 2 regions in Europe. The left-hand panel represents 2014, when aggregated concentration reached the highest. The right-hand panel represents 2020, when COVID caused significant market disruptions. Overall, concentration levels declined between 2014 and 2020, with lower values observed across all quintiles.

Figure 18: Capital concentration in NUTS 2 regions by quintile, Europe 2014 (left) and 2020 (right)

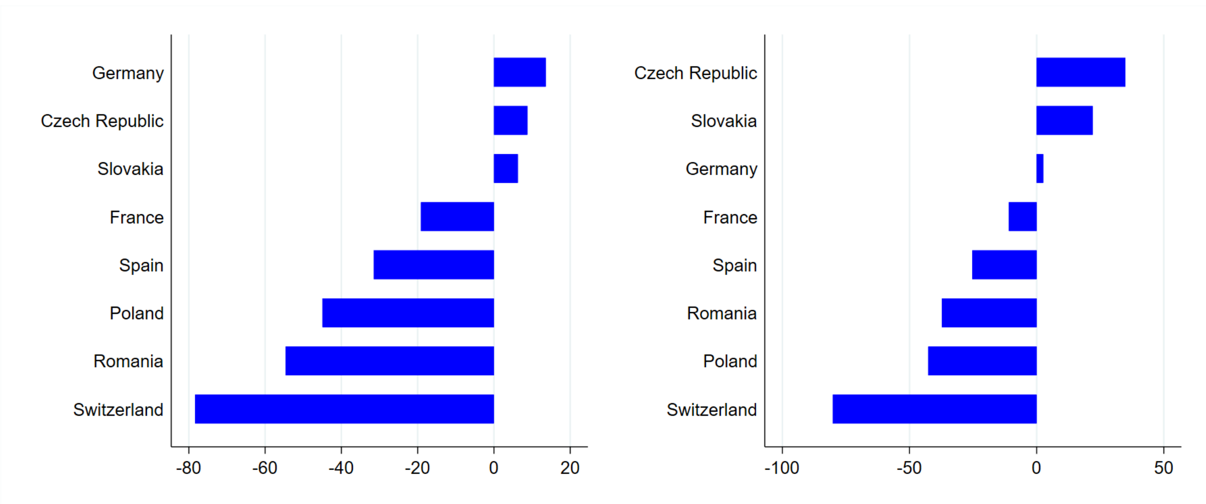


Source: author's calculation using CompNet 10th Vintage (unconditional_nuts2_20e_weighted) & Eurostat (GISCO statistical unit dataset). Countries with more than 2 available regions are included. Some regions in Poland are not available.

Similar to EU aggregated trends, national concentration followed a similar decreasing trend between 2014 and 2020 (Figure 19). Most countries became less concentrated, except for Germany, the Czech Republic, and Slovakia. Switzerland saw the most significant decrease, with a reduction of approximately 80%.

Comparing country-level changes with shifts in concentration in the regions with the largest capital shares reveals a consistent pattern: a decline in national concentration is almost always accompanied by a corresponding decrease in HHI capital at the regional level.

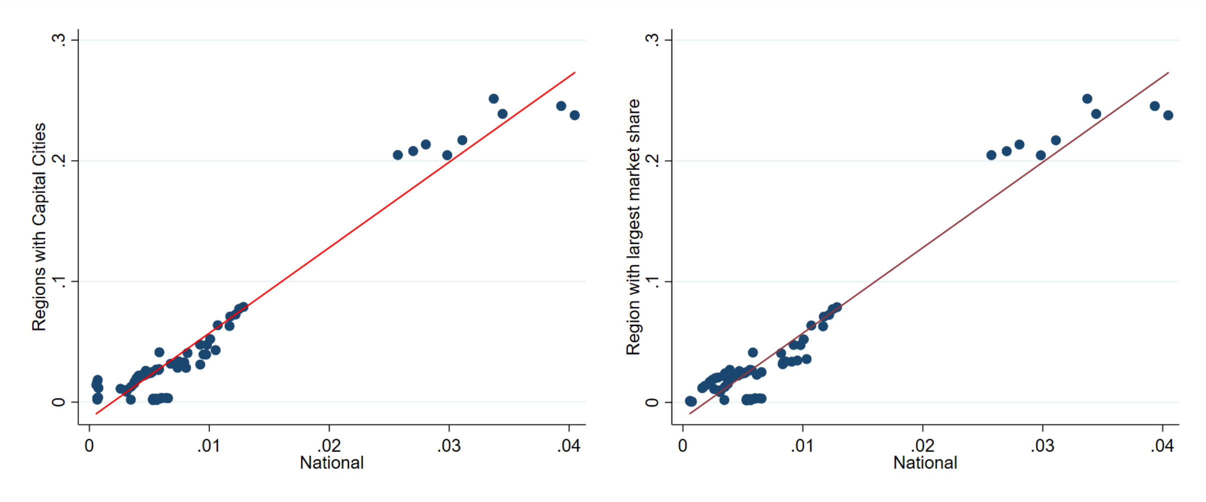
Figure 19: Capital concentration, changes in % between 2014 – 2020, country (left) & region with the largest capital share (right)



Source: author's calculation using CompNet 10th Vintage (unconditional_nuts2_20e_weighted).

We further investigate the impact of capital concentration at the regional level by analyzing the correlation between regional and national HHI. We focus on two types of local regions: those containing capital cities and those with the largest capital shares. These regions tend to have significant economic influence within their respective countries and could be key drivers of changes in capital concentration at the national level. Overall, we find a positive association between regional HHI and national HHI, suggesting that regional concentration trends often align with national patterns (Figure 20).

Figure 20: Capital concentration, national & region with capital city (left), national & region with largest market share (right)

