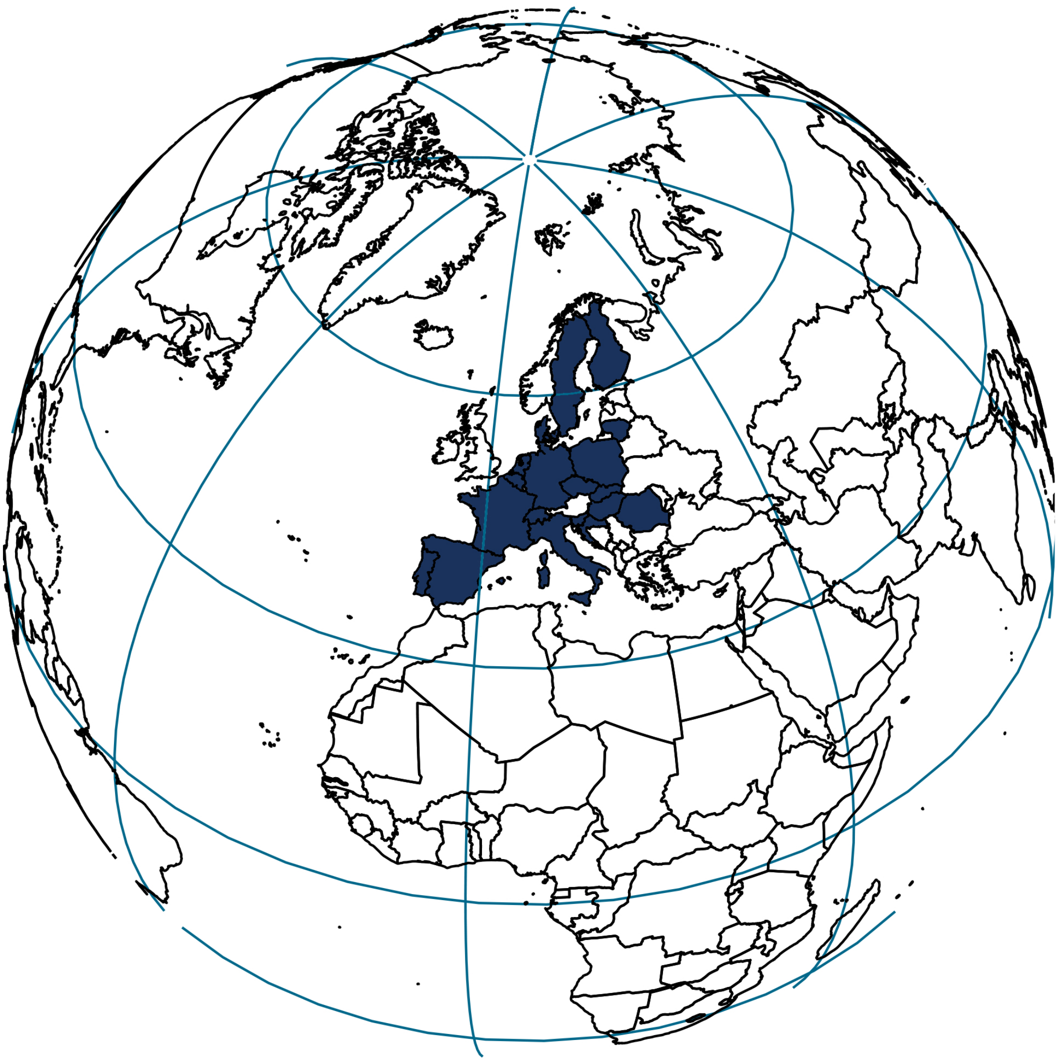
CompNet

The Competitiveness Research Network

Firm Productivity Report

July 2023



Funded by
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Table of Content

Acknowledgement 4

Introduction 6

Executive summary 7

CompNet Dataset 9th vintage 9

1 The productivity puzzle revisited: Firm performance after COVID-19 10
- 1.1 Heterogeneity in firm performance following COVID-19 . . . 10
- 1.2 Technology and knowledge intensity: Implications for productivity . . . 12
- 1.3 Comparison of frontier and laggard firms . . . 14
- 1.4 Output gaps and the Phillips Curve for heterogeneous firms[1] . . . 17
- 1.5 Conclusions . . . 20

2 EU firms in the global economy: A competitiveness assessment 21
- 2.1 Trade and COVID-19 shock . . . 22
- 2.2 Productivity shocks transmission within GVCs . . . 23
- 2.3 Unit labor cost as a driver of firm competitiveness . . . 26
- 2.4 Disentangling firm competitiveness: The results of a composite Indicator (ECI) . . . 29
  - 2.4.1 Methodology . . . 29
  - 2.4.2 Results . . . 31
- 2.5 Conclusions . . . 34

3 Resource reallocation over the business cycle: A cross-country comparison 36
- 3.1 Resource allocation . . . 37
- 3.2 Firm responsiveness . . . 39
- 3.3 The role of labor market rigidity . . . 40
- 3.4 Conclusions . . . 43

4 Reacting to energy price shocks 44
- 4.1 Data sources and stylized facts . . . 45
- 4.2 The impact of short-term energy price shocks on firms' results: average results . . . 50
- 4.3 Impact of short-term energy price shocks: Cross-firm distribution . . . 55
- 4.4 Conclusions . . . 57

[1] This section is based on work by Daniele Aglio and Eric Bartelsman.

5 Constrained SMEs 59
- 5.1 Credit constraints 60
- 5.2 Credit constraints: Firm size and age 63
- 5.3 Differences between unconstrained and constrained firms 65
- 5.4 Impact of credit constraints on firm performance 67
- 5.5 Conclusions 69

Box: Macro-sectoral drivers of startup types 70

6 Concentration and productivity: Lessons for a high inflation environment 74
- 6.1 Evolution over the last decade 75
- 6.2 Concentration, productivity, and market power 77
- 6.3 Conclusions 80

7 Appendix 82
- 7.1 The GVC frontier 91
- 7.2 Firm-level equivalence of the micro-aggregated ECI 91
- 7.3 Disclaimer 93

8 References 94

Acknowledgement

European Commission

Alessandro Turrini and Luis Garcia Lombardero (DG-ECFIN), William Connell (DG-GROW), Clemens Domnick and Juan Ruiz Garcia (Joint Research Centre Seville), Elodie Boulch, Kaspar Richter, Melina Raykovska and Stratis Kastrissianakis (DG-REFORM).

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Partners

The report preparation was funded by the European Union via the Technical Support Instrument; Directorate-general for Structural Reform Support under grant agreement No 101101853. Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or Directorate-general for Structural Reform Support. Neither the European Union nor the granting authority can be held responsible for them. The project (Microdata platform for productivity) involves the National Productivity Boards (NPBs) of the following six countries: France, Germany, Latvia, Portugal, Slovakia, Slovenia. Some of the above NPBs have co-authored the report (see below). This support is gratefully acknowledged.

The Report was coordinated by Filippo di Mauro with the critical assistance of Marco Matani and Marcelo Piemonte Ribeiro. It is coauthored by Daniele Aglio, Sara Azzarito, Eric Bartelsman, Anmol Kaur Grewal, Leonardo Indraccolo, Neeharika Kakunuri, Laura Lehtonen, Laura Lufray, Marco Matani, Marcelo Piemonte Ribeiro, and Alessandro Zona Mattioli. It includes contributions by participants to the above mentioned EU Program (Microdata platform for productivity), namely Eva Pereira (GEE, Portugal), Urska Cede (IMAD, Slovenia), and Jan Sebo (Slovakia). Critical inputs and comments by Eric Bartelsman, Matthias Mertens, and Javier Miranda are gratefully acknowledged. The Report was edited by Tim Phillips. Marcelo Piemonte Ribeiro curated the overall design. The Report should be quoted as ***CompNet (2023)***.

CompNet Data providers

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Introduction

As we recover from the COVID-19 crisis, policymakers and economists alike have been trying to disentangle the impact of the many shocks that the pandemic delivered to the global economy. If we want policies that increase the productivity of Europe's firms, we must first identify which firm- and sector-specific factors are associated with the worst of those impacts, and which factors cushioned them.

Using the latest vintage of CompNet data, the *2023 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 post-COVID firm-level productivity and potential output; Chapter 2 investigates EU firms' competitiveness by considering the drivers of their involvement in the global economy; Chapter 3 documents how efficiently capital and labor are reallocated across sectors during expansionary and recessionary periods; Chapter 4 investigates how firms respond to energy price shocks; in Chapter 5, we use CompNet financial data to assess how small and medium-sized enterprises (SMEs) are affected by tighter credit constraints; and Chapter 6 investigates several dimensions of EU firms concentration, and their consequences for well-functioning economic systems.

Executive summary

The *2023 Flagship Firm Productivity Report* offers critical insights on the short-term impact of the COVID-19 crisis on the European economy across several important dimensions: firm-level productivity, competitiveness, potential output, the reallocation of resources, and firms concentration. We also investigate firm response to fluctuating energy prices and tighter credit constraints. Our results show the heterogeneity in post-COVID outcomes across firms, sectors, and countries; the story they tell is relevant both for post-COVID recovery across Europe, and for building resilience while we wait for the next crisis.

In Chapter 1, we use the latest vintage of CompNet data to examine post-COVID firm-level productivity and potential output. We show that the COVID-19 crisis was followed by a decline in total factor productivity (TFP) in the short term in Europe, though its impact was smaller than that following the Global Financial Crisis. We find a large and unprecedented increase in TFP dispersion among countries in 2020, perhaps reflecting the highly different government policy responses to the COVID-19 crisis. When we look closer at the outcomes across sectors and levels of technology and knowledge intensity, we find that manufacturing firms in high-technology-intensity industries had relatively higher productivity growth. On the other hand, in the service sector, productivity growth declined for firms in both high- and low-knowledge-intensity industries. Did the shock narrow the gap in productivity between the most productive (frontier) and the least productive (laggard) firms? Unfortunately, it did not. The gap has actually grown after the COVID-19 crisis. Finally, we show that firm heterogeneity can lead to different inflationary pressure, due to varying marginal costs along the productivity distribution. The Phillips curve is flatter for the most productive firms – the ones that increase their sales the most when aggregate demand increases.

In Chapter 2, we analyze how COVID-19 impacted the trade patterns of European firms. Using the richness of firm-level based CompNet data, merged with 2021 OECD ICIO tables, we ask how the diffusion of productivity and technology across international and domestic networks was affected by the pandemic. We investigate what aspects of firm competitiveness drive EU firms to participate in global markets. Small firms were most likely to cease exporting in the face of the pandemic; large firms managed to secure their presence in international markets. At the same time, domestic firms heightened their exposure to global producers, intensifying the transmission of GVC disruption impacts. Turning to the assessment of firms competitiveness we report on traditional indicators - such as the Unit Labor costs (ULC) - as well as on an innovative composite measure (i.e. the Enterprise Competitiveness indicator - ECI). Neither indexes show any considerable improvements in the European firms competitiveness profile. Moreover, any gains in terms of competitiveness were driven by firm profitability and productivity, while the structure of costs, particularly labor did not result always under control; at the same time, European firms reduced their adoption of more sophisticated production processes. Overall, our competitiveness measures correlate well with developments in countries' export market shares, adding significant explanatory power to the mere price based measures.

In Chapter 3, we use the CompNet data to investigate how efficiently resources (capital and labor) are reallocated across sectors during expansionary and recessionary periods, and how indirect measures of firm responsiveness, captured by job creation and destruction rates, vary over the business cycle and relate to country-specific institutional features. Our main finding is that allocative efficiency improves during recessions, consistent with resources moving from less- to more-productive firms. We also find that firm responsiveness strictly follows the business cycle: expansionary periods are characterized by increases in job creation rates, while job destruction rates peak during downturns. Also, flexible labor markets are associated with more dynamic economies – as measured by job creation and destruction rates – and this translates into faster resource reallocation.

In Chapter 4, we examine firm responses to energy price shocks. Despite fluctuating energy prices, energy mix and energy intensity have remained relatively stable for European firms. Instead, shocks in energy prices are associated with a reduction in firm profits, and depending on the country, with an increase in energy efficiency or reduction in labor inputs. Electricity price shocks are associated with an increase in the dispersion in energy cost share. However, smaller and more productive firms are less affected by such shocks. Also, capital-intensive firms seem to mitigate electricity price shocks impact through economies of scale.

In Chapter 5, we use CompNet financial data to assess how small and medium-sized enterprises (SMEs) are affected by tighter credit constraints. We illustrate the evolution of firm financing conditions, and how CompNet credit constraint information strongly correlates with alternative external sources. Micro (fewer than ten employees) and young (less than ten years old) firms are up to four times more credit constrained than medium (50 to 249 employees) and large firms (more than 249 employees), and twice as constrained as small firms (10 to 49 employees). While young micro and small firms became more credit constrained after the GFC, this was not the case during the COVID-19 pandemic, when larger firms were more affected. Access to finance matters: credit-constrained firms are associated with lower job creation, growth rates, and productivity growth.

In Chapter 6, we illustrate the evolution of firm concentration, and investigate its consequences for productivity, allocative efficiency, market power, and other firm-level characteristics. Firm concentration in Europe has been driven by production factors that are increasingly important in competitive dynamics: intangibles. While market power was subdued, concentration of value added is strongly and positively associated with enhanced allocation of resources. Also, concentration of intangibles relates positively to average industry productivity. The benefits from concentration of value added and intangibles are not linear, but this nevertheless sends a clear message to European policymakers: assess rising concentration against welfare losses from excessive market power, particularly when inflation is high.

CompNet Dataset 9th vintage

The 2023 flagship report employs the 9th vintage of the CompNet dataset. It is an unbalanced panel dataset covering non-financial corporations from 22 European countries.

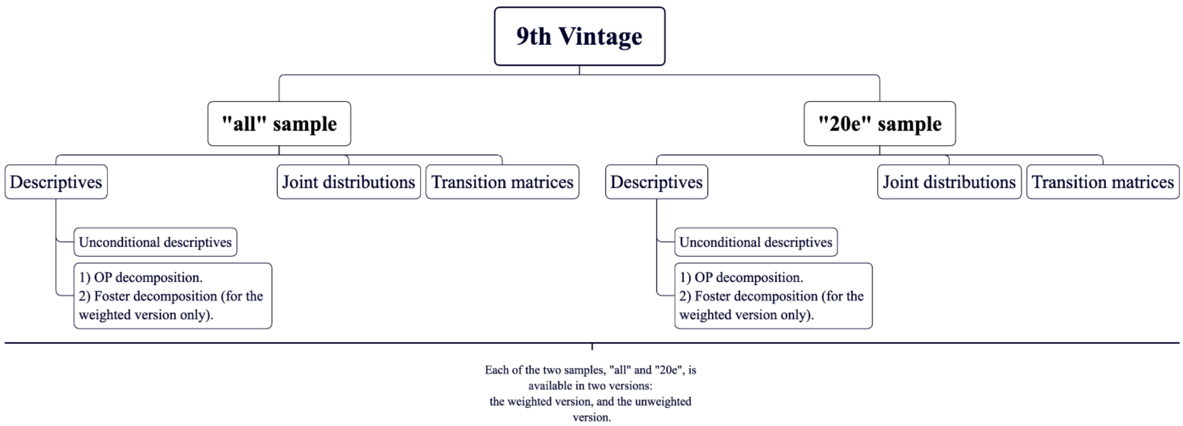
The CompNet dataset is collected by the Competitiveness Research Network. The network is hosted by the Halle Institute for Economic Research and includes several partner institutions: the European Commission, the European Bank for Reconstruction and Development, the European Investment Bank, the European 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 22 European countries. Using the distributed micro-data approach,[2] 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 the variables, list of countries, coverage and data sources, readers should refer to the CompNet User Guide (2022).

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.[3]

The CompNet Dataset is publicly available on request for research purposes.[4]

Figure 1: Structure of the CompNet Dataset



[2] See Bartelsman et al. (2004) and Lopez-Garcia and di Mauro (2015).
[3] See Altomonte et al. (2018) for a discussion of cross-country comparability of CompNet.
[4] The application procedure is available here. See Altomonte and di Mauro (2021) for a comprehensive review of policy research applications of the dataset.

1 The productivity puzzle revisited: Firm performance after COVID-19

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The COVID-19 crisis was followed by a short-term decline in TFP in Europe, though the decline was smaller than that after the Global Financial Crisis (figure 2).

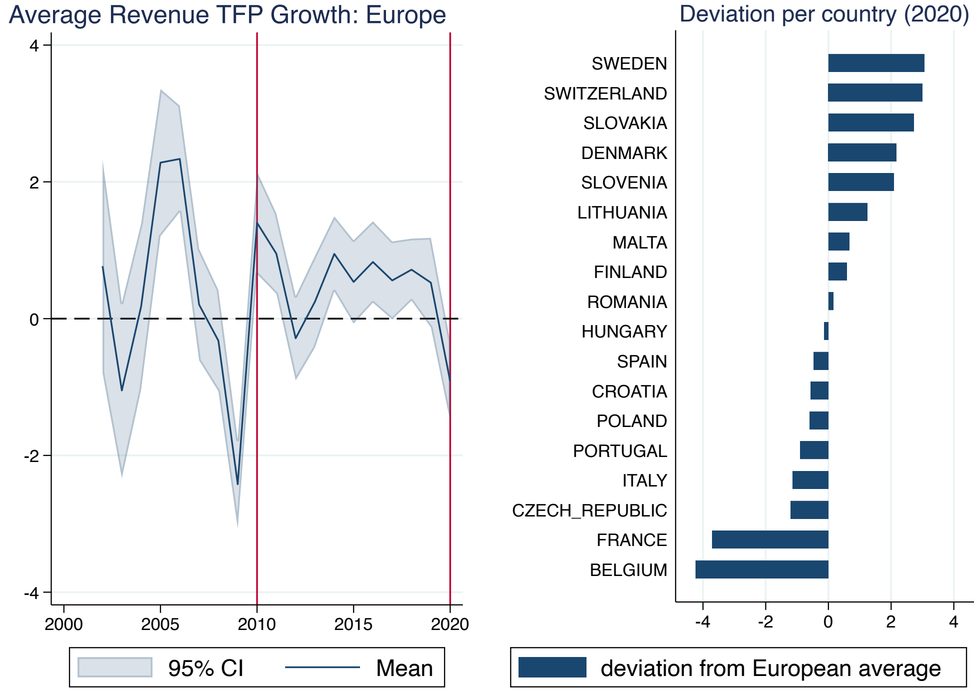
The COVID-19 pandemic caused severe economic shocks that reduced demand and disrupted supply chains, impacting firm productivity in the short and possibly long term. We can use the latest CompNet data[5] to examine post-COVID firm-level productivity and potential output. This chapter contains four sections. Section 1.1 examines the heterogeneity in post-COVID total factor productivity (TFP) and value-added labor productivity by country, sector, and firm size. Section 1.2 explores the interaction between industry-level technology and knowledge intensity, and productivity growth. Section 1.3 benchmarks the performance of European "frontier" and "laggard" firms following the pandemic. Section1.4 estimates Phillips curves for firms in different productivity quintiles.

1.1 Heterogeneity in firm performance following COVID-19

When COVID appeared, economists were uncertain of the impact on productivity (di Mauro and Syverson, 2020). While value chains would be disrupted, labor mobility would decline, and some businesses would close, there would also be positive effects from technology adoption and reallocation. CompNet data shows that the COVID-19 crisis was followed by a short-term decline in TFP in Europe, though the decline was smaller than that after the Global Financial Crisis (figure 2).

[5] The 9th vintage includes post-COVID data for the year 2020 for 18 European countries in the CompNet sample, covering more than 90% of EU GDP.

Figure 2: **TFP growth trends (year-on-year changes)**



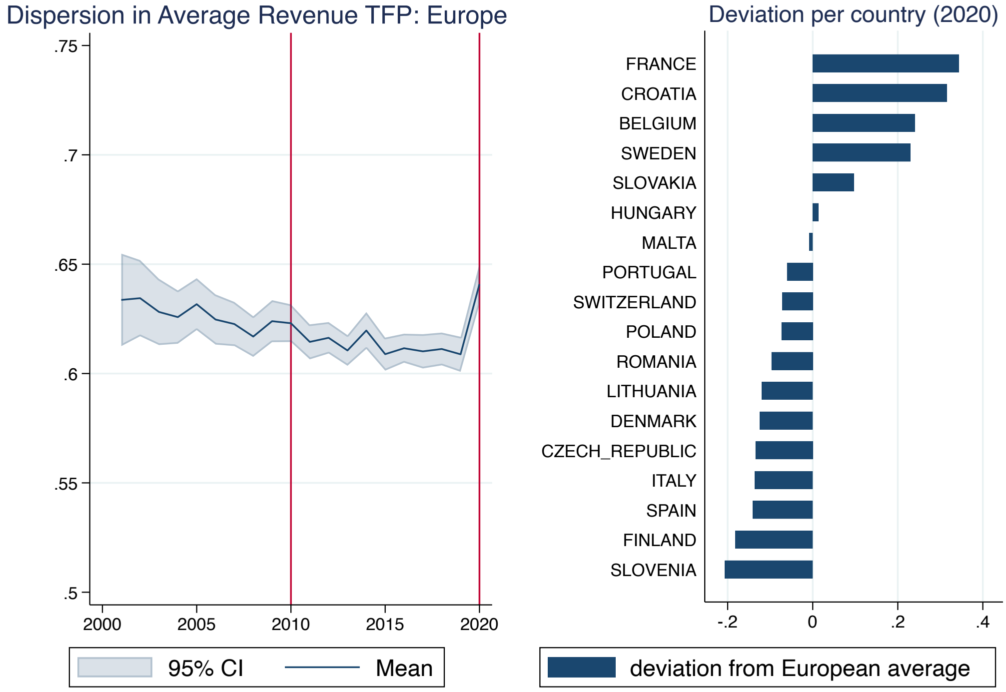
Source: CompNet 9th Vintage (*op_decomp_industry2d_20e_weighted*)
Note: Average predicted revenue based TFP growth in Europe for each year, derived from OLS regressions of the TFP growth rate on a full set of year dummies and country-industry pair dummies. Standard errors are clustered at the country-industry level. All available 2-digit industries and countries are pooled. Note that the coverage of countries and sectors changes over time. Between 2010 and 2020, we have a balanced country sample of 18 countries indicated by the vertical red lines. Germany, Latvia, Netherlands & the United Kingdom are excluded due to unavailability of 2020 data. On the right-hand side, the respective deviations per country from the European average in 2020 are depicted for the balanced sample. Note that the European average excludes Switzerland.

The COVID-19 crisis resulted in a large and unprecedented increase in TFP dispersion among countries in 2020 (figure 3).

Not surprisingly, the COVID-19 crisis was followed by an increase in TFP dispersion among countries in 2020, likely also reflecting different policy responses to COVID-19 (figure 3).

The impact of COVID-19 on sectors varied. The accommodation and food service activities sector experiencing the sharpest decline in labor productivity; across firms in that sector, the largest firms experienced the highest decline. In wholesale and retail and information and communication services sectors, firms with more than 50 employees reported higher productivity – possibly due to their ability to make use of e-commerce and remote work technologies.

Figure 3: **TFP dispersion trends and dispersion**[6]



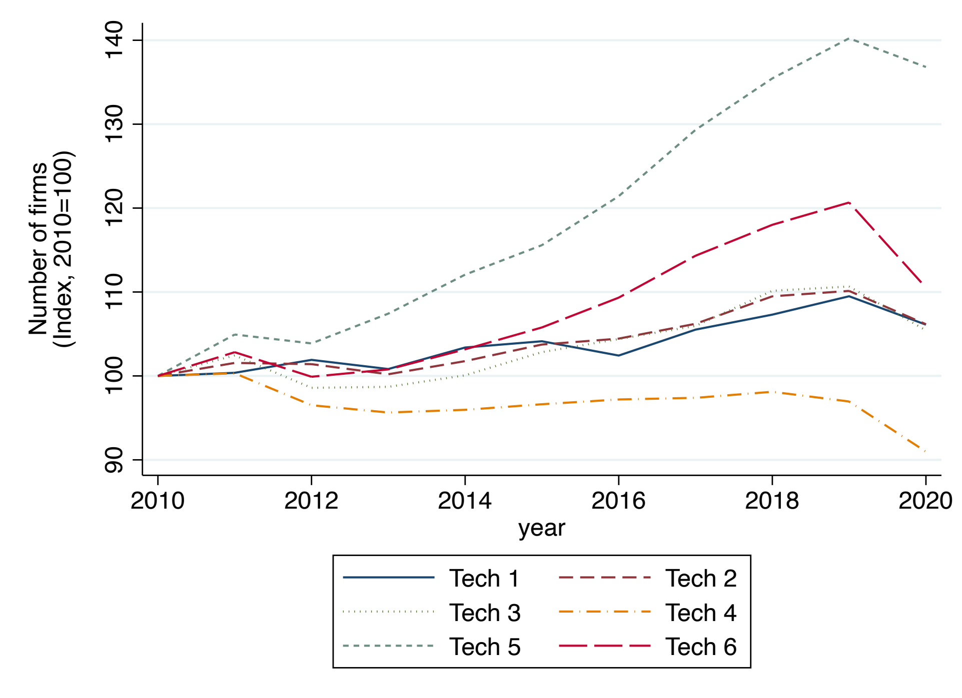
Source: CompNet 9th Vintage (*unconditional_country_20e_weighted*).
Note: Average predicted 90th-10th percentile range of revenue-based TFP for Europe for each year, derived from OLS regressions of the 90th-10th percentile range on a full set of year dummies and country-industry pair dummies, with standard errors clustered on the country-industry level. All available sectors and countries are pooled. Between 2010 and 2020, we have a balanced country sample of 18 countries indicated by the vertical red lines. Germany, Latvia, Netherlands & the United Kingdom are excluded due to unavailability of 2020 data. On the right-hand side, the respective deviations per country from the European average in 2020 are depicted for the balanced sample. Note that the European average excludes Switzerland.

The number of firms in high knowledge-intensity (service) sectors increased rapidly over the years, with only a small decline in the year 2020. On the other hand, the number of firms in high-technology-intensity (manufacturing) sectors has grown relatively slowly.

1.2 Technology and knowledge intensity: Implications for productivity

Historically, technology and knowledge intensity levels have been important drivers of labor productivity growth, most notably for manufacturing firms. Recently, there has also been rapid growth in knowledge-intensive services sectors on account of advancements in digital technology. To identify whether the number of firms in service sector activities has evolved over time, we classify sectors in the CompNet dataset into six categories of technology- and knowledge-intensive industries based on Eurostat's classification of activities. Figure 4 shows the number of firms in high-knowledge-intensity (service) sectors (*Tech 5*) increasing rapidly over the years, with only a small decline in the year 2020. On the other hand, the number of firms in high-technology-intensity (manufacturing) sectors (*Tech 1*) has grown relatively slowly.

Figure 4: **Growth of number of firms in different sectors by technology intensity**

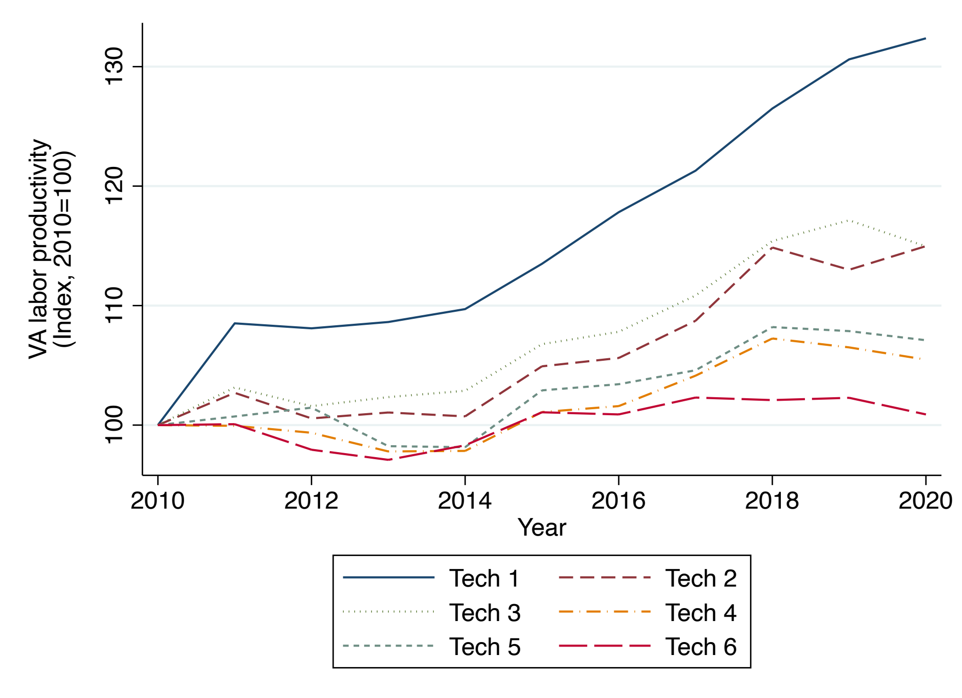


Source: CompNet 9th Vintage (*unconditional_techknol_20e_weighted*).
Note: Categories 1-4 refer to technology sophistication in manufacturing industries (1 being more technology-intensive), while categories 5-6 to knowledge intensity in service industries (5 being more knowledge-intensive) based on EUROSTAT's classification of activities. The chart is based on a balanced sample of 18 countries between 2010 & 2020.

In 2020, high technology-intensity manufacturing industries saw higher productivity growth; while in the service sector, productivity growth declined for firms in both high and low knowledge intensity industries (figure 5).

How do these trends relate to labor productivity? Technology and knowledge intensity industries have been important drivers of productivity growth, as shown by the widening of the productivity gap for both manufacturing and services between firms in high-technology-intensity industries and the rest in figure 5. The COVID-19 crisis was associated with a widening of the productivity gap. Even during the COVID-19 crisis, manufacturing firms in high-technology-intensity industries were able to increase their labor productivity; while in the service sector, labor productivity declined for firms in both high- and low-knowledge-intensity industries.

