European Business dynamism, Firm Responsiveness, and the Role of Market Power and Technology

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Abstract

We study the changing patterns of business dynamism in Europe using representative and comparable micro-aggregated data from 19 European countries. We document a widespread reduction in job reallocation rates in Europe, accompanied by a decline in the number and the share of activity of young firms. This decline concerns all economic sectors and appears to be driven mainly by within-sector dynamics, rather than cross-sectoral reallocations. This is consistent with existing evidence in the US (Decker, Haltiwanger, Jarmin, & Miranda, 2020). However, we rationalize this decline with a firm-level framework relating the responsiveness of employment to productivity to changes in market power and technology, rather than adjustment costs.

Keywords: *Business Dynamism, Productivity, Responsiveness of labor demand, Market power, European cross-country data.*

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1 Introduction

One of the most debated secular trends in the past decades is the decline in US business dynamism that has been documented with a variety of measures and data sources (e.g. Decker, Haltiwanger, Jarmin, and Miranda, 2014; Decker, Haltiwanger, Jarmin, and Miranda, 2016; Dent, Karahan, Pugsley, and Şahin, 2016; Guzman and Stern, 2020; Akcigit and Ates, 2021). The slowdown in business dynamism and reallocation dynamics has potentially far-reaching implications for innovation (Haltiwanger, Hathaway, and Miranda, 2014; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018), aggregate productivity growth (Decker, Haltiwanger, Jarmin, and Miranda, 2017; ; Decker, Haltiwanger, Jarmin, and Miranda, 2020; Alon, Berger, Dent, and Pugsley, 2018) and the pace of economic recoveries (Pugsley & Șahin, 2019). However, the underlying drivers of this decline continue to be debated. Among others, the role played by rising market power (De Loecker, Eeckhout, & Mongey, 2021), declines in knowledge diffusion (Akcigit and Ates, 2021; Andrews, Criscuolo, and Gal, 2015), rise in capital intangible (De Ridder, 2019) or more broadly rising adjustment costs (Decker et al., 2020) have been recently explored in literature.

While the decline in business dynamism is well established for the US economy, we still face a dramatic lack of evidence for European economies. This is critical in the context of the recent productivity slowdown in Europe and the ongoing challenges posed by slow job growth and lacklustre innovation. This lack of evidence is mainly due to the fact that comparable and representative data on indicators of business dynamism across multiple European countries are not readily available to researchers.[1] On one hand, each country hosts its own National Statistical Institute which collects and stores representative firm-level data. Combining administrative firm-level country datasets is legally prohibited and accessing any of these datasets is tied to significant administrative costs. On the other, the existing publicly available European firm-level databases do not represent a viable source, given their low cross-country comparability (Bajgar, Berlingieri, Calligaris, Criscuolo, & Timmis, 2020) and shortcomings in terms of coverage and representativeness.

In this study, we collect a unique micro-aggregated dataset to study business dynamism across 19 European countries. We gathered data by distributing harmonized data collection protocols (i.e. program codes) across multiple administrative and highly representative firm-level databases located within National Statistical Institutes and Central Banks. These data collection protocols generated a series of relevant statistics which we can use to study business dynamism and related factors in Europe. Such indicators are aggregated at the industry-country level and are comparable across countries. In general, our data covers the last two decades, from 1999 to 2019, although with some differences for a few countries. Given its administrative nature, our data is representative of the firm population in each country. The multi-country environment affords a unique setting to explore factors common across European economies and those that are more specific to particular

[1] One notable exception is the work coming out of the OECD's DynEmp project (Berlingieri, Blanchenay, Calligaris, & Criscuolo, 2017). These studies make use of micro-aggregated cross-country data contributed by a network of researchers, which is accessible at the OECD.

countries, thus offering clues as to strength of alternative explanations. We publish the data as part of the 8^{th} vintage of the CompNet database. In a related project, the previous data vintage has been also used to study firm concentration in Europe (Bighelli, Di Mauro, Melitz, & Mertens, 2021).

The first contribution of our paper is to document how job reallocation rates and young firm activity have changed in recent years in Europe, finding a widespread and strong decline in business dynamism metrics across almost all countries under analysis. We observe a structural aging of European firms: firms are getting older and growth rates of young firms have slowed down. As young firms are typically more dynamic, these composition effects lead to an overall decline in dynamism. In this regard it is important to note that While the decline in the share of young firm activity is an important part of the decline in business dynamism it is not the main driver of the decline. We find the decline in European business dynamism is common to all economic sectors, firm sizes, as well as young and old firms. Most of these findings are consistent with existing evidence on the US (Decker et al., 2020) and on a sample of OECD countries (Calvino, Criscuolo, & Verlhac, 2020).

As aggregate job reallocation rates are ultimately tied to the decisions of individual firms, the second contribution of our paper is to analyze the microeconomic mechanisms underlying such a decline. Our goal here is to explain broad declines in dynamism that are common across industries and firms thus abstracting away from compositional shifts which might be driven by changes in technology.[2] Given the availability of detailed information at the product-firm-level data, we focus on Germany, the largest economy in Europe, and in particular on its manufacturing sector, which is at the core of many continental value chains. In theory, a decline in reallocation can be the result of a decline in the dispersion in productivity/profitability realizations (i.e. a more tranquil business environment), or a decline in the responsiveness to those realizations. As in Decker et al. (2020), we find supportive evidence for the latter also in Europe. However, while they rationalize the declining responsiveness with an increase in adjustment costs, in this paper we highlight the role of technology and of firm market power, both in the product and labor markets. We find evidence of a declining trend in responsiveness among large and old firms, whereas young and small firms do not show statistically significant changes in their responsiveness over time. We show that larger firms have a higher market power than smaller ones and are more likely to adopt labor-saving technologies which hints at an important role for firm market power in determining responsiveness.[3] We do not consider adjusment costs in our model thus our results might alternatively be interpreted as being consistent with adjusment costs that are disproportionally tilted towards the largest firms.

The remainder of the paper is structured as follows: Section 2 reviews the literature. Section 3 discusses the data. Section 4 presents stylized facts on European business dynamism. Section 5 studies the mechanisms behind declining business dynamism. Section 6 concludes.

[2]Technological shocks are a standard explanation for firm age compositional shifts. See Decker et al. (2020) for a review. Here, like them, we abstract away from these types of explanations.

[3]We are further exploring these early results within a simple framework which allows us to decompose the role of technological change, wages, and firms' market power as key drivers of firms' derived labor demand.

2 Related Literature

Interest in business dynamics is not new going back at least to Schumpeter's notion of the dynamic "creative destruction" process. Since then economists have understood, in broad strokes, the way in which new and superior ideas, processes, and goods replace obsolete ones in modern market economies, and new and more productive firms are born or expand while less productive ones fail. However, the last few years have seen a renewed interest and empirical applications as a result of advances in economic measurement and specifically the development of new firm and establishment level administrative datasets in the United States. One of the most striking and now well-established patterns to have emerged from these new datasets is the secular decline in business dynamism. Decker et al. (2014) document trend declines in the rate of business startups and the pace of employment dynamism in the US economy over recent decades and a trend acceleration after 2000. One key to this decline is the decreasing role of dynamic young businesses in the economy accounting for 26% of the decline in job reallocation.