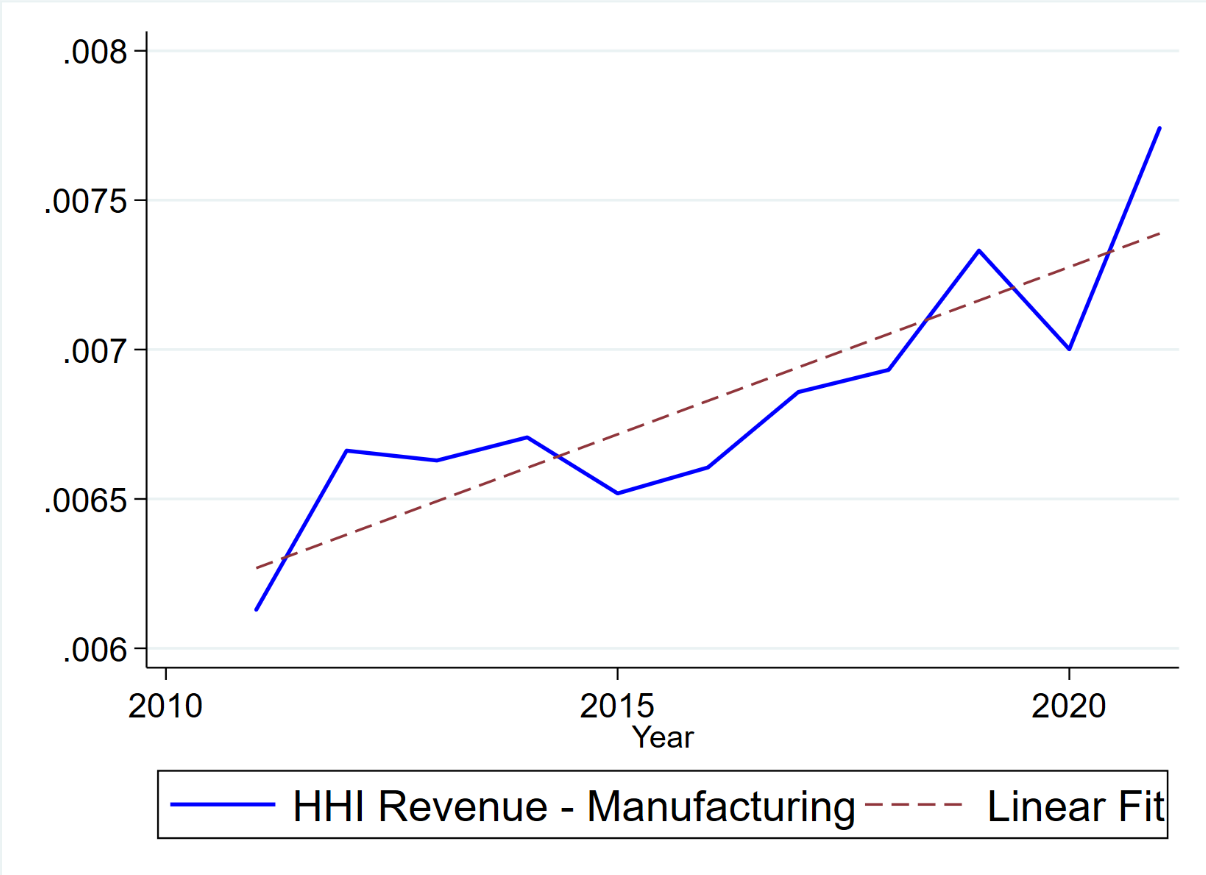


Source: author's calculation using CompNet 10th Vintage (unconditional_nuts2_20e_weighted & unconditional_country_20e_weighted). Data points are taken by country-year dimension. Countries are CH, CZ, DE, ES, FR, PL, RO, SK.

6.2 HHI Revenue and Post-COVID Concentration

The previous section discussed the shift in concentration up to 2020, which is the last year available for our German country-level dataset . In this section, we extend our analysis to post-COVID period of revenue concentration, focusing on the manufacturing sector.

Figure 21: Revenue concentration – manufacturing sector, EU aggregated, 2011-2021

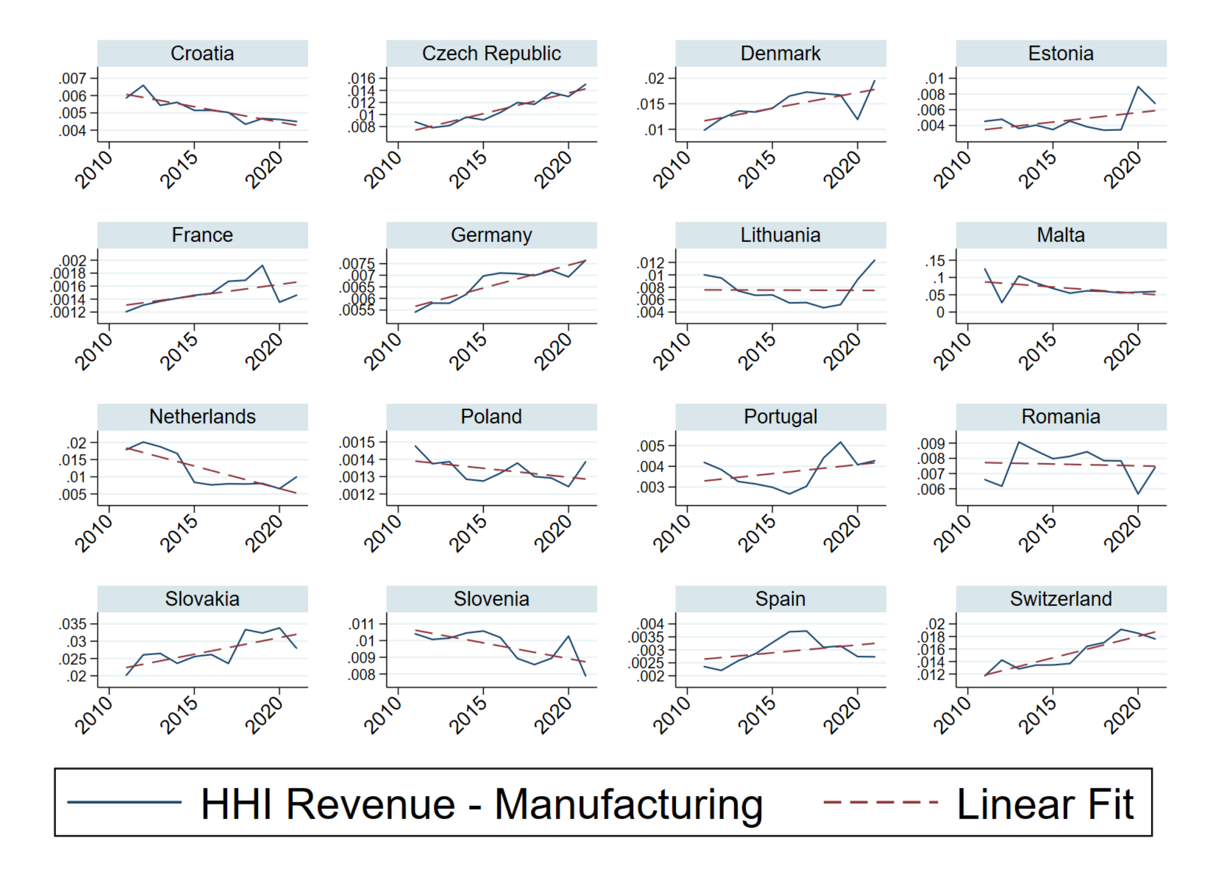


Source: author's calculation using CompNet 10th Vintage (unconditional_mac_sector_20e_weighted). Countries are CH, CZ, DE, DK, EE, ES, FR, HR, LT, MT, NL, PL, PT, RO, SI, SK.

Aggregated concentration showed an upward trend with a significant increase post-Covid (Figure 21). Between 2020 and 2021, HHI increased by 10.23%. After COVID-19, larger firms with stronger balance sheets were more likely to survive or even grow, thus exacerbating the inequality between firms and leading to rising concentration (Lopez-Garcia and Szörfi (2021)).

Going into HHI by country, Figure 22 reveals diverging post-COVID concentration trends across Europe. While many Western economies - including Germany and France - experienced rising revenue concentration, a contrasting pattern is observed in several Eastern European countries where concentration either declined or remained relatively stable. In these Eastern markets, structural differences such as market fragmentation, limited dominance by large firms, or more resilient SMEs may have played a buffering role.