Figure 5: **Value-added labor productivity by technology intensity categories**



Source: CompNet 9th Vintage (*unconditional_techknol_20e_weighted*).
Note: Categories 1-4 refer to technology sophistication in manufacturing industries (1 being more technology-intensive), while categories 5-6 to knowledge intensity in service industries (5 being more knowledge-intensive) based on EUROSTAT's classification of activities. The chart is based on a balanced sample of 18 countries between 2010 & 2020.

The productivity gap between frontier and laggard firms worsened sharply in the aftermath of the COVID-19 crisis (figure 6).

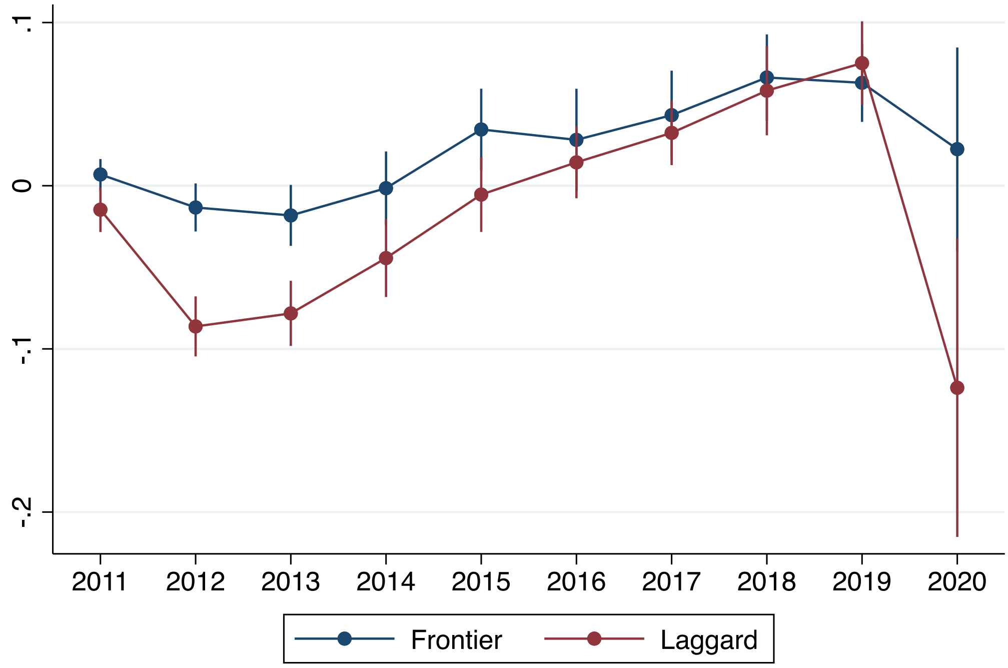
1.3 Comparison of frontier and laggard firms

Why is there increased dispersion in productivity across firms within sectors? Which firm-level characteristics distinguish the best performing firms from the rest? Both macroeconomic and microeconomic research address this issue. The macroeconomic approach assumes all firms in a region converge to the productivity frontier, disregarding heterogeneity across firms (Melitz, 2003); (Acemoglu et al., 2006). The microeconomic approach takes account of heterogeneity across firms and attempts to distinguish the best-practice frontier firms using firm-level data (Añón Higón et al., 2022); (Bartelsman et al., 2008). In this section we take this microeconomic approach using CompNet's micro-aggregated data.

The data allows us to examine productivity convergence across several dimensions. We define a "frontier firm"as one of the 10% most productive firms in terms of value-added labor productivity, within a specific sector, in a given year. "Laggard firms" are in the bottom 10% of the same ranking. Building on Zheng et al. (2021), we compare frontier firms and laggard firms across four dimensions: firm size, value-added, real wage, and labor productivity. Note that section 1.4 of this chapter focuses on the measurement of potential output using a standard frontier production function model.

Latest data from CompNet shows that the productivity gap between frontier and laggard firms was at its widest in 2012 and has since reduced as seen by the parallel lines in figure 6 between 2015-2018. However, in 2020, labor productivity between frontier and laggard firms sharply diverged, because the immediate decline in labor productivity following the COVID-19 shock was much larger for laggard firms relative to frontier firms. Figure 7 shows how the size of the frontier-laggard productivity gap varied by country in 2020.

Figure 6: Predicted labor productivity gap between frontier and laggard firms in Europe



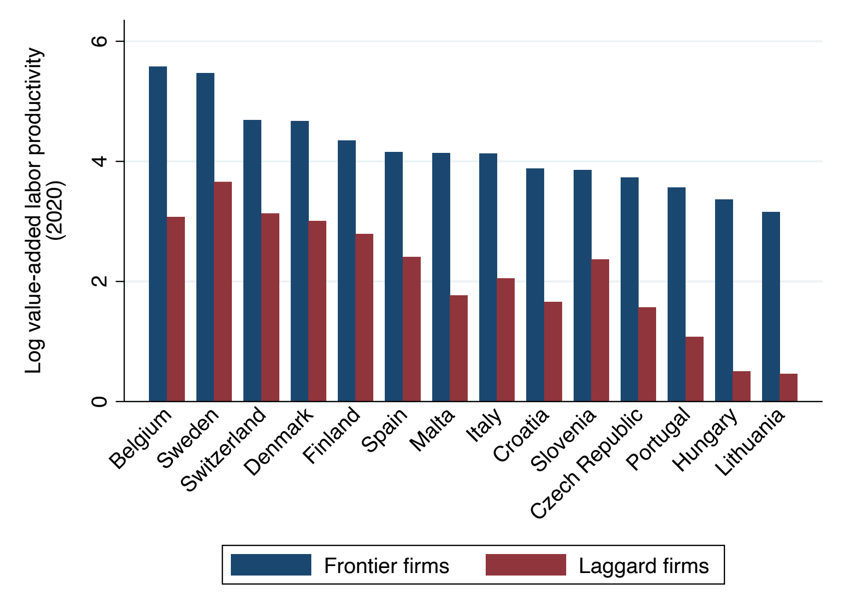
Source: CompNet 9th Vintage (*unconditional_industry2d_all_weighted*).
Note: Frontier firms are firms in the top 10% of the log value-added labor productivity distribution in a sector for a given year. Laggard firms are firms in the bottom 10% of the log value-added labor productivity distribution in a sector for a given year. The vertical axis measures predicted within-industry labor productivity growth from size-weighted regressions of labor productivity on year dummies & country-industry pair dummies for a balanced sample of 14 countries from 2010 to 2020. The weighted regressions also control for capital intensity. Standard errors are clustered at the 2-digit industry level.

Frontier firms differ from laggard firms (table 1), e.g. the former are about twice the size of the former.

Frontier firms differ from laggard firms. Table 1 summarizes differences by country in these firm-level characteristics in 2020. Frontier firms are generally about twice the size of laggard firms, and the extent of the gap in productivity and wages varies rather sharply across countries. For the former for instance is about 10 for Portugal and less than two for Sweden.

Persistent differences between frontier and laggard firms in European countries may be due to slow technology diffusion, hindering productivity catchup. Firms with higher human capital, access to foreign inputs, better technology, and technical know-how can innovate and improve efficiency (Berlingieri et al., 2020). If there is no technology diffusion to laggard firms, the productivity gap widens. Therefore, government policies should focus on enhancing the absorptive capacity of laggard firms through investments in human and intangible capital such as ICT infrastructure, facilitating foreign market exposure, and reducing financial constraints for technology adoption.

Figure 7: **Labor productivity gap in 2020 between frontier and laggard firms by country**



Source: CompNet 9th Vintage (*unconditional_industry2d_all_weighted*). Note:Frontier firms are defined as the firms in the top 10% of the log value-added labor productivity distribution in a sector for a given year. Laggard firms are defined as the firms in the bottom 10% of the log value-added labor productivity distribution in a sector for a given year. Vertical axis measures the average log value-added labor productivity pooled across all sectors for a balanced sample of 14 countries in the year 2020. Labor productivity refers to log value-added labor productivity. The large negative value for Hungary reflects the concentration of very low labor productivity firms in the laggard firms category.

Table 1: **Ratio of characteristics (frontier firms vs laggard firms) by country, 2020**

Country	Labor Productivity	Value-added	Real Wage	Size
Belgium	2.59	109.58	2.85	3.13
Croatia	3.67	64.19	2.49	2.93
Czech Republic	6.83	35.16	3.11	1.23
Denmark	2.04	29.00	3.65	1.75
Finland	2.05	33.37	3.17	2.34
Hungary	-12.33	192.55	4.14	3.80
Italy	3.58	48.31	3.90	2.49
Lithuania	8.00	40.52	2.05	1.30
Malta	4.09	37.68	3.26	1.50
Portugal	9.75	92.03	3.12	3.00
Slovenia	2.56	37.92	2.02	3.71
Spain	2.81	68.91	3.46	2.91
Sweden	1.76	19.87	4.02	1.54
Switzerland	1.88	33.83	3.25	2.30
Full sample	3.00	37.73	3.24	2.20

Source: CompNet 9th Vintage (*jd_inp_prod_mac_sector_all_weighted*).
Note: Frontier firms are defined as the firms in the top 10% of the log value-added labor productivity distribution in a sector for a given year. Laggard firms are defined as the firms in the bottom 10% of the log value-added labor productivity distribution in a sector for a given year. Values in each cell indicate the ratio of mean firm characteristics of frontier firms compared to laggard firms in the year 2020. Labor productivity refers to log value-added labor productivity. The large negative value for Hungary reflects the concentration of very low labor productivity firms in the laggard firms category.

Firm heterogeneity can lead to different inflationary pressure due to varying marginal costs curve along the productivity distribution. It is crucial, then, to understand which firms respond to demand shocks to have a better estimate of the Phillips curve and inflation forecast.

1.4 Output gaps and the Phillips Curve for heterogeneous firms[7]

The Phillips curve summarizes the relationship between economic slack and changes in prices or wages, conditional on expected inflation. Micro-based data allows us to study how inflationary pressure increases as different types of firms respond to market tightness, which may be of considerable interest for monetary policy.

We find that the slope of a Phillips curve based on firm productivity varies considerably by productivity quintile, meaning there is firm-level heterogeneity in the macroeconomic relationship between price changes and market tightness.

Macroeconomic research, although not yet conclusive, suggests a flattening of the aggregate Phillips Curve after the great recession (Ciccarelli et al., 2017); we use CompNet data to explore inflationary responses of heterogenous firms, while using the theoretical concepts behind the Phillips curve. We group firms in an industry into productivity quintiles, generating country-industry time-series of a synthetic "firm" that represents firms at each productivity level. Productivity and costs are inversely related: if demand for output of an industry 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*. Further, the curvature of marginal costs curves may also differ across, resulting in different slopes of the gap-inflation relationship for the different groups of firms.

We measure potential output as the estimated maximum production in each country, 2-digit industry, productivity quintile, and year using a standard frontier production function model.[8] We measure the output gap as the log of actual real sales minus the log potential output.[9] The price change in the Philips curve is given by the change in real wages, and so the curve estimates the slope of marginal costs of firms. Table 2 presents results from panel regressions, including all the countries and industries available in the CompNet database of:

[7]This section is based on work by Daniele Aglio and Eric Bartelsman.

[8]We use CompNet joint distribution data, in which firms are grouped by TFP (specification 1) quintiles. The production frontier model is:

$$Y_{cidt} = \gamma + \alpha K_{cidt} + \beta L_{cidt} + \varepsilon_{cid} - v_{cidt} \tag{1}$$

where Y_{cidt}, K_{cidt}, and L_{cidt} are real sales, real capital, and real labor respectively, in country *c*, industry *i*, productivity quintile *d*, and year *t*. All variables are in log terms. The disturbance is assumed to be a mixture of two components v_{cidt} and ε_{cid}, which have a strictly non-negative and symmetric distribution, respectively. The non-negative distribution component (a measurement of inefficiency) is assumed to be from a half-normal. Potential output is calculated setting the disturbance to zero.

[9]This is a measure of economic slack, and the higher it is, the lower the slack is (y is closer to $\hat{y}$), meaning production is closer to potential. In theory, this leads to a higher increase in marginal costs and inflationary pressure.

$$\Delta\%W_{cidt} = \alpha + \beta OutputGap_{cidt} + \beta X_{cidt} + \gamma_{cid} + \sigma_t + \epsilon_{cidt} \qquad (2)$$

where $\Delta\%W_{cidt}$, $OutputGap_{cidt}$, and X_{cdt} are real wage growth rate, output gap in log-points, and controls (lagged wage growth rate, lagged country level inflation), respectively, in country *c*, industry *i*, productivity quintile *d*, and year *t*, and γ_{cid} and σ_t are country-industry-quintile and year fixed effects.

The closer firms are to potential output, the higher the inflationary pressure through a larger increase in real wages. On average, for a 1 percentage point rise in output gap, real wages increase by around 0.13 percentage points.

Table 2: The Phillips curve for $\Delta\%$ real wages

Models	(1)	(2)
Output Gap	0.136***	0.123***
	(0.007)	(0.008)
$\Delta\%$ Real Wages$_{t-1}$	-0.311***	-0.313***
	(0.009)	(0.010)
Country Inflation$_{t-1}$		0.119***
		(0.042)
Constant	0.0548***	0.0481***
	(0.006)	(0.0108)
Country-Industry-Quintile FE	Yes	Yes
Year FE	Yes	Yes
Observations	35,600	27,611
R-squared	0.167	0.163

Model (1) and (2) dependent variable: $\Delta\%RealWages_t$. Panel regressions at the country-industry-productivity quintile level of real wage growth on output gap, lagged real wage growth, lagged country-level inflation (model 2), and year fixed effects, for the period 2001-2021. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The closer firms are to potential output, the higher the inflationary pressure through a larger increase in real wages. On average, for a 1 percentage point rise in output gap, real wages increase by around 0.13 percentage points.

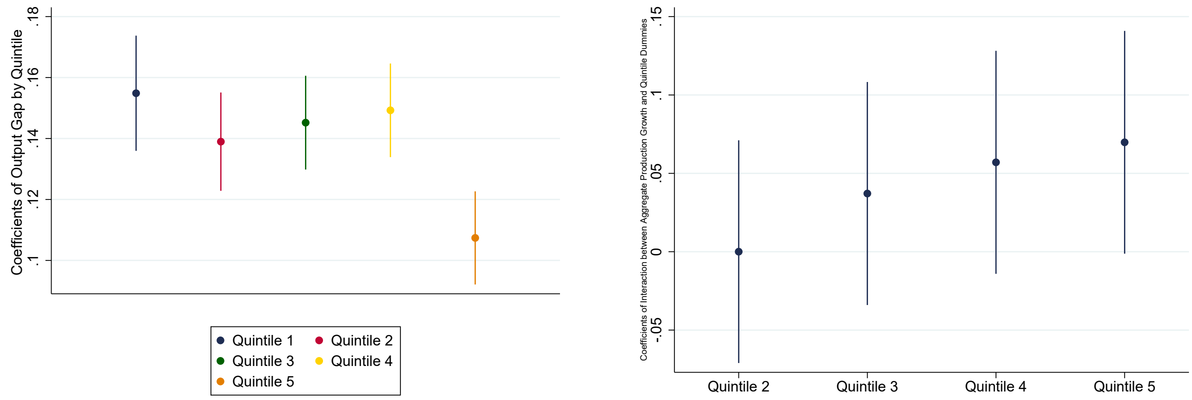
We focus on real wage and not on price inflation, and so these findings are not directly comparable to macro estimates. But they are in line with those estimates: Ball and Mazumder (2021) estimated a basic Phillips curve for the euro area around 0.22. The ECB-BASE semi-structural model slope of the Phillips curve estimates a slope of 0.12 (Eser et al., 2020). Therefore, macro- and micro-based estimations are consistent.

We can implement model (2) in Table 2 separately in each productivity quintile, with labor market power as further control. Figure 8a shows the slopes of the Phillips curve for each quintile. The Phillips curve is flatter for the most productive firms. When demand for output of high-productivity firms increases, inflationary pressure is lower than when it increases for lower productive firms, *ceteris paribus*.

Figure 8: Slope of the Phillips curve and productivity

(a) *Slope of the Phillips curve by productivity quintile (% changes)*

(b) *Increase in production by productivity quintile, using Quintile 1 as reference (Year-on-year changes)*



Source: CompNet 9th Vintage (*jd_inp_prod_industry2d_20e_weighted*); industry-level deflators from the Eurostat database *nama_10_a64* and EUKLEMS.
(a) Note: Coefficients of output gap, derived from panel regressions at the country-industry-productivity quintile level of real wage growth on output gap, lagged real wage growth, lagged country-level inflation, labor market power, and year fixed effects, for the period 2001-2021. Regressions are taken separately for each productivity quintile group of firms. All available industries and countries are pooled. 90% confidence intervals are included.
(b) Note: Coefficients of interaction between aggregate real sales growth and productivity quintile dummies, derived from panel regressions at the country-industry-productivity quintile level of real sales growth on country-industry production growth dummy (1 if growth rate is positive, 0 otherwise), interaction of the dummy with productivity quintiles, and year fixed effects, for the period 2001-2021. All available industries and countries are pooled. 90% confidence intervals are included.

The Phillips curve is flatter for the most productive firms. When demand for output of high-productivity firms increases, inflationary pressure is lower than when it increases for lower productive firms, ceteris paribus.

Our calculations (not shown here for space purposes) imply also that, on average, the Phillips curve slope remains at its pre-2008 levels, without evidence of flattening in recent years.

The most productive firms are the ones that increase their sales the most when aggregate demand increases. Figure 8b shows this. In periods of sales growth at the industry level, the most productive firms are the ones which feature higher production growth rate relative to the others. Given that the slope of Phillips curve varies along the TFP distribution, this may lead to flattened estimates of the Phillips curve.

Micro-aggregated data helps us understand the relationship between price changes and tightness in markets. Firm heterogeneity can lead to different inflationary pressure due to varying marginal costs along the productivity distribution. A better understanding of how individual firms respond to demand shocks provides insight that can lead to better inflation forecasts.

1.5 Conclusions

With the latest vintage of CompNet data, we highlight the heterogeneity in post-COVID outcomes across firms, sectors, and countries; the story they tell is relevant both for post-COVID recovery across Europe, and for building resilience while we wait for the next crisis. We show that the COVID-19 crisis was followed by a decline in total factor productivity (TFP) in the short term in Europe, though its impact was smaller than that following the Global Financial Crisis. We also find a large and unprecedented increase in TFP dispersion among countries in 2020, perhaps reflecting the highly different government policy responses to the COVID-19 crisis. When we look closer at the outcomes across sectors and levels of technology and knowledge intensity, we find that manufacturing firms in high-technology-intensity industries had relatively higher productivity growth. On the other hand, in the service sector, productivity growth declined for firms in both high- and low-knowledge-intensity industries. Did the shock narrow the gap in productivity between the most productive (frontier) and the least productive (laggard) firms? Unfortunately, it did not. The gap has actually grown sharply after the COVID-19 crisis.

Micro-aggregated data also helps us understand the relationship between price changes and tightness in markets. Firm heterogeneity can lead to different inflationary pressure due to varying marginal costs along the productivity distribution. The Phillips curve is flatter for the most productive firms – the ones that increase their sales the most when aggregate demand increases. A better understanding of how individual firms respond to demand shocks provides insight that can lead to better inflation forecasts.

2 EU firms in the global economy: A competitiveness assessment

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We study competitiveness (the ability of firms to prevail over their domestic and global competitors) during the pandemic.

The COVID-19 recession had a profound impact on global supply chains, leading to significant disruptions and detrimental effects on firm competitiveness (Bricongne et al., 2022; Espitia et al., 2022; Georgieva et al., 2022; Gerschel et al., 2020; Lafrogne-Joussier et al., 2023; Lebastard et al., 2023). Partly in response, national regulations and industrial policy - exemplified by the United States' Inflation Reduction Act, also have an impact on the competitive environment (Kleimann et al., 2023). Against this backdrop, understanding the drivers of competitiveness has become even more imperative for informed policy-making.

Defining competitiveness as the ability of firms to prevail over their domestic and global competitors, this chapter studies changes in trade patterns during the pandemic and asks how economic shocks transmit across production networks. Drawing from a rather vast literature[10] we also leverage traditional and novel competitiveness indicators, respectively the Unit Labor Cost (ULC) and the Enterprise Competitiveness Indicator (ECI), to ascertain what are the determinants of EU firms' participation in global markets.

We find that small firms (less than 50 employees) were most likely to cease exporting in the face of the pandemic, as opposed to large firms (250 employees or above) being more resilient. While in 2020 productivity losses were more severe at the bottom of the productivity distribution, relatively productive national firms became more exposed to global producers, intensifying the transmission of impacts from GVC disruption. Our indicators do not point to any considerable improvements in terms of competitiveness in Europe over the last decade. However, they provide substantial explanation of countries' export market shares in addition to pure export price driven measures, such as the real effective exchange rate.

The remainder of this chapter is organized as follows. Section 2.1 addresses

[10] While evaluations of a given country's ability to compete often revolve around its current account or export market shares Aussilloux and Mavridis (2022), external assessments are typically accompanied by the consideration of more structural factors. The latter are for instance at the core of the IMF External Balance Assessment (EBA) framework (Cubeddu et al., 2019), which encompasses macroeconomic policies, international investment position, productivity, and other country- and firm-specific features. Karadeloglou et al. (2015) regard competitiveness as a comprehensive concept. Attempting to account for the intertwining levels of analysis, the authors recommend both to assess country macro and trade outcomes and to "zoom in" into firm-level data. di Mauro and Forster (2008) share a similar view of competitiveness being a multifaceted dimension which needs a combination of traditional macro measures with firm-level information on productivity. The authors call for developing sounder competitiveness indicators employable in policy analysis.

participation in export markets. Section 2.2 focuses on how productivity shocks transmit within GVCs. Section 2.3 investigates the drivers of competitiveness by considering a traditional measure: the ULC. Section 2.4 embraces a more holistic approach and proposes a micro-aggregated composite ECI encompassing additional firm characteristics that are relevant for competitiveness.

Small businesses tended to completely stop serving international markets when hit by the COVID-19 shock (figure 9).

2.1 Trade and COVID-19 shock

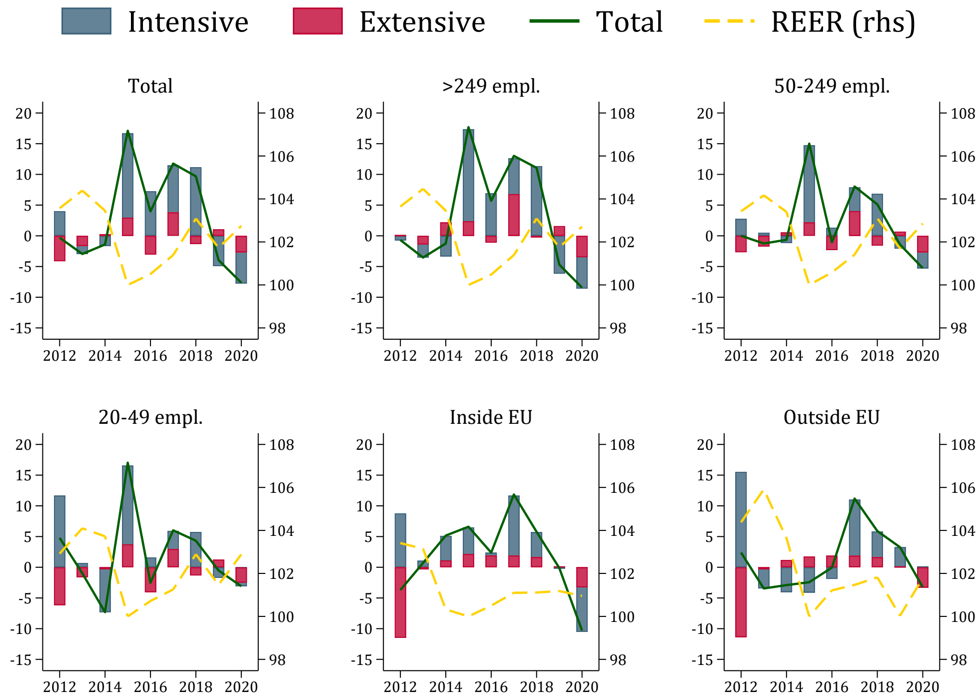
We start by documenting how changes in the volume of exports in 2020 related to firm characteristics. We further document to what extent changes in exports resulted from changes in export intensity among firms already exporting (intensive margin) or from changes by firms newly entering or leaving export markets (extensive margin).

We decompose yearly export growth rates into an intensive and extensive margin for firms of different size classes (figure 9). Big firms (>249 employees) in 2020 experienced the most severe drop in overall export levels compared to 2019, with the intensive and extensive margin playing a similar role. Small firms with less than 49 employees experienced a smaller drop in exporting activity, although this was driven entirely by the extensive margin. This implies that many small businesses stopped serving international markets when hit by the COVID-19 shock, suggesting that small exporting firms are less equipped to face unanticipated changes in their business conditions.

Changes in aggregate exports within and outside the EU followed different patterns. The bottom right two panels of figure 9 show that almost all the drop in total exports outside the EU can be attributed to firms shutting down their exporting activity, while in Europe a large fraction of the drop in total exports is explained by the intensive margin.

International linkages and trade patterns shape country consumption baskets and characterize how ideas and know-how flow from more to less technologically-advanced countries. Next, we study how the COVID-19 shock affected technology diffusion in Europe merging CompNet data with the 2021 OECD Inter-Country Input-Output (ICIO) tables.

Figure 9: Export developments by margin. European countries, 2012-2020 (y-o-y growth rate)



Source: CompNet 9th Vintage (*unconditional_country_20e_unweighted* and *unconditional_macsec_szl_20e_unweighted*) and Eurostat. Note: Year-on-year 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. *Total* 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 are for NACE Rev.2 section C - Manufacturing in CZ, DK, FI, FR, HR, HU, LT, MT, PL, PT, RO, SI, SK, and SE. For size classes, figures are for CZ, DK, FI, FR, HR, HU, LT, MT, PL, PT, RO, SI, SK, and SE. For destinations, figures are for CZ, FI, LT, MT, PT, SI, SK, and SE. Balanced sample over years.

We investigate how cross-country productivity diffusion was affected by COVID-19.

2.2 Productivity shocks transmission within GVCs

Following Bartelsman et al. (2013, 2008) and Chiacchio et al. (2018), we assume that technology, as well as firm-specific know-how, transmits across countries in two phases. In a first phase technology flows from the global value chain (GVC) productivity frontier to firms at the national productivity frontier through international linkages. From the perspective of a given country and macro-sector A, the GVC productivity frontier is constructed as an index of the average TFP of firms operating in other countries and macro-sectors with which country and macro-sector A engages in trade, with volumes of imports used as weights.[11] The GVC productivity frontier index is intended to capture the level of productivity of firms in other countries and macro-sectors

[11] See the appendix 7.1 for more details on how the GVC frontier is computed. In this Section, we compute the GVC frontier only basing on imports.

with which country and macro-sector A is linked through international trade, and from which domestic firms in country and macro-sector A can learn. In a second phase, after a learning process, technology trickles down to other national firms through domestic production networks.

To understand if (and how) this learning process changed during the COVID-19 recession, we categorize domestic firms into three different productivity levels (national frontier firms, middle productive firms and laggard firms),[12] and first run a regression for changes in TFP of national frontier firms in a given country *c* and given sector *s*:

$$\Delta TFP^{nat\_front}_{c,s,t} = \alpha + \beta_1 \Delta TFP^{GVC\_front}_{c,s,t} + \beta_2 \ln\left(\frac{Prod^{GVC\_front}_{c,s,t-1}}{Prod^{nat\_front}_{c,s,t-1}}\right) + \beta_3 \Delta GVC_{c,s,t} + \delta_{c,s} + \tau_t + \varepsilon_{c,s,t} \tag{3}$$

where:

- β_1 captures the correlation between TFP changes of domestic national frontier firms and changes in TFP stemming from the GVC frontier.
- β_2 controls for the "catch-up" effect – the scope for different growth patterns depending on the lagged distance of national frontier firms from the GVC frontier in terms of labor productivity.
- β_3 controls for the effects of changes in GVC participation – increases in the macro-sectoral share of imports on turnover from one year to the other.
- τ_t are time dummies for COVID-19 and the 2008 financial crisis.

As expected, the β_1 coefficient on *TFP growth GVC (import) frontier* is positive and significant for national frontier firms suggesting a correlation between the performance of GVC firms and top national performers. The effect is half the size for national firms in the middle of the productivity distribution. Its interaction with the COVID-19 recession dummy, *TFP growth GVC (import) frontier × 2020 dummy* is positive for national frontier firms only and an order of magnitude stronger (column 1 in table 3). This indicates the 2020 COVID-19 shock and associated GVC disruptions had a particularly strong effect for these firms.[13]

Next, we ask whether this relationship is true for domestic firms which are not at the national productivity frontier (mid-productive and laggard firms) by estimating an equation similar to (3):

[12] Frontier firms belong to the top 20% of the productivity distribution of a given country and macro-sector. Mid-productive firms are those firms in deciles 3-8, while laggard firms are in the bottom 20%.

[13] When weighing country and macro-sectors by value added, the average year-on-year TFP growth rate in 2020 was -0.22% for the GVC (import) frontier and –0.40% for national frontier firms.

$$\begin{aligned}\Delta TFP^{nat\_other}_{c,s,t} =& \alpha + \beta_1 \Delta TFP^{GVC\_front}_{c,s,t} + \beta_2 \ln\left(\frac{Prod^{GVC\_front}_{c,s,t-1}}{Prod^{nat\_other}_{c,s,t-1}}\right) + \beta_3 \Delta GVC_{c,s,t} \\ &+ \beta_4 \Delta TFP^{nat\_front}_{c,s,t} + \beta_5 \ln\left(\frac{Prod^{nat\_front}_{c,s,t-1}}{Prod^{nat\_other}_{c,s,t-1}}\right) + \delta_{c,s} + \tau_t + \varepsilon_{c,s,t}\end{aligned} \tag{4}$$

where nat_other indicates either mid-productive or laggard firms (estimated separately) and, on top of the regressors already in (3):

- β_4 captures how TFP of middle- or low-productive domestic firms varies with changes in the TFP of the most productive domestic firms (those at the national frontier).
- β_5 proxies the "catch-up" effect with respect to frontier firms in the same country and macro-sector.