The decline in the startup rate and young firm activity in the U.S. is concerning since this population disproportionally contributes to jobs and productivity growth. Evidence from the US population of employer businesses indicates that 12% of them are high growth - defined as those that exhibit growth rates in excess of 25%. They account for 50% of gross output amongst continuing firms. In terms of employment, 17% of businesses are high growth and they account for 60% of gross job creation. Young firms are more likely to be high growth and startups alone contribute disproportionately to output and employment growth accounting for an additional 25 percent of gross job creation and a 15 percent of output creation.

Declines in dynamism are broad-based and not limited to startup activity. They are pervasive across all types of firms regardless of age and size, and across industries, and geographies. Compositional shifts account for about 15% of the overall decline in business dynamism (Decker et al., 2016).[4] Patterns of business dynamism are however sector-specific and the high-tech sector is of particular interest given the role young firms play in the innovation process - conditional on being innovative young firms are more R&D intensive than large mature firms (Acemoglu et al., 2018). In this regard, Haltiwanger et al. (2014) document the declines in business dynamism that occurred broadly across the U.S. economy also occurred in the high-tech sector in the post-2000 period.[5] Of concern is the fact that the high-tech sector which used to exhibit a relatively large amount of startup and high-growth activity now exhibits patterns similar to those of less innovative sectors. Not only has the pace of startup activity declined since 2000, businesses that do enter are less likely to be high-growth (Decker et al., 2016).

The decline in business dynamism is unlikely to have a single cause given industry-specific patterns, on the one hand, and common economy-wide patterns, on the other. Drawing insights from canonical models

[4]Industry effects work against and compensate for the decline in dynamism due to age composition effects.

[5]Prior to 2000 the U.S. high-tech sector bucked the overall trend and experienced a significant growth in dynamism driven in part by a surge of startups and reallocation activity.

of business dynamics, Decker et al. (2020) explore the role that adjustment costs play in the decline in business dynamism and the impact on the aggregate productivity decline. In these models reallocation arises as a business response to their individual productivity and profitability realizations. A decline in business dynamism will result from either a decline in innovations or a decline in responsiveness from an increase in adjustment costs. These authors find productivity dispersion has actually increased during this period in the U.S., whereas business employment responsiveness to productivity innovations has declined. They find the decline in responsiveness is responsible for a considerable drag on productivity growth of about -2.3 log points.

The decoupling of productivity dispersion and business dynamism can alternatively be interpreted as a decline in knowledge diffusion between frontier and laggard firms (Andrews, Criscuolo, and Gal, 2015; Akcigit and Ates, 2021). The decline in knowledge diffusion (e.g. due to more intense use of intellectual property protection or firm-specific customer data) implies higher concentration as market leaders are shielded from competition, higher markups, higher productivity dispersion, and less reallocation. Another mechanism possibly at play is the increase in market power in product markets over this period (De Loecker et al., 2021). These authors emphasize the effects of technological change and changing market structure as the primary drivers for the increase in market power which in turn drive the decline in reallocation. Finally, an increase in the use of intangible inputs in production (such as information technology) can also drive the decline in business dynamism through its effects on production and competition (De Ridder, 2019). In this framework intangibles reduce marginal costs and raise fixed costs, which gives firms with low adoption costs a competitive advantage and deters competitors from entering the market.

While much of the research focus has been on the U.S., an economy for which we have had detailed microdata for a few years now, there is a growing literature on business dynamics across several developed countries. Biosca, Criscuolo, and Menon (2013) find that the large contribution of young firms and high-growth firms to job creation that has been documented in the U.S. also hold in many European and other developed countries. Using a similar cross-country sample, Criscuolo, Gal, and Menon (2014) find that young firm activity fell between 2001 and 2011 in most countries, though the Great Recession makes inference of secular trends difficult. More recently, Calvino et al. (2020) analyse the trends in business dynamism across 18 OECD countries and 22 industries over the last two decades. They show pervasive declines in most industries. They find these declines are more strongly associated with factors related to market structure such as market concentration and productivity dispersion.

Our paper expands on this literature in two ways. First, we document patterns of business dynamism in European economies using a new micro-aggregated dataset which is representative and comparable across countries. Second, we explore the impacts on productivity growth from the decline in business dynamism in the European context and the role played by market power and technology (rather than adjustment costs) using a simple integrated model of derived labor demand.

3 Data

3.1 The CompNet data

We use micro-aggregated data from the 8^{th} vintage of the Competitiveness Research Network dataset (henceforth, CompNet) to derive stylized facts on European business dynamism. CompNet contains micro-aggregated firm-level-based information at the industry-country level for 19 European countries. We collected the data by running harmonized data collection protocols across administrative firm-level databases that are representative of the population of firms and which are located within national statistical institutes and national banks across European countries. As CompNet is based on firm-level data but aggregated at various levels (at the industry, sector, regional, and country level), we can circumvent legal restrictions that prevent combining administrative firm-level data across National Statistical Institutes and National Central Banks in Europe. To ensure the representativeness and comparability of the data, variables are weighted by firm population weights and, in the case of monetary variables, deflated by PPP-adjusted deflators.[6]

The data collection protocols calculate various firm and market performance measures aggregated at the industry, sector, regional, and country level. Most notably, this contains information on firm productivity, aggregate job reallocation rates, the number of young firms by size classes and other relevant statistics for studying business dynamism. We weight all these statistics using population weights from Eurostat to recover population statistics. Importantly, although CompNet is a micro-aggregated database, it contains rich information on the distribution of various statistics (i.e. various percentiles and standard deviations of variables). The data covers the years 1999-2019 and the NACE rev. 2 industries 10-33 (manufacturing), 41-43 (construction), 45-47 (wholesale/retail trade and repair of motor vehicles and motorcycles), 49-53 (transportation/storage), 55-56 (accommodation/food services), 58-63 (ICT), 68 (real estate), 68-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities).[7] As we aim for a comparable set of countries and sectors, in our analysis we drop the Real Estate sector as it is not consistently reported for all countries.[8]

The dataset comes in two versions: one contains firms with at least 20 employees (labelled ”20e sample”), while the other features firms with at least one employee. We focus most of our analysis on the 20e sample as this is available for all countries, however our results are robust to including smaller firms. We refer the readers to CompNet's User Guide for an in-depth discussion and provide detailed descriptive statistics for the data in Appendix A.1. In an accompanying study, the 7^{th} vintage of the data has been recently used to study the recent evolution of firm concentration in Europe (Bighelli et al., 2021).[9]

[6]The CompNet user guide (CompNet, 2021), accessible here, provides details on the procedures and data used for deflation.

[7]Time and industry coverage differ between countries and years, with complete coverage for all countries and sectors from 2009 to 2015. When aggregating results at the sector level, we remove France from the analysis in order to have a longer time series. We present results for France just in the country-level analysis for the years unaffected by the changes in the definition of the firm (2009-2015).

[8]Moreover, we exclude the sectors i) wholesale/retail trade and repair of motor vehicles and motorcycles and ii) accommodation/food services for Germany due to several unexplainable jumps in the underlying firm data.

[9]Additionally, older vintages of our data have been already used by several researchers, e.g. Autor, Dorn, Katz, Patterson, and Van Reenen (2020), Gutiérrez and Piton (2020).