Figure 22: Revenue concentration - manufacturing sector, by EU country, 2011-2021



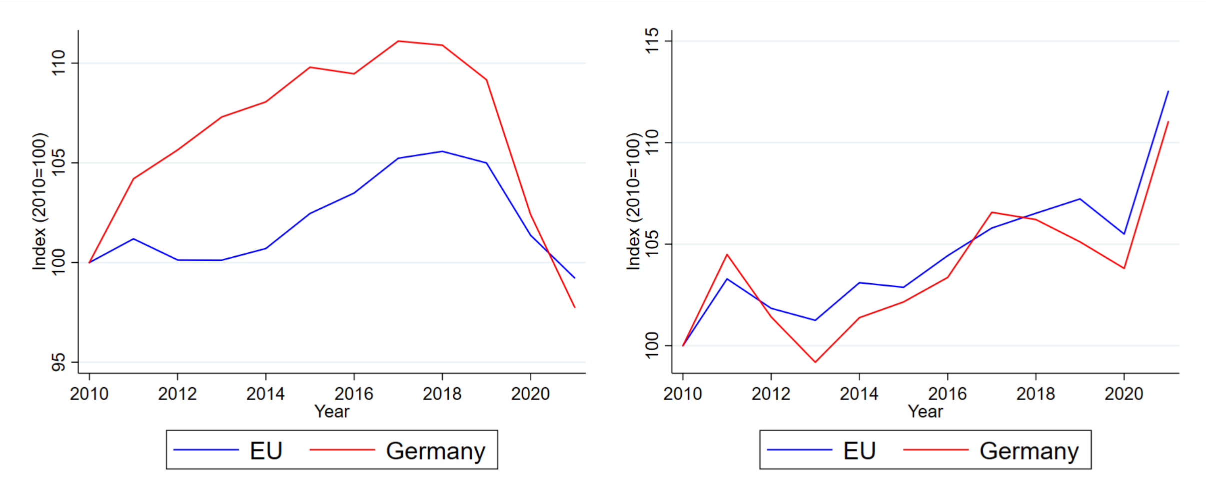
Source: author's calculation using CompNet 10th Vintage (unconditional_mac_sector_20e_weighted).

6.3 Examining the Manufacturing sector in Europe

Author: *Hoang Duy*

De-industrialization has been a significant trend in many countries in recent years, particularly in Europe, where some of the world's leading economies are located. This process - characterized by a decline in manufacturing and a growing service sector - has reshaped the industrial landscape, affecting employment and productivity patterns. In this section, we will examine its impact by looking into the manufacturing sector in Europe, with an emphasis on Germany and post-COVID recovery in 2021.

Figure 23: Total employment (left) and labor productivity (right), manufacturing - EU & Germany



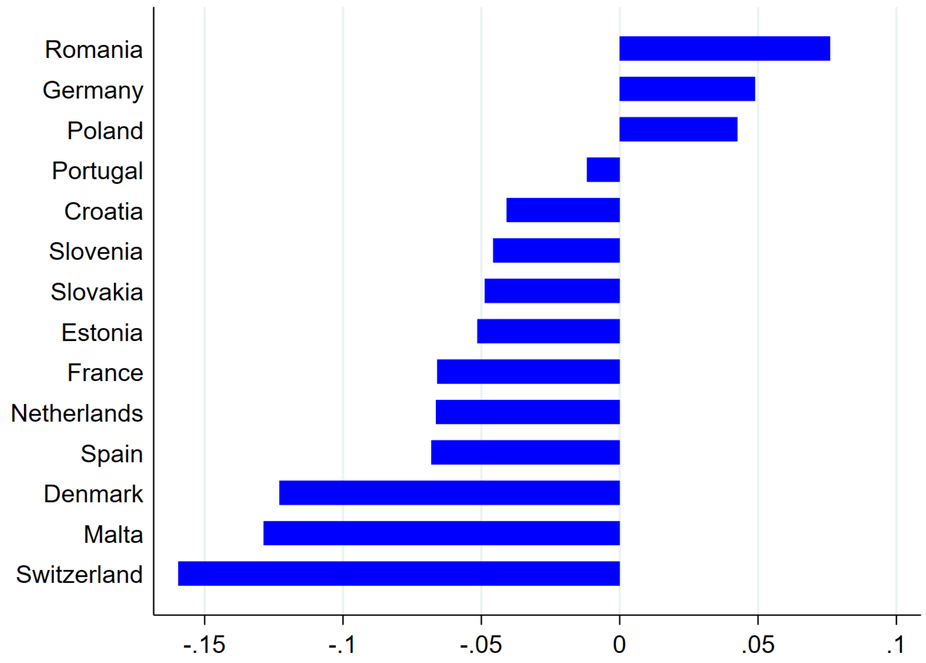
Source: author's calculation using CompNet 10th Vintage (unconditional_mac_sector_20e_weighted). Countries are CH, DE, DK, EE, ES, FR, HR, MT, NL, PL, PT, RO, SI, SK.

Employment in Europe experienced a slowdown starting from 2018 (Figure 23). In Germany, total employment in 2021 fell below 2010 level. In contrast, labor productivity showed sign of recovery in 2021, with strong growth observed in both Germany and the EU as a whole. This divergence suggests that manufacturing became leaner but more efficient. It's plausible that automation, digitization, and capital deepening played a role in sustaining output even as headcount dropped (Acemoglu and Restrepo (2019)).

6.3.1 Productivity growth across Europe

Countries in the region contributed differently to the significant productivity growth in 2021 (Figure 24). Most notably, Romania, Germany, and Poland recorded above average growth rates, while Switzerland exhibited the weakest growth, trailing the average by over 15%. Despite these variations, productivity movements across European countries remained relatively uniform. Most growth rates clustered around 5% from the average, indicating a broad-based recovery pattern, likely tied to post-COVID synchronized reopening of economies, policy stimuli, and supply chain reactivation across the EU (European Commission (2020)).