National firms deepened connections with international producers during COVID-19 (directly or indirectly), which exposed them more intensely to the shock propagating within GVCs (table 3).

We see that for domestic firms that are not at the frontier (mid-productive and laggard firms), TFP changes in the GVC frontier are much less relevant in explaining their changes in productivity (columns 2 and 3 in table 3). This is captured by the coefficient β_1 of row *TFP growth GVC (import) frontier* in columns 2 and 3, which is small and scarcely significant.

Instead, the coefficient β_4, *TFP growth national frontier*, and its interaction with the COVID-19 dummy, *TFP growth national frontier x 2020 dummy*, are positive and statistically significant. This suggests that for this kind of firms the technology diffusion process, as well as the pandemic shock from GVC disruptions, took place more indirectly through domestic interactions than international linkages.[14]

These results show that aggregate events like the COVID-19 pandemic have affected the technology transmission process differently across two critical dimensions of firms, i.e., their respective productivity as well as their degree of participation to global production networks.

[14] When weighing country and macro-sectors by value added, the average year-on-year TFP growth rate in 2020 was -1.06% for mid-productive firms and –2.43% for laggard firms.

Table 3: **TFP growth transmission with time interactions. European countries, 2005-2020**

	(1)	(2)	(3)
	Frontier	Middle	Laggards
TFP growth GVC (import) frontier	0.4636***	0.2243**	0.2342
	(0.1352)	(0.0905)	(0.1466)
TFP growth GVC (import) frontier × 2008-2010 dummy	0.1790	0.1652	0.7637**
	(0.2684)	(0.1614)	(0.3617)
TFP growth GVC (import) frontier × 2020 dummy	1.5797**	0.1781	0.9058
	(0.7425)	(0.7159)	(1.2805)
Lagged labor productivity gap with GVC (import)	0.1138***	0.0345*	0.0575**
	(0.0191)	(0.0207)	(0.0260)
GVC (import) participation growth	-1.5198	0.3132	0.7987
	(1.6663)	(1.4075)	(2.0903)
TFP growth national frontier		0.5267***	0.5121***
		(0.0457)	(0.0682)
TFP growth national frontier × 2008-2010 dummy		0.5842***	0.8458***
		(0.1285)	(0.1966)
TFP growth national frontier × 2020 dummy		0.5762***	0.8796***
		(0.1311)	(0.2848)
Lagged labor productivity gap with national frontier		0.0277	-0.0227
		(0.0227)	(0.0390)
2008-2010 dummy	-0.5013**	-0.3058*	-0.6612***
	(0.2156)	(0.1681)	(0.2421)
2020 dummy	-0.3018	-0.6983***	-2.1518***
	(0.3260)	(0.2302)	(0.4884)
Constant	1.0791***	-1.2086**	-1.9191**
	(0.2399)	(0.5449)	(0.9170)
Country-MacroSector FE	YES	YES	YES
Observations	1,872	1,867	1,835
Adjusted R-squared	0.0468	0.6793	0.4658

Source: CompNet 9th Vintage (*jd_inp_prod_industry2d_20e_weighted*) and OECD ICIO.
Note: Robust standard errors in parentheses, clustered at the country-sector level. *** p<0.01, ** p<0.05, * p<0.1. In column 1, *Frontier* are frontier firms that belong to the last two deciles of the TFP distribution for each country and macro-sector. In column 2, *Middle* are mid-productive firms that belong to deciles between the third and the eighth of the TFP distribution for each country and macro-sector. In column 3, *Laggard* are laggard firms that belong to the first two deciles of the TFP distribution for each country and macro-sector. Results for trade linkages between BE, CH, CZ, DE, DK, ES, FI, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SI, SK, and SE. Unbalanced sample over 2005-2020. The latest available year is 2018 for DE, and 2019 for LV and NL. Country-macrosector fixed effects are included. Results for the GVC frontier computed on exports are omitted for the sake of brevity and are available upon request to the authors.

2.3 Unit labor cost as a driver of firm competitiveness

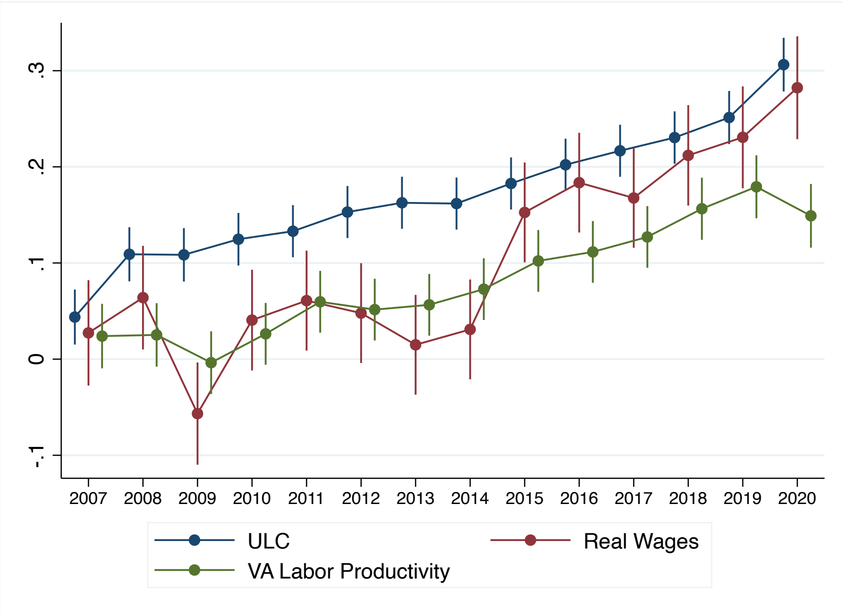
In this section we focus on unit labor cost (ULC), a widely used indicator of firm competitiveness. It is calculated as the ratio of hourly compensation over labor productivity (gross value added per hour worked): lower ULC indicates higher competitiveness. In the following section we will present the results of a more comprehensive indicator of competitiveness that includes not only costs and productivity but a wider range of firm characteristics.

ULC appears to have been increasing in Europe over the last decade also due to real wages growing at a more sustained pace since 2015 (figure 10).

ULC has been increasing also due to the continuous growth in real wages since 2015 (figure 10).

To examine whether improvements in value-added labor productivity can offset the rise in ULC and the subsequent loss in firm competitiveness through improved production processes and labor-replacing technologies[15] we look at the changes in ULC, real wage, and value-added labor productivity for firms at the top and the bottom of the productivity distribution in two representative EU countries (figure 11).

Figure 10: Growth in Value-Added Labour Productivity, Real Wages and ULC. European Countries, 2007-2020 (y-on-y changes)

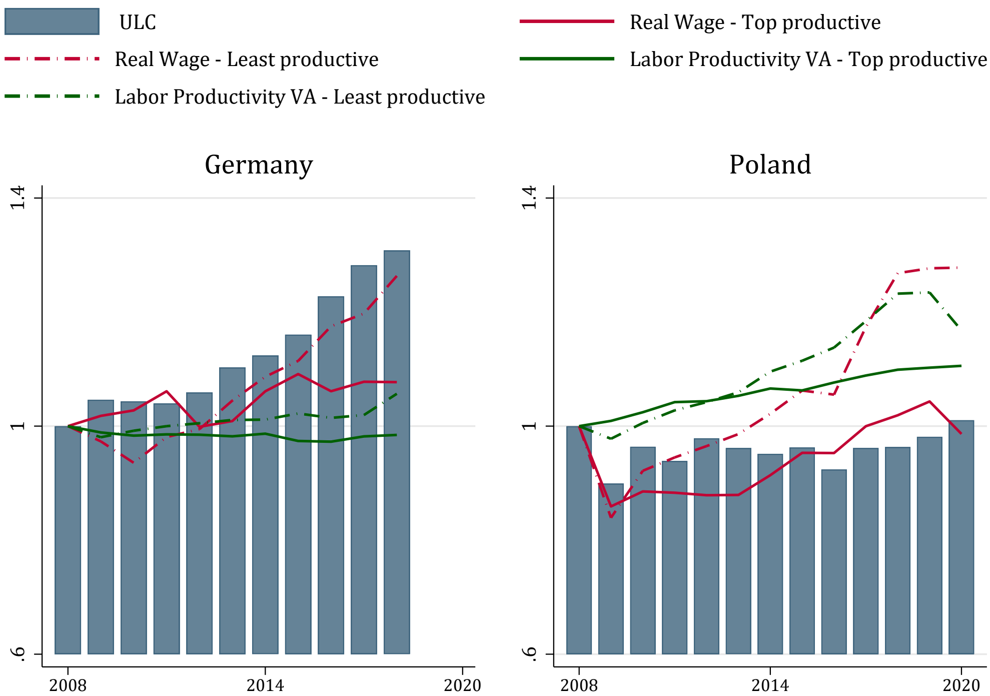


Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Predicted growth of medians at the industry level obtained by regressing on a full set of years, industry and country fixed effects. *ULC* is the ratio of nominal labor cost over real value added. *Labor Productivity VA* is value added per employee. Countries are BE, CH, CZ, DE, DK, ES, FI, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SI, SK, and SE. Unbalanced panel of countries between 2006 and 2020. The latest available year is 2017 for LV, 2018 for DE, and 2019 for NL.

In Germany rising real wages paid by the least productive firms appears to have driven the whole economy ULC out of whack (falling competitiveness in the period of observation). In Poland instead, wage increases both at the bottom and the top of the firm productivity distribution were on balance offset by productivity gains resulting in a stationary ULC overall.

[15] See Nilsson Hakkala et al. (2019) who find that in Finland cost competitiveness improvements are more relevant than innovation and industrial shifts for improving firm competitiveness.

Figure 11: **Growth in Value-Added Labour Productivity, Real Wages and ULC by productivity deciles. Germany and Poland, 2008-2020 (index with base year = 2008)**



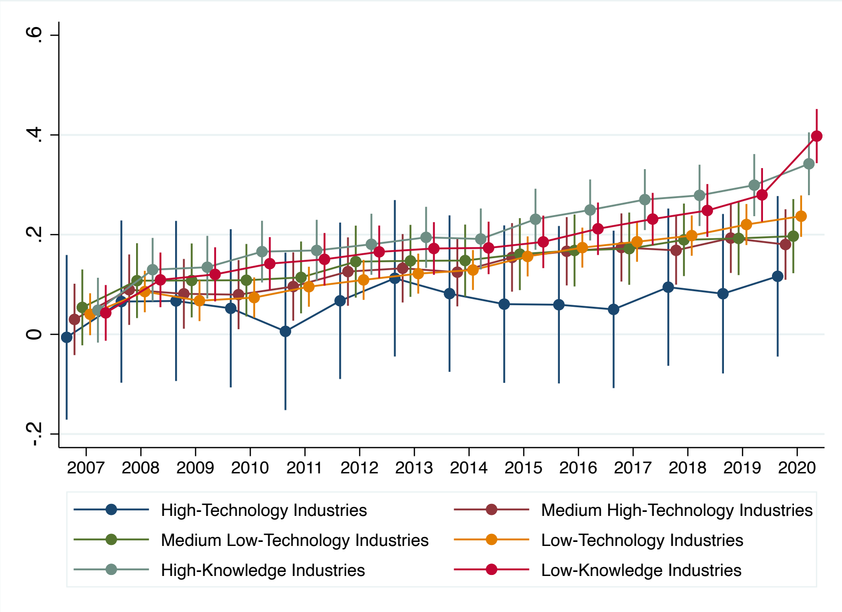
Source: CompNet 9th Vintage (*unconditional_country_20e_weighted*) and (*jd_inp_prod_country_20e_weighted*).
Note: Figures for *Top* and *Least productive* are the medians, respectively, for firms in the 10^{th} and 1^{st} deciles of the distribution of value-added labor productivity within the country. *ULC* is the median at the country level of the ratio between nominal labor cost and real value added. *Labor Productivity VA* is value added per employee. The latest available years for Germany is 2018.

This example points to the need of carefully assessing at the country level cost competitiveness drivers, and to the rich insights that, on this, the CompNet dataset can provide.

High-technology industries maintained their levels of competitiveness over time (figure 12).

Technology and knowledge intensity associate to higher productivity, so we also look at how they relate to ULC. Contrasting with aggregate evidence, high technology industries maintained their levels of competitiveness over time (figure 12).

Figure 12: **Growth in ULC by technology and knowledge categories. European Countries, 2007-2020 (y-on-y changes)**



Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Predicted growth of medians at the industry level obtained by regressing on a full set of years, industry and country fixed effects. *ULC* is the ratio of nominal labor cost over real value added. The assignment of industries to technology and knowledge categories follows Eurostat. Countries are BE, CH, CZ, DE, DK, ES, FI, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SI, SK, and SE. Unbalanced panel of countries between 2006 and 2020. The latest available year is 2017 for LV, 2018 for DE, and 2019 for NL.

2.4 Disentangling firm competitiveness: The results of a composite Indicator (ECI)

There are several firm-level characteristics that play a crucial role in shaping competitive dynamics (Karadeloglou et al., 2015); (di Mauro and Forster, 2008). Policymakers need to identify those critical aspects of firm activity and, if necessary, address problems by designing policies to maintain and enhance the competitiveness at a national level.

Broadening the previous analysis based on single cost competitiveness indicators, in this section we present a novel micro-aggregated composite indicator. Drawing from existing research on drivers of competitiveness, it considers five dimensions of performance, namely returns, costs, productivity, risks and quality orientation for the average firm in each country. The indicator is constructed as a micro-aggregated version of the *Enterprise Competitiveness Indicator* (ECI) proposed by Amador et al. (2022) and Lourenço et al. (2022), following the *OECD Handbook on Constructing Composite Indicators* (Nardo et al., 2005).

2.4.1 Methodology

Supposing we were using firm-level data, similarly to Lourenço et al. (2022), our ECI would be computed for the firm i as the average of five dimensions $\{D_i^n\}_{n=1,\ldots,5}$ with each dimension being weighted the same. Each dimension would be computed as the average of a number NV^n of variables $X_i^{n,v}$. As a preliminary stage, each variable $X_i^{n,v}$ would be standardized into a 0-1 scale using the cross-country minimum and maximum over the sector *s* to which firm *i* belongs:

$$SX_i^{n,v} = \frac{(X_i^{n,v} - min_s(X^{n,v})}{max_s(X^{n,v}) - min_s(X^{n,v})} \tag{5}$$

Hence, the ECI for firm *i*, ECI_i, would be calculated as follows:

$$ECI_i = \frac{1}{5}\sum_{n=1}^{5} D_i^n = \frac{1}{5}\sum_{n=1}^{5}\frac{1}{NV^n}\sum_{v=1}^{NV^n} SX_i^{n,v} \tag{6}$$

Appendix 7.2 shows how CompNet data can be used to compute the simple average of the firm-level ECI ECI_i like in equation 6, $E^{c,s}[ECI_i]$, for all macro-sectors $s = 1, \ldots, S$ of country *c* starting from the standardized micro-aggregated averages of the variables at the macro-sectoral level. The simple average firm-level ECI at the country level $E^c[ECI_i]$ is obtained by averaging over macro-sectors using population weights.

We proxy the five dimensions of the ECI building on the theoretical background proposed by Buckley et al. (1988) and applied by Lourenço et al. (2022). Table 4 summarises the variables considered for each dimension.

Table 4: Dimensions and variables of the Enterprise Competitiveness Indicator (ECI)

Dimension D^n	Firm Characteristics	Variables $X^{v,n}$
1. Return	Profit orientation	Return on assets (ROA); Estimated markup; Value added on Revenues; Operating profits on revenue
2. Production Costs	Control of production costs	Price cost margin; Revenue coverage of capital costs; Revenue coverage of labor costs; Revenue coverage of intermediate costs
3. Productivity	Efficiency of production factors	Labor productivity; Capital productivity; Capital Intensity
4. Risk$^{[i]}$	Financial risks	Collateral on total assets; Debt/Total assets; Cash flow/Total assets
5. Quality Orientation	Ability to develop future competitive advantages	Intangible fixed assets on Revenues; Wage premium$^{[ii]}$; Estimated returns to scale$^{[iii]}$

Notes: $[i]$ Risk: A higher score for Dimension 4 - Risk implies better financial soundness. $[ii]$ Wage premium: For each macro-sector, the wage premium is computed by dividing average real wage by the minimum wage. For each year, the country-level minimum wage is taken as the first percentile of real wage for the population composing the first decile for real wage within the country-level Joint Distribution (jd_inp_country_20e_weighted). $[iii]$ Estimated returns to scale: Returns to scale are estimated at the firm level by assuming a Cobb-Douglas production function with output elasticities of each input equal to the respective country-sector-year median cost-share, i.e., the ratio between the expenditure in the given input and total costs (the latter being the sum of fixed assets, labor, and intermediate inputs).

The European competitiveness stagnated over the last decade (figure 13a).

2.4.2 Results

Starting with the overall dynamics of the ECI, the European competitiveness has been generally stable. The changes in the average firm's ECI were small[16] except for the Northern Europe group (whose average rose by 5.16%). The dimension growing the most for the average firms in Northern Europe was *Productivity* (up by 15.44%), which also drove advancements in average firm competitiveness for the other countries: it improved by 2.29% in the Western group, 7.87% in the Eastern group, and 3.53% in the Southern group.

Quality Orientation does not appear to have improved much over the period. In most regions it declined: it changed by -1.55% in Northern countries, -1.35% in Western Europe, -3.74% in Southern Europe, and 0.20% in Eastern Europe. The Netherlands are an outlier: its average firm strengthened its leading role in adopting sophisticated technologies and production processes.[17]

Germany, France, and Sweden were the most competitive countries on average (figure 13a).

Across countries, the average firms in Germany, France, and Sweden were the most competitive in Europe between 2012 and 2020[18] (figure 13a). France has high average scores across all dimensions except *Quality Orientation*; Germany is strongest in *Return* and *Risk*. Swedish average firm performs well in *Return* and *Productivity*. Despite a volatile French performance during the last few years, the two largest European economies kept the Western European average at the top of the ranks for most dimensions.

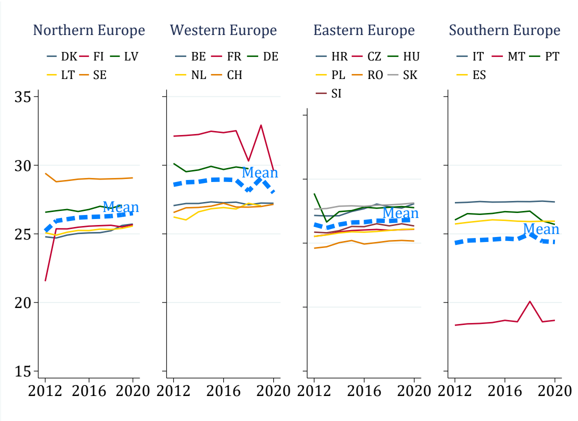
[16] These were -2.03% for Western Europe, 1.33% for Eastern Europe, and 0.30% for Southern Europe.

[17] Regarding the relationship of dimension 5 (Quality Orientation) in our ECI with technology sophistication, Corrado et al. (2021) find a positive relationship between intangible fixed assets (measured as a ratio on total assets) and higher productivity levels. Lourenço et al. (2022) consider wage premium as a proxy for human capital. Also, in List and Zhou (2007) increasing returns to scale are viewed as an important source of long-run firm growth since they arise from stronger fixed costs associated with the adoption of more advance technologies. Romero and Britto (2017) find suggestive results that research intensity has a more relevant impact on the magnitude of returns to scale than on productivity growth directly.

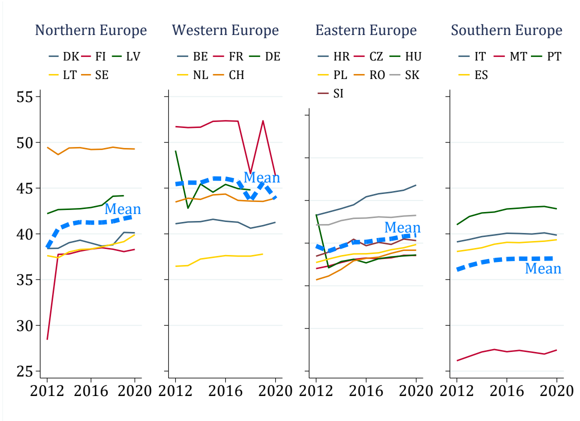
[18] Although our ECI measures are standardized as in equation 5, cross-country comparisons on the standardized levels should be interpreted with caution. Please note CompNet productivity comparisons across countries do not always line up with official statistics and there remain breaks in the data series for some countries. For this reason, in our analysis we focus primarily on within country variation across dimensions, as well as changes over time. Results in this regard are robust. It is still interesting to note that despite country specific idiosyncrasies of the data collection France, Germany, and Sweden appear to rise to the top of our ECI.

Figure 13: **The Enterprise Competitiveness Indicator (ECI). European countries, 2012-2020 (standardized percentage)**[19]

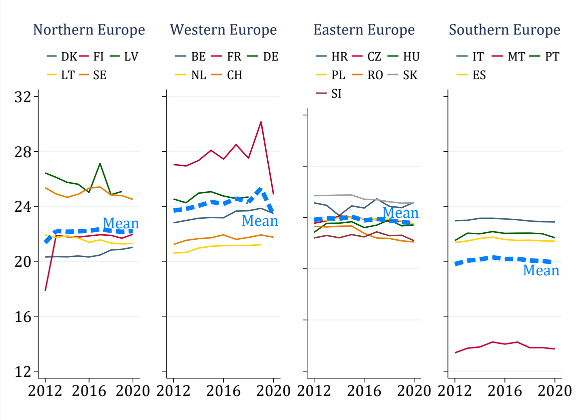
(a) *Overall*



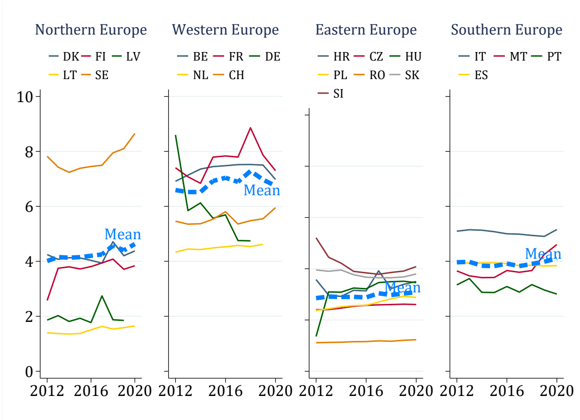
(b) *Return*



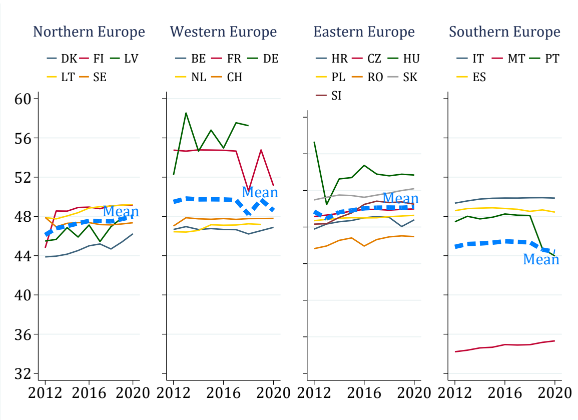
(a) *Production costs*



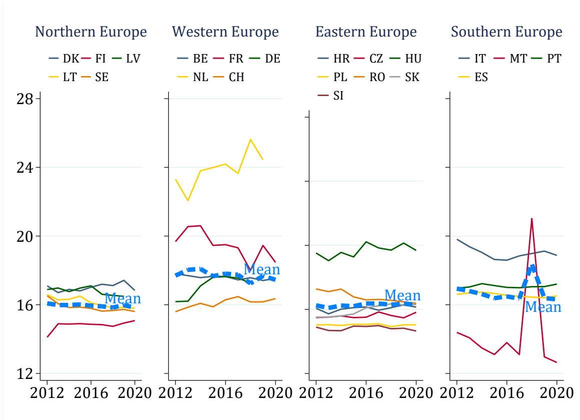
(b) *Productivity*



(a) *Risk*



(b) *Quality orientation*



[19] Source: CompNet 9th Vintage (*unconditional_mac_sector_20e_weighted*).

The average firm in Eastern and Southern European countries lags in *Productivity* and *Risk* dimensions. This is consistent with the sluggish catch-up of the most recent EU member states and a weaker macroeconomic outlook for most Mediterranean EU economies.

Our micro-aggregated ECI explains well countries' market shares (table 5).

Putting our indicator at worth, we find that the ECI helps explaining export market shares, calculated as country's exports over total world exports, both Goods and Services. When confronted with the ECI, for instance real effective exchange rates (REERs) are only scarcely significant, and their coefficients have opposite signs than expected (table 5).

Table 5: ECI, REER and Market Shares. European countries, 2012-2020

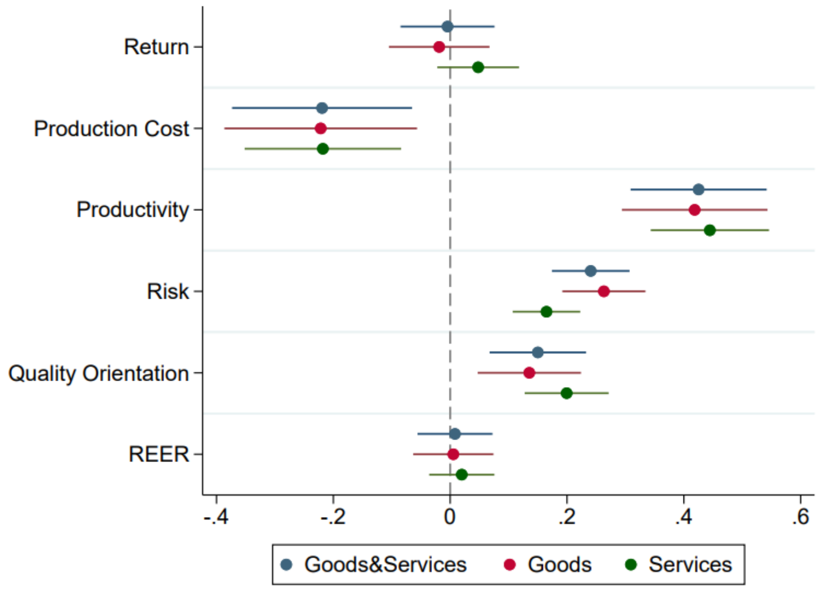
	(1) Goods and Services	(2) Goods	(3) Services
ECI	0.3263***	0.3216***	0.3429***
	(0.0428)	(0.0448)	(0.0400)
REER	0.0699*	0.0686	0.0761**
	(0.0397)	(0.0416)	(0.0371)
Constant	-14.5172***	-14.2904***	-15.4898***
	(4.1744)	(4.3745)	(3.8990)
Year FE	YES	YES	YES
Observations	176	176	176
Adjusted R-squared	0.2355	0.2107	0.2874

Source: CompNet 9th Vintage (*unconditional_mac_sector_20e_weighted*) and Eurostat.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Coefficients from regressing market share on the ECI (computed like in Appendix 7.2) and on real effective exchange rates (REERs) with year fixed effects. REERs aim to assess a country's price or cost competitiveness relative to its principal competitors in international markets. REERs are the nominal effective exchange rates (NEERs) for 42 trading partners deflated by consumer price indices (CPIs). Results for BE, CZ, DE, DK, ES, FI, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SI, SK, and SE. The latest available years are 2019 for LV and NL, and 2018 for DE.

Going deeper into the most important dimension within the ECI explaining export market shares, we uncover that *Productivity* is the main driver. *Risk*, *Quality Orientation*, and, with the opposite sign, *Production cost*, are also relevant (figure 16).

Note: The ECI variables are standardized like in equation 5 using the minima and maxima taken over the entire time span. *Mean* is the unweighted average for countries with complete time series in each group. Data for FI does not include "Information and communication" and "Professional, scientific and technical activities". Data for DE does not include "Construction" and "Wholesale and retail trade; repair of motor vehicles and motorcycles". Data for MT are only representative of "Wholesale and retail trade; repair of motor vehicles and motorcycles". Data for SI does not include "Information and communication". The latest available years are 2019 for LV and NL, and 2018 for DE.

Figure 16: **ECI by dimension, REER, and Market Shares. European countries, 2012-2020**



Source: CompNet 9th Vintage (*unconditional_mac_sector_20e_weighted*).
Note: Coefficients from regressing market shares on ECI dimensions (pooled, each computed like in Appendix 7.2) and real effective exchange rates (REERs) with year fixed effects. REERs aim to assess a country's price or cost competitiveness relative to its principal competitors in international markets. REERs are the nominal effective exchange rates (NEERs) for 42 trading partners deflated by consumer price indices (CPIs). Results for BE, CZ, DE, DK, ES, FI, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SI, SK, and SE. The latest available years are 2019 for LV and NL, and 2018 for DE.

2.5 Conclusions

Looking at the international dimension, firm size was yet again an important determinant of the impact of the COVID-19 shock. Small firms with less than 50 employees mostly reacted by ceasing serving international markets in 2020, while firms with more than 250 employees were more likely to continue being present in such markets.

Also, participation of firms in global production networks was an important determinant of productivity transmission across countries. National frontier firms were exposed more intensely to the COVID-19 shock propagating within GVCs. Mid-productive and laggard firms, mostly serving domestic markets, remained only indirectly affected by this shock through the channel of national frontier firms.

A traditional indicator of firm competitiveness, the ULC, shows a deteriorating competitiveness performance for Europe as a whole. Significant heterogeneity across countries points to the need to carefully assess the extent in which real wages developments are consistent with the productivity outcomes of the respective firms.