Table 1. Coverage of CompNet data

Country	Years	Available sample	Excluded sectors
Belgium	2000-2018	20e/all firms	
Croatia	2002-2019	20e/all firms	
Czech Republic	2005-2019	20e/all firms	
Denmark	2001-2018	20e/all firms	
Finland	1999-2019	20e/all firms	
France	2009-2015	20e/all firms	
Germany	2001-2018	20e	Heterogeneous time coverage. Manufacturing starts in 2001, Wholesale & retail trade, and Accommodation & Food Service in 2005, the rest in 2003.
Hungary	2003-2019	20e/all firms	
Italy	2006-2018	20e/all firms	
Lithuania	2000-2019	20e/all firms	
Netherlands	2007-2018	20e/all firms	Real Estate
Poland	2002-2019	20e/all firms	
Portugal	2005-2018	20e/all firms	
Romania	2007-2019	20e	Real Estate
Slovenia	2002-2019	20e/all firms	
Slovakia	2000-2019	20e	
Spain	2008-2018	20e/all firms	
Sweden	2008-2018	20e/all firms	
Switzerland	2009-2018	20e/all firms	

3.2 German manufacturing data (at firm-product-level)

For the second part of this study, we use detailed firm-product-level data for the German manufacturing sector from 1995 to 2017. The data is supplied by the Research Data Centres of the Federal Statistical Office of Germany and contains, among others, information on firms' employment, investment, costs, and product quantities and prices at a ten-digit product classification. The firm-specific product price information in the data allows us to estimate quantity-based production functions (De Loecker, Goldberg, Khandelwal, & Pavcnik, 2016), which is essential to properly analyze how production technologies, markups, and labor market power affect firms optimal growth policy and thus business dynamism. To limit administrative burden, the statistical offices collect these data only for firms with at least 20 employees. Moreover, some variables are only collected for a representative and periodically rotating firm sample, covering 40% of all manufacturing firms with at least 20 employees. The latter includes information on intermediate input expenditures and labor costs by various categories.[10] As information on intermediates are key, we will focus our analysis on the representative 40% sample. The data has been used most recently in Mertens (2020, 2022) and we follow the data preparation steps in Mertens (2022). Beyond that, Appendix A.2 contains also all variable definitions and the sector classification, explains how to access these data, and provides relevant summary statistics.

[10] We clean the data from the top and bottom two percent outliers with respect to value-added over revenue and revenue over labor, capital, intermediate input expenditures, and labor costs. We drop quantity and price information for products' displaying a price deviation from the average product price located in the top and bottom one percent tails.

4 Business Dynamism in Europe

4.1 Measurement

To study business dynamism in Europe, we rely on two measures, which we calculate via our data collection protocols for various aggregation levels. Our main measure of interest is the job reallocation rate ($JR_{n,t}$), defined as in Davis, Haltiwanger, and Schuh (1996) by the weighted average firm growth rates,

$$g_{i,t} = \frac{L_{i,t} - L_{i,t-1}}{\overline{L}_{i,t,1}} \quad \text{with} \quad \overline{L}_{i,t,1} = 0.5(L_{i,t} + L_{i,t-1})\,. \tag{1}$$

Defining the aggregation weight as $s_{i,t} = \frac{\overline{L}_{i,t,1}}{\sum_n \overline{L}_{i,t,1}}$, the aggregate job reallocation rate is given by:

$$JR_{n,t} = \sum_n s_{i,t}\, g_{i,t} \tag{2}$$

where $n = c, k, j$ indicates the country, sector, and two-digit industry level respectively.

Our second measure is the share of young firms. We define firms as young if they are not older than five years. Whereas we can calculate the job reallocation rate for all countries, the share of young firms can only be defined for a subset of countries as several countries do not report the birth year of firms in their data. When calculating these measures at the country level, we start from sector-level results in our data and aggregate them to the country level.[11] This allows us to address differences in the sector coverage across countries.

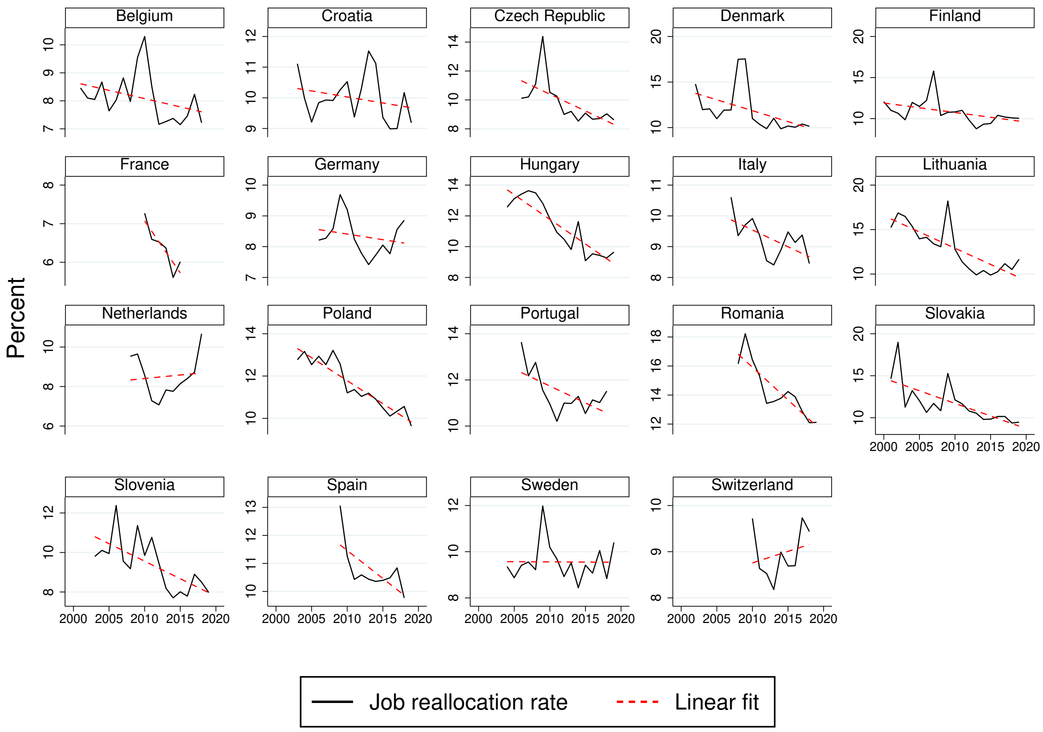
4.2 Facts on Business Dynamism in Europe

Fact 1. *There is a pervasive decline in job reallocation rates and young firm activity in Europe.*

Figure 1 and Figure 2 display job reallocation rates and the share of young firms out of the total number of firms by country for our sample of firms with at least 20 employees, respectively. 15 out of 19 countries show a declining trend in job reallocation rates. Only Switzerland and the Netherlands show a weakly positive trend. In levels, changes range from -35 percent for Romania to $+5$ percent for Switzerland. When we rely on the full sample data (i.e. including smaller firms), we find similar results. Similar to the job reallocation rate, there is a strong decline in the share of young firms. When we study the full sample, for most countries the picture is qualitatively unchanged. Except for Croatia and Slovenia where the estimated trend turns positive, it strongly increases for the Netherlands, and becomes more negative for other countries such as Italy. In some countries, the share of young firms with at least 20 employees falls by 30 percentage points and reaches almost zero in recent years. Figure 3 shows that the decline in the share of young firms is also associated with a severe decline in the share of workers employed in young firms.