Figure 24: Labor productivity growth, deviation from EU average - manufacturing, 2021

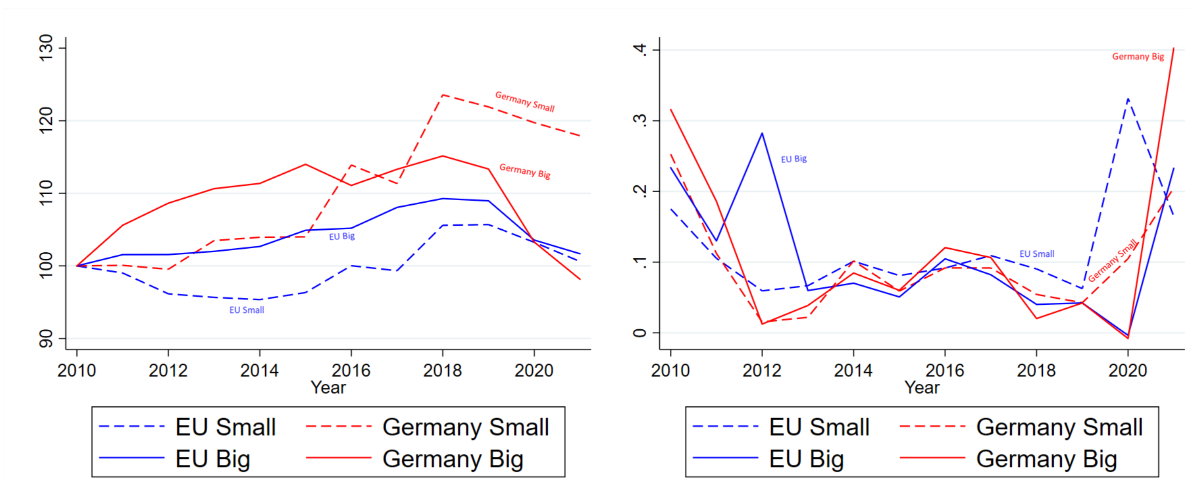


Source: author's calculation using CompNet 10th Vintage (unconditional_mac_sector_20e_weighted).

6.3.2 Employment and productivity by firm size

A closer look at employment and productivity trends by firm size reveals distinct patterns. Employment in both big firms (at least 250 employees) and small firms (under 50 employees) declined from 2018, with most returning to 2010 levels by 2021. The exception was small German firms, which remained relatively stable during this period (Figure 25). The employment fall of big German firms could be the driver behind the drop at the country level, which resulted in a sharp increase in productivity.

Figure 25: Employment (left) and labor productivity (right) by size class, manufacturing - EU & Germany



Source: author's calculation using CompNet 10th Vintage (unconditional_macsec_szcl_20e_weighted). Countries are CH, DE, DK, EE, ES, FR, HR, MT, NL, PL, PT, RO, SI, SK.

The YoY growth rate of labor productivity stayed relatively flat between 2013 and 2019 for all firms. In 2020, despite the impact of Covid-19, small firms displayed positive growth, with EU aggregated productivity increasing by as much as 30%.

The big firms stagnated in 2020 with a 0% rate. They rebounded in 2021 with high growth for both EU and Germany. Big German firms achieved the highest growth in this post-COVID period, reaching a 40% rate between 2020 and 2021. This surge suggests that big firms played a key role in the overall economic recovery shown in Figure 23.

6.4 Pandemic and Post-pandemic Zombie Growth Developments and Potential Factors

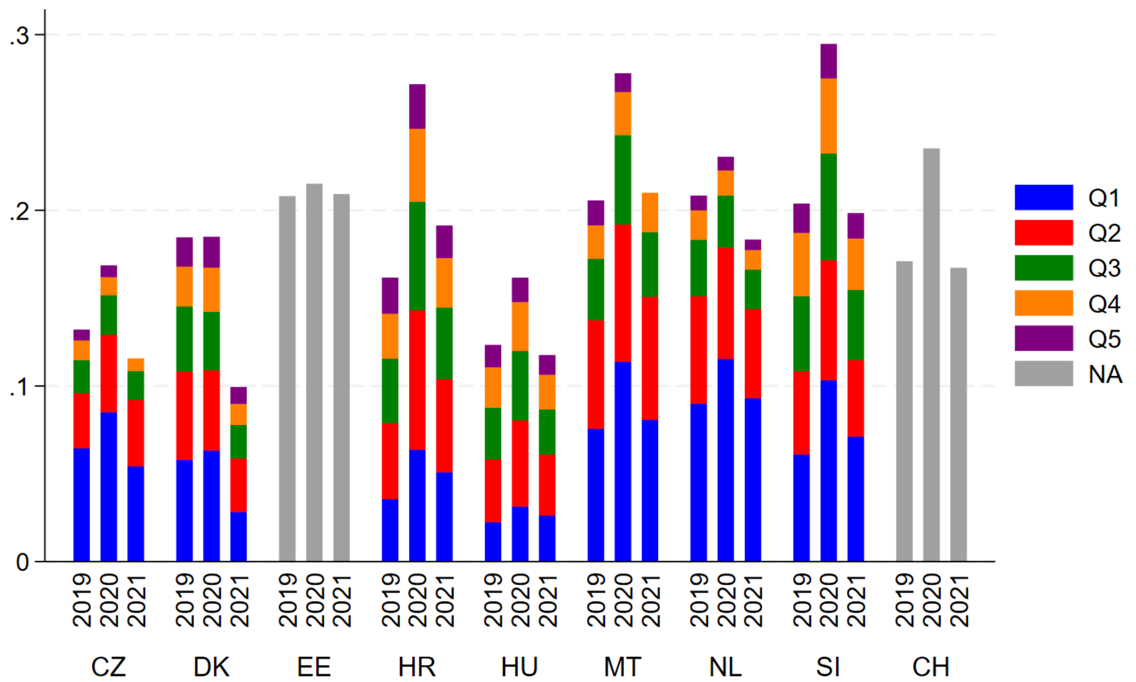
Author: *Tibor Lalinsky, National Bank of Slovakia*

During economic downturns, more firms experience financial distress due to declining demand and revenue. As a result, depending on the severity or duration of the recession and various underlying factors, the share of zombie firms – companies that are unable to generate enough profit to cover their debt servicing costs – may rise. More labour and capital tied up in zombies can lead to higher inefficiency and a reduction in productivity.

As documented by Criscuolo (2021), Harasztosi and Savšek (2022), and Lalinsky et al. (2024), the pandemic recession and its effect on productivity differed from previous recessions. We saw a temporary increase in labour productivity per hour worked, while productivity per employee declined across countries, sectors, and firms, also due to the widespread use of job retention schemes.

Data from the recent 10th CompNet data collection confirms that the creation of zombie firms remained linked to firm productivity. As shown in Figure 26, both euro and non-euro area countries experienced an increase in the share of financially constrained firms in 2020. In addition, the figure shows that low-productivity firms continued to dominate the group of firms unable to cover their interest expenses with their profits.