A new composite indicator of firm competitiveness, the micro-aggregated ECI, confirmed that European competitiveness stagnated over the last decade. The few gains were driven by firm profitability and productivity, whereas the average firm was generally reducing its orientation towards adoption of more sophisticated production processes. Overall, the ECI is an useful tool of analysis, as it adds significantly to explain developments in export market shares, over and above mere price based indicators. This is particularly so as it concerns the dimensions of productivity, risk, quality orientation, and production cost.

3 Resource reallocation over the business cycle: A cross-country comparison

Coordinator: *Leonardo Indraccolo*

Reference CompNet persons: *Leonardo Indraccolo* and *Laura Lufray*

Cleansing effects: Economic mechanism by which during recessions average firm productivity increases because the least productive firms are driven out of the market.

If we want to design productivity-enhancing public policies, we need a solid understanding of how efficiently resources are allocated across firms, especially when the aggregate state of the economy changes.

An economic crisis can, in theory, increase average firm productivity through so-called "cleansing" effects. This is the process by which, during economic downturns, the least productive firms are driven out of the market leaving the most efficient businesses in operation with an improved use of market resources.[20] While the mechanism can be rationalized in a simple dynamic model, we still do not have robust cross-country empirical evidence to confirm this hypothesis.[21]

Below we document how efficiently capital and labor are reallocated across sectors during expansionary and recessionary periods, using our European CompNet dataset. We also examine indirect measures of firm responsiveness: how they vary over the business cycle, and how they relate to country-specific institutional features.

Foster et al. (2016) showed that the amount of resource reallocation over the business cycle in the US is tightly linked to how firms respond to unanticipated changes in their profitability that have been caused by changes in demand or productivity.

Firms respond to these changes through labor market and investment choices. We study firm responsiveness as measured by the intensity by which firms adjust their labor force in response to exogenous profitability shocks, and measure it indirectly through job creation and destruction rates at the sector level, giving us an insight into the pace of resource reallocation. The more firms respond to exogenous shocks, the more resources will flow from less productive to more productive firms.

We find that recessionary periods – including the one caused by COVID-19 – are associated with improved resource allocation (3.1). This is true across almost all European countries, potentially suggesting that economic downturns have cleansing effects that enhance productivity. Also, firm responsiveness strictly follows the business cycle (3.2). Expansionary periods are characterized by increases in job creation rates, and job destruction rates peak during downturns. The patterns are qualitatively (though not quantitively) the same

[20] See Caballero and Hammour (1994) for the theory behind the cleansing effects of recessions.

[21] Some evidence of the cleansing effect on the manufacturing sector during the great recession is provided by Foster et al. (2016), while Kozeniauskas et al. (2022) provide similar findings using Portuguese administrative data during the COVID-19 crisis.

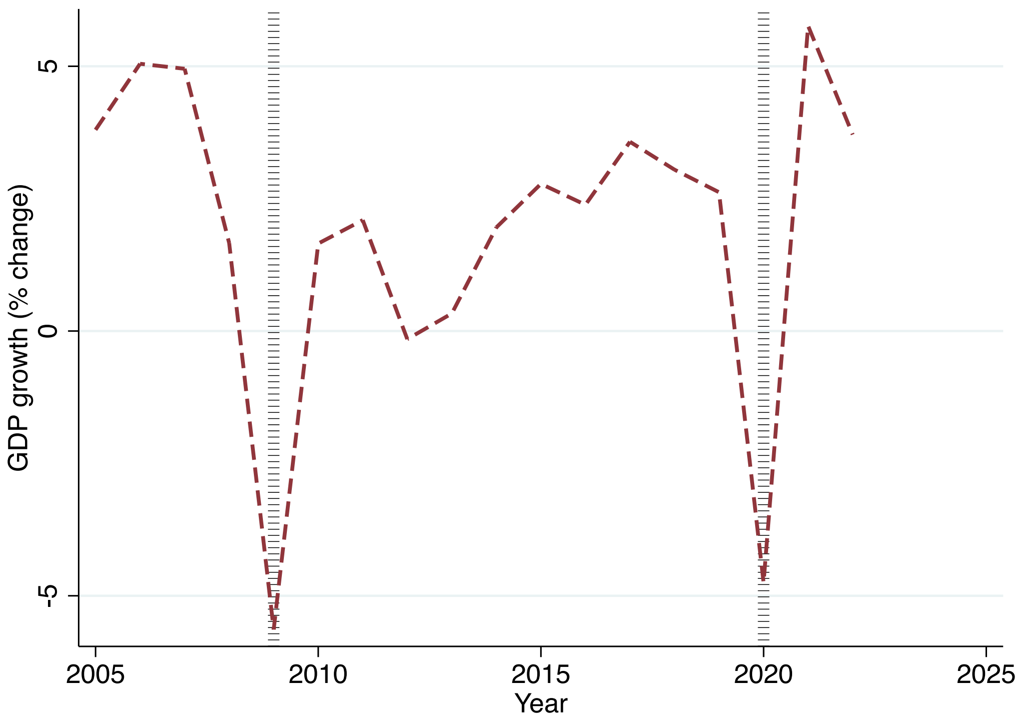
across geographic areas. Finally, we point out how flexible labor markets are on average associated with more dynamic economies, as measured by job destruction rates, regardless of the aggregate state of the economy (3.3).

Resources are better allocated during economic downturns than expansionary periods (table 6).

3.1 Resource allocation

Using the CompNet 9th vintage 20e dataset, which contains aggregated firm-level statistics for all firms with at least 20 employees,[22] we group countries into four geographical areas: Nordic, Central-Eastern, Western, and Southern European.[23] We define recessionary and expansionary periods based on the average European GDP growth between 2008 and 2020 (figure 17).[24] Recessionary years are 2009 and 2020; other years are expansionary.

Figure 17: Real GDP growth (annual percent change) over the business cycle in Europe, 2005-2022 (GDP growth % changes)



Source: International Monetary Fund (IMF)
Note: The figure shows real GDP growth in Europe over time. The vertical grey bars indicate recessionary events.

The CompNet dataset provides several standard measures of allocative efficiency. Given our interest in comparing how resources are allocated across

[22] We focus on the 20e sample because for some countries, like Germany, the data is only available for firms with at least 20 employees in certain sectors.
[23] Nordic countries: Finland, Denmark, and Sweden. Central-Eastern countries: Czech Republic, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia. Western countries: Belgium, France, Germany, and Netherlands. Southern countries: Italy, Portugal, Spain. See EuroVoc.
[24] Data from the International Monetary Fund (IMF). For details see IMF Datamapper - Real GDP growth.

firms in different states of the economy, we use the "OP" measure, the covariance between firm productivity and size. This is a static measure of allocative efficiency proposed by Olley and Pakes (1996a): when covariance is high, resources are better allocated as more productive firms use a greater share of total employment in the economy.[25]

To understand resource allocation changes during the business cycle, we pool observations and regress the OP measure on a flag for recessionary periods. In this way, we exploit both country and industry variation. Table 6 shows that, there is an improvement in the allocation of resources during economic downturns as low productivity firms exit or contract. The difference in the OP covariance measure between expansionary and contractionary periods is statistically significant.

Table 6: OP covariance over the business cycle for European countries across sectors, 2008-2020

	Expansions	Recessions	Difference
Covariance (OP)	3.291	4.535	1.244 (0.471)

Notes: The difference is statistically significant at the 5% significance level. Standard error of the difference in parenthesis.

This evidence points towards the idea that recessions in Europe can have a positive cleansing effect by which resources which were previously locked up in low productivity firms are freed up to flow to more productive firms. Table 7 shows that this finding applies in three of the four country groups. Southern countries are the exception: for them, there is almost no difference in the OP measure between business cycle peaks and troughs. The magnitude of the OP measure is an order of magnitude higher in Western and Nordic countries than in Central-Eastern European and Southern economies. This has obvious implications for the productivity gains these economies can achieve from reallocation.

Table 7: OP measure across countries and aggregate states of the economy for European regions, 2008-2020

	Expansions	Recessions
	Op measure	Op measure
Nordic countries	8.057	12.239
Southern countries	0.149	0.152
Central-East countries	0.699	0.979
Western countries	6.566	8.119

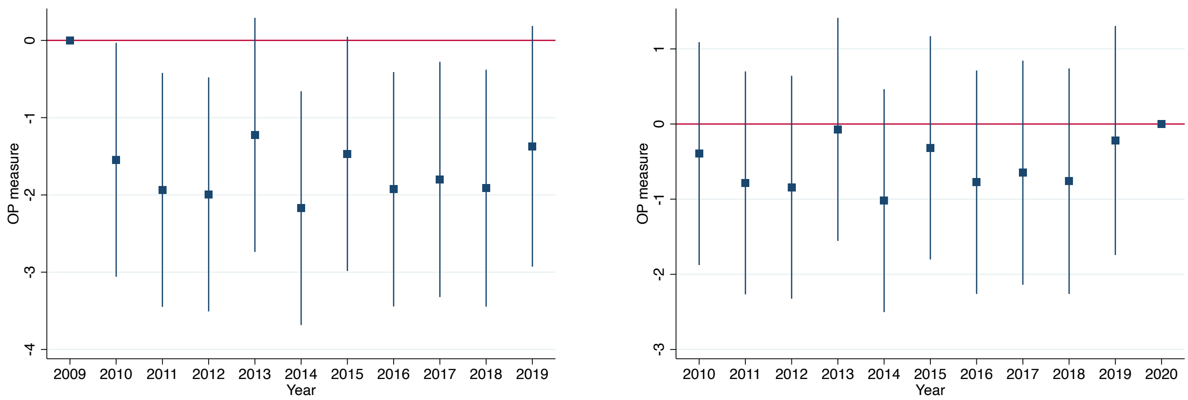
Figure 18 distinguishes between the two recessionary events in the sample. It plots the evolution of the OP measure in the great recession (figure 18a) and the COVID-19 recession (figure 18b). The negative coefficients reveal that our findings hold true for both recessions separately, but that the sta-

[25]The CompNet dataset provides the OP measure at the 2-digit sector level where firm productivity is computed as total factor productivity (in levels), obtained after a production function estimation procedure and size is the number of employees. The production function is estimated using a control function approach as proposed by proposed by Ackerberg et al. (2015).

tistical significance comes from the great recession of 2009. Using 2020 as the reference year, we see that while all point-estimates are still negative in sign, they are not statistically significant. This partly results from more heterogeneous responses in terms of factor reallocation across sectors during the COVID-19 recession, compared to the Great Recession.

Figure 18: **Allocative efficiency for European countries across sectors, 2008-2020, with reference to recessions in 2009 and 2020**

(a) *OP measure with reference year 2009* **(b)** *OP measure with reference year 2020*



Source: CompNet 9th Vintage (*op_decomp_industry2d_20e_weighted*)
Note: In panel (a) we plot the OP measure over time with reference year 2009. In panel (b) we plot the same measure with reference year 2020. Please note that the y-axes are on a different scale, underlying the subdue values taking 2020 as reference.

Job destruction rates are higher in recessions, while job creation rates are higher in expansionary periods. Positive job creation is still observed during economic crisis, indicating that some firms are expanding also when hit by negative aggregate conditions.

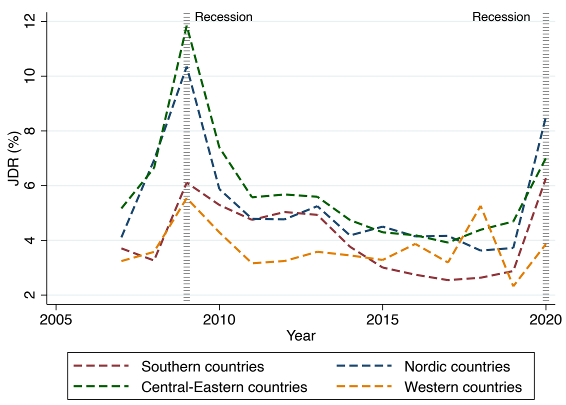
3.2 Firm responsiveness

From Foster et al. (2016) we know that how well – and how quickly – resources get reallocated is strictly related to whether, and how intensively, firms respond to unanticipated changes in profitability.

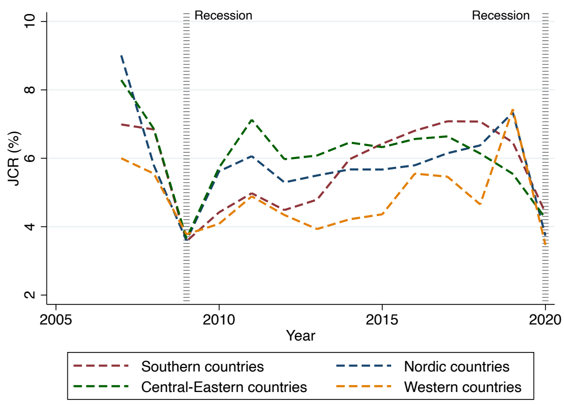
We can use CompNet data to indirectly measure firm responsiveness. Figure 19a plots how the job destruction rate (JDR) changes during the business cycle, across groups of countries. Figure 19b plots the equivalent job creation rate (JCR). Job creation and destruction rates in CompNet are measured with the sector-level average growth rate in employment. As expected, job destruction rates are higher in recessions, while job creation rates are higher in expansionary periods. This pattern holds true across all European regions independently of the geographic area. However, the magnitude of the increase in job destruction rates during recessions is remarkably higher in Central and Northern countries compared to the rest. To be noted here is that even during broad economic downturns many firms still create jobs (either at the intensive or extensive margin) such that job creation rates never go to zero even during economic crises.

Figure 19: **JDR and JCR over the business cycle by European countries across sectors, 2008-2020**

(a) *JDR over the business cycle*



(b) *JCR over the business cycle*



Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*)
Notes: In panel (a) we plot the job destruction rate over the business cycle, while in panel (b) we plot the job creation rate. The vertical grey bars indicate recessionary events.

We observe a positive relationship between the two variables of labor market rigidity, i.e. hiring and firing indexes (figure 20).

3.3 The role of labor market rigidity

In standard firm dynamic models, firms respond to exogenous shocks by changing employment when the benefits exceed the costs. Some of these costs are associated with the institutional framework in which firms operate. For example, when the bureaucratic and legal costs of hiring and firing are high, firms are less likely to act – and so they will be less responsive to changes in profitability.[26]

The OECD Employment Protection Legislation (EPL) database gives us data to study whether countries with more rigid labor markets have less dynamic economies, as captured the JCR and JDR. The EPL database distinguishes between indicators of dismissal regulations for regular workers and indicators of hiring regulations for temporary workers.[27] In table 8 we show summary statistics of the two indexes, computed on a sample of 17 European countries. In a country with a high index, it is complex and tedious to hire or fire a worker. European countries have a wider variation in the index that measures regulatory restrictions to hiring temporary workers than in the index capturing restrictions on dismissing workers on regular contracts.

Table 8: **Summary statistics for dismissal and hiring regulations for European countries, 2019**

	Mean	Max	Min	Sd
Index for dismissal regulations of regular workers	2.439	3.017	1.776	0.341
Index for hiring regulations of temporary workers	2.245	3.625	1.479	0.585

[26] In turn this leads to a loss of productivity from the reallocation of resources towards more valuable activities.
[27] More details on the OECD data construction at OECD 2020

Table 9 breaks down these statistics by region. In general, Southern countries have more rigid labor markets, both for firing and hiring regulations, and Nordic countries have the easiest procedures. Statistics by country are included in the appendix (table 20).

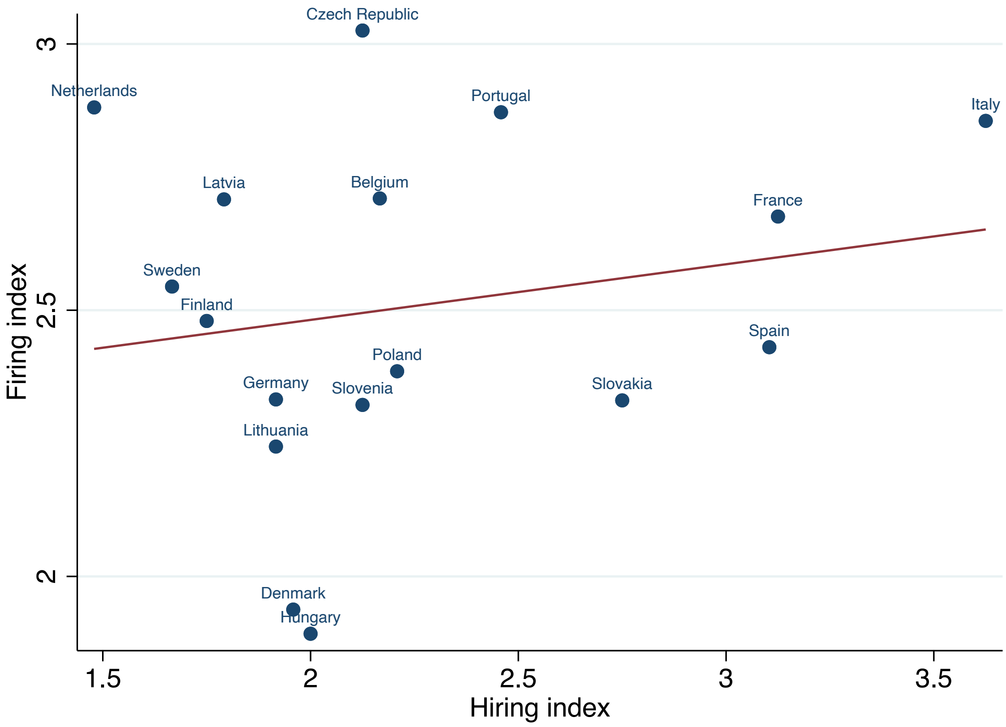
Table 9: Dismissal and hiring regulations by European regions, 2019

	Dismissal regulations	Hiring regulations
Nordic countries	2.383	1.817
Southern countries	2.719	3.063
Central-East countries	2.391	2.242
Western countries	2.650	2.172

The Czech Republic is the country with the costliest dismissal regulations, followed by Portugal and the Netherlands. On the other hand, Italy is the country in which it is bureaucratically most complex and time-consuming to hire a worker on a fixed-term or temporary work contract. This is reflected in its high value in the index for hiring temporary workers.

Figure 20 shows that hiring restrictions and dismissal restrictions are positively correlated.

Figure 20: Correlation between firing and hiring restrictions, European countries, 2019

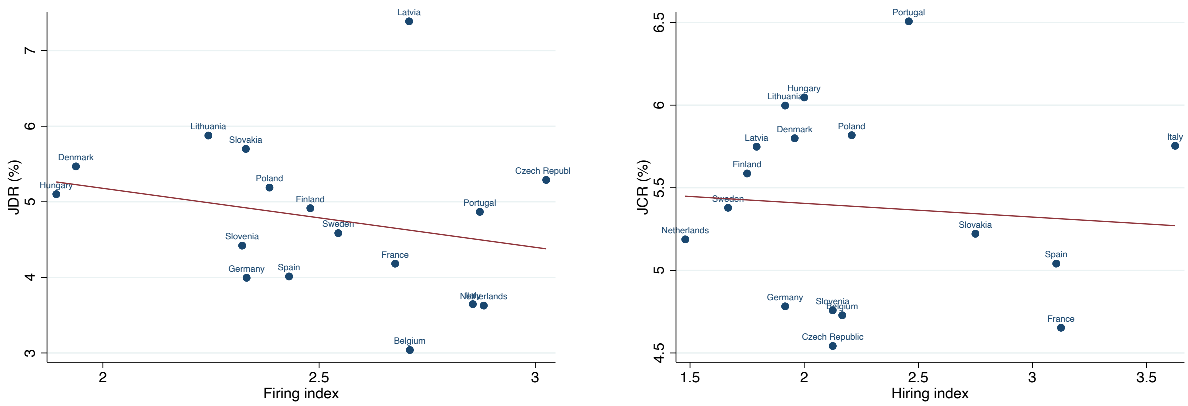


Source: OECD Employment Protection Legislation (EPL) database.
Notes: The plot shows the association between the firing (dismissal of regular workers) and hiring (hiring of temporary workers) index.

Next, we study how the CompNet measures of firm dynamism relate to the OECD statistics on labor market rigidity. Figure 21 shows the association between JDR and the index capturing the ease of firing regular workers (panel 21a), and JCR and with the equivalent hiring index (panel 21b). In countries in which it is more difficult to fire, the JDR tends to be lower. There is an association between labor market institutions and firm responsiveness in this case, though we cannot say if this is causal. There is almost no association instead between JCR and the index of ease of hiring, although the OECD data refers only to fixed-term contracts: in Europe 85% of workers are employed on long-term contracts.[28] This may explain why there is no correlation in this case.

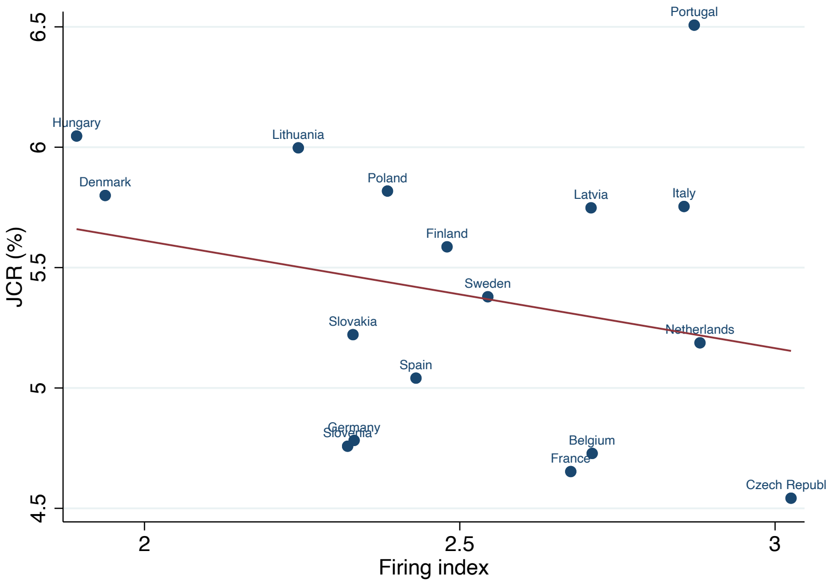
Figure 21: **JDR & JCR and indexes of labor market rigidity, European countries, 2008-2020**

(a) *JDR over firing index of the labor market* **(b)** *JCR over hiring index of the labor market*



Notes: In panel (a) we plot the job destruction rate over the index that measures how difficult it is to fire regular workers. In panel (b) we plot the job creation rate over an index measuring how hard it is to hire temporary workers.

Figure 22: **JCR over firing index of the labor market, European countries, 2008-2020**



CompNet 9th Vintage, (*unconditional_industry2d_20e_weighted*), and OECD EPL database .
Notes: The plot shows the job creation rate over the index that measures how difficult it is to fire regular workers.

[28]See Eurostat for more details

Noteworthy is the fact that in countries in which it is more difficult to fire, job creation rates also seem to be lower. Together with our previous results, this shows that understanding labor market regulation is crucial to gain insights on firm behavior and the factor reallocation.

In countries where it is more difficult to fire, job destruction rates are on average lower.

3.4 Conclusions

CompNet data captures how allocative efficiency changes across countries and over the business cycle. Also, firm responsiveness as captured by the JCR and JDR closely tracks the business cycle. We find allocative efficiency improves during recessions, consistent with resources moving from less productive and valuable businesses to more productive ones, particularly in Northern and Western European economies. On the other hand, job reallocation during recessions is less common in Southern economies. Firms operating in more rigid labor markets tend to respond less to changes in profitability. This has potentially important implications for allocative efficiency and the productivity gains from reallocation these economies can achieve.

4 Reacting to energy price shocks

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Reference CompNet persons: *Laura Lehtonen*, *Sara Azzarito*, *Alessandro Zona Mattioli* and *Marcelo Piemonte Ribeiro*

Collaborating National Productivity Board: *Urska Cede* (Institute of Macroeconomic Analysis and Development, Slovenia)

Amid global tensions and climate concerns, firms are facing turbulent energy markets and demands to transition to sustainable energy sources. Understanding how firms react in this uncertain environment is crucial for assessing the broader economic implications.

We are entering a new phase of globalization. Amid global tensions, production is being reconfigured in regional clusters, rather than truly global ones. Energy sourcing is part of this process, with countries shuffling their energy providers to ensure security and continuity.

This process is not frictionless. It creates turbulence in energy markets, increasing volatility and on occasion high prices. Higher price levels harm firm cashflows and profitability in the short run. When associated with high volatility, they increase uncertainty, in turn reducing investment and hiring, slowing economic activity.

Additionally, the climate transition goals demands countries to use more sustainable energy sources and cut their reliance on fossil fuels. This requires adjustments at the firm level, with some firms in a better position to achieve a sustainable energy mix than others.

How do firms react to energy price shocks? Which firms can cope with these shocks without severe losses in profitability and employment? We use firm-level information and cross-country heterogeneity to understand which countries or industries have higher resilience to energy-market turbulence.

Firms can react to energy price shocks in multiple ways. We focus on the five following, and investigate which channels are prevalent:

- **Pass-through:** Firms pass price shocks on to customers by adjusting sales prices, depending on the demand elasticity they face (Ganapati et al., 2020).
- **Increase energy efficiency:** Firms reduce the quantity of energy required per unit of output, for example by turning off energy inefficient equipment. The potential to do this depends on technological requirements and energy infrastructure of the economy. It may be limited in the short run (Costantini and Mazzanti, 2012).
- **Reduce expenditure in other inputs:** These include intermediate inputs or labor (Marin and Vona, 2021).
- **Cost-bearing:** Firms may decide to reduce profit margins or even incur a loss (Rentschler and Kornejew, 2017).
- **Switching to alternative energy sources:** They opt for relatively cheaper energy sources, possibly because of favorable taxation (Rentschler and Kornejew, 2017).

The prices of different energy sources vary significantly over time (figure 23)

4.1 Data sources and stylized facts

To analyze the firm responses to energy price shocks, we combine energy prices data from the International Energy Agency (IEA), industry-level energy consumption by energy source from the World Input-Output Database Environmental Accounts (WIOD), and firm variables aggregated at the country-industry level from the CompNet 9th vintage 20e sample data. We express energy consumption in TeraJoules (TJ) and prices in EUR/TJ. Finally, we adjust the level of aggregation of the external data sources to make them compatible with CompNet 2-digit industry classification and merge them. Our analysis focuses on Denmark, Finland, Germany, Lithuania, Poland, Portugal, Slovakia, and Slovenia, eight countries for which the available energy data is comparable.[29]

We have data on industry level prices after taxes[30] for a wide range of sources, and we focus on diesel, electricity, fuel oil, gasoline and natural gas. These account for around 75% of energy consumption, while allowing us to use a large estimation sample.

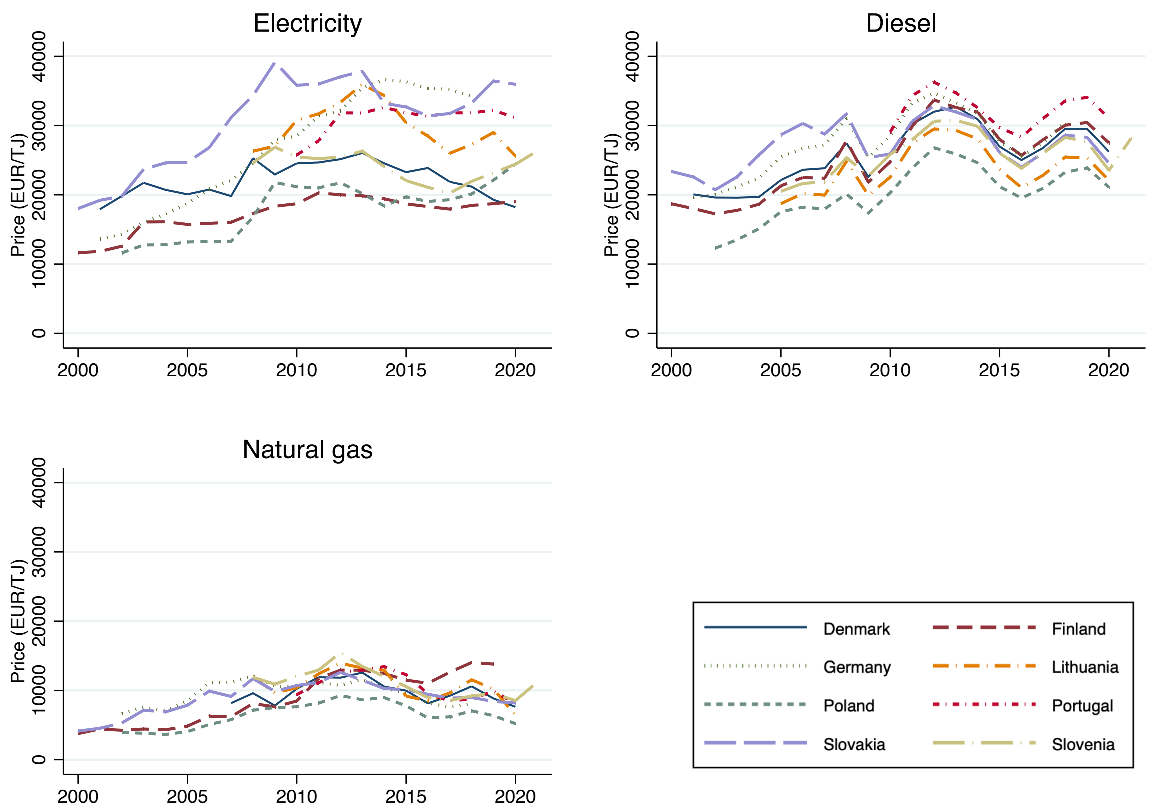
Figure 23 shows the trends in energy prices (after tax) averaged over industries and countries for electricity, diesel, and natural gas across the sample of countries.