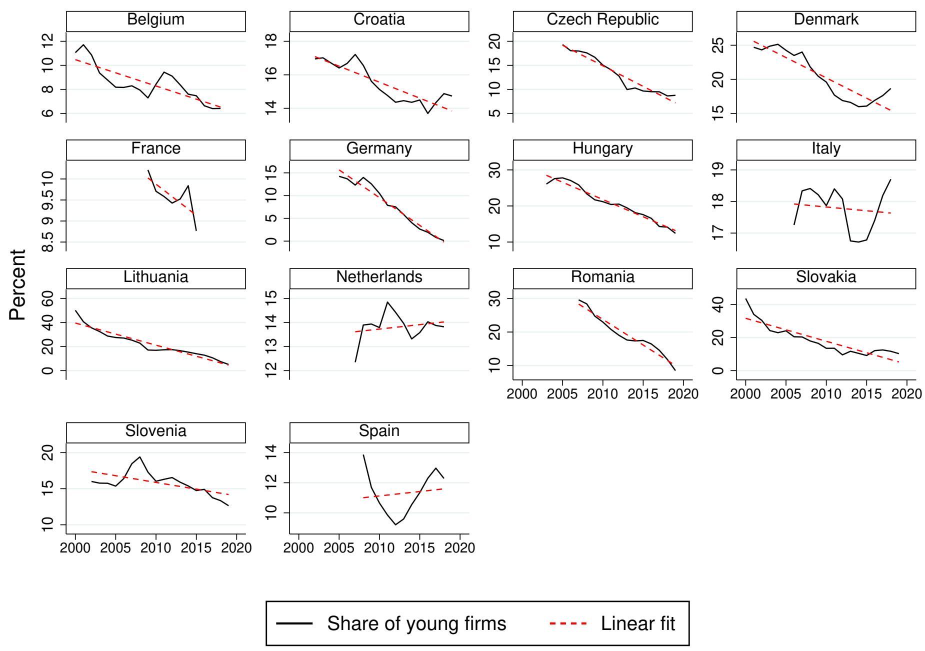
[11] The share of young firms can be readily aggregated by using information on the total number of firms in the population. We aggregate job reallocation rates using sector employment weights consistent with the definition of $s_{i,t}$ above.

Figure 1. Job reallocation rates in European countries.



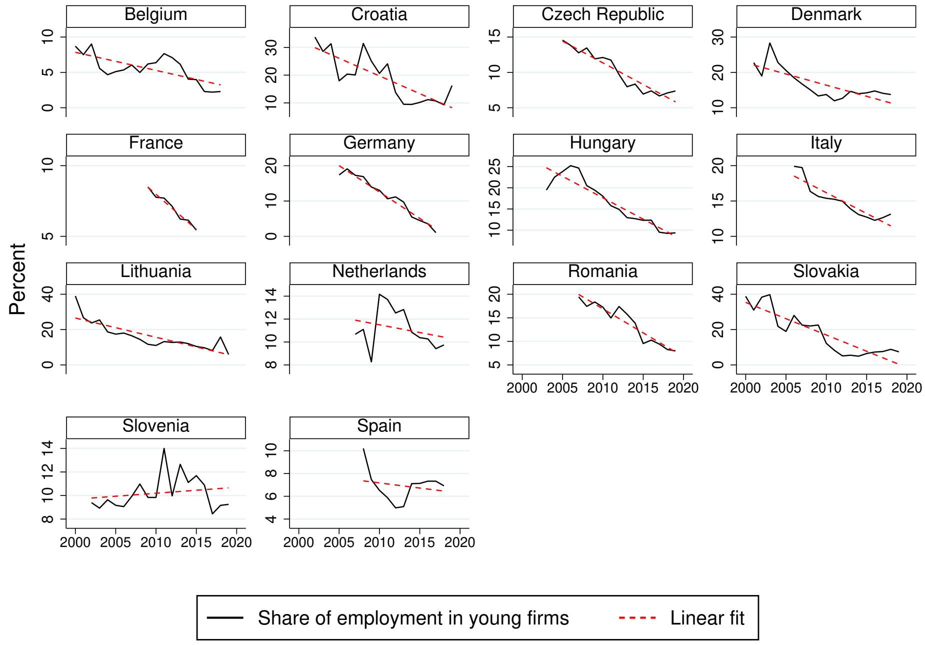
Notes: the black solid line shows country-level job reallocation rates as defined in Eq. (2). Real estate sector excluded.
Source: own calculations based on CompNet data. Firms with at least 20 employees.

Figure 2. Share of young firms in European countries.



Notes: the black solid line shows country-level shares of young firms in total firm counts. Real estate sector excluded. Young firms are firms not older than 5 years.
Source: own calculations based on CompNet data. Firms with at least 20 employees.

Figure 3. Employment shares of young firms in European countries.



Notes: the black solid line shows country-level shares of employment in young firms in total employment. Young firms are firms not older than 5 years.

Source: own calculations based on CompNet data. Firms with at least 20 employees.

Fact 2. *The decline in business dynamism is accompanied by a decline in high-growth young firms.*

Figure 4 shows the share of young firms by firm size-classes using data on all firms (i.e. we exclude Germany, France, Romania, Slovakia) and aggregating our results to the European level. We divide firms into 5 size classes: 0-9, 10-19, 20-49, 50-249, and larger than 250 employees. To account for different time coverage across countries, the shaded area in Figure 4 indicates the period for which we have a fully balanced panel. We find a particularly strong decline in young firm activity among the larger size-classes. In particular, the presence of young firms is declining by 21% in the first size-class, whereas the decrease is similarly steeper in the other ones: 44% in the second one, 52% in the third and fourth, and 45% in the fifth and largest size-class. Since this is by definition the set of fastest growing firms the implication is that not only there are fewer startups, but fewer of them become high-growth.

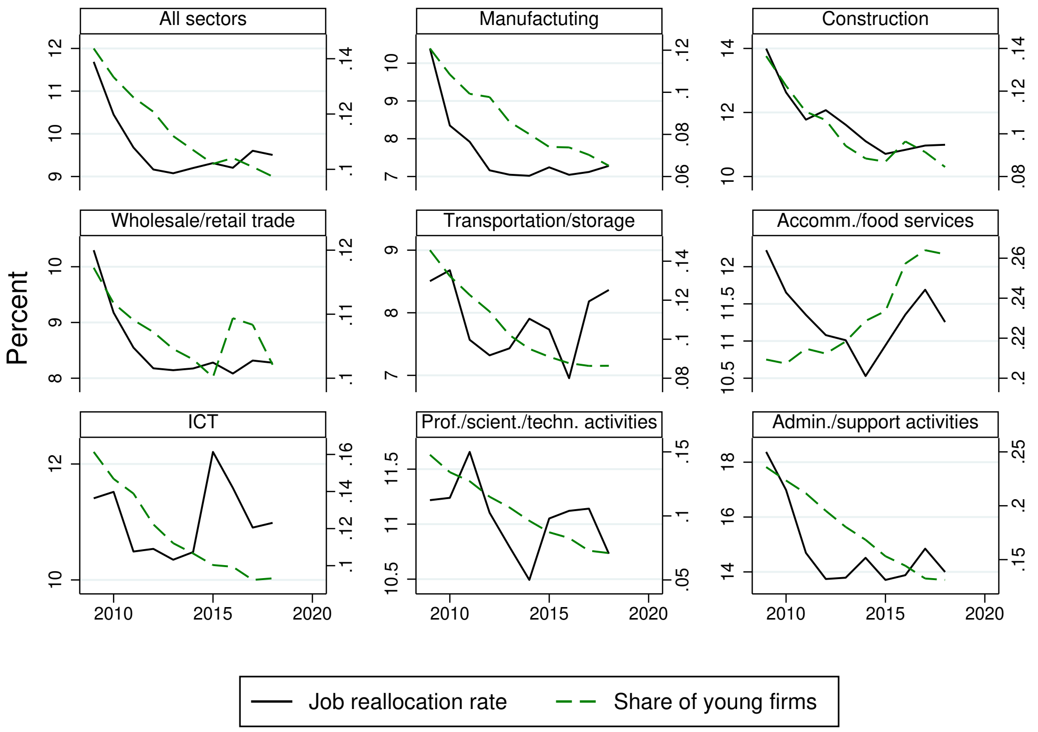
Figure 4. Young firms by size classes.