Figure 26: Share of financially constrained firms by productivity quintiles

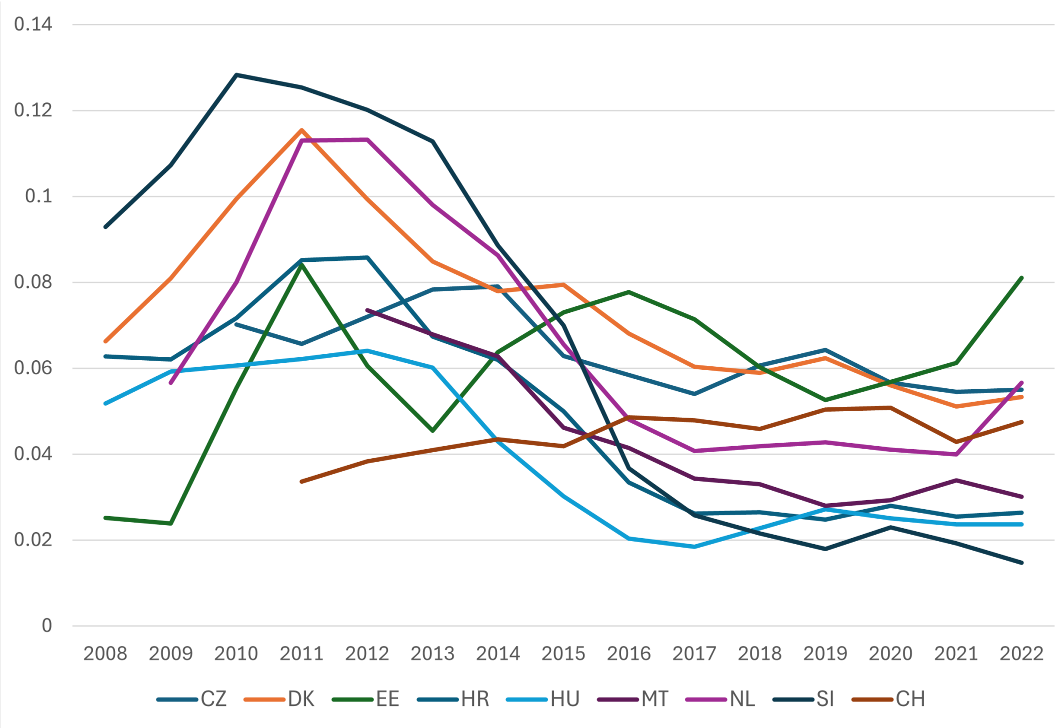


Note: Financially constrained firms are those with an interest coverage ratio (ICR) of less than 1. Productivity breakdown not available for Estonia and Switzerland.

Our data suggest that the pandemic led to reduced demand and a temporary drop in revenue. However, many firms with interest costs exceeding their profits remained fundamentally viable and recovered as economies reopened. As a result, we did not observe a widespread increase in zombie firms.[11]

[11] Albuquerque and Iyer (2024) also show that the share of unproductive and unviable firms has been rising worldwide

Figure 27: Zombie share developments across countries



We may consider two key channels at play during the pandemic: i) The COVID-19 pandemic and lockdowns boosting zombie firm entries, and ii) Pandemic support measures preventing zombie firm exits. Therefore, we decompose pandemic-related zombie firm developments into their main components.

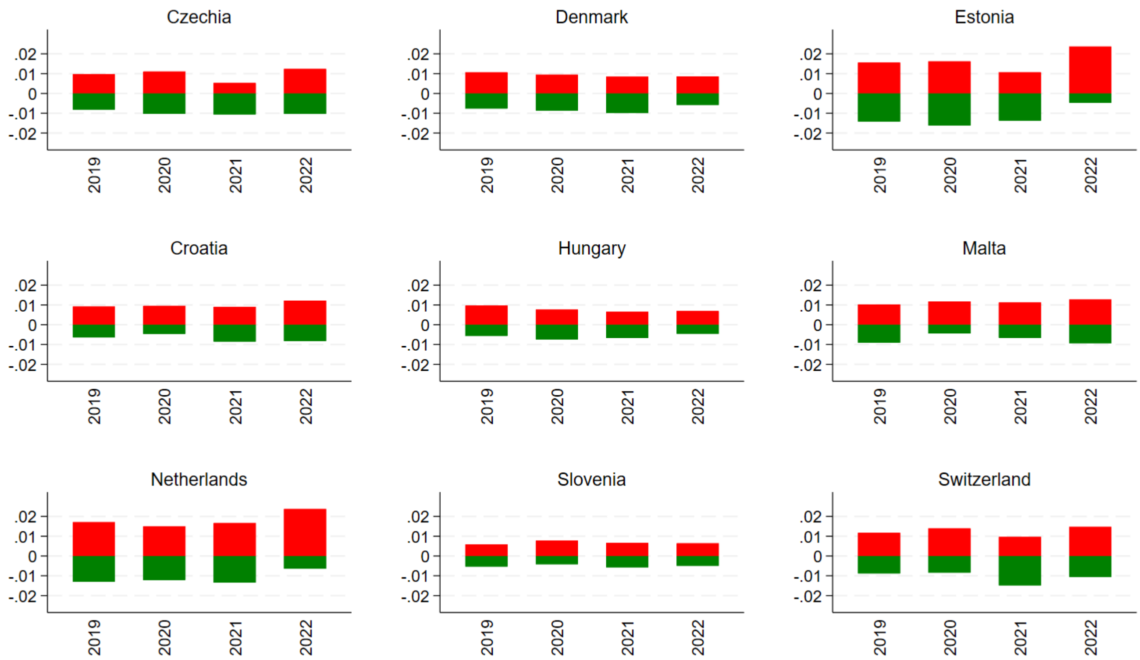
When we narrow our focus to incumbent firms entering or exiting zombie status, we find no evidence of major zombie reallocation during the pandemic. The share of firms exiting zombie status remained relatively stable between 2019 and 2021. Similarly, zombie firm entries remained stable or showed only a mild increase in most countries in 2020, followed by a somewhat stronger correction in 2021. However, Figure 28 suggests a potential delayed increase in zombie entries and a reduction in zombie exits in 2022.

The post-pandemic zombie firm development in 2022 raises important questions about the role of COVID-19-specific factors, particularly the impact of extensive policy support provided to firms. Generous employment subsidies, prevalent in Europe, may have helped not only viable but also non-viable firms sustain the pandemic recession, potentially delaying the entry of non-viable firms into zombie status.

Our preliminary findings, based on the unconditional relationship between the scale of job retention schemes and changes in zombie status entries across the analyzed countries, do not confirm that policy support led to higher zombie status entries recorded in 2022. In fact, Figure 29 countries with higher pandemic job retention scheme take-up rates experienced a lower increase in zombie entries.

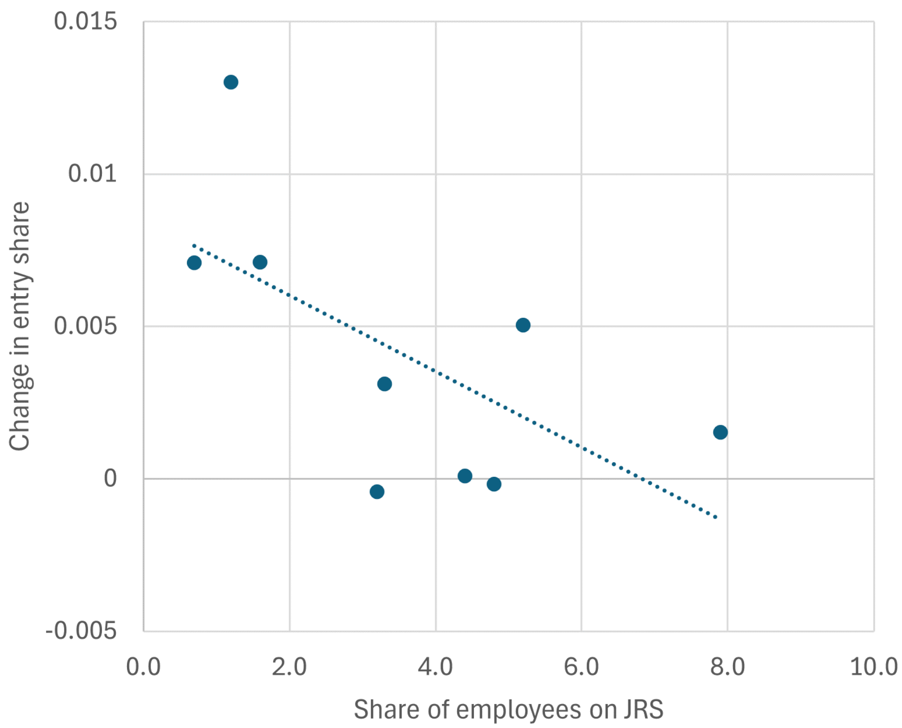
since the Global Financial Crisis (GFC), began to decline after 2016, and then increased somewhat during the COVID-19 pandemic.