Electricity exhibits the largest price heterogeneity across country: its prices have a special market determination and countries produce electricity in different ways. Natural gas shows also cross-country variation, but less than for electricity. Diesel shows similar trends across countries: prices are determined at international markets, so taxation and subsidies are the source of cross-country variation. Other energy sources follow similar patterns to diesel (largely homogenous parallel trends). Pre-tax graphs and graphs for prices of each of the remaining energy sources can be found in the appendix (figure 39).

[29] CompNet 9th Vintage has a variable for energy costs, collected for 10 countries: Croatia, Denmark, Finland, Germany, Lithuania, Malta, Poland, Portugal, Slovakia and Slovenia. For compatibility with the IEA and WIOD data, Croatia and Malta had to be dropped from the selected sample of countries.

[30] Prices after tax include all taxes and levies, including VAT and carbon taxes. Prices are not corrected for inflation or consider any national subsidies. We use after-tax prices to include potentially endogenous policy responses that could be activated after a price shock. Taxes are heterogeneous across countries and can represent a large share of the final price, so ignoring them would lead to a downward bias in a measure of energy impact on firm costs.

Figure 23: **Trends in energy prices (EUR/TJ), selected European countries, 2000-2020.**



Source: International Energy Agency.
Notes: Prices after tax used, ie., prices after all taxes and levies, including VAT and carbon taxes.

Electricity, natural gas and fossil fuels make up around 75% of the energy consumption in the countries studied, however the shares of each vary across countries and industries (figure 24)

When estimating the impact of energy prices on firms' behavior, including all of them in the same specification may lead to collinearity issues, particularly for oil-derived fuels (diesel, gasoline, fuel oil). On the other hand, excluding some of them may lead to omitted variable bias. For these reasons we use principal component analysis (PCA) to reduce dimensionality and identify the primary sources of variation. This solves the problem of collinearity by design but does not omit the relevant impact of some energy sources.[31] Figure 24 shows the results of the decomposition. The first principal component (PC1) accounts for approximately 63% of combined variance; the first three components explain more than 95% of total variance. Therefore we focus on PC1 to PC3 in our analysis.[32]

[31] We use a standard approach in estimating PCA: we standardize the time series data based on the country mean across industries and years, and we base our decomposition on the variance-covariance matrix of the resulting dataset. We also try different dimensions for the standardization (industry, industry-country) and the results do not change substantially. We then extract eigenvalues and eigenvectors and use them to project the data on a lower dimensional space (from 5 to 3), to obtain the final series.

[32] The eigenvalues of the three PCs are respectively 3.12, 1.17 and 0.5, which suggests that the first two are already sufficient for a satisfactory dimensionality reduction.

Figure 24: **Percentage of total variance in energy costs explained by each component**

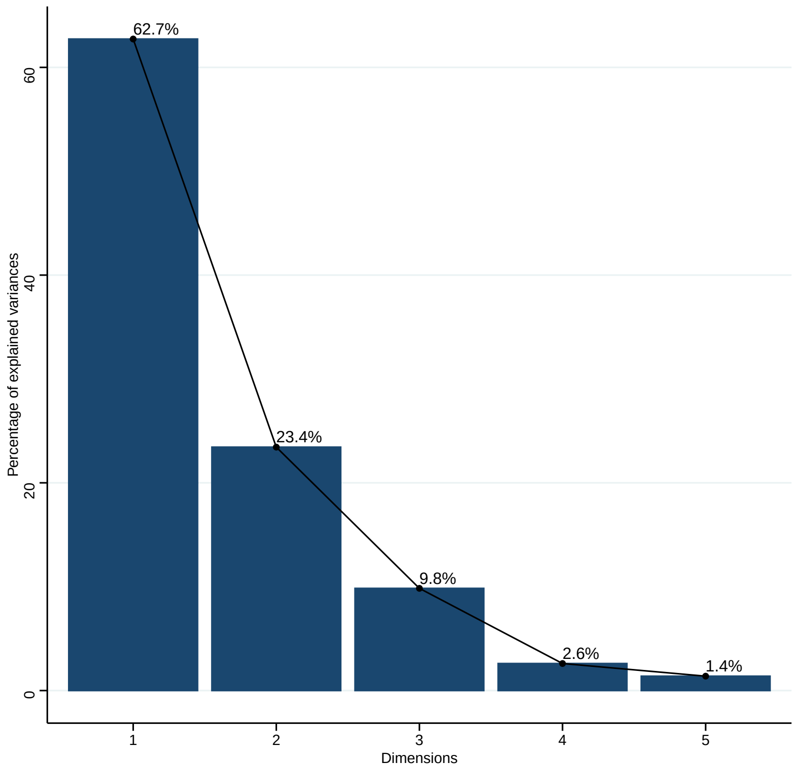


Table 10 provides insights into the composition of these three PCs: PC1 consists mainly of fossil fuels, PC2 mainly of electricity, and PC3 largely of natural gas.[33] Consequently, we use these components in our analysis, referring to PC1 as "Fossil fuels", PC2 as "Electricity", and PC3 as "Natural gas".

Table 10: **Contribution to PC (%)**

	PC1	PC2	PC3
Diesel	28.2	3.2	8.0
Electricity	2.1	78.6	0.1
Fuel Oil	23.2	16.4	1.3
Natural Gas	21.1	0.5	62.9
Gasoline	25.4	1.3	27.8

Source: International Energy Agency. Note: Share of the variance of each PC represented by the baseline prices.

[33] Although PC1 only contains 21% of natural gas, PC3 is predominantly 63% made up of natural gas, likely because of the different features of this fossil fuel compared to the other oil-derived products. This leads us to determine the final allocation of natural gas into PC3 instead of PC1.

Both aggregate level energy mix and firms' energy intensity stay relatively stable overtime (figure 24, figure 25, and figure 26)

Figure 25 shows the energy mix by country and figure 26 by sector over time, for the selected energy sources, summarized by the principal components: electricity, natural gas and fossil fuels.[34]

These energy sources make up around 75% of the energy consumption in almost all countries. While electricity and fossil fuels are widely used across countries, the reliance on natural gas varies: Finland has a lower dependency on natural gas than Germany and Slovakia, for example. Factors such as infrastructure, access to natural resources, and primary economic activities are behind a country's energy source preferences and determine its exposure to each source's price shocks.

Macro-sectors show greater variation in their energy mix, possibly due to different technologies and energy inputs. Manufacturing is the main source of natural gas demand, and so manufacturing-intensive countries such as Germany or Poland are more exposed to shocks in gas prices. Transport is the industry most intensive in fossil fuels, mainly due to a high reliance on truck transportation (powered by diesel and gasoline) compared to electrically powered railways. Understanding this heterogeneity across countries and sectors is important because it helps explain why certain energy price shocks may impact some countries and sectors more than others.

The energy mix remains relatively stable for countries and macro sectors. This implies low likelihood that countries or firms switch to alternative energy sources following a price shock.

We compute an index of energy intensity, defined as energy over total costs, to measure the sensitivity of firms to price changes. On average, energy intensity has remained stable over time, but with substantial level differences (Portugal at around 2.5%, declining, Denmark $< 1\%$; see figure 27). The decline may be due to technological improvements that lead to energy efficiency, or due to the offshoring or phasing out of energy-intensive production.

[34] We use the weights of the raw energy sources in each PC from table 10 to construct a weighted sum of energy used in each country/industry.

Figure 25: Energy mix at the country level, selected European countries, 2007-2016.

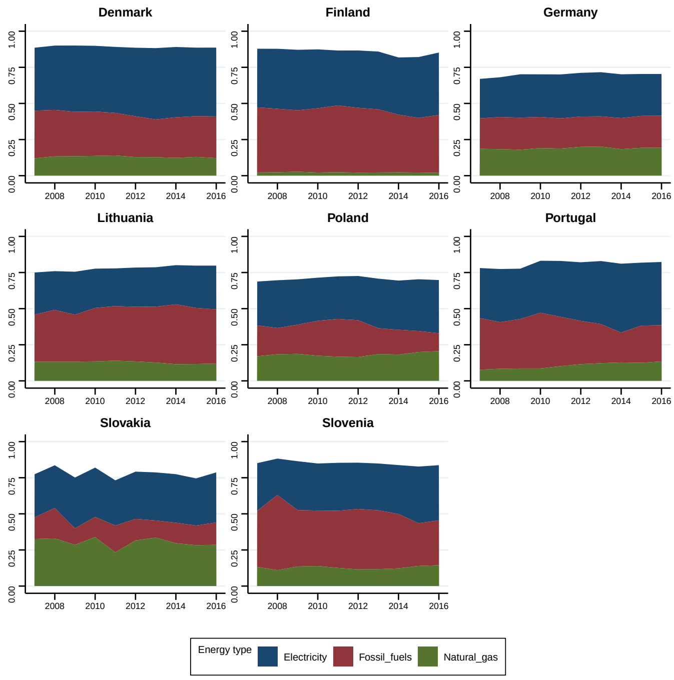
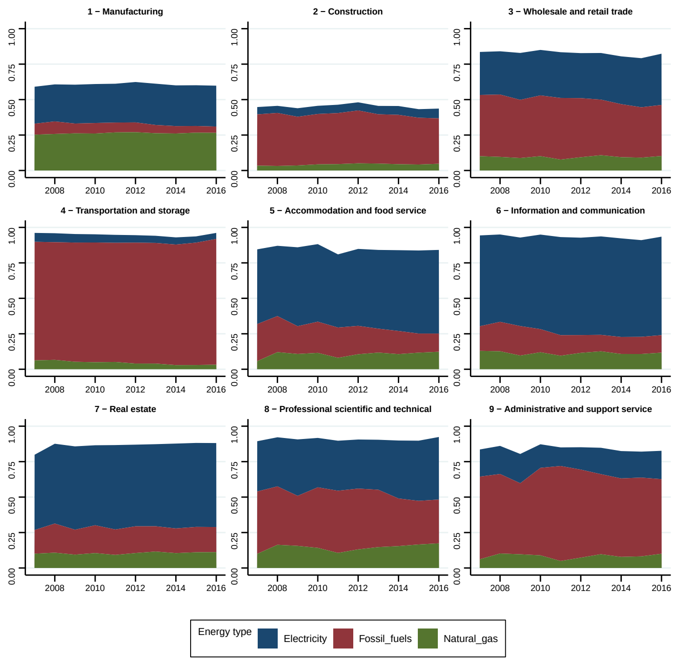
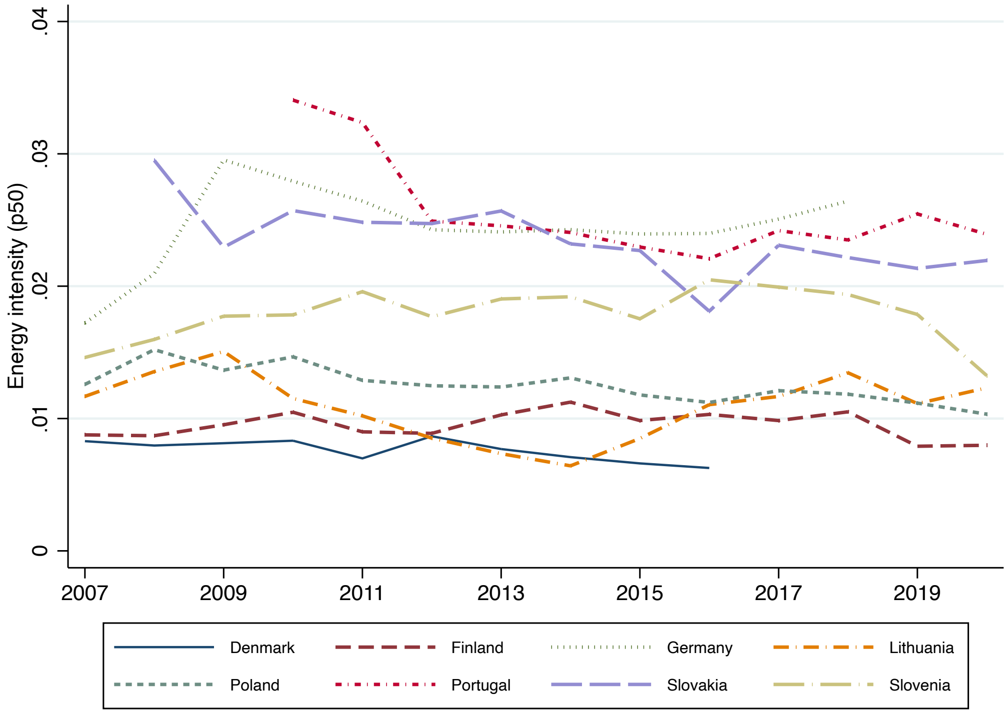


Figure 26: Energy mix at the macro-sector level, all macro-sectors, 2007-2016.



Source: WIOD.
Notes: Percentage share of total energy consumption.
Share of fossil fuels combines diesel, gasoline and fuel oil.

Figure 27: **Median firm level energy intensity, selected European countries, 2007-2020.**



Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*)
Note: Energy intensity is defined as nominal energy costs over total costs.

Overall this preliminary analysis shows that:

1. There is large historical variation in energy prices, which we can exploit in an analysis of firm response.
2. The energy mix at country and sector level stays stable over time, suggesting that there is little evidence of switching to other energy sources.
3. Firm energy intensity remains also stable over time.

We look next at how firms react to energy price shocks, both on average (section 4.2) and across firms (section 4.3).

In the short run, an energy price shock is associated with an increase in costs and reduction in firm profits (table 11 and table 12)

4.2 The impact of short-term energy price shocks on firms' results: average results

We use the three PCs from the PCA (PC1, Fossil fuels; PC2, Electricity; PC3, Natural gas) as independent variables in our analysis. We construct an industry-wide energy mix using the WIOD, matching energy consumption by main sources to CompNet industry-level data for years 2007-2016.[35] This approach means that, for each industry, we construct an ex-ante exposure measure to the fluctuations of energy prices, which we use on a set of the following main dependent variables:

[35]We focus the analysis on years 2007-2016 as WIOD's energy consumption data is only available until 2016, and selecting years before 2007 will result in a smaller sample of countries from CompNet 9th vintage data.

- Changes in average industry level profitability.[36]
- Changes in average industry level energy demand per unit of value added (total energy (TJ) / total real value added),[37] an "inverse" of energy efficiency.
- Average industry level job destruction rate.[38]
- Changes in average energy cost share, defined as energy cost / labor and material cost.[39]
- Changes in average trade intensity (exports per revenues).[40]
- Changes in average industry level investment intensity (investment over asset).[41]
- Changes in the "green" share of firms' energy mix.[42]

We estimate the following regression:

$$Y_{jct} = \alpha_0 + \alpha_j + \alpha_t + \sum_e \beta_e * w_{jct-1e} * \Delta\rho_{et} + \gamma^{'} * X_{jct} + \epsilon_{jct} \quad (7)$$

where *c*, *j*, *t*, *e* denote country, industry, year, energy type, respectively. y_{jct} stands for one of the dependent variables mentioned in the previous section, available at the industry-country-year level.[43] α_0, α_j, α_t are a constant term, industry and year fixed effects, useful to control for some unobservables that may affect the outcome variable. X_{jct} is a set of industry-country-year controls.[44] The main coefficients of interest are the β_e, one per principal component representing an energy type *e*. These are referred to the main regressors, which are % changes in the price indexes of energy source e from year *t-1* to year *t* $\Delta\rho_{et}$, weighted by the ex-ante exposure of industry *j* to energy shock $e * w_{jct-1e}$. The explicit computation of the weights and price changes is:

$$w_{jct-1e} * \Delta\rho_{et} = \frac{Q_{jct-1e}}{\sum_e Q_{jct-1e}} * \frac{\rho_{et} - \rho_{et-1}}{\rho_{et-1}} \quad (8)$$

where Q_{jcte} is the amount of energy source *e* demanded by industry *j* in country *c* at time *t*. It is clear from the above formula that weights are essentially the share of energy source *e* in the total energy mix. Finally, ϵ_{jct} is an error term, which we cluster at the industry level to keep into account serial correlation.[45]

[36] $FR22profitmargin$ from CompNet 9th vintage
[37] Total energy (TJ) taken from the WIOD, while real value added are taken from CompNet ($FV18rva$).
[38] $LV15jdrpop2D$ from CompNet 9th vintage.
[39] $FR40enercostsmn$ variable from CompNet 9th vintage.
[40] $TR02expadjrevmn$ from CompNet.
[41] $FR37investkmn$ from CompNet 9th vintage.
[42] Green share is defined as the share of renewables over total energy consumption, both from the WIOD.
[43] By default, it would be ideal to use the 2D industry dimension to have more power in the regressions, but for some results (e.g. conditional regressions at the size class – industry level), we may consider using only the 1D industry.
[44] We will include average firm size, average sales, average relative input demand, and average energy intensity.
[45] Creating a weighted average of price shocks (interacting industry-level energy prices with industry-level energy mix) does not allow to identify the energy source-specific price shock impact. Regardless, we did test for this, and the results were insignificant.

We assume that the energy mix of an industry cannot be adjusted flexibly from one year to the other after price shocks occur. This would mean that there are no omitted variables that can jointly affect the weights 8 and the outcome variable 7, after controlling for additional regressors. However, we cannot effectively test this assumption, therefore caution is needed when giving the regression coefficients a causal interpretation.

What is then the prevailing strategy that the European firms adopt – out of the five indicated above – when the energy shock hits? Table 11 and 12 present the results of the main regression with the three PCs and break it down into positive and negative energy shocks respectively:

- **In the short run, firms seem to absorb the price shocks by mainly compressing their profits** (see column (1) of both tables). Perhaps because firms do not seem to manage to increase energy efficiency (reduce energy demanded per unit of VA) – the coefficients in column (4) are not statistically significant.
- **Energy price shocks seem to have an impact on firm total costs.** Positive price shocks in fossil fuels and natural gas are associated with an increase in energy cost share, see column (3).
- **The impact on job destruction rate is not significant** (column (2) of table 11). There are stringent labor laws in many of the countries in the sample, so perhaps firms cannot cut their labor cost by firing workers after energy shocks. Even when we separate positive and negative shocks results concerning job destruction rates are not intuitive. Possibly they are driven by labor market outcomes determined by factors independent from energy prices.

These results are mainly driven by electricity and natural gas, rather than by fossil fuels.

Table 11: **Impact of energy price shocks on profitability, job destruction rate, energy cost share, energy / VA, export share, investment / assets, and green share, selected European countries, 2007-2016.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
weigh. Δ PC:							
Fossil Fuels	-0.063	-0.009	0.118*	-0.152	0.187	5.176	0.000
	(0.049)	(0.097)	(0.070)	(0.105)	(0.221)	(42.169)	(0.048)
Electricity	-0.029**	-0.039	0.006**	0.002	-0.016	-38.845	-0.027
	(0.014)	(0.036)	(0.003)	(0.002)	(0.018)	(38.431)	(0.017)
Natural Gas	-0.117***	0.074	-0.018**	-0.008	-0.238***	156.338	-0.097**
	(0.045)	(0.048)	(0.009)	(0.009)	(0.068)	(153.538)	(0.046)
Constant	-0.032***	0.121***	-0.015***	0.000	0.011	10.037	0.000
	(0.009)	(0.024)	(0.003)	(0.002)	(0.024)	(11.033)	(0.003)
Observations	1,978	2,054	2,036	2,046	1,170	1,433	2,058
R-squared	0.458	0.345	0.286	0.032	0.134	0.044	0.034
Number of ID	253	254	254	253	142	188	254
Year FE	YES	YES	YES	YES	YES	YES	YES

Columns' names: (1) Profitability, (2) Job destruction rate, (3) Energy cost share, (4) Energy/VA, (5) Export share, (6) Investment/assets, (7) Green share. Results are from a fe-panel regression at the country-industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

Since the final effect on profitability captures the net effect of pass-through and ability to cut costs, we cannot fully conclude whether the reduction we observe is determined more by the inability of firms to raise prices or to cut costs. We provide partial evidence in favor of the costs channel: the energy cost share increases substantially for positive price shocks both in fossil fuels and electricity.[46]

Finally, energy price shocks are associated with a reduction in exports, especially in the event of a natural gas price increase. The impact on energy efficiency (energy / value added) and investments are inconclusive, also when dividing the shocks into positive and negative.

There is also no sign that firms shift toward a greener energy mix, as indicated by the green share. In table 12 there is a decrease in the green share as natural gas prices decrease. This may suggest that the response to switching to alternative, cheaper energy sources holds; however not towards renewables because renewable energy has historically been more expensive.[47]

[46]When using CompNet data, the energy costs capture prices of fuels used for energy production and consumption, but also for non-energy production consumption (fossil fuels as raw materials and not consumed as fuel or transformed into another fuel, used for energy and for some other chemical processes). Therefore we capture both shocks in energy cost as strictly defined, as well as shock in costs of intermediate inputs. This definition of non-energy consumption follows Eurostat definition.

[47]We also replicate the regression results with pre-tax energy prices (appendix table 21). When replicating the regressions with pre-tax prices, we see insignificant impacts on profitability, and more nuanced increases on energy cost share, unlike when regressing with post-tax prices. This could be because taxes increase prices significantly enough where they increase firms' energy cost share more and therefore also impact profitability.

Table 12: **Impact of positive vs. negative energy price shocks on profitability, job destruction rate, energy cost share, energy / VA, export share, investment / assets, and green share, selected European countries, 2007-2016.**

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fossil Fuels							
price decreases	0.137	-0.350	-0.003	-0.316	0.791*	-235.558	0.003
	(0.152)	(0.314)	(0.058)	(0.212)	(0.478)	(263.304)	(0.091)
price increases	-0.195**	0.221	0.196**	-0.045	0.013	151.592	-0.000
	(0.097)	(0.199)	(0.093)	(0.043)	(0.414)	(143.047)	(0.064)
Electricity							
price decreases	0.031	-0.177**	0.005	0.011*	-0.033	1.941	-0.062
	(0.039)	(0.068)	(0.006)	(0.006)	(0.090)	(17.657)	(0.050)
price increases	-0.043**	0.022	0.010***	0.002	-0.002	-45.661	-0.030
	(0.018)	(0.046)	(0.003)	(0.002)	(0.028)	(44.660)	(0.030)
Natural Gas							
price decreases	-0.017	0.379***	-0.008	-0.022	0.126	145.272	-0.281***
	(0.061)	(0.114)	(0.012)	(0.020)	(0.092)	(141.672)	(0.105)
price increases	-0.225**	-0.145**	-0.022	0.008	-0.573***	167.120	0.071
	(0.088)	(0.069)	(0.016)	(0.020)	(0.147)	(167.341)	(0.071)
Constant	-0.029***	0.114***	-0.016***	-0.001	0.007	8.520	-0.000
	(0.009)	(0.024)	(0.004)	(0.002)	(0.023)	(9.525)	(0.004)
Observations	1,978	2,054	2,036	2,046	1,170	1,433	2,058
R-squared	0.462	0.354	0.292	0.039	0.156	0.046	0.046
Number of ID	253	254	254	253	142	188	254
Year FE	YES	YES	YES	YES	YES	YES	YES

Columns' names: (1) Profitability, (2) Job destruction rate, (3) Energy cost share, (4) Energy/VA, (5) Export share, (6) Investment/assets, (7) Green share. Results are from a fe-panel regression at the country-industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

Depending on the country, it seems that firms respond to price shocks by increasing their energy efficiency and to a lesser extent by reducing their labor inputs (table 22).

We replicate these results on a country-by-country basis for profitability, job destruction rate, energy cost share and energy efficiency, to understand if there are any cross-country heterogeneities (table 22 in appendix):

- **Elasticity to shocks in profitability is strongest in Germany and Lithuania.** Although this is for different energy sources (electricity and fossil fuels respectively).
- **Job destruction rate varies significantly cross-country.** The overall results do not capture this. Price shocks in fossil fuels and electricity are associated with an increase in layoffs in Germany and Lithuania and

the same is true in Poland following an electricity price shock.

- **Finland, Poland, Portugal, and Slovakia seem to improve energy efficiency.** Their fossil fuel consumption per unit of VA decreases following a price shock. This also occurs with other energy sources, though less pronounced.

Overall, countries which seem to be more affected by price shocks have a relatively lower share of renewables in electricity generation[48] and a higher energy import dependency.[49] This suggests interplay between macro-level policies (electricity generation is largely determined by the government through public investment) and firm-level behavior.

To understand whether specific sectors are driving the results, we run the regression splitting between Manufacturing and Construction vs. Services. From the results (table 23 in the appendix), this does not seem to be the case.

On average, energy price shocks are associated with an increase in costs for firms and lower profits. In some countries, also, they are related with increases in energy efficiency and slight reductions in labor, with the size of the response depending on the country.

Shocks in electricity prices are associated with an increase in the dispersion of energy cost share, while shocks in natural gas prices is associated with a decrease in the dispersion of the energy cost share (table 13).

4.3 Impact of short-term energy price shocks: Cross-firm distribution

The average responses hide substantial differences across multiple firms' dimensions, including size, productivity, and contractual power. Also, size, productivity, and capital intensity may moderate the impact of price shocks on the energy cost share. Results are reported in table 13.

[48] Germany and Poland generate less than 15% of their electricity from renewables in this period, in contrast with Denmark, Finland, and Portugal who generate 25-40% of their electricity from renewables. Source: Eurostat

[49] Germany and Lithuania have high energy import dependency. Source: Eurostat

Table 13: Impact of energy price shocks on profitability and energy cost share dispersion, selected European countries, 2007-2016.

	SD		p90-p10		p75-p25	
Weighted Δ PC:	(1)	(2)	(3)	(4)	(5)	(6)
Fossil Fuels	-0.051	0.028	-0.239	0.217*	-0.120*	0.123*
	(0.151)	(0.056)	(0.162)	(0.122)	(0.070)	(0.065)
Electricity	0.019	0.007**	0.029	0.018***	-0.024	0.011**
	(0.043)	(0.003)	(0.053)	(0.007)	(0.023)	(0.005)
Natural Gas	-0.055	-0.028***	0.033	-0.053***	-0.003	-0.030***
	(0.079)	(0.011)	(0.166)	(0.017)	(0.052)	(0.010)
Constant	0.009	-0.006	0.012	-0.018**	0.018	-0.008
	(0.014)	(0.005)	(0.036)	(0.009)	(0.029)	(0.008)
Observations	2,055	2,033	2,039	2,015	2,039	2,015
R-squared	0.046	0.110	0.078	0.201	0.063	0.075
Number of ID	254	254	254	254	254	254
Year FE	YES	YES	YES	YES	YES	YES

Columns' names: (1), (3), (5) Profitability, (2), (4), (6) Energy cost share. Results are from a fe-panel regression at the country-industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

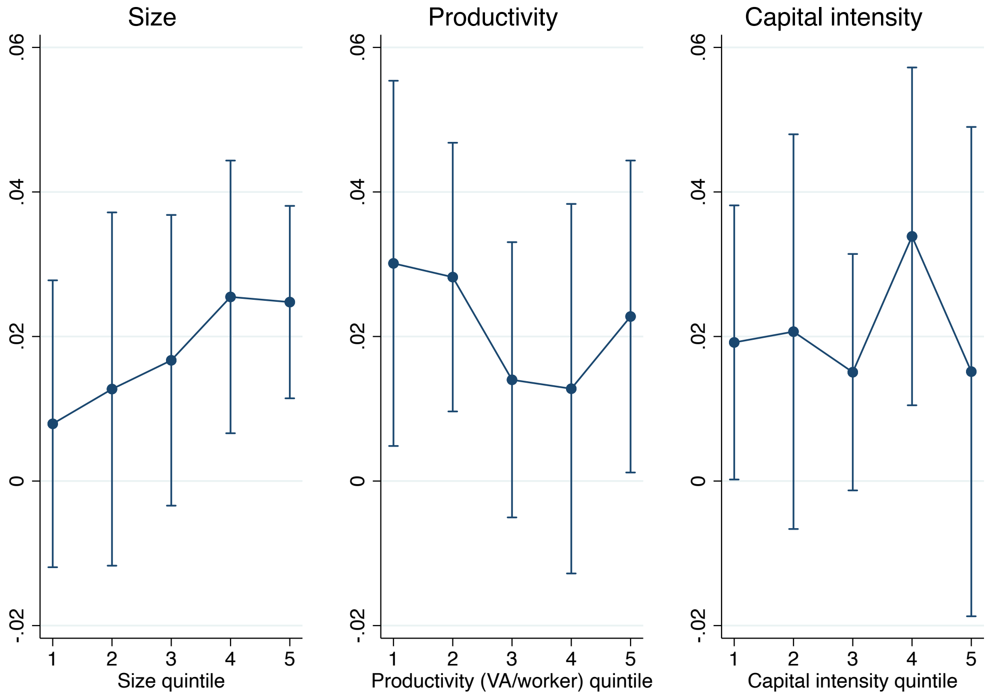
Smaller and more productive firms seem to be less affected by electricity price shocks. The impact of price shocks, although increasing with capital intensity, seems to moderate at the top segment of the distribution, pointing at gains in efficiency due to e.g. economies of scale (figure 28)

Profitability dispersion seems to be only slightly affected. Electricity shocks increase dispersion in the share of energy cost, while the opposite is true for natural gas. This may be because natural gas at the firm level is used also for tasks like manufacturing of chemical or pharmaceutical products, and so it is also intermediate input expenditure: in this case if natural gas becomes more expensive, then total costs would increase relative to energy expenditure, implying a reduction in energy share.

To better understand which firm level characteristics are behind the increased dispersion, we run a regression of changes in mean energy cost share, but this time conditioning on quintiles of firm size (measured by employment), productivity (log value added per worker) and capital intensity (capital stock per worker). Firm heterogeneity seems to matter only for electricity shocks. Figure 28 shows each quintile specific coefficient, for size, productivity, and capital intensity. The main takeaways are as follows:

- **Energy price shocks seem to be more harmful for large companies than SMEs.** The left panel shows that impact of electricity shocks on energy cost share is greater for large than small companies. The coefficient increases in magnitude as we focus on higher size quintiles, although our sample does not include firms with fewer than 20 employees.
- **The most productive firms seem to be affected the least from energy price shocks.** Price shocks become less relevant for energy

Figure 28: **Heterogeneous impact of electricity on energy cost share, selected European countries, 2007-2016.**



Results are from a fe-panel regression at the country-industry-quintile level. Robust standard errors in parentheses, $p<0.01$, $p<0.05$, $p<0.1$. Clustered std. errors at the country-industry-quintile level. The dependent variable is always the energy cost share, while omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on the joint distribution energy inputs 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

cost share as productivity increases (center panel). Therefore energy price shocks may force the least productive firms out of the market.