Notes: the black solid line shows European-level shares of young firms in total firm counts by size classes. Young firms are firms not older than 5 years. Real estate sector excluded.
Source: own calculations based on CompNet data for Belgium, Croatia, Czech Republic, Denmark, Hungary, Italy, Lithuania, Netherlands, Slovenia, Spain. Firms with at least one employee.

Fact 3. *The decline in business dynamism is evident across all economic sectors in Europe.*

Figure 5 displays job reallocation rates and young firm activity by economic sectors, using our balanced sample of countries and sectors. The results are aggregated to the European level. With the exception of the ICT sector, there is a clear negative trend in job reallocation rates across all sectors. Young firm activity declined consistently across all economic sectors.

Figure 5. European business dynamism by sectors.



Notes: the black solid (green dashed) line shows European-level job reallocation rates (shares of young firms in total firm counts) by sectors. Young firms are firms not older than 5 years and not defined for Finland, Poland, Switzerland, Portugal, and Sweden. Real estate sector excluded.
Source: own calculations based on CompNet data. Firms with at least 20 employees.

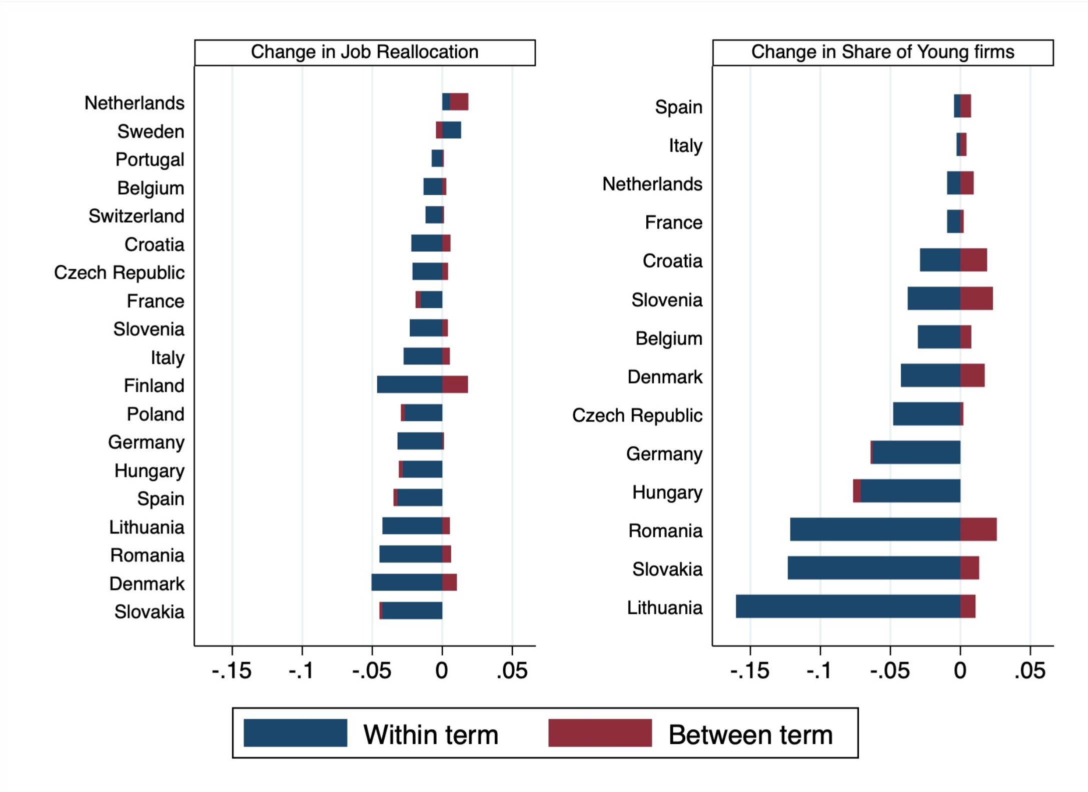
Fact 4. *The decline in business dynamism is driven by within-sector dynamics.*

The decline in European business dynamism can be driven by changes within sectors or by reallocation processes from more dynamic to less dynamic sectors. To study the role of such dynamics, we apply the following shift-share decomposition:

$$\Delta JR_{n,t} = JR_{n,t} - JR_{n,t-1} = \underbrace{\sum_n s_{j,0}\,\Delta JR_{j,t}}_{\text{within term}} + \underbrace{\sum_n \Delta s_{j,t}\,JR_{j,0} + \sum_n \Delta s_{j,t}\,\Delta JR_{j,t}}_{\text{reallocation term}} \tag{3}$$

where j indicates the sector within country n. $s_{j,0}$ is the fixed employment weight of industry j in the first year of observation for each country. $\sum_n s_{j,0}\,\Delta JR_{j,t}$ indicates within-sector changes, whereas the latter two terms capture all changes in aggregate job reallocation rates due to shifts in economic activity between sectors. We can apply a similar shift-share decomposition for the share of young firms. Figure 6 shows the results of these decompositions by country.

Figure 6. Results of shift-share decomposition.



Source: own calculations based on CompNet data. Firms with at least 20 employees.

Summing up, we document a widespread and strong decline in business dynamism across almost all 19 countries in our database. The fall in European business dynamism is accompanied by a decline in high-growth young firms. It occurs in all economic sectors and is mainly driven by within-sector dynamics. Overall, the European evidence is consistent with findings for the US.