Figure 28: Zombie status entries and exits across countries



Note: The figure shows the share of firms entering and exiting zombie status. Only firms with interest coverage data available for at least four consecutive years are considered. Firms that became zombies or non-zombies for only one year are not included.

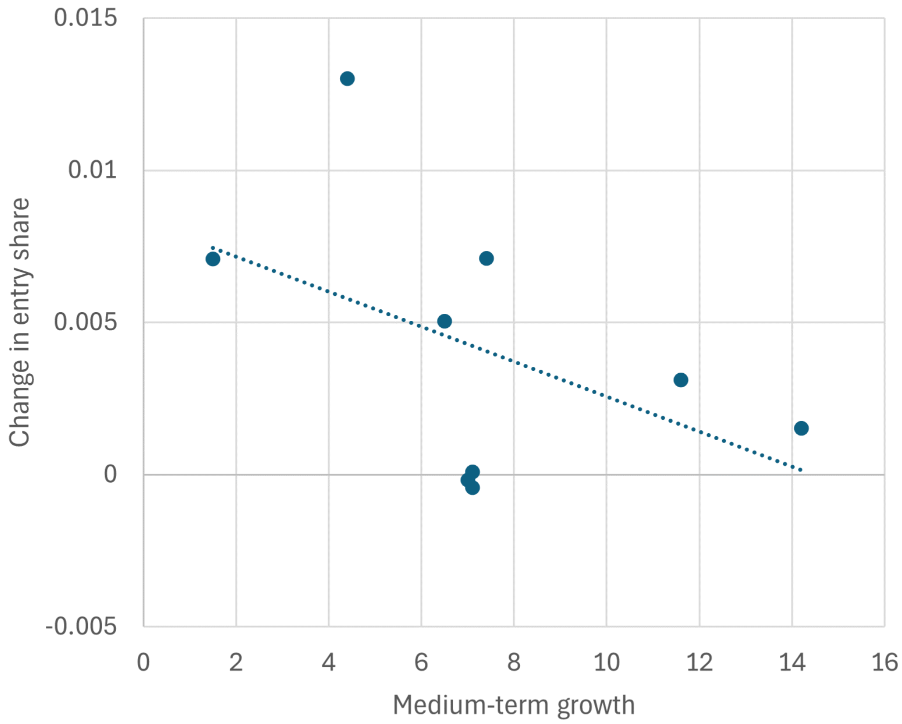
Figure 29: The scale of job retention schemes and changes in zombie status entries



Note: The figure shows the take-up rates of job retention schemes from Corti et al. (2023) and the change in the zombie status entry share between 2021 and 2022.

As suggested by Figure 30, which depicts the unconditional relationship between medium-term growth and zombie status entries, the relative increase in zombie entries recorded in 2022 appears to be negatively related to cumulative real GDP growth from 2020 to 2022.

Figure 30: Post-pandemic growth and changes in zombie status entries



Note: The figure shows cumulative real GDP growth from 2000 to 2022, based on Eurostat data, and the change in the zombie status entry share between 2021 and 2022.

In addition to a delayed effect of medium-term economic conditions, 2022 marked a shift in monetary policy. The ECB implemented the most aggressive monetary tightening in its history, with four increases in interest rates translating into higher lending rates for non-financial corporations. As a result, rising interest costs may have been one of the key factors contributing to the increase in zombie status entries in 2022.

6.5 The EU Post-COVID-19 Export Performance

Author: *Marco Matani, IHEID*

The unique structure of the CompNet dataset enables the decomposition of logarithmic rates of change for each quantity into intensive and extensive margins:

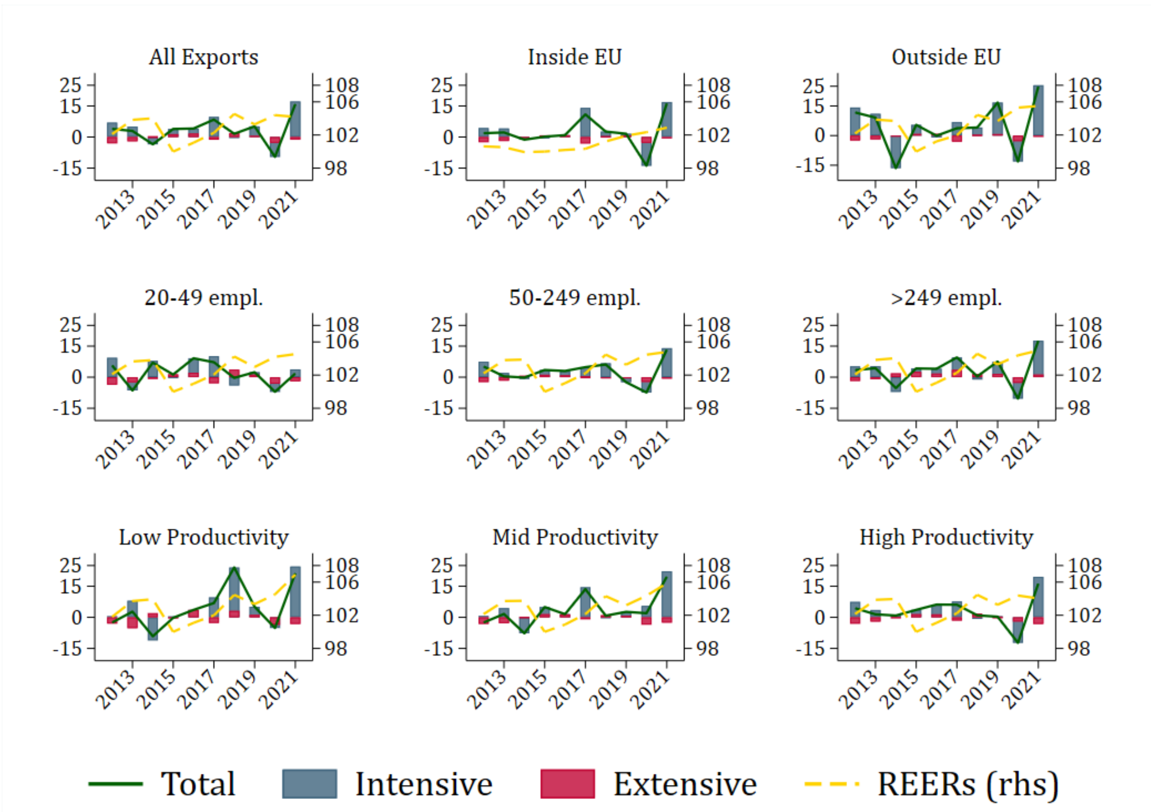
$$\ln \frac{X_t}{X_{t-1}} = \ln \frac{\overline{X}_t}{\overline{X}_{t-1}} + \ln \frac{N_t^X}{N_{t-1}^X} \tag{12}$$