- **The impact increases with capital intensity, but not monotonically.** It even declines once we reach the highest quintile. This may suggest economies of scale: firms with the highest level of capital stock per worker have higher gains in their energy efficiency, and this offsets the impact of energy price increases on their energy cost shares. Alternatively, these capital intensive firms may be securing their own sources of energy or have the ability to negotiate prices more flexibly.

4.4 Conclusions

Energy price shocks are a threat to firm competitiveness. They increase pressure on costs in the short run, hampering profits and potentially driving firms out of the market.

We find that, in the short run, increased energy prices are mainly associated with lowered firm profits, which captures the net effect of bearing the increased energy costs and the inability to fully pass-through these costs to customers. At a country-level, energy price shocks are associated with an increase in energy efficiency in Finland, Poland, Portugal and Slovakia, while associated with an increase in job destruction rate in Germany, Lithuania and Poland.

Policies to increase the flexibility of the overall energy mix could prove beneficial in increasing a country's resilience to future energy shocks, with particular emphasis on the renewable energy sources. Indeed, countries where the share of electricity generated by renewables is highest are also the least affected by energy price shocks.

We also find that electricity price shocks seem to affect dispersion in energy cost share, and that firm size, productivity and capital intensity play a role in moderating the impact of price shocks on the firm-level energy cost share. Smaller and more productive firms seem to be less affected by energy price shocks, and firms with high level of capital per worker seem to experience gains in energy efficiency. This allows workers to move to more productive, capital-intensive firms, which fosters resilience to energy price shocks.

5 Constrained SMEs

Coordinator and Reference CompNet person: *Marcelo Piemonte Ribeiro*

Collaborating National Productivity Board: *Jan Sebo* (Úrad vlády Slovenskej republiky, Slovakia)

Micro and young firms are significantly more credit constrained than larger firms, notably during the GFC, but not during COVID-19, affecting negatively their return on assets, growth, and productivity rates.

Small and medium-sized enterprises (SMEs) are the backbone of the EU economy. The overwhelming majority (98.9%) of the non-financial businesses in the European Union in 2017 are categorized as small: they employ fewer than 50 people. Another 0.9% are medium enterprises, employing between 50 and 249 people. The remaining 0.2% are large enterprises. Small enterprises also employ half of the EU27 workforce, and medium firms employ a further 17% (Carsa et al., 2017).

Asymmetric information issues,[50] agency risks, shorter operating history, and inadequate collateral mean SMEs face more obstacles when accessing funding and have less diverse sources of funding than large firms.They do not have the ability to access bond and equity markets (Jaffee and Russell (1976); Stiglitz and Weiss (1981); Berger et al. (2005)), and so must rely on bank loans. Not surprisingly, SMEs are particularly sensitive to business cycle shocks (Fort et al., 2013).[51]

Access to finance is often as an important factor limiting the growth and survival of SMEs. And so, during the Global Financial Crisis (GFC) and the COVID-19 pandemic, SMEs were hurt by credit rationing (Ferrando and Griesshaber (2011); Bank (2023)). Financial constraints are negatively associated with total factor productivity, especially among small, young and private firms, and particularly during the GFC (Ferrando and Ruggieri, 2018).

On the upside, financing creates productivity-enhancing investments in all factors contributing to labor productivity in SMEs (Bakhtiari et al., 2020).[52]

We link data on financing,[53] to first illustrate how SME credit constraints have evolved. Then, using CompNet 9th vintage data, we investigate the relationship between firm characteristics and performance, and their financial and credit constraints. Particularly, we study how financial constraints, interacted with firm size and age, influence return on assets, growth rate, and productivity levels at the firm level.

[50] Young companies face extra obstacles to access finance. They have no track record, and so there is information asymmetry. This often leads them to use their own assets as collateral for bank loans (for example, the CEO's house).

[51] These authors show SMEs and young firms (which are for the most part SME too) are particularly sensitive to shocks.

[52] Managerial skills and practices, worker's training, ICT implementation, network, R&D, innovation, etc.

[53] We link CompNet data with the BLS (Bank lending survey for the euro area) and the SAFE (Survey on the access to finance of enterprises) both from the ECB, the World Bank Doing Business and Enterprise surveys, World Development Indicators from the World Bank, Eurostat data, and data from the OECD Financing SMEs and Entrepreneurs.

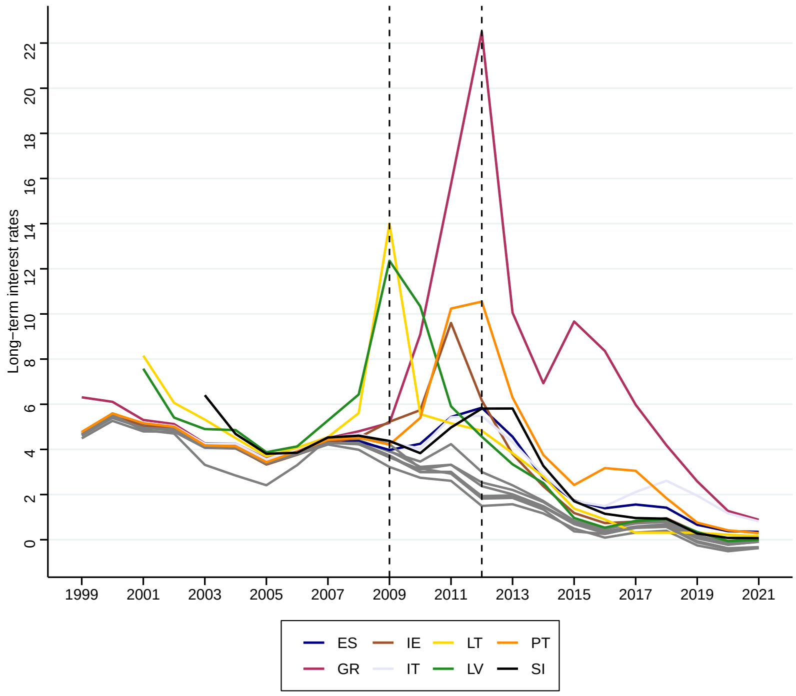
Higher interest rates followed the Greek and the GFC. Governments responded with more guaranteed loans and banks with more credit rejection and less credit provided to SMEs.

5.1 Credit constraints

The early literature identifies information asymmetry between borrowers and lenders as the root obstacle impeding firms from fully accessing external credit.[54] Lenders can make use of tools such as collateral, covenants, short-term loans, and long-established relationships to mitigate this information asymmetry. [55] The country specific setting– for example, legal and financial development – also influences firm likelihood to access credit.[56]

At the macro level, the first obstacle to firm's financing is the interest rate when borrowing.[57] Although interest rates have decreased in recent years in Europe, the GFC in 2008 and the Greek government-debt crisis were two episodes that tightened considerably the financial market (figure 29). Short-term interest rates reacted immediately to the shocks.

Figure 29: **Yearly long-term interest rates among eight European countries, 1999-2021 (% points)**



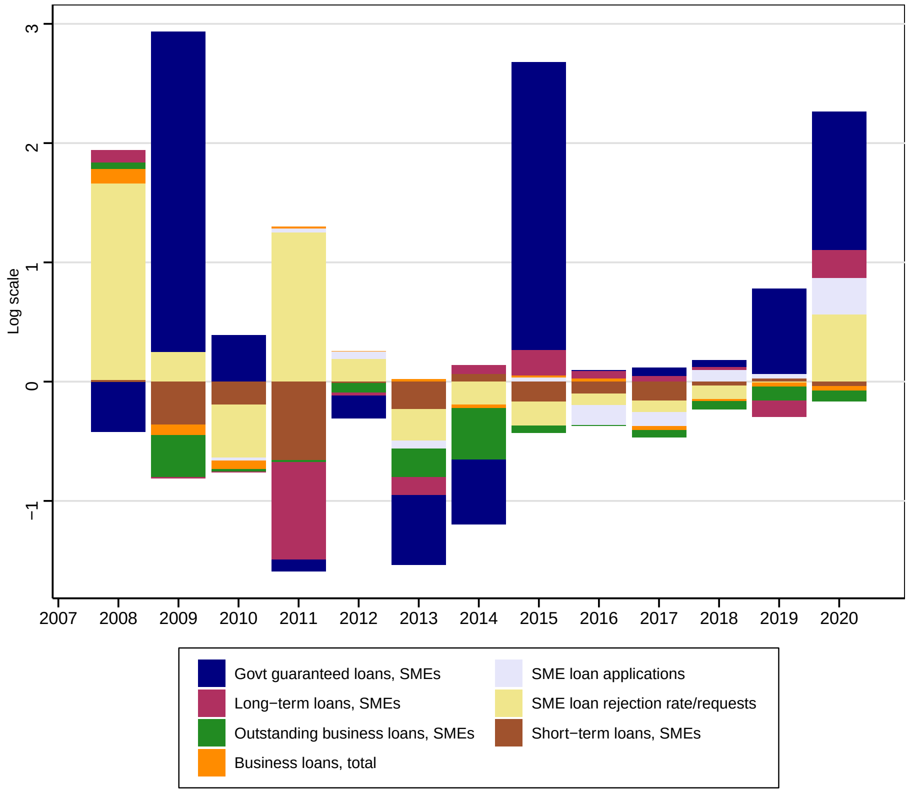
Source: OECD Financing SMEs and Entrepreneurs.
Note: Countries in grey: AT, BE, EE, FI, FR, DE, LU, NL.

Recognizing this problem, many countries put in place policies to facilitate access to small business finance. Figure 30 shows governments responded to the GFC and COVID-19 shocks by providing more guaranteed loans for SMEs to compensate the tightening conditions imposed by the private credit

[54] Imperfect information results in moral hazard and adverse selection.
[55] See Steijvers and Voordeckers (2009) literature survey.
[56] See Beck et al. (2008) literature review regarding countries features influencing firms credit constraints.
[57] European SMEs face on average about 2% higher rates than larger firms (OECD).

market. After the GFC, SME loan rejection increased, and their short- and long-term loan provision decreased relative to loan applications.

Figure 30: **European credit supply market conditions among European countries, 2007-2020 (Log scale)**



Source: OECD Financing SMEs and Entrepreneurs.

Overall, firms seek refinancing, restructuring, and renegotiation loans during crisis times. In particular, during COVID-19, loans for inventories and working capital financing needs as well as short-term loans (figure 31).

European banks tightened considerably credit supply tools (e.g., collateral requirements, loan-convenants, banks risk tolerance, etc.), see for example the black line in figure 31. The latter also shows that long-term loans increased after the Greek debt crisis, reflecting the low interest rates prevalent at the time (figure 29). In this period firms demanded loans, particularly long-term loans, to finance their fixed investments. In contrast, during the financial crisis and in the more recent 2020 COVID crisis, firms seeked to prolongate their debts to avoid defaulting, as illustrated by the purple bar in figure 31. During the COVID-19 crisis, only short-term loans demand increased, reflecting firms' financing need for short-term cash flows, reflected by the increase of firms' inventories and working capital financing needs.

Figure 31: **European credit supply and demand market conditions (diffusion index in %)**

Source: BLS (Bank lending survey for the euro area).

Notes: The black line indicates overall supply market conditions. They include variation of the diffusion index regarding collateral requirements, impact of several factors on loan supply (e.g., bank competition, general economic activity, liquidity position, etc.), loan covenants, margins on average and riskier loans, non interest rate charges, size of loans, banks risk perception and tolerance, etc.

Countries: AT, BE, CY, DE, EE, ES, FI, FR, GR, HR, IE, IT, LT, LU, LV, MT, NL, PT, SI, SK.

BLS provides information about credit demand and supply conditions. The diffusion index is a measure that calculates the variation between the combined percentages of banks that responded with "tightened considerably" and "tightened somewhat", and the combined percentages of banks that responded with "eased considerably" and "eased somewhat". When it comes to loan demand, the diffusion index is calculated by comparing the combined percentages of banks that reported "increased considerably" and "increased somewhat" with the combined percentages of banks that reported "decreased considerably" and "decreased somewhat", using a weighting system.

Demand for credit is harder to estimate, but if we cannot observe firm credit-seeking behavior, or decision-making about credit-seeking, we cannot know when constraints exist. If a large number of firms do not apply for credit, this does not mean they are credit constrained; they may choose not to apply due to the risk of incurring transaction costs without obtaining loans (Bigsten et al., 2003).[58].

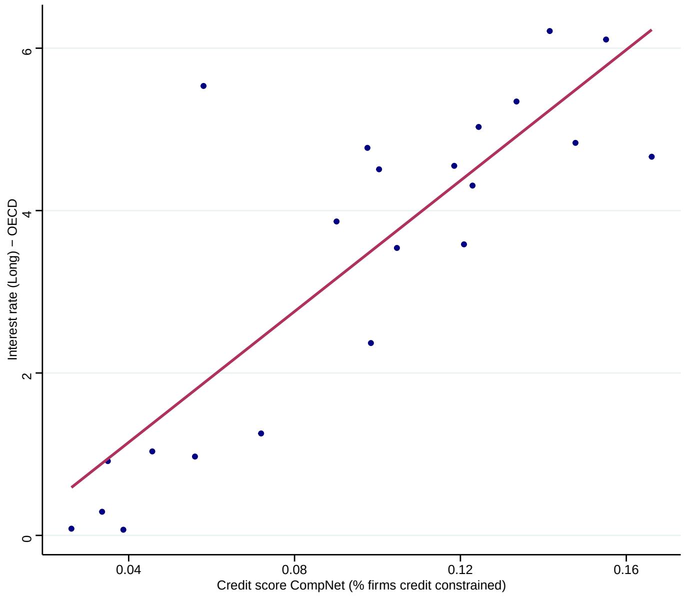
[58]Most of the studies overcame such selection issue by employing Heckman twostep regression methods, (Nguyen et al., 2019); (Rand, 2007); (Fafchamps, 2000)

Micro-young firms are up to four times more credit constrained than medium and large firms. Such difference was evident in the GFC, but not during COVID-19.

5.2 Credit constraints: Firm size and age

CompNet uses different databases to provide information about the level of credit constraints faced by firms.[59] We find a high correlation between this variable and interest-rates in European countries (figure 32).

Figure 32: Correlation between CompNet *safe* variable and long-term interest rates (diffusion index in %)



Note: CompNet provides a score, *safe*, that can take a value of 1 or 0 to indicate firms' credit constraint levels. See CompNet 9th vintage User Guide (p.94).

Do small and micro firms face more credit constraints? We investigate using CompNet data.[60] In particular we run the following regression:

$$Safe = \alpha + \beta size + \phi age + \rho size * age + \gamma + \lambda + \epsilon \tag{10}$$

Where *Safe* represents the CompNet credit score, *size* is a categorical variable indicating whether a firm is large (more than 249 employees), medium

[59] CompNet provides an estimated credit constraint score, *safe*, taking into account country-industry-time fixed-effects and uses ECB SAFE and Orbis data. Particularly, this credit constraint score is calculated for each firm by summing the coefficients of the following specification

$$P(credit_{con}) = \alpha + \beta_1 finlev + \beta_2 ifp + \beta_3 profit + \beta_4 collateral + \beta_5 cash + \beta_6 \ln(TA) + \gamma + \epsilon \tag{9}$$

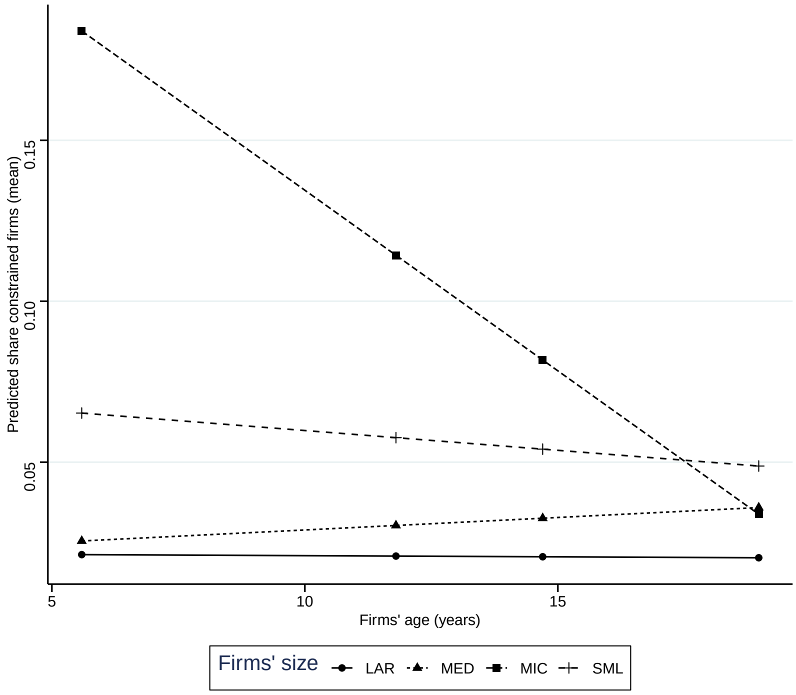
Where *finlev* represents financial leverage, *ifp* financial pressure, *profit* profit margin and *TA* total assets. The specification includes time, industry, firm-size and country-specific effects. After that the credit constraint score above which we can define firms as being credit constrained is calculated. The value of the threshold is time-varying and country-specific. This score can take a value of 1 or 0 to indicate credit constraint, but CompNet provides its mean, which gives the share of credit constrained firms in any given level of aggregation. See CompNet 9th vintage User Guide (p.94)

[60] CompNet 9th vintage ($unconditional\_macsec_s zcl\_all\_weighted$).

(50 to 249 employees), small (10 to 49 employees) or micro (1 to 9 employees), *age* indicate the mean age of firms in each of the previous categories. The last variables indicate respectively country and time (years) fixed effects and an error term.

Results are summarized in figure 33. Although small and particularly micro firms are on average more credit constrained than large firms, such difference decreases as firms become older. This is particularly true among micro firms.

Figure 33: Predicted share of credit constrained firms (mean) by firms' age and size, European countries, 2002-2021



Source: CompNet 9th Vintage (*unconditional_macsec_szcl_all_weighted*).
Age: indicate the mean age of firms in each of the size categories.
Firms' size: Large (more than 249 employees), medium (50 to 249 employees), small (10 to 49 employees) or micro (1 to 9 employees).

Small and young businesses are more likely to face higher constraints during a crisis (Ferrando and Ruggieri, 2018). But existing research is ambivalent over whether all or only some are more constrained during crisis.[61] We test this question by expanding the previous specification, imposing a triple interaction between firm size, age and year (figure 34). The results indicate that younger and micro firms are in general more credit constrained. After the GFC they suffered from the tighter credit market; in 2020 large firms seemed instead to be comparatively more constrained, confirming the different nature of these crises.[62]

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[61] While high innovative intensive firms are more likely to have their financing sources tightened (Lee et al., 2013), fast-growing small firms are still able to secure financing, (Bartz and Winkler, 2016).

[62] Lockdowns in COVID-19 crisis constrained demand and also supply, differently from the GFC when supply could be adjusted. However, figure 34 contain limited data and any conclusion in this way should be taken with caution.

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Figure 34: Predicted share of credit constrained firms in time according to their size and age, European countries, 2002-2021

Source: CompNet 9th Vintage (*unconditional_macsec_szcl_all_weighted*).
Age: indicate the mean age of firms in each of the size categories. Age categories reflect age quantiles.
Firms' size: Large (more than 249 employees), medium (50 to 249 employees), small (10 to 49 employees) or micro (1 to 9 employees). Unbalanced panel include HR, CZ, DK, HU, LV, MT, PL, SI, SE. However, 2021 includes only HR and SI. LV is present only up to 2017, MT, CZ, and SI are present only after 2010, 2007 and 2006 respectively.

Smaller, younger and credit constrained firms are characterised by lower return on assets and productivity rates.

5.3 Differences between unconstrained and constrained firms

Firm financing needs depend on many different factors.[65] On first approach there are significant differences between constrained and non-constrained

[63] While high innovative intensive firms are more likely to have their financing sources tightened (Lee et al., 2013), fast-growing small firms are still able to secure financing, (Bartz and Winkler, 2016).
[64] Lockdowns in COVID-19 crisis constrained demand and also supply, differently from the GFC when supply could be adjusted. However, figure 34 contain limited data and any conclusion in this way should be taken with caution.
[65] Such as firms' size, age, financial indicators, management characteristics, network, sector of operation, ownership nature, and growth aspirations. Firms also face different constraints depending on the maturity of the needed loan.

firms depending on their size (table 14).

Table 14: Mean differences between credit constrained and not constrained firms, European countries

sizeclass	Firms' characteristics	Not constrained	Constrained	Difference
1-9 empl	Real-value added	0.33	0.33	0.00
10-19 empl	Real-value added	0.54	0.31	-0.23
20-49 empl	Real-value added	0.54	0.35	-0.19
50-249 empl	Real-value added	0.60	0.58	-0.02
>249 empl	Real-value added	1.07	0.95	-0.12
1-9 empl	Real inv/Tot.assets	0.09	0.05	-0.04
10-19 empl	Real inv/Tot.assets	0.11	0.04	-0.07
20-49 empl	Real inv/Tot.assets	0.11	0.06	-0.05
50-249 empl	Real inv/Tot.assets	0.11	0.03	-0.08
>249 empl	Real inv/Tot.assets	0.05	0.08	0.03
1-9 empl	Log labor product.	2.87	3.00	0.13
10-19 empl	Log labor product.	2.91	2.85	-0.06
20-49 empl	Log labor product.	2.83	2.75	-0.08
50-249 empl	Log labor product.	2.68	2.64	-0.04
>249 empl	Log labor product.	2.76	2.44	-0.32
1-9 empl	Leverage	2.96	0.41	-2.55
10-19 empl	Leverage	0.72	0.39	-0.33
20-49 empl	Leverage	0.60	0.51	-0.09
50-249 empl	Leverage	0.42	0.38	-0.04
>249 empl	Leverage	0.27	0.36	0.09
1-9 empl	Job creation	0.11	0.02	-0.09
10-19 empl	Job creation	0.13	0.09	-0.04
20-49 empl	Job creation	0.13	0.12	-0.01
50-249 empl	Job creation	0.12	0.10	-0.02
>249 empl	Job creation	0.09	0.11	0.02
1-9 empl	Growth rate	4.46	1.73	-2.73
10-19 empl	Growth rate	5.09	4.36	-0.73
20-49 empl	Growth rate	5.78	4.03	-1.75
50-249 empl	Growth rate	6.49	2.25	-4.24
>249 empl	Growth rate	28.13	3.63	-24.50
1-9 empl	Collateral/Tot.assets	0.43	0.16	-0.27
10-19 empl	Collateral/Tot.assets	0.29	0.27	-0.02
20-49 empl	Collateral/Tot.assets	0.27	0.23	-0.04
50-249 empl	Collateral/Tot.assets	0.25	0.22	-0.03
>249 empl	Collateral/Tot.assets	0.17	0.21	0.04

Source: CompNet 9th Vintage (*unconditional_mac_sector_20e_weighted*).

Overall, constrained firms are less productive, invest less, are less leveraged, and have less collateral than non-constrained firms. They also display lower job creation and growth rates. Micro firms present a slightly different dynamic. For instance, labor productivity is higher among credit-constrained micro firms, and age is correlated with credit constraints only among micro firms – perhaps indicative that credit constraints are particularly relevant for young firms without a credit history. Bank (2023) finds that micro firms presented a higher financing need during a crisis and find it more difficult to access public financing support, than larger firms.

5.4 Impact of credit constraints on firm performance

These has been much research into the impact of limited financing on to SME growth and development.[66]. We use CompNet data to test the impact of credit constraints on firm return on total assets (ROA) growth, and productivity. The following specification, with countries being the unit of observation, aims to capture the influence of credit constraints on firms.

$$Y = \alpha + \beta_1 safe + \beta_2 age + \beta_3 size + \beta_4 size * age * safe + \gamma + \lambda + \rho + \epsilon \tag{11}$$

The dependent variable represents three outcome variables to be investigated: medians of returns on assets (ROA), of growth rates, and of productivity growth, measured using the Solow residual. *Size* is a categorical variable which indicates whether country firms are large, medium, small, or micro. *Safe* represents CompNet credit constraint variable described previously, i.e., the mean share of credit constrained firms, *Age* reflects the median age of firms. The last terms include country, macro sector and year fixed effects and an error term. In summary, such specification attempts to uncover how firms‘ age and credit constraints levels correlates with their ROA, growth and productivity rates within a given firm size category.

[66] See review (Bakhtiari et al., 2020)

Table 15 illustrates the results. Age is associated with less ROA, growth and productivity rates. Smaller, younger and more credit constrained firms present a significant lower ROA in relation to larger firms, as illustrated by figure 35. Coefficients related to productivity rates behave similarly, i.e., micro, younger and credit constrained firms present lower productivity rates compared to larger firms,[67] but such difference reduces throughout the years. When it comes to growth rates, the coefficients showed to be not statistically significant.

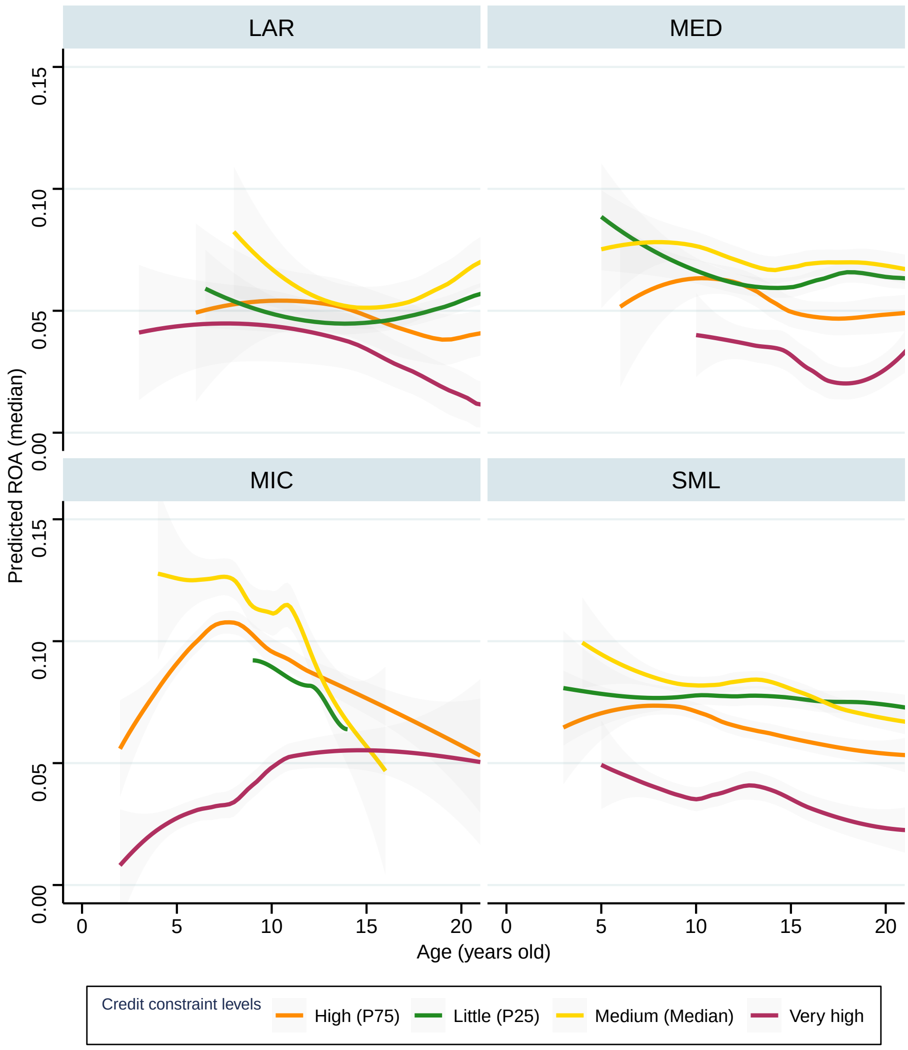
Table 15: Credit constraints, ROA, growth, and productivity, European countries, 2002-2021

	ROA	Growth rate (from t-1)	Log. Solow residual
Constant	0.05 (0.01)***	0.07 (0.01)***	2.54 (0.07)***
MED	0.02 (0.01)***	−0.01 (0.01)	0.15 (0.06)***
MIC	0.07 (0.01)***	−0.05 (0.01)***	−0.38 (0.07)***
SML	0.04 (0.01)***	−0.01 (0.01)	−0.01 (0.05)
Age (median)	−0.001 (0.0002)***	−0.002 (0.0003)***	0.01 (0.002)***
safe (mean)	−0.06 (0.10)	−0.03 (0.19)	1.01 (1.00)
MED: Age	−0.0002 (0.0003)	0.0001 (0.001)	−0.01 (0.003)**
MIC: Age	−0.003 (0.001)***	0.0002 (0.001)	0.03 (0.01)***
SML: Age	−0.001 (0.0003)***	−0.0004 (0.001)	0.0001 (0.003)
MED: safe	−0.26 (0.15)*	0.19 (0.26)	−1.58 (1.42)
MIC: safe	−0.44 (0.11)***	0.03 (0.20)	1.00 (1.07)
SML: safe	−0.24 (0.11)**	0.16 (0.20)	−0.70 (1.09)
Age: safe	0.001 (0.004)	0.001 (0.01)	−0.09 (0.04)**
MED: Age: safe	0.01 (0.01)	−0.01 (0.01)	0.04 (0.07)
MIC: Age: safe	0.02 (0.01)***	−0.001 (0.01)	−0.15 (0.06)**
SML: Age: safe	0.01 (0.01)	−0.01 (0.01)	0.05 (0.05)
Observations	4,917	4,915	4,790
R^2	0.51	0.48	0.88
Adjusted R^2	0.51	0.47	0.88
Residual Std. Error	0.03 (df = 4867)	0.06 (df = 4865)	0.32 (df = 4740)
F Statistic	104.66*** (df = 49; 4867)	91.12*** (df = 49; 4865)	726.53*** (df = 49; 4740)

Source: CompNet 9th Vintage (*unconditional_mac_sector_20e_weighted*).
Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Omitted coefficients for macro sectors, year and country fixed-effects. Reference firm size category: Large firms. Firms' size: Large (more than 249 employees), MED are medium (50 to 249 employees) firms, SML are small (10 to 49 employees) firms, and MIC are micro (1 to 9 employees) firms.