5 Understanding business dynamism

5.1 Firms' responsiveness

In the following, we focus on job reallocation rates to study potential mechanisms behind changes in business dynamism. Job reallocation rates can be related to individual firms' labor demand. Decker, Haltiwanger, Jarmin, and Miranda (2020) (henceforth DHJM) use a general framework that shows that firms' labor demand can be expressed as a function of firms' revenue-productivity (or, more generally, profitability). Under a wide set of models, firms will increase (decrease) their labor demand if they experience a positive (negative) shock to their revenue-productivity, where revenue-productivity is a composite of technical efficiency and product demand. Formally, DHJM motivate a growth policy function that relates the labor growth ($g_{i,t}$) firm i to revenue productivity ($TFPR_{i,t}$) and their labor force ($L_{i,t}$):

$$g_{i,t} = h_t(TFPR_{i,t}, L_{i,t-1}) \quad \text{where} \quad \frac{\partial h_t}{\partial TFPR_{i,t}} > 0 \; .$$

That is, holding initial labor fixed, firms with a higher $TFPR_{i,t}$ realization will have a higher growth rate. Using this setting, they run the following reduced-form firm-level regression:

$$g_{i,t} = \beta_0^{DHJM} + \beta_1^{DHJM} tfpr_{i,t} + \beta_2^{DHJM} l_{i,t-1} + \epsilon_{i,t} \tag{4}$$

where lower case letters denote logs and β_1^{DHJM} measures the responsiveness of firms to productivity and demand shocks. The key result in DHJM is that a decline in the responsiveness of firms' employment growth to productivity shocks contributes significantly to the observed declines in business dynamism in the US and is a significant drag on productivity growth (i.e. a decline in β_1 conditional on controls).[12]

As our CompNet data is already aggregated at the industry-level, we cannot replicate the analysis of DHJM for the European data (yet).[13] We therefore use our firm-product-level data for the German manufacturing sector to estimate responsiveness parameters. Germany is the largest economy of Europe and manufacturing is a particular important sector in Germany. Similar as in DHJM, we augment Equation (4) by controlling for detailed four-digit industry times year fixed effects and estimate the model by periods and with a linear trend interaction. We follow DHJM and define $g_{i,t}$ as Equation (1). We derive $TFPR_{i,t}$ from a production function estimation as the product of firms' quantity-based productivity ($TFPR_{i,t}$) and an output price index. We detail the estimation of productivity and the associated production function in Appendix B.

We start by documenting in Figure 7 the overall decline in the manufacturing sector job reallocation rates in

[12]Note that Eq. (4) is specified in terms of productivity levels instead of productivity changes. This formulation is a result of controlling for lagged employment levels and is consistent with DHJM. Equation (4) can be derived by reformulating firms' first order condition from a standard profit maximization problem. We discuss this in more detail in Section 5.2.

[13]We are currently extending the data program of CompNet data collection procedures that will be run in the next months in each of the 19 European countries.

Germany. The German manufacturing data is an unbalanced panel of firms with at least 20 employees. It does not explicitly include entry or exit events so we focus only on the subset of continuing firms for which we have consecutive data for at least two years. Between 1996 and 2016 job reallocation rates fell from approximately 7% to less than 5%, a 28% decline.[14] In terms of mechanism, this decline can be the result of a decline in the dispersion in productivity/profitability realizations (i.e. a more tranquil business environment), or from a decline in the responsiveness to those realizations.

Figure 7. Evolution of job reallocation rates in the German manufacturing sector.

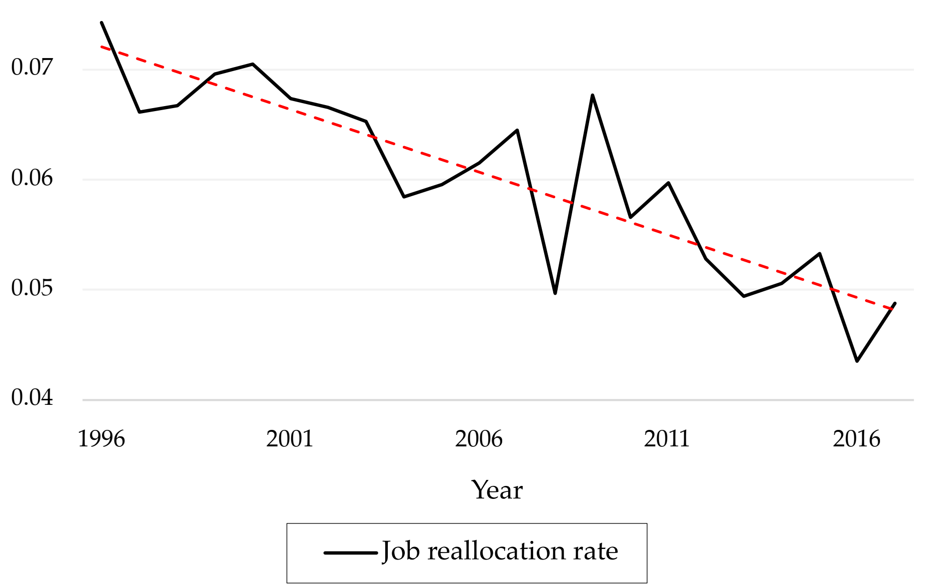


Table 2 presents the results from estimating the responsiveness regressions (Equation (4)). Starting with column (1), we estimate an average responsiveness to TFPR over this whole time period of β_1 = 0.02. Moving to columns 3 through 8 we can see this average reflects a consistent trend decline from 0.037 in the late 1990's to 0.0158 in the late 2010's. This decline is consistent with findings in the U.S. (Decker et al., 2020). Although our baseline responsiveness estimate is considerably lower than that estimated for the U.S. we find the responsiveness coefficient experiences stronger declines.[15]

[14]Job reallocation rates are considerably lower than comparable estimates for the U.S.. There are several reasons for this. In addition to excluding entry and exit events, we are also looking at a subset of the population of larger firms. Finally, job reallocation rates are at the firm level and as such they represent net job reallocation rathen than the sum of the establishment components.

[15]Differences is unit of analysis (firms vs establishments) and sample composition account for the level differences.

Table 2. Responsiveness in the German manufacturing sector.

	Dependent variable: firm-level DHS labor growth rate (g_{it})							
	All years (1)	**All years (2)**	**1995-98 (3)**	**1999-02 (4)**	**2003-06 (5)**	**2007-10 (6)**	**2011-14 (7)**	**2015-17 (8)**
$tfpr_{it}$	0.020***	2.790***	0.0370***	0.0284***	0.0185***	0.0180***	0.0156***	0.0158***
	(0.00116)	(0.373)	(0.00481)	(0.00332)	(0.00245)	(0.00216)	(0.00190)	(0.00265)
l_{it-1}	-0.0055***	-0.00522***	-0.00726***	-0.00524***	-0.00905***	-0.00361***	-0.00160***	-0.00296***
	(0.000315)	(0.000316)	(0.000904)	(0.000727)	(0.000640)	(0.000610)	(0.000580)	(0.000847)
$tfpr_{it} * year_{it}$		-0.00138***						
		(0.000186)						
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	174,799	174,799	26,584	33,453	36,117	33,810	32,102	12,733
# of firms	37,737	37,737	16,925	12,144	10,908	11,758	10,640	9,548
R-squared	0.073	0.073	0.072	0.065	0.064	0.112	0.034	0.059

Notes: results from estimating Eq. (4) for separate intervals and while controlling for industry-year fixed effects. Significance: *10 percent, **5 percent, ***1 percent. German manufacturing sector firm-product-level data.