where X_t, $\overline{X}_t$, and N_t^X represent, respectively, the total quantity of variable X, its mean, and the underlying firm numerosity at a given level of aggregation at time t. We apply (12) to decompose yearly export growth rates into intensive and extensive margins for firms across different export destinations, size classes, and sections of their respective country's productivity distribution.

The largest (more than 249 employees) and most productive exporters were the hardest hit by COVID-19 in 2020. In 2021, the strongest rebound was observed among the largest exporters, though not necessarily the most productive ones (Figure 31). The smallest and least productive exporters experienced most of the trade adjustment to COVID-19 through the extensive margin. For example, 44.56% of the 2020 total export decline for firms with 20–49 employees occurred at the extensive margin, compared to only 26.80% for firms with more than 249 employees.

In other words, overall productivity has likely improved because smaller, less productive firms were more likely to stop exporting entirely due to the pandemic's impact. In 2021, smaller exporters continued to experience significantly negative extensive margins compared to larger firms, indicating that the challenges faced by smaller exporters during the pandemic persisted and contributed to this ongoing trend.

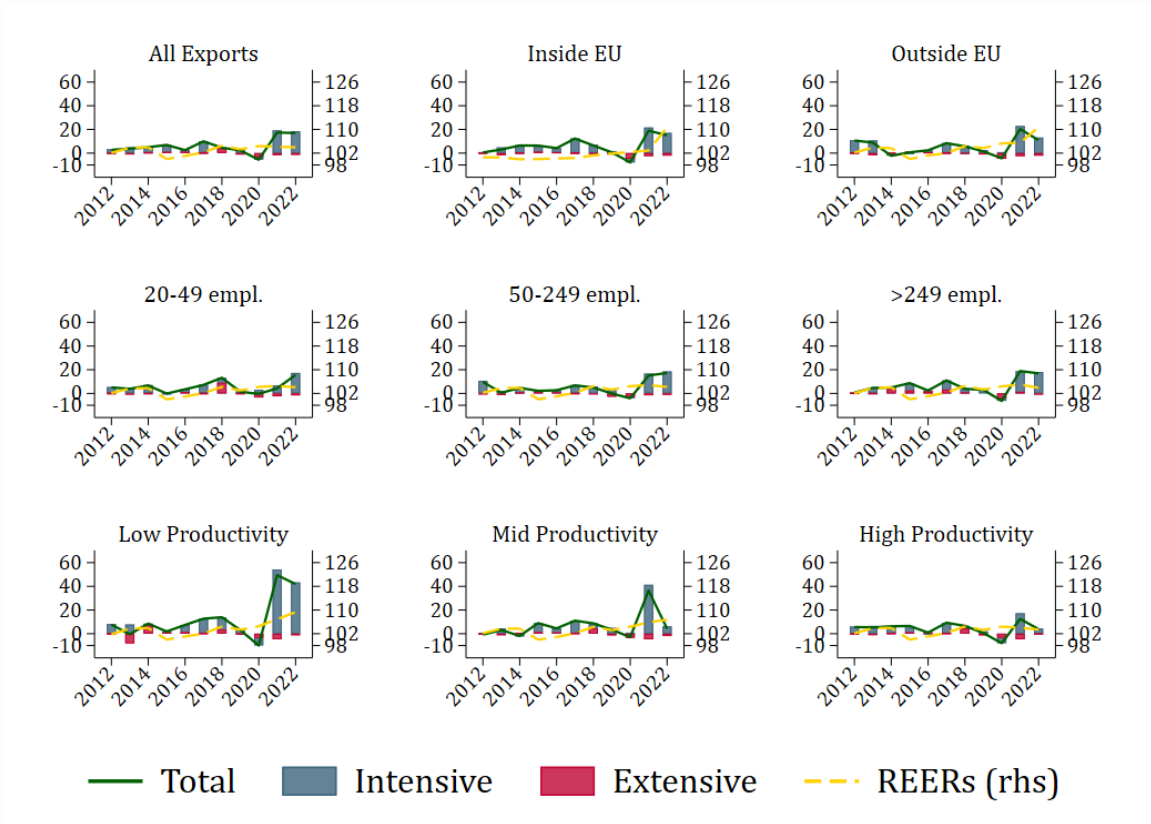
Figure 31: Export developments by margin. European countries, 2012-2021 (log y-o-y growth rate)



Source: CompNet 10th Vintage (unconditional_country_20e_weighted, unconditional_macsec_szl_20e_weighted, and jd_inp_trad_country_20e_weighted.dta) and Eurostat.
Note: Year-on-year logarithmic growth rates. *Intensive* is the mean export value obtained as the ratio between total export amount and number of exporters, both pooled over countries. *Extensive* is the number of exporters pooled over countries. *All Exports* is total export amount pooled over countries. *REER* are real effective exchange rates, i.e., the nominal effective exchange rates (NEERs) deflated by consumer price indices (CPIs), and are computed for each panel like the average over countries weighted by the respective export share. The REER for Inside EU covers 27 trading partners in the European Union, while for all other panels the REER covers 15 additional trading partners: AU, BR, CA, CH, CN, HK, JP, KR, MX, NO, NZ, RU, TR, UK, and US. Figures are for NACE Rev.2 section C - Manufacturing in CZ, DK, EE, ES, FR, HR, HU, LT, MT, NL, PL, PT, RO, SI, and SK. For destinations, figures are for CZ, EE, FR, LT, MT, NL, PT, RO, SI, and SK. For productivity groups, "*Low Productivity*" are exporters in the first three deciles of labor productivity in their respective countries, "*High Productivity*" are exporters in the last three deciles of labor productivity in their respective countries, and "*Mid Productivity*" are exporters in the other deciles of labor productivity in their respective countries. Balanced sample over years.

The country coverage in CompNet enables us to focus our analysis on Central, Eastern, and South-eastern European (CESEE) countries, extending the decomposition of export growth rates through 2022. What stands out in this group of countries is the surge in exports from low-productivity exporters after COVID-19, with exceptional growth compared to the average of other exporters, both within the EU as a whole and within the CESEE sample, continuing in 2022 despite the steep rise in the real effective exchange rate (REER).