[67] Such difference is less clear among small, medium and large firms.

Figure 35: **Credit constraints and ROA, European countries, 2002-2021**



Source: CompNet 9th Vintage (unconditional_mac_sector_20e_weighted).
Note: This figure illustrates the coefficients of the first column from table 15. Firms' size: LAR are large (more than 249 employees) firms, MED are medium (50 to 249 employees) firms, SML are small (10 to 49 employees) firms, and MIC are micro (1 to 9 employees) firms.

5.5 Conclusions

Starting from evidence documented by the literature about SMEs, credit constraints and firm growth, this chapter adds to it by using CompNet data. First, it shows how close the CompNet credit constraints indicator, *safe*, correlates with classical proxies of credit market supply, i.e. interest rates. Using such indicator, this chapter confirms some findings from the literature and adds to it by showing how firms' age and size are associated with firms' dynamics, especially during economic crise.

Macro-sectoral drivers of startup types

Contributors and CompNet person *Ralph De Haas* (European Bank for Reconstruction and Development), *Vincent Sterk* (University College London), *Neeltje van Horen* (Bank of England), and *Marco Matani* (CompNet)

Startups play a crucial role in job creation and productivity growth (Foster et al., 2001; Haltiwanger et al., 2013). Recent work by De Haas et al. (2022), based on a special module of the CompNet 8^{th} Vintage data collection code, used machine learning to cluster 1.3 million European startups into five types:[a]

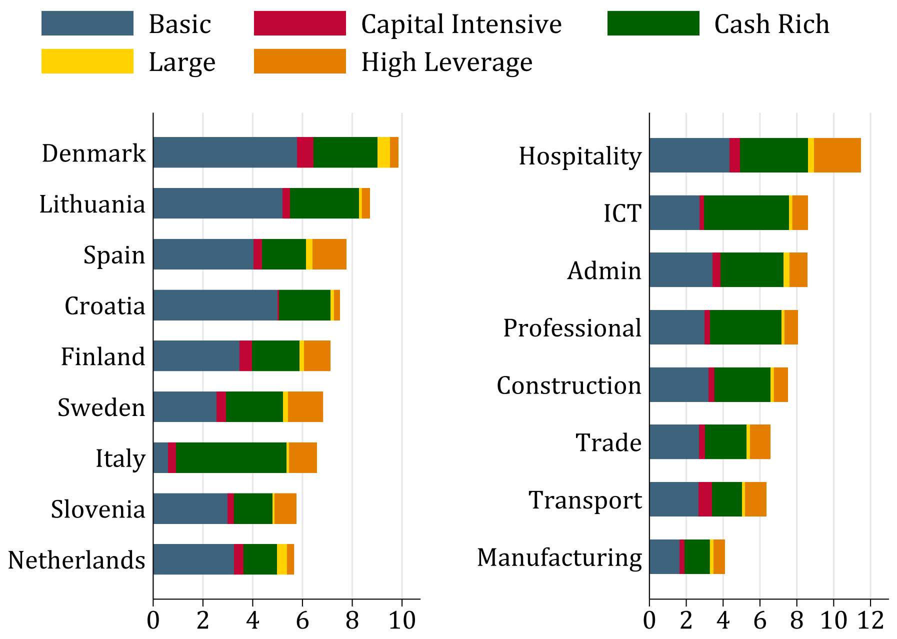
- **Capital Intensive**, starting on average with 93.18 capital intensity against 8.56 for basic startups;
- **Cash Rich**, starting on average with 54% of their assets as cash against 12% for basic startups;
- **Large**, starting on average with 20 employees against 4 for basic startups;
- **High Leverage**, starting on average with a leverage ratio of 1.18 against 0.23 for basic startups;
- **Basic**, looking average across the different dimensions.

The share of startups on all firms is the highest in Denmark and, among macro-sectors, in Hospitality and ICT. Basic and Cash Rich are the most common startup types. The Cash Rich type is relatively ubiquitous in Italy, ICT, and Professional services while the High Leverage type has particularly high incidence in Hospitality (figure 36a). Not surprisingly, macro-sectors with larger proliferation of startups are also overrepresented among startups than among all firms (figure 37a). By contrast, Manufacturing dwarfs dramatically when only looking at startups.

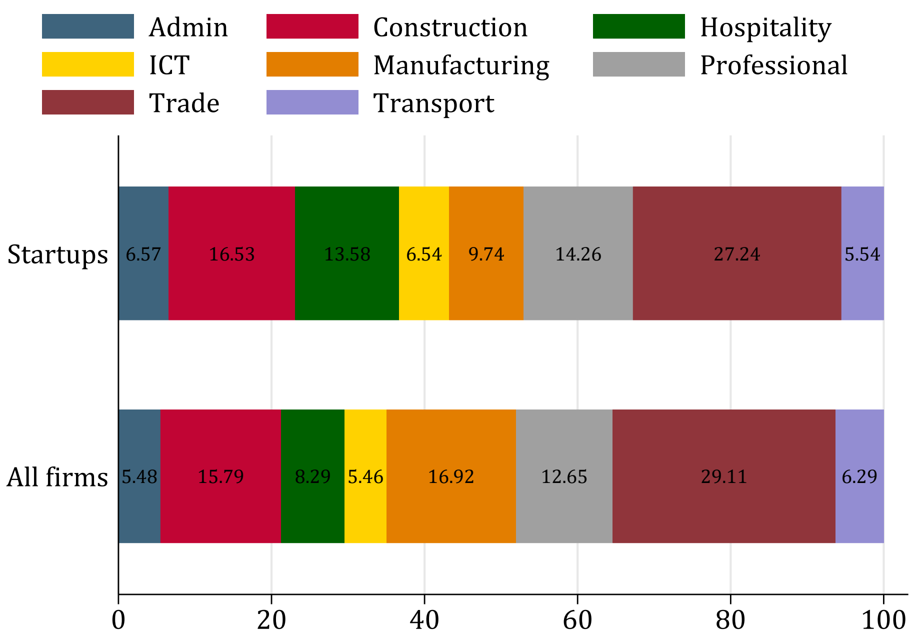
[a] In De Haas et al. (2022), the cluster algorithm groups startups (firms that commence their operations in a particular year) according to five factors used by entrepreneurs to decide when and if to start a business, namely: the initial number of employees; real total assets; capital intensity (amount of real fixed assets per employee); cash to total assets; and leverage (total debt to total assets).

Figure 36: **Startups in Europe. European countries, 2010-2019.**[68]

(a) *Startups on all firms (%)*



(a) *Share on startups and on all firms (%)*



[68]Source: CompNet 9th Vintage (*unconditional_mac_sector_all_unweighted*) and data from De Haas et al. (2022). Note: Figures for countries and macro-sectors are averages over 2010 and 2019. Countries are DK, ES, FI, HR, IT, LT, NL, SI, and SE. Macro-sectors are “Manufacturing”, “Construction”, “Wholesale and retail trade; repair of motor vehicles and motorcycle” (“Trade”), “Transportation and storage” (“Transport”), “Accommodation and food service activities” (“Hospitality”), “Information and communication” (“ICT”), “Professional, scientific, and technical activities” (“Pro-

Startups are most common in macro-sectors that are dynamic, and less so in those that are financially constrained and concentrated. (Table 16).

Besides initial differences between startup types being persistent over time, De Haas et al. (2022) also find that different types of startups develop along diverging patterns in terms of employment, productivity, and survival. Capital Intense, Large, and Cash Rich startup types display consistently higher levels of productivity and are the least likely to exit within the first decade of operations, whereas High Leverage and Basic types systematically underperform in terms of productivity and likelihood to survive. It follows that shifts in the composition of startups impact overall macroeconomic performance and policymakers need to be aware of levers that structurally encourage the entry of high-performance startups.

We go deeper in this direction by regressing the shares of startups (all and by types) on firm characteristics at the macro-sectoral level. We find that startups are more widespread in most dynamic macro-sectors with stronger growth of revenues, employment, and productivity although this is mostly the case for the Basic type and only to a lesser extent for the Capital Intensive and Cash Rich ones (table 16, a-c). Startups are largely discouraged from entering financially constrained macro-sectors, apart for the underperforming High Leverage type (table 16, d). Finally, startups are also less likely to sprout in macro-sectors where capital concentration is high (table 16, e), with intangibles concentration especially counteracting valuable Cash Rich startups (table 16, f).

fessional"), and "Administrative and support service activities" ("Admin"). The latest available year is 2015 for LT and 2018 for DK, IT, NL, and ES.

Table 16: **Macro-sector characteristics and startups. European countries, 2010-2019**

% Startups on total firms	(1) All	(2) Basic	(3) Capital Intensive	(4) Cash Rich	(5) Large	(6) High Leverage
		a)				
Revenues growth %	0.044*** (0.011)	0.025*** (0.009)	0.005** (0.002)	0.014** (0.006)	0.002 (0.001)	-0.002 (0.003)
L.Revenues growth %	0.040*** (0.011)	0.018* (0.009)	0.003 (0.002)	0.013** (0.006)	0.002* (0.001)	0.005* (0.003)
		b)				
Employment growth %	0.027 (0.019)	0.006 (0.015)	-0.008*** (0.003)	0.019* (0.011)	-0.001 (0.002)	0.012*** (0.004)
L.Employment growth %	0.054*** (0.019)	0.039*** (0.015)	0.005 (0.003)	0.004** (0.011)	0.004** (0.002)	0.001 (0.004)
		c)				
Productivity growth %	0.005*** (0.001)	0.003*** (0.001)	0.000 (0.000)	0.001 (0.001)	0.000** (0.000)	-0.000 (0.000)
L.Productivity growth %	0.002* (0.001)	0.001 (0.001)	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	0.000 (0.000)
		d)				
Financial constraint %	-0.139*** (0.030)	-0.104*** (0.025)	-0.015*** (0.005)	-0.040** (0.018)	-0.005 (0.003)	0.024*** (0.007)
L.Financial constraint %	-0.085*** (0.029)	-0.051** (0.024)	-0.015*** (0.005)	-0.029* (0.017)	-0.014*** (0.003)	0.023*** (0.006)
		e)				
Capital HHI	-0.049** (0.020)	-0.026 (0.016)	-0.008** (0.003)	-0.016 (0.011)	-0.000 (0.002)	0.000 (0.004)
L.Capital HHI	-0.065*** (0.020)	-0.040** (0.016)	-0.006* (0.003)	-0.018 (0.011)	-0.003 (0.002)	0.001 (0.004)
		f)				
Intangibles HHI	-0.025** (0.010)	-0.010 (0.008)	0.001 (0.002)	-0.021*** (0.006)	-0.000 (0.001)	0.005** (0.002)
L.Intangibles HHI	-0.015 (0.010)	-0.018** (0.008)	-0.002 (0.002)	0.006 (0.006)	-0.003*** (0.001)	0.001 (0.002)
Country-macro sector FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Source: CompNet 9th Vintage (*unconditional_mac_sector_all_unweighted*) and data from De Haas et al. (2022).
Note: Coefficients from regressing the share of startups over total firms in the macro-sector on macro-sectoral averages of firm characteristics, with country-macro sector and year fixed effects. *Revenues growth* is the year-on-year Davis-Haltiwanger-Schuh growth rate of revenues. *Employment Growth* is the year-on-year Davis-Haltiwanger-Schuh growth rate of employment. *Productivity Growth* is the year-on-year growth rate of labour productivity (value added per employee). *Financial Constraint* is the share of firms that are financially constrained, identified through the classification proposed by Ferrando and Ruggieri (2018) basing on the ECB Survey on Access to Finance of Enterprises (SAFE). *Capital HHI* is the Hirschman-Herfindahl Index for capital. *Intangibles HHI* is the Hirschman-Herfindahl Index for intangibles. Countries are DK, ES, FI, HR, IT, LT, NL, SI, and SE. Macro-sectors are “Manufacturing”, “Construction”, “Wholesale and retail trade; repair of motor vehicles and motorcycles”, “Transportation and storage”, “Accommodation and food service activities”, “Information and communication”, “Professional, scientific, and technical activities”, and “Administrative and support service activities”. The latest available year is 2015 for LT and 2018 for DK, IT, NL, and ES. Additional statistics were excluded for the sake of brevity and are available upon request to the authors.

6 Concentration and productivity: Lessons for a high inflation environment

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We study how concentration of value added and intangibles associates to productivity and market power.

Industries are increasingly dominated by fewer firms, and so we should ask what the impact of this has been on productivity, innovation, and economic efficiency. We examine the relationship between firm concentration and welfare by looking at its possible different channels. Concentration tells us about the degree of competition among firms. Policymakers need to strike a delicate balance when designing antitrust and industrial policies to achieve the optimal efficiency gains and productivity, considering the effects of market power.

In theory, concentration is determined by industry dynamics (Bajgar et al., 2023), technological change (Autor et al., 2020), and the regulatory framework (Eeckhout, 2021). The empirical evidence about the relation between concentration, market power, and productivity is mixed: Bighelli et al. (2023) aggregate the contributions of each country and macro sector into concentration at the European level, and find that increasing concentration of revenues in Europe associates with gains in productivity and allocative efficiency, and does not correlate with the mark-up. According to Koltay et al. (2022), concentration and market power are only positively related in industries at the upper tail of the concentration distribution. Mertens and Mottironi (2023) show that large firms charge lower markups while leveraging their negotiating power in labor markets. We expand the analysis in Bighelli et al. (2023)[69] to:

- Illustrate the evolution of concentration and market power for several additional firm dimensions.
- Study how concentration of value added and intangibles[70] associates

[69] Bighelli et al. (2023) find that the European revenues-based Hirschman-Herfindahl index (HHI) – a widely used proxy for market concentration - increased by 42.87% between 2009 and 2016 on a comparable set of countries and macro-sectors. Considering any partition of European firms into *N* groups according to an index $i \in \{1, ..., n, ..., N\}$, the authors show how the aggregate European HHI for a given variable *x*, HHI^x, can be written in terms of the HHIs for the same variable *x* for each group *n*, HHI_n^x; by defining q_i^x and q_n^x like the quantity of variable *x* respectively for firm *i* and group *n*, so that $q_n^x = \sum_{i \in n} q_i^x$, the following holds true:

$$HHI^X = \sum_i \left(\frac{q_i^x}{\sum_{n=1}^N q_n^X} \right)^2 = \sum_{n=1}^N \left[\sum_{i \in n} \frac{(q_i^x)^2}{\left(\sum_{n=1}^N q_n^x \right)^2} \right] = \sum_{n=1}^N \left[\left(\frac{q_n^x}{\sum_{n=1}^N q_n^x} \right)^2 \sum_{i \in n} \frac{(q_i^x)^2}{(q_n^x)^2} \right] = \sum_{n=1}^N \left[\left(\frac{q_n^x}{\sum_{n=1}^N q_n^x} \right)^2 HHI_n^x \right] \tag{12}$$

Therefore, the aggregate European HHI for variable *x* is equivalent to the weighted mean of the HHIs for the same variable *x* over the *N* groups, where weights are the squared shares on total *x* for each group *n*.

[70] We expect concentration measures for value added and intangibles to reproduce evidence about, respectively, concentration of revenues in Bighelli et al. (2023) and (*mutatis mutandis*) concentration of labor inputs in Berger et al. (2019). In other words, we expect industries with higher concentration of value added (intangibles) to be characterized, if any, by stronger oligopoly (oligopsony) power when bargaining the price of output (capital inputs). According to Crouzet

across industries[71] to productivity, allocative efficiency, market power, and other firm-level characteristics.

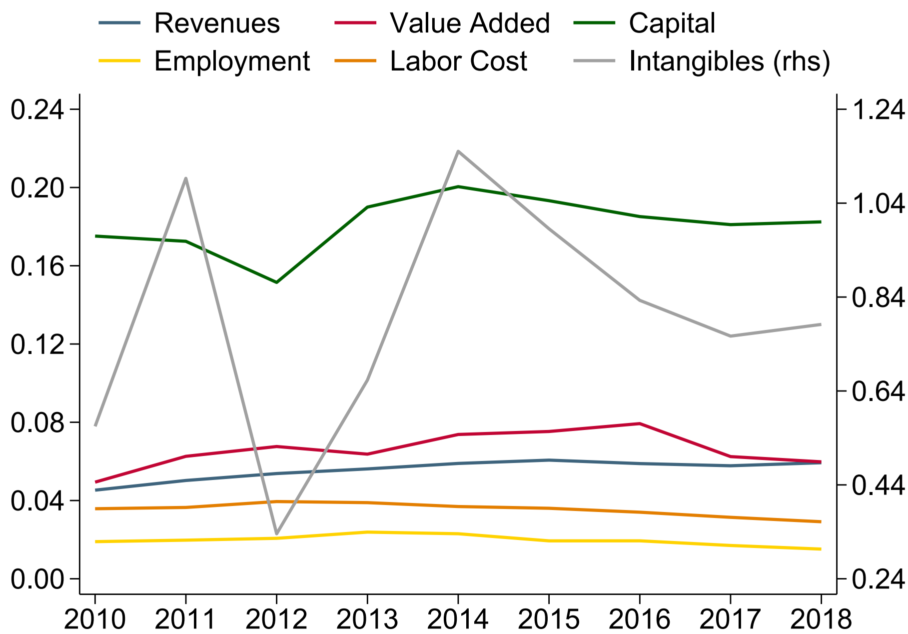
The drivers of European concentration coincide with production factors that are crucial in competitive dynamics like intangibles (figure 38).

6.1 Evolution over the last decade

The HHI for revenues increased by 30.91% between 2010 and 2018 (figure 38). Only the HHI for intangibles showed a stronger growth rate (38.43%), despite a much more volatile trend. The European intangibles HHI was the highest, followed by the HHI for capital (which increased by 4.15%) and for value added (which increased by 21.00%). HHIs for employment and labor cost were the lowest, and fell further (-20.06% and -18.55% respectively).

Overall, the above patterns highlight how the drivers of European concentration have been shifting away from traditional variables like revenues and employment. Instead, concentration is driven by intangibles: factors of production that are becoming more important in competitive dynamics. Capital and value added appear to have played a role as well.

Figure 38: Concentration at the European level. European aggregate, 2010-2018 (Hirschman-Herfindahl Index)



Source: CompNet 9th Vintage (unconditional_mac_sector_20e_weighted).
Note: European HHIs are computed from the contributions of each pairwise combination of countries and macro-sectors like in Bighelli et al. (2023). Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Macro-sectors are “Manufacturing”, “Transportation and storage”, “Information and communication”, “Real estate activities”, “Professional, scientific and technical activities”, and “Administrative and support service activities”. Balanced country sample over years.

Firms that attain a dominant position can extract rents either by putting up

et al. (2022), intangibles might induce higher concentration by encouraging firms to merge and share the fixed cost of creating intangible assets.

[71] With industries we refer in this section to 2-digit NACE Rev. 2 divisions.

output prices above marginal costs or by lowering input prices below competitive levels.[72] This may generate excessive market power, which distorts the efficient allocation of resources. To test this hypothesis, we pair the changes in the European HHIs with their respective closest proxy of firm market power (table 17).[73]

For the HHI and market power of each variable, we report both the average between 2010 and 2018 (columns 1 and 3) and the percentage changes over the same time span (columns 2 and 4).

The increase in the product markup[74] was relatively small (14.86%) compared to large changes in European concentration of revenues and value added. Instead, with a growth of 41.22% the capital markdown largely outpaced the capital HHI but matched the rhythm of intangibles concentration. Finally, labor markdown fell less quickly (-6.70%) than employment and labor cost concentration.

In conclusion, we do not find systematic co-movements between concentration and market power across all the different dimensions, in line with previous research.

Table 17: EU aggregate concentration (HHI) and market power (markup or markdown) for several dimensions. European aggregate, 2010-2018

Dimension	(1) Avg concentration	(2) % Δ concentration	Mkt power measure	(3) Avg mkt power	(4) % Δ mkt power
Revenues	0.06	30.91	Markup	1.52	14.86
Value added	0.07	21.00			
Capital	0.18	4.15	Capital mkdwn	4.73	41.22
Intangibles	0.80	38.43			
Employment	0.02	-20.06	Labor mkdwn	1.27	-6.70
Labor cost	0.04	-18.55			

Source: CompNet 9th Vintage, (unconditional_mac_sector_20e_weighted) Note: Averages and percentage changes over 2010-2018 for European HHIs (columns 1 and 2) computed from the contributions of each pairwise combination of countries and macro-sectors like in Bighelli et al. (2023). The measures that we use for *Market power* are: 1) *Markup* for revenues and value added, 2) *Capital markdown* for capital and intangibles, and 3) *Labor markdown* for employment and labor cost. Averages and percentage changes over 2010-2018 for aggregated European market power figures (columns 3 and 4) related to the above variables are computed using weighted averages over pairwise combinations of countries and macro-sectors. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Macro-sectors are “Manufacturing”, “Transportation and storage”, “Information and communication”, “Real estate activities”, “Professional, scientific and technical activities”, and “Administrative and support service activities”. Balanced sample of countries over years.

[72] In this case one has the so-called markdown, in other words when production factors are paid at levels below their marginal revenue product.

[73] In CompNet, markup and markdown are computed basing on the framework of De Loecker and Warzynski (2012). The indicators are thus derived by dividing the output elasticity of each input for the respective expenditure share, the output elasticity being recovered from estimating a translog production (for markup) or revenue (for markdowns) function using OLS with year fixed effects. For additional details see CompNet (2022). Also, for studies separating product and input market power see Mertens and Mottironi (2023), (Mertens, 2022, 2020a,b), and Morlacco (2019).

[74] Our markup estimates and their changes for Europe are broadly in line with De Loecker and Eeckhout (2018) who report an increase in the European aggregate markup from 2009 to 2016 from 1.40 to 1.60, as our measures for the same years are respectively 1.43 and 1.73.

6.2 Concentration, productivity, and market power

We use variation across CompNet country-industry pairs to assess whether higher concentration is associated with a more efficient market environment or excessive market power. Our productivity measure is value added per worker, which can be decomposed into the unweighted mean firm productivity and the covariance between firm employment share and productivity, see (Olley and Pakes, 1996b)[75]. As mentioned in Chapter 3, the covariance term reflects allocative efficiency, i.e., the effect of market share reallocation to more productive firms on aggregate productivity. We estimate the following equation at the country *n* – two-digit industry *j* – year *t* level with fixed effects:

$$HHI_{n,j,t} = \beta_{\Omega}\Omega_{n,j,t} + C'_{n,j,t}\gamma + \nu_{n,j} + \nu_t \qquad (14)$$

Concentration of value added associates with enhanced allocative efficiency (table 18).

with $HHI_{n,j,t}$ and $\Omega_{n,j,t}$ denoting respectively concentration and the various labor productivity components (aggregate, unweighted mean, or covariance term). $C'_{n,j,t}$ is a vector of controls, including (depending on the specification) average firm size, industry market power measures, and industry capital-labour ratios. The use of industry-country and year fixed effects ($\nu_{n,j}$ and ν_t) controls country-specific industrial policies and allows us to identify coefficients from within-industry-country variation over time.

We find a strong, significant, and robust association between aggregate productivity and concentration for value added (columns 1-3 of table 18). As for the other components of the Olley and Pakes (1996b) decomposition of $\Omega_{n,j,t}$ in equation 14, we find that the positive relation of value added HHI with productivity is entirely driven by allocative efficiency (columns 7-9 of table 18). This strongly supports a winner-takes-all model in which concentration is an outcome of efficient markets allocating shares to the best-performing firms.[76]

Concentration of intangibles is positively related with average industry productivity (table 19).

At the same time, a robust positive correlation emerges between concentration for intangibles and the unweighted mean productivity component (columns 4-6 in Table 19) suggesting that innovative firms hoarding intangibles increase average efficiency either by enhancing their own productivity, or by catalyzing a more productive environment within their industry.[77] Manufacturing as well as High-tech-knowledge-intensive industries, especially

[75] We do this by implementing a static Olley and Pakes (1996b) decomposition, that is, defining the aggregate productivity of a given country-industry combination at time *t* with Ω_t, its unweighted mean firm productivity with $\overline{\omega}_t$, and with $cov_t\left(\omega_{i,t}, s^L_{i,t}\right)$ the covariance between firms' employment share $s^L_{i,t}$ and productivity:

$$\Delta\Omega_t = \Delta\bar{\omega}_t + \Delta\text{cov}_t(\omega_{i,t}, s^L_{i,t}) \qquad (13)$$

where *i* is the firm index and Δ indicates changes.

[76] See Autor et al. (2020) and Van Reenen (2018).

[77] Our results for revenues and capital overlap with, respectively, those for value added and intangibles (tables 24 and 25). Instead, we do not find any significant relationship of the HHIs for employment and labor cost with productivity and its components (tables 26 and 27).

Information and Communication, show the largest effect of concentrated intangibles on unweighted mean productivity (see table 28 in the appendix).

There is no robust or statistically significant association between concentration and market power when conditioning on productivity.[78] The HHI based on intangibles displays consistent positive correlation with markup (table 19), though with small statistical significance.

Welfare losses overcome productivity benefits after concentration reaches some critical threshold (table 19).

Following Koltay et al. (2022), we examine if the relationship between concentration and market power is different for the most concentrated industries. Our results suggest that for industries in the top two deciles of the HHI distribution, coefficients for markups become positive with strong statistical significance for both value added and intangibles (column 10 in tables 18 and 19).[79] This suggests that welfare losses dominate productivity benefits when concentration is higher than a critical threshold. Higher intangibles concentration also appears to reduce markdown of intermediates, perhaps the consequence of innovative firms sourcing technologically advanced inputs from providers that have stronger bargaining power.[80]

[78]Similarly to value added, correlation between concentration and market power is not found for revenues, capital, employment, and labor cost (see tables 24 to 27 in the appendix).

[79]Contrarily to our expectations, intangibles concentration correlates positively with markup, rather than input markdowns. This may stem from our measures for capital markdown not being tailored enough on intangible capital inputs. In any case, further investigation should be dedicated to the channels through which firms that dominate intangibles in their industries also achieve higher output market power. Bajgar et al. (2023), e.g., find that intensive investment in intangibles strongly associates with rising concentration, which in turn has implications on competition in terms of higher markups.

[80]Results in the appendix show how the relation between concentration and market power does not change when considering only top concentrated industries for revenues, capital, employment, and labor cost (column 10 in tables 24 to 27).

[81]Source: CompNet 9th Vintage, (unconditional_industry2d_20e_weighted) and (op_decomp_industry2d_20e_weighted). Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. For each country-industry, *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 9 only for industries in the top two deciles of the value-added HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

Table 18: **Value added concentration and productivity at the two-digit-industry level. European countries, 1999-2020**[81]

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg. prod.	0.01***	0.01***	0.02***							
	(0.00)	(0.00)	(0.00)							
Unweighted avg. prod.				0.00	0.00	0.00				
				(0.00)	(0.00)	(0.00)				
Allocative efficiency							0.03***	0.03***	0.03***	0.02**
							(0.01)	(0.01)	(0.01)	(0.01)
Capital intensity	0.00	0.00	-0.00	0.00*	0.00*	0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L(avg firm size)			5.44***			5.34***			5.49***	3.83**
			(0.94)			(0.93)			(0.91)	(1.66)
L(agg. markup)		-1.12	0.58		1.63	3.41		-2.54	-0.86	6.88**
		(1.45)	(2.65)		(1.31)	(2.77)		(1.54)	(2.21)	(2.92)
L(agg. mkdown L)		0.87	1.22*		0.95	1.30*		0.87	1.22*	1.58
		(0.74)	(0.68)		(0.74)	(0.68)		(0.72)	(0.66)	(1.85)
L(agg. mkdown K)		-0.22	-0.22		-0.27	-0.26*		-0.25	-0.24	-0.47
		(0.17)	(0.16)		(0.17)	(0.16)		(0.18)	(0.16)	(0.62)
L(agg. mkdown Int.)		1.65	-0.04		-0.78	-2.54		3.11**	1.44	-4.29
		(1.40)	(2.52)		(1.35)	(2.63)		(1.48)	(2.06)	(4.04)
Constant	4.41***	4.38***	-21.42***	5.20***	5.17***	-20.14***	5.20***	5.17***	-20.80***	-0.95
	(0.30)	(0.36)	(4.56)	(0.16)	(0.26)	(4.35)	(0.08)	(0.23)	(4.29)	(8.78)
Country-macro sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	1,314
R-squared	0.82	0.82	0.84	0.81	0.81	0.83	0.83	0.83	0.84	0.76
N° Clusters	47	47	47	47	47	47	47	47	47	43

Table 19: **Intangibles concentration and productivity at the two-digit-industry level. European countries, 1999-2020**[82]

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg. prod.	0.01	0.01	0.01							
	(0.01)	(0.01)	(0.01)							
Unweighted avg. prod.				0.02***	0.02***	0.02***				0.02*
				(0.01)	(0.01)	(0.01)				(0.01)
Allocative efficiency							0.01	0.01	0.01	
							(0.01)	(0.01)	(0.01)	
Capital intensity	0.00	0.00*	0.00	0.00	0.00*	0.00	0.00*	0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
L(avg firm size)			3.71***			3.68***			3.70***	-2.04
			(1.30)			(1.32)			(1.29)	(2.60)
L(agg. markup)		14.03*	15.19*		15.08*	16.31*		14.44*	15.57*	52.36***
		(7.68)	(8.50)		(8.58)	(9.48)		(7.38)	(8.15)	(15.75)
L(agg. mkdown L)		0.18	0.41		0.18	0.41		0.20	0.44	2.99
		(1.11)	(1.13)		(1.13)	(1.15)		(1.11)	(1.12)	(3.42)
L(agg. mkdown K)		-0.12	-0.11		-0.10	-0.10		-0.14	-0.13	-0.86
		(0.51)	(0.52)		(0.52)	(0.52)		(0.52)	(0.53)	(1.39)
L(agg. mkdown Int.)		-12.53	-13.68		-13.59	-14.80		-12.81*	-13.93*	-47.02***
		(7.70)	(8.54)		(8.49)	(9.39)		(7.40)	(8.18)	(15.10)
Constant	15.74***	15.50***	-2.10	15.27***	15.03***	-2.40	16.35***	16.02***	-1.47	56.67***
	(0.43)	(0.65)	(6.20)	(0.36)	(0.66)	(6.28)	(0.14)	(0.54)	(6.10)	(12.42)
Country macro sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,231	10,231	10,231	10,231	10,231	10,231	10,231	10,231	10,231	1,450
R-squared	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.54
N° Clusters	47	47	47	47	47	47	47	47	47	47

6.3 Conclusions

Between 2010 and 2018 concentration in Europe was driven by production factors that are increasingly more important in competitive dynamics, such as intangibles. The growth of market power was typically smaller, except for markdown measures of capital. Concentration of value added strongly and positively associated to higher productivity and enhanced allocation of

[82]Source: CompNet 9th Vintage, (unconditional_industry2d_20e_weighted) and (op_decomp_industry2d_20e_weighted). Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. For each country-industry, *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 6 only for industries in the top two deciles of the intangibles HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

resources. Also, there was a positive relation between intangibles concentration and average productivity. Although benefits from concentration of value added and intangibles may not be linear, we take a positive view of rising European concentration: the increasing share of resources held by large, innovative, and productive firms has been a key driver of European productivity growth without surging market power.