5.2 Mechanisms behind declining business dynamism

Using German manufacturing firm data, we document a decline in firms' responsiveness to productivity shocks that is consistent with U.S. evidence. In this section we ask: What can explain a decline in responsiveness and ultimately job reallocation rates between firms? DHJM discuss that declining responsiveness may signal an increase in adjustment costs or more generally an increase in "wedges" in firms' first order conditions. While they focus on the adjustment costs hypothesis, in our analysis we focus on the role of technology and of firm market power, both in the product and labor markets. To do that, we derive a simple framework that adds additional structure to the setting considered by DHJM. This allows us to decompose the role of technological change, wages, and firms' market power as key drivers of firms' employment growth functions and thus job reallocation rates between firms. Consider that firms produce physical output ($Q_{i,t}$) by combining labor ($L_{i,t}$), capital ($K_{i,t}$), and intermediates ($M_{i,t}$):

$$Q_{i,t} = f_{i,t}(L_{i,t}, K_{i,t}, M_{i,t})\, TFP_{i,t}. \tag{5}$$

$TFP_{i,t}$ denotes total factor productivity. Revenues are given by $P_{i,t}Q_{i,t}$, with $TFP_{i,t} * P_{i,t} \equiv TFPR_{i,t}$ defining revenue productivity, i.e. the composite from firms' technical efficiency and demand conditions. Ultimately, a firms' growth function will depend on $TFPR_{i,t}$. We do not restrict the production function to any specific form and only require it to be continuous and twice differentiable.

Firm operating profits are given by:

$$P_{i,t}(Q_{i,t})Q_{i,t} - w_{i,t}(L_{i,t})L_{i,t} - z_{i,t}M_{i,t} - r_{i,t}K_{i,t}, \tag{6}$$

where $w_{i,t}$, $z_{i,t}$, and $r_{i,t}$ denote unit costs for labor, intermediates, and capital. Note that output prices and wages are functions of quantities and labor inputs, respectively. This allows for the presence of firm market power in firms' product and labor markets. From the first order condition for labor, we find:

$$w_{i,t}\left(1+\frac{1}{\varepsilon^L}\right)=\frac{P_{i,t}}{\mu_{i,t}}MPL_{i,t} \tag{7}$$

where ε^L is the inverse labor supply elasticity, $\mu_{i,t}$ firms' product markup, and $MPL_{i,t}$ denotes the marginal product of labor. As standard in the literature, $1+\frac{1}{\varepsilon^L}\equiv\gamma_{i,t}$ is a measure of firms' monopsony power. Reformulating Equation (7) gives an expression for derived labor demand:

$$L^*=\frac{(P_{i,t}\,Q_{i,t})}{(\mu_{i,t}\,\gamma_{i,t})}\frac{\theta^L_{i,t}}{w_{i,t}}=\left[K_{i,t}^{\theta^K_{i,t}}\,M_{i,t}^{\theta^M_{i,t}}\,\frac{TFPR_{i,t}}{\mu_{i,t}\,\gamma_{i,t}}\,\frac{\theta^L_{i,t}}{w_{i,t}}\right]^{\frac{1}{1-\theta^L_{i,t}}}, \tag{8}$$

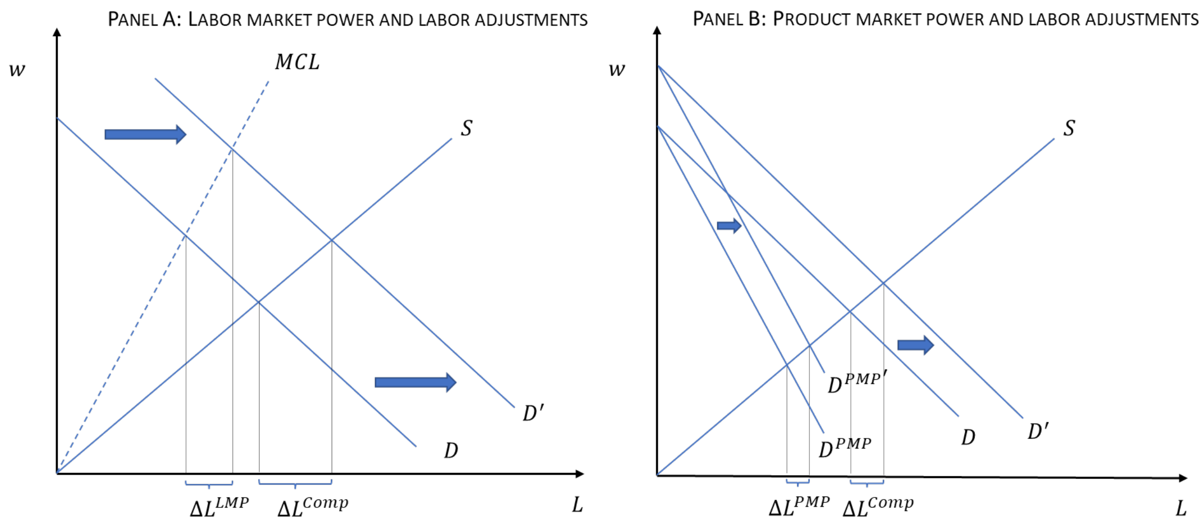
where $\theta^X_{i,t}$, with $X=L,K,M$ is the output elasticity of input X. In particular, $\theta^L_{i,t}$ reflects the technological importance of labor in production processes. Equation (8) shows that the pass-through of revenue productivity to labor demand is governed by several factors. First, a higher wage decreases labor demand. Intuitively, at a higher wage firms will hire fewer workers for a given increase in revenue productivity. Second, a lower technological importance of labor decreases labor demand. At the extreme, firms that do not need any workers ($\theta^L_{i,t}\to 0$), will increase less their labor demand when experiencing a positive productivity shock. Third, both higher product and labor market power decrease the responsiveness of labor demand. Firm markup affects the pass-through by a reduction in firms' output which lowers the demand for all factors. The effect of firms' monopsony power operates through the marginal cost curve of labor being steeper than the labor supply curve.[16] The term $K_{i,t}^{\theta^K_{i,t}}M_{i,t}^{\theta^M_{i,t}}$ enters Eq. (8) to capture the interdependence between labor and these other input factors.

To build the intuition of the role of market power, Figure 8 illustrates the comparative statics of derived labor demand after a revenue productivity shock in the presence (or not) of product and labor market power.[17] Panel A shows that when a firm has (some) monopsony power, it will equalize labor demand with their marginal costs of labor (MCL) instead of labor supply (S). As a result, we expect the change in firms' labor under monopsony (ΔL^{LMP}) to be lower than under competitive labor markets (ΔL^{Comp}) for a given labor demand shock (shift from D to D'). Panel B shows the adjustment process when a firm has product market power, but no monopsony power. The labor demand curve will rotate inward when firms have product market power, as the firm adjusts along its marginal revenue curve (rather than the demand curve). In the first-order

[16]Intuitively, firms with monopsony power pay wages below their marginal revenue product of labor. This leads to lower job reallocation between firms as they will not be as responsive to productivity shocks. On the downside, firms can retain workers in the face of a negative productivity shocks as there is a gap between what workers earn and what they produce. On the upside, firms would only be able to hire more workers by raising overall wages and giving up rents. Both factors lead to less job reallocation. As the market power of firms increases job reallocation across firms also decreases.

[17]A similar argument has been made in De Loecker et al. (2021) for product market power. The effect of labor market power on job dynamism has, to our knowledge, not been discussed yet.

Figure 8. Firm derived factor demand with and without market power.



Notes: Panel A shows how labor market power affects firms' labor adjustments. Panel B shows how product market power affects firms' labor adjustment

condition it is the marginal revenue product of labor $MRPL_{i,t} = \frac{P_{i,t}}{\mu_{i,t}} \frac{\partial Q_{i,t}}{\partial L_{i,t}}$ that must be equated to the wage. In general, this will cause a lower labor adjustment (ΔL^{PMP}).