Figure 32: Export developments by margin. CESEE countries, 2012-2022 (log y-o-y growth rate)



Source: CompNet 10th Vintage (unconditional_country_20e_weighted, unconditional_macsec_szl_20e_weighted, and jd_inp_trad_country_20e_weighted.dta) and Eurostat.
Note: Year-on-year logarithmic growth rates. *Intensive* is the mean export value obtained as the ratio between total export amount and number of exporters, both pooled over countries. *Extensive* is the number of exporters pooled over countries. *All Exports* is total export amount pooled over countries. *REER* are real effective exchange rates, i.e., the nominal effective exchange rates (NEERs) deflated by consumer price indices (CPIs), and are computed for each panel like the average over countries weighted by the respective export share. The REER for Inside EU covers 27 trading partners in the European Union, while for all other panels the REER covers 15 additional trading partners: AU, BR, CA, CH, CN, HK, JP, KR, MX, NO, NZ, RU, TR, UK, and US. Figures are for NACE Rev.2 section C - Manufacturing in CZ, EE, HR, HU, LT, PL, RO, SI, and SK. For destinations, figures are for CZ, EE, LT, RO, SI, and SK. For productivity groups, figures are for CZ, EE, HR, HU, PL, RO, SI, and SK. "*Low Productivity*" are exporters in the first three deciles of labor productivity in their respective countries, "*High Productivity*" are exporters in the last three deciles of labor productivity in their respective countries, and "*Mid Productivity*" are exporters in the other deciles of labor productivity in their respective countries. Balanced sample over years.

6.6 Reassessing EU Comparative Advantage: The Role of Technology

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Strengthening the competitive position of the European Union is critical in an increasingly fragmented and security threatened global economy. The Draghi report (Draghi, 2024) has documented the EU's loss of technological prowess with respect to the United States, and increasingly China, in several sectors and suggested active industrial policy to reverse the trend. Yet, the very first necessary block of this process, consisting of clear, solidly theoretically grounded, and readily computable measurements of Europe's relative state of technology vis-à-vis the rest of the world, is still largely absent.

To contribute to filling this gap, di Mauro, Matani, and Ottaviano (2024) apply the 'sufficient statistics' approach recently developed by Huang and Ottaviano (2024) for China to international trade data and firm information - sourced from the OECD and CompNet, respectively - to infer the relative technological prowess of European countries from their sectoral export specialization with respect to the rest of world.

While this resembles the idea behind the traditional Balassa index of 'revealed' comparative advantage (BRCA), the model presented by Huang and Ottaviano (2024) accounts for disturbances such as factor prices, scale economies, imperfectly competitive product markets, and firm heterogeneity, which hinder simple export specialization from accurately reflecting a country's relative state of technology in a given sector. Huang and Ottaviano (2024) show how a more comprehensive assessment can be conducted using a single equilibrium equation and a short list of empirical moments ('sufficient statistics'), mostly related to the country of interest, without the need to calibrate the entire model.

This approach offers a handy index of (revealed) 'Relative State of Technology' (RST), which is larger than one in sectors where the country has a better state of technology than the rest of the world. This can be interpreted as relative 'start-up productivity', which is the minimum productivity firms in sector z can expect to achieve when entering the market, and is determined by export intensity $\theta(z)$ (share of exports in the output of sector z), trade freeness $\rho(z)$, firm heterogeneity $k(z)$, and relative unit input prices $\frac{\omega(z)}{\omega^*(z)}$:

$$\frac{C_M^*(z)}{C_M(z)} = \left(\frac{\omega(z)}{\omega^*(z)}\right)^{\frac{k(z)+1}{k(z)}} \left[\rho\left(1-\theta(z)\right)+\rho^{-1}\theta(z)\right]^{\frac{1}{k(z)}} . \tag{13}$$

Providing the first comprehensive evaluation of Europe's RST in manufacturing, di Mauro, Matani, and Ottaviano (2024) find that Europe has a better state of technology than the rest of the world ($RST > 1$) in all manufacturing sectors, but especially in wearing apparel, food, basic metals, furniture, and non-metallic mineral products (Figure 33). Among these sectors, however, only in food and non-metallic mineral products Europe also exhibits export specialization ($BRCA > 1$). In other sectors, such as motor vehicles, wood, paper products, and machinery, Europe has strong export specialization despite less pronounced technological advantage.

Figure 33: Balassa Revealed Comparative Advantage and Relative State of Technology in the EU

Source: CompNet (*unconditional_industry2d_20e_weighted.dta*), OECD ICIO, and calculations by the authors.
Note: *Relative State of Technology* is computed like in equation (13). *Balassa Index of Revealed CA* and *Relative State of Technology* are represented on the left-hand and right-hand axes, respectively. The dashed blue line represents the threshold for the *Balassa Index of Revealed CA* to indicate specialization. The figures for the EU are derived by aggregating components (exports, export intensity, export propensity, trade freeness, and relative unit input prices) across the EU countries included in our sample: HR, CZ, DK, FI, FR, DE, HU, LT, MT, NL, PL, PT, RO, SK, SI, and SE. The OECD ICIO tables consolidate sectors 10, 11, 13, 14, 15, 31, 32, and 33 into broader categories. For these sectors, the *Balassa Index of Revealed CA* for the corresponding category is reported. Average from 2010 to 2018.

Besides confirming that revealed comparative advantage is an imperfect measure of a country's technological strengths due to the concurrent influences of factor prices, market size, markups, firm selection, and market share reallocation, the lack of systematic correlation between RST and BRCA in Europe calls for urgent actions to substantiate export specialization with heightened technological standing to maintain the global competitive edge in key industries.

Conclusion

This report presents the 10th vintage of the CompNet dataset and our latest tool, the Micro Data Infrastructure (MDI). Both provide a platform to facilitate cross-country research, albeit at different levels of granularity. In this report, we present analysis of Europe's post-COVID economic landscape which reveals that the continent is at a critical junction, marked by significant divergences in productivity, energy transitions, and firm behaviours across countries. Eastern European nations are now leading productivity growth while some Western counterparts lag behind, with high-technology and knowledge-intensive sectors demonstrating superior performance. Research that is based on our MDI tool highlights several crucial insights: a widening productivity gap between frontier and laggard firms; substantial differences in energy price elasticity across countries that necessitate tailored carbon tax approaches; varied firm responses to productivity shocks depending on country and economic conditions; the importance of incorporating firm-level heterogeneity in monetary policy decisions to better anticipate inflation pressures; and a concerning misalignment between Europe's technological advantages and export specializations. These findings collectively demonstrate that a one-size-fits-all approach to policy is insufficient. Instead, European policymakers must prioritize strengthening laggard firms' absorptive capacity through human and intangible capital investments; design country-specific environmental policies that recognize differing energy substitution capabilities; implement countercyclical measures that account for national differences in firm adjustment behaviours; utilize more granular models of inflation that incorporate technological diversity; and develop targeted industrial policies to align technological strengths with export specializations. By embracing these differentiated policy approaches while fostering greater cross-border coordination, European leaders can narrow productivity gaps, accelerate the clean energy transition, and enhance the continent's global competitiveness while building greater resilience against future economic shocks.

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