This has important consequences for European antitrust and industrial policy: rising concentration should be considered alongside measurements of welfare losses from excessive market power, which may include impacts on inflation. It might be therefore more relevant to consider concentration thresholds for firm dimensions such as value added and intangibles, even though they are more difficult to measure than conventional revenues.

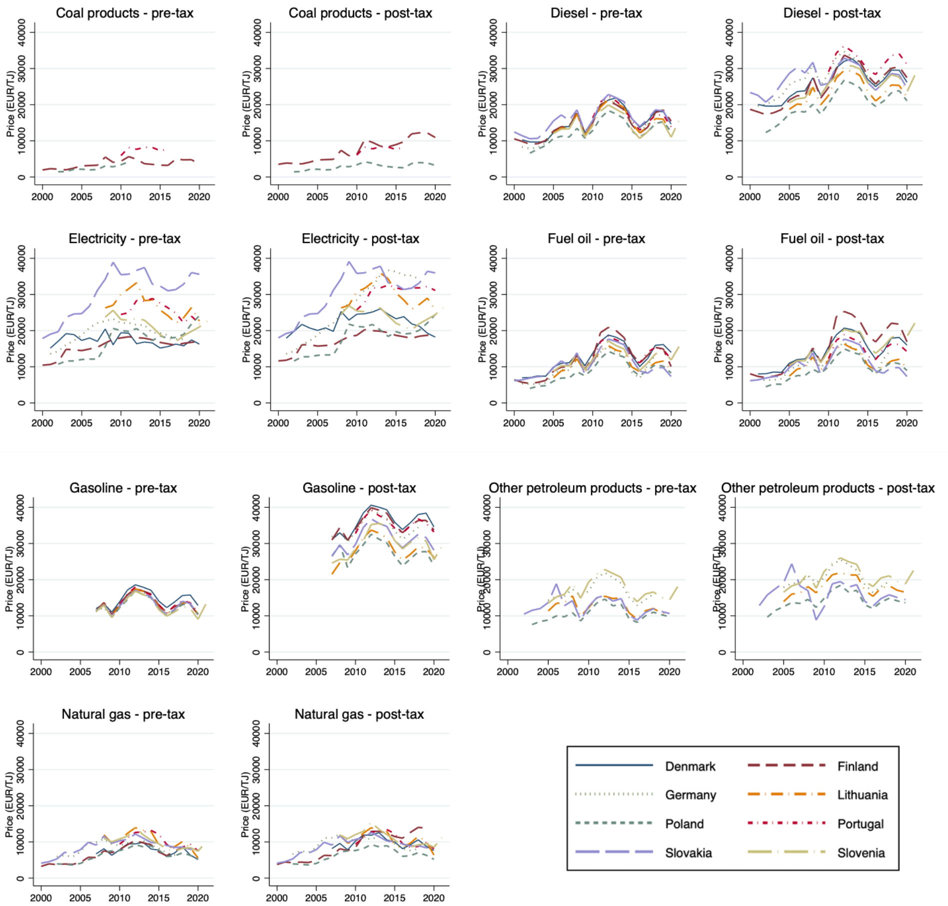
7 Appendix

Table 20: **Average indicators for dismissal and hiring regulations by European countries, 2019**

Country	Dismissal Regulations	Hiring Regulations
Belgium	2.71	2.17
Czech Republic	3.03	2.13
Denmark	1.94	1.96
Finland	2.48	1.75
France	2.68	3.13
Germany	2.33	1.92
Hungary	1.89	2.00
Italy	2.86	3.63
Latvia	2.71	1.79
Lithuania	2.24	1.92
Netherlands	2.88	1.48
Poland	2.38	2.21
Portugal	2.87	2.46
Slovakia	2.33	2.75
Slovenia	2.32	2.13
Spain	2.43	3.10
Sweden	2.54	1.67

Source: OECD Employment Protection Legislation (EPL) database.

Figure 39: Trends in energy prices before and after taxes



Source: International Energy Agency.
Note: Dashed line indicates pre-tax prices, while solid line indicates after tax prices.

Table 21: Impact of pre-tax and post-tax energy price shocks on profitability, job destruction rate, energy cost share, and energy efficiency, selected European countries, 2007-2016.

	Profit.		JDR		Ener. Cost share		Energy/VA	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Weigh. Δ PC	0.01	-0.06	-0.24***	-0.01	0.01**	0.12*	-0.08	-0.16
	(0.04)	(0.05)	(0.08)	(0.01)	(0.05)	(0.07)	(0.06)	(0.11)
Electricity	0.01	-0.03**	-0.01	-0.04	0.00	0.01**	-0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
Natural gas	-0.00	-0.12**	-0.15***	0.07	0.00	-0.02**	0.02	-0.01
	(0.04)	(0.05)	(0.05)	(0.05)	(0.01)	(0.01)	(0.02)	(0.01)
Constant	-0.04***	-0.03***	0.12***	0.12***	-0.02***	-0.02***	-0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	1,957	1,978	2,036	2,054	2,017	2,036	2,027	2,046
R2	0.46	0.46	0.35	0.35	0.30	0.29	0.03	0.03
N° of ID	253	253	254	254	254	254	253	253
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

	Export %		Inv./Assets		Green share	
	Pre	Post	Pre	Post	Pre	Post
Weigh. Δ PC	0.14	0.19	11.3	5.2	0.06**	0.00
	(0.15)	(0.22)	(13.6)	(42.2)	(0.03)	(0.05)
Electricity	0.06***	-0.02	0.33	-38.8	-0.01	-0.03
	(0.01)	(0.02)	(0.45)	(38.4)	(0.01)	(0.02)
Natural gas	-0.17***	-0.24***	-1.50	156.3	-0.04	-0.1**
	(0.05)	(0.07)	(1.8)	(153.5)	(0.03)	(0.05)
Constant	-0.00	0.01	-1.32	10.04	-0.01	0.00
	(0.03)	(0.05)	(1.08)	(11.03)	(0.01)	(0.00)
Obs	1,152	1,170	1,415	1,433	2,039	2,058
R2	0.10	0.13	0.01	0.04	0.04	0.03
N° of ID	142	142	188	188	254	254
Year FE	YES	YES	YES	YES	YES	YES

Note: Results are from a fe-panel regression at the industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

Table 22: Cross-country heterogeneity

a) *Profitability*

	Energy sources: Weighted Δ PC							
	DK	FI	DE	LT	POL	PT	SK	SI
Fossil Fuels	0.10	0.13	-0.42	-0.52**	-0.06	0.24	-0.04	0.04
	(0.13)	(0.11)	(0.45)	(0.19)	(0.05)	(0.24)	(0.20)	(0.24)
Electricity	0.05	-0.15	-0.41***	-0.07	-0.02	-0.12	-0.10	-0.16
	(0.03)	(0.12)	(0.13)	(0.09)	(0.03)	(0.15)	(0.09)	(0.11)
Natural Gas	-0.09	0.19	-0.03	-0.21	0.06	0.50***	0.13	0.11
	(0.17)	(0.30)	(0.34)	(0.20)	(0.05)	(0.18)	(0.15)	(0.11)
Constant	-0.05	-0.03**	-0.07**	-0.05***	-0.04***	-0.04**	0.01	-0.01
	(0.04)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Observations	261	300	159	243	311	192	274	238
R-squared	0.60	0.60	0.58	0.60	0.46	0.57	0.59	0.47
Number of ID	32	34	19	34	35	34	33	32
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Results are from a fe-panel regression at the industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

b) *Job destruction rate*

	Energy sources: Weighted Δ PC							
	DK	FI	DE	LT	POL	PT	SK	SI
Fossil Fuels	0.30	-0.67*	0.60*	1.01***	-0.10	-0.33	0.65	-0.28
	(0.43)	(0.39)	(0.33)	(0.23)	(0.23)	(0.20)	(0.39)	(0.32)
Electricity	-0.04	-0.04	0.27***	0.54**	0.13**	0.18	0.23	0.12
	(0.23)	(0.20)	(0.08)	(0.20)	(0.05)	(0.17)	(0.18)	(0.22)
Natural Gas	0.26	0.17	-0.06	0.03	0.02	-0.06	0.18	-0.03
	(0.38)	(0.73)	(0.08)	(0.21)	(0.12)	(0.10)	(0.37)	(0.13)
Constant	0.52*	-0.03	-0.02	0.23***	0.20***	0.13***	0.08**	0.00
	(0.30)	(0.05)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.08)
Observations	265	305	169	268	312	207	285	243
R-squared	0.58	0.32	0.62	0.78	0.47	0.65	0.57	0.46
Number of ID	32	34	19	34	35	35	33	32
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

c) *Energy cost share*

	Energy sources: Weighted Δ PC							
	DK	FI	DE	LT	POL	PT	SK	SI
Fossil Fuels	0.01	0.44	0.08	0.11*	-0.01	0.20	1.13**	0.35*
	(0.01)	(0.27)	(0.07)	(0.06)	(0.01)	(0.18)	(0.32)	(0.18)
Electricity	-0.00	-0.01	0.04**	-0.02	0.02***	0.07**	-0.13	0.09*
	(0.00)	(0.04)	(0.02)	(0.03)	(0.00)	(0.03)	(0.13)	(0.05)
Natural Gas	0.01	-0.36	-0.04**	0.01	0.00	-0.10**	-0.46**	-0.01
	(0.01)	(0.30)	(0.01)	(0.05)	(0.01)	(0.04)	(0.20)	(0.05)
Constant	-0.01***	-0.00	-0.02***	-0.01	-0.01***	-0.03***	0.01	-0.03***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	267	305	169	268	312	207	264	244
R-squared	0.43	0.41	0.63	0.63	0.59	0.78	0.47	0.57
Number of ID	32	34	19	34	35	35	33	32
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

d) *Energy efficiency*

	Energy sources: Weighted Δ PC							
	DK	FI	DE	LT	POL	PT	SK	SI
Fossil Fuels	0.11	-0.12*	0.15	-0.13	-0.47*	-0.18*	-0.76**	-0.19*
	(0.21)	(0.06)	(0.13)	(0.11)	(0.14)	(0.10)	(0.18)	(0.10)
Electricity	-0.01	0.04**	0.01	0.01	-0.04*	0.03	-0.09	0.00
	(0.01)	(0.01)	(0.02)	(0.05)	(0.02)	(0.04)	(0.09)	(0.03)
Natural Gas	-0.06	-0.22	-0.03	0.40	0.15**	0.01	0.14*	-0.02
	(0.12)	(0.19)	(0.02)	(0.29)	(0.05)	(0.07)	(0.06)	(0.04)
Constant	-0.03	-0.00	-0.01*	-0.03	0.01**	0.02***	0.01*	0.01*
	(0.04)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	263	303	170	268	312	207	280	243
R-squared	0.19	0.12	0.09	0.34	0.38	0.08	0.25	0.30
Number of ID	31	34	19	34	35	35	33	32
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 23: **Macro-sector heterogeneity**

	Profitability		JDR		Energy Cost Share		Energy Efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
weigh. Δ PC:								
Fossil Fuels	0.14	-0.03	-0.35*	-0.08	0.06**	0.15	0.11*	-0.25*
	(0.20)	(0.05)	(0.21)	(0.13)	(0.03)	(0.10)	(0.06)	(0.13)
Electricity	-0.04*	-0.02	0.03	-0.12**	0.01***	0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.04)	(0.05)	(0.00)	(0.00)	(0.00)	(0.01)
Natural Gas	-0.15**	-0.11**	0.07	0.21**	-0.02***	-0.00	-0.01	-0.04
	(0.06)	(0.04)	(0.06)	(0.10)	(0.00)	(0.03)	(0.01)	(0.03)
Constant	-0.05**	-0.03***	0.07**	0.15***	-0.02***	-0.02***	-0.00	0.00
	(0.02)	(0.01)	(0.03)	(0.04)	(0.00)	(0.01)	(0.00)	(0.01)
Observations	1,211	767	1,234	820	1,222	814	1,229	817
R-squared	0.47	0.46	0.45	0.29	0.50	0.25	0.01	0.12
Number of ID	150	103	150	104	150	104	150	103
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Results are from a fe-panel regression at the country-industry level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Clustered std. errors at the country-industry level. Omitted coefficients for control variables: profitability, revenues, firm size (employment), number of firms, average markup on intermediate inputs, average industry energy intensity. Results based on 20e weighted sample, countries included: DK, DE, FI, HR, LT, PL, PT, SI, SK. Industries included: 10, 13, 14, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 42, 45, 46, 47, 60, 61, 70, 78, 80, 81, 82. Dependent variables are in first differences.

Table 24: **Revenues concentration and productivity at the two-digit-industry level. European countries, 1999-2020**

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg. prod	0.01***	0.01***	0.01***							0.01***
	(0.00)	(0.00)	(0.00)							(0.00)
Unweighted avg. prod.				0.00	0.00	0.00*				
				(0.00)	(0.00)	(0.00)				
Allocative efficiency							0.03***	0.03***	0.03***	
							(0.01)	(0.01)	(0.01)	
Capital intensity	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L(avg firm size)			4.94***			4.84***			4.98***	2.22
			(0.97)			(0.97)			(0.93)	(1.67)
L(agg. markup)		-1.99*	-0.45		0.62	2.23		-3.25**	-1.72	-0.79
		(1.18)	(2.29)		(1.00)	(2.36)		(1.28)	(1.92)	(5.94)
L(agg. mkdown L)		0.81	1.12		0.89	1.20		0.81	1.13	0.63
		(0.79)	(0.76)		(0.79)	(0.76)		(0.77)	(0.74)	(1.70)
L(agg. mkdown K)		0.11	0.12		0.07	0.08		0.09	0.09	0.74
		(0.20)	(0.20)		(0.19)	(0.19)		(0.20)	(0.20)	(0.47)
L(agg. mkdown Int.)		2.03*	0.50		-0.27	-1.87		3.34***	1.83	-0.38
		(1.14)	(2.14)		(1.12)	(2.24)		(1.23)	(1.75)	(5.83)
Constant	4.68***	4.38***	-19.03***	5.38***	5.05***	17.89***	5.43***	5.15***	-18.40***	6.14
	(0.28)	(0.41)	(4.75)	(0.15)	(0.26)	(4.61)	(0.15)	(0.31)	(4.47)	(8.75)
Country MacSect FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	1,265
R-squared	0.79	0.79	0.81	0.78	0.78	0.80	0.80	0.80	0.81	0.74
N°Clusters	47	47	47	47	47	47	47	47	47	41

Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 3 only for industries in the top two deciles of the revenues HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

Table 25: **Capital concentration and productivity at the two-digit-industry level. European countries, 1999-2020**

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg prod.	0.01	0.01	0.01							
	(0.00)	(0.00)	(0.01)							
Unweighted avg. prod.				0.01***	0.01***	0.01***				0.01*
				(0.00)	(0.00)	(0.00)				(0.00)
Allocative efficiency							0.01	0.01	0.01	
							(0.01)	(0.01)	(0.01)	
Capital intensity	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
L(avg firm size)			5.67***			5.63***			5.66***	1.37
			(1.07)			(1.08)			(1.06)	(1.12)
L(agg. markup)		1.08	2.86		1.99	3.87		1.25	2.99	12.29
		(1.92)	(3.06)		(2.27)	(3.72)		(1.96)	(3.01)	(9.62)
L(agg. mkdown L)		1.25	1.62**		1.26	1.63**		1.27*	1.63**	0.73
		(0.76)	(0.74)		(0.76)	(0.74)		(0.75)	(0.74)	(2.06)
L(agg. mkdown K)		-0.44	-0.43		-0.43	-0.43		-0.46	-0.45	-0.09
		(0.29)	(0.28)		(0.29)	(0.28)		(0.30)	(0.29)	(0.59)
L(agg. mkdown Int.)		-0.49	-2.25		-1.38	-3.24		-0.58	-2.29	-11.31
		(2.03)	(3.21)		(2.38)	(3.83)		(2.05)	(3.11)	(9.20)
Constant	6.81***	6.98***	-19.88***	6.53***	6.72***	-19.97***	7.25***	7.38***	-19.39***	17.26***
	(0.52)	(0.53)	(5.13)	(0.43)	(0.52)	(5.11)	(0.32)	(0.44)	(4.99)	(5.78)
Country MacSect FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	1,332
R-squared	0.75	0.75	0.77	0.75	0.75	0.77	0.75	0.75	0.77	0.63
N° Clusters	47	47	47	47	47	47	47	47	47	41

Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 6 only for industries in the top two deciles of the capital HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

Table 26: Employment concentration and productivity at the two-digit-industry level. European countries, 1999-2020

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg prod.	0.00	0.00	0.00							0.00
	(0.00)	(0.00)	(0.00)							0.00
Unweighted avg. prod.				0.01	0.00	0.01				
				(0.00)	(0.00)	(0.00)				
Allocative efficiency							-0.00	-0.00	-0.00	
							(0.01)	(0.01)	(0.00)	
Capital intensity	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
L(avg firm size)			7.31***			7.31***			7.30***	7.31***
			(0.89)			(0.89)			(0.87)	(1.53)
L(agg. markup)		-2.37	-0.08		-2.52	-0.08		-2.01	0.24	1.37
		(2.87)	(1.28)		(3.21)	(1.42)		(2.36)	(1.17)	(6.16)
L(agg. mkdown L)		0.12	0.59		0.11	0.58		0.13	0.59	2.09*
		(0.48)	(0.40)		(0.49)	(0.41)		(0.48)	(0.40)	(1.11)
L(agg. mkdown K)		-0.30*	-0.29**		-0.29*	-0.28**		-0.31*	-0.30**	-0.67*
		(0.17)	(0.13)		(0.16)	(0.13)		(0.17)	(0.14)	(0.38)
L(agg. mkdown Int.)		3.45	1.18		3.54	1.13		3.11	0.90	3.58
		(2.84)	(1.26)		(3.10)	(1.36)		(2.38)	(1.19)	(6.42)
Constant	3.93***	3.97***	-30.69***	3.62***	3.69***	-30.96***	3.97***	3.99***	-30.56***	-23.67***
	(0.17)	(0.27)	(4.18)	(0.30)	(0.23)	(4.33)	(0.08)	(0.18)	(4.10)	(8.69)
Country MacSect FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	1,165
R-squared	0.82	0.82	0.87	0.82	0.82	0.87	0.82	0.82	0.87	0.81
N° Clusters	47	47	47	47	47	47	47	47	47	38

Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 3 only for industries in the top two deciles of the employment HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

Table 27: Labor cost concentration and productivity at the two-digit-industry level. European countries, 1999-2020

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI	(7) HHI	(8) HHI	(9) HHI	(10) HHI
Agg prod.	0.00	0.00	0.00							0.00
	(0.00)	(0.00)	(0.00)							(0.00)
Unweighted avg. prod.				0.00	0.00	0.00				
				(0.00)	(0.00)	(0.00)				
Allocative efficiency							0.00	0.00	0.00	
							(0.00)	(0.00)	(0.00)	
Capital intensity	0.00*	0.00	0.00	0.00*	0.00*	0.00	0.00*	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L(avg firm size)			4.93***			4.90***			4.93***	0.23
			(0.83)			(0.82)			(0.83)	(2.85)
L(agg. markup)		-1.65	-0.11		-1.14	0.50		-1.87	-0.36	0.98
		(2.41)	(1.40)		(2.34)	(1.36)		(2.51)	(1.49)	(4.74)
L(agg. mkdown L)		0.35	0.67		0.37	0.68		0.35	0.67	0.86
		(0.57)	(0.51)		(0.57)	(0.51)		(0.56)	(0.51)	(0.90)
L(agg. mkdown K)		-0.21	-0.20		-0.21	-0.21		-0.21	-0.21	-0.26
		(0.14)	(0.13)		(0.14)	(0.13)		(0.14)	(0.13)	(0.40)
L(agg. mkdown Int.)		2.61	1.09		2.15	0.54		2.85	1.35	0.77
		(2.48)	(1.48)		(2.46)	(1.47)		(2.56)	(1.54)	(4.53)
Constant	4.63***	4.55***	-18.79***	4.72***	4.65***	-18.57***	4.80***	4.70***	-18.63***	17.17
	(0.21)	(0.22)	(3.98)	(0.14)	(0.25)	(3.89)	(0.09)	(0.19)	(3.90)	(15.54)
Country MacSect FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	10,233	1,221
R-squared	0.85	0.85	0.87	0.85	0.85	0.87	0.85	0.85	0.87	0.79
N° Clusters	47	47	47	47	47	47	47	47	47	38

Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Robust standard errors in parentheses, clustered at the sector level. *** p<0.01, ** p<0.05, * p<0.1. Int. stands for intermediaries, L labour, K capital, and L() log. *Unweighted* (Unweigh.) *mean productivity* (prod.) and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). *Capital intensity* is the average firm ratio between real capital and labor. *Average firm size* is the average firm labor force. Column 10 replicates the analysis in column 3 only for industries in the top two deciles of the labor-cost HHI for each year. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

Table 28: **Intangibles concentration and productivity at the two-digit-industry level, by macro-sector. European countries, 1999-2020**

Sector	(1) Aggregate productivity		(2) Unweighted mean productivity		(3) Allocative efficiency	
Manufacturing	0.0592***	(0.00967)	0.0303**	(0.0149)	0.101***	(0.0143)
Transportation & storage	0.00123	(0.00315)	0.0199**	(0.00928)	-0.00369	(0.00561)
Information & communication	0.0117*	(0.00705)	0.0222**	(0.00914)	0.00583	(0.00876)
Real estate activities	0.0144	(0.0881)	0.0704	(0.0896)	-0.114	(0.133)
Professional scientific & technical activities	-0.00611	(0.0193)	0.0147	(0.0207)	-0.0383	(0.0305)
Administrative & support & service activities	-0.0446***	(0.0172)	-0.0263	(0.0208)	-0.0175	(0.0204)
High tech & & knowledge-intensive	0.00974**	(0.00384)	0.0210***	(0.00638)	0.00947**	(0.00468)
Low tech & not knowledge-intensive	0.0230**	(0.0111)	0.0172	(0.0136)	0.0246	(0.0181)

Source: CompNet 9th Vintage (*unconditional_industry2d_20e_weighted*).
Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. *Unweighted mean productivity* and *Allocative efficiency* are the components of *Aggregate productivity* like in Olley and Pakes (1996b). Coefficients from regressing the intangibles HHI on *Aggregate productivity, Unweighted mean* productivity and *Allocative efficiency* like in column 3, 6 and 9 of table 19 but separately for each macro-sector. The identification of *High tech and knowledge intensive* and *Low tech and not knowledge intensive* industries follows Eurostat. Countries are BE, CH, CZ, DE, ES, FI, FR, HU, IT, LT, MT, NL, PL, PT, RO, SK, and SE. Data until 2020 except for DE and NL respectively until 2018 and 2019.

7.1 The GVC frontier

The GVC frontier is specific to each country *c*, macro-sector *s*, and year *t*. The TFP growth of the GVC frontier is the weighted average of the year-on-year TFP growth of national frontier firms in each partner country *c'* and macro-sector *s'*:

$$\Delta TFP^{GVC\_front\_f}_{c,s,t} = \sum_{c'} \sum_{s'} \frac{\chi^{f}_{c,s,c',s',t}}{\sum_{c'} \sum_{s'} \chi^{f}_{c,s,c',s',t}} \Delta TFP^{nat\_front}_{c',s',t} \tag{15}$$

where $\chi^{f}_{c,s,c',s',t}$ is the amount of flow *f* (export or import) traded between macro-sector *s* in country *c* and macro-sector *s'* in country *c'* at time *t*. $\Delta TFP^{nat\_front}_{c',s',t}$ is the year-on-year logarithmic TFP growth of national frontier firms in partner country *c'* and macro-sector *s'* in year *t*, that is, of firms in the top two deciles of the TFP distribution for *c'* and *s'* at time *t*.

7.2 Firm-level equivalence of the micro-aggregated ECI

Assume that we want to compute the simple average of the firm-level ECI $E^{c,s}[ECI_i]$ for all macro-sectors $s = 1, \dots, S$ within a country c. For each variable $X^{n,v}$, the micro-aggregated CompNet dataset provides the corresponding macro-sectoral mean $E^{c,s}(X^{v,n})$. Supposing we were using firm-level data instead, and letting $N^{c,s}$ be the number of firms in country c and macro-sector s, we would proceed as follows by combining equations 5 and 6:

$$
\begin{aligned}
E^{c,s}[ECI_i] &= \frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}} ECI_i = \frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}\frac{1}{5}\sum_{n=1}^{5} D_i^n = \frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}\left(\frac{1}{5}\sum_{n=1}^{5}\frac{1}{NV^n}\sum_{v=1}^{NV^n} SX_i^{n,v}\right) = \\
&\frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}\left(\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}SX_{i^{n,v}}\right) = \frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}\left[\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left(\frac{X_i^{n,v}-min_s(X^{n,v})}{max_s(X^{n,v})-min_s(X^{n,v})}\right)\right] = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\left\{\frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}\left[\frac{1}{5}\frac{1}{NV^n}\left(\frac{X_i^{n,v}-min_s(X^{n,v})}{max_s(X^{n,v})-min_s(X^{n,v})}\right)\right]\right\} = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left\{\left(\frac{1}{max_s(X^{n,v})-min_s(X^{n,v})}\right)\frac{1}{N^{c,s}}\sum_{i=1}^{N^{c,s}}[X_i^{n,v}-min_s(X^{n,v})]\right\} = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left\{\left(\frac{1}{max_s(X^{n,v})-min_s(X^{n,v})}\right)\frac{1}{N^{c,s}}\left[\left(\sum_{i=1}^{N^{c,s}}X_i^{n,v}\right)-N^{c,s}min_s(X^{n,v})\right]\right\} = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left\{\left(\frac{1}{max_s(X^{n,v})-min_s(X^{n,v})}\right)\left[\left(\frac{1}{NV^n}\sum_{i=1}^{N^{c,s}}X_i^{n,v}\right)-min_s(X^{n,v})\right]\right\} = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left[\frac{\left(\frac{1}{NV^n}\sum_{i=1}^{N^{c,s}}X_i^{n,v}\right)-min_s(X^{n,v})}{max_s(X^{n,v})-min_s(X^{n,v})}\right] = \\
&\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left[\frac{\left(E^{(c,s)}(X_i^{n,v})-min_s(X^{n,v})\right)}{max_s(X^{n,v})-min_s(X^{n,v})}\right]
\end{aligned} \tag{16}
$$

The last row of equation 16 proves that the simple average of the firm-level ECI $E^{c,s}[ECI_i]$ for country c and macro-sector s can be also computed by utilizing standardized micro-aggregated simple averages of each composing variable (the term $\frac{E^{(c,s)}(X^{(v,n)})-min_s(X^{n,v})}{max_s(X^{n,v})-min_s(X^{n,v})}$) for the same country and macro-sector.

One can further show that, within a certain country, taking the population-weighted average of macro-sectoral simple averages of firm-level ECI delivers the country average of the firm-level ECI; supposing there are N^c firms in country c:

$$
E^c[ECI_i] = \frac{1}{N^c}\sum_i I_i = \sum_s \frac{N^{c,s}}{N^c}E^{c,s}[ECI_i] = \sum_s \frac{N^{c,s}}{N^c}\sum_{n=1}^{5}\sum_{v=1}^{NV^n}\frac{1}{5}\frac{1}{NV^n}\left[\frac{E^{(c,s)}(X_i^{n,v})-min_s(X^{n,v})}{max_s(X^{n,v})-min_s(X^{n,v})}\right] \tag{17}
$$

Equation 17 is how we revert the country-level simple average of the firm-level ECI starting from standardized micro-aggregated macro-sectoral averages of each composing variable.

The cross-country least (largest) 1^{st} (99^{th}) percentile of the respective distribution within macro-sector s is used as the minimum (maximum) when standardizing variables like in equation 5. We take the cross-country minimum and maximum for a given macro-sector over the entire time span.

7.3 Disclaimer

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