In sum, our simple framework predicts that a decline in labor responsiveness to revenue productivity shocks can be driven by i) a rise in firm product or labor market power, ii) by a decrease in the ratio of labor technological importance to firms to wages. In the aggregate, a reallocation of activity towards firms with high market power, high wages, and less labor-intensive technology can explain the decline in job reallocation rates documented in this paper.

5.3 Adding market power and technology to the responsiveness analysis

Taking logs of Eq. (8) and subtracting the log of lagged labor gives firms' growth policy function from our framework:

$$\begin{aligned} g_{i,t}(1-\theta^L_{i,t}) =& \beta_1 \theta^K_{i,t} k_{i,t} + \beta_2 \theta^M_{i,t} m_{i,t} + \beta_3 tfpr_{i,t} + \beta_4 ln(\mu_{i,t}) + \beta_5 ln(\gamma_{i,t}) \\ &+ \beta_6 ln(\theta^L_{i,t}) + \beta_7 ln(w_{i,t}) + \beta_8 l_{i,t-1}(1-\theta^L_{i,t}) \,, \end{aligned} \tag{9}$$

where $l_{i,t}$, $k_{i,t}$, $m_{i,t}$, $tfpr_{i,t}$ denote logs or labor, capital, intermediates and TFPR.[18] Equation (9) is a much more general growth policy function than in Equation (4) as it takes into account the impact of firm-specific technology ($\theta^X_{i,t}$), market power ($\mu_{i,t}$ and $\gamma_{i,t}$), and wages on firms growth policy.[19] We call the parameter β_1^{DHJM} from Eq. (4) the unconditional responsiveness parameter that is used by DHJM, while we estimate several

[18] In Eq. (9) $g_{i,t}$ is derived in terms of log differences. In our empirical application, we follow DHJM and use growth rates as in Eq. (1) instead of log differences. Following Davis et al. (1996), these growth rates have the desirable property that they reflect firm-level equivalents of the aggregate job reallocation rate as the job reallocation rate is a weighted sum of firm-level growth rates. Moreover, they are less sensitive to outliers.

[19] Decker et al. (2020) also mention the role of "correlated wedges" which can be interpreted as market power terms.

versions of Eq. (9) after conditioning on market power, technology, and wages, which recovers a conditional responsiveness parameters that holds constant either market power, technology, or wages. When moving from the unconditional specification in (4) to the conditional version (9), we can assess the role of technology, firm market power, and wages in reducing the responsiveness of labor demand to a change in its productivity. In future versions of this study, we will incorporate an analysis on the explaining power of each of these four factors for declining job reallocation rates in future versions of this study. For now, we focus on preliminary evidence on the results for (4) that replicate for Germany those of DHJM.

We estimate output elasticities, TFPR, and firms' market power using a production function approach that we describe in Appendix B. We rely on a flexible translog production function that we estimate separately by two-digit industries. To allow for time-variation in the estimated parameters of the production we estimate the model using moving averages for 5 year intervals. As a result we drop the first and last two years of data from our sample. Importantly, as we observe firm-specific price information in our data, we can control for firms' output and input price variation when estimating the production function. We estimate the production function using a control function approach, similar to Wooldridge (2009). We precisely describe how we recover our parameters of interest from the production function estimation in Appendix B. To estimate market power parameters, we use a ratio estimator as, among others, in De Loecker and Warzynski (2012), Mertens (2020, 2022), and Morlacco (2019). Table 3 provides descriptive statistics on how market power and technology differ across firms and over time.

Table 3. Overview of changes in average outcomes by firm size class.

Panel A	Share of Total Employment (FTE)			Average output elasticity of labor		
Size class (# employees)	1995	2014	*Change*	1995	2014	*Change*
≤ 50	0.05	0.04	*-0.01*	0.27	0.26	*-0.01*
51-100	0.08	0.08	*+0.00*	0.30	0.29	*-0.01*
101-250	0.17	0.18	*+0.01*	0.34	0.30	*-0.04*
> 250	0.70	0.70	*+0.00*	0.37	0.34	*-0.03*

Panel B	Average labor market power			Average product market power		
Size class (# employees)	1995	2014	*Change*	1995	2014	*Change*
≤ 50	0.83	0.79	*-0.04*	1.09	1.12	*+0.02*
51-100	0.98	0.92	*-0.06*	1.07	1.11	*+0.04*
101-250	1.12	1.11	*-0.01*	1.06	1.09	*+0.03*
> 250	1.30	1.34	*+0.04*	1.03	1.06	*+0.03*

Notes: Table 3 shows firm-level domestic employment shares, average output elasticities of labor, average labor market power parameters, and average product markups by firm employment size classes. German manufacturing sector. Firms with at least 20 employees.

In levels, we find that more than 70% of workers in our sample (in FTE) are employed by largest firms, which on average have higher labor output elasticities and firm labor market power, but not necessarily higher product market power. By comparing these values over time, we don't find evidence of significant reallocation of domestic employment share towards larger firms. However, their average average output elasticities decreased by more among them. In terms of market power, while we observe a generalized increase in product market power, labor market power has increased only among largest firms.

Table 4 reports our estimates for the differences in the unconditional responsiveness parameters between large vs. small and young vs. old firms. We define a firm as being small when it is below the 25th percentile of the size distribution and large if above the 75th, while medium firms are all firms in between. To measure firm age, we exploit the fact that some variable of our data are collected only for the population of firms with at least 20 employees and define age as the years since firms are first occurring in our data, i.e. we define age in terms of years after employing at least 20 employees for the first time. In this regard, we define a firm young when it has reached this threshold in the last three years.[20] We find that larger and older firms display lower responsiveness. The unconditional responsiveness coefficient on large (small) firms is 0.019 (0.031), implying that an increase in revenue productivity by one percent is associated with 0.02 (0.03) percent employment growth, holding constant the initial size of the firm. Similarly, young firms show a much higher responsiveness coefficient than old firms (columns 7 and 9). As larger firms have a higher labor market power than smaller ones, these heterogeneities suggests already an important role for labor market power in determining responsiveness, which we are further exploring at the moment. Table 4 also shows how responsiveness has changed over time for the individual firm groups. We find a negative trend in responsiveness for large and old firms, whereas young and small firms do not show statistically significant changes in their responsiveness over time. The decline in responsiveness for large firms is consistent with the increase in market power, most notably labor market power, and the fall in the technological importance of labor among these firms.

[20] Moreover, we set all age values to missing before 2002 to allow for a period of time between the first year in our data and the definition of age (100% of firms are defined as being young in the early years).

Table 4. Responsiveness in the German manufacturing sector, by firm size and age.

Dependent variable: firm-level DHS labor growth rate (g_{it})

	Firm size class					
	Small (1)	**Small** (2)	**Medium** (3)	**Medium** (4)	**Large** (5)	**Large** (6)
$tfpr_{it}$	0.0312*** (0.00274)	1.107 (0.979)	0.0236*** (0.00168)	3.401*** (0.600)	0.0186*** (0.00226)	3.587*** (0.696)
l_{it-1}	-0.0410*** (0.00297)	-0.0411*** (0.00297)	-0.00474*** (0.00101)	-0.00457*** (0.00101)	-0.00204** (0.000894)	-0.00123 (0.000891)
$tfpr_{it} * year_{it}$		-0.000536 (0.000487)		-0.00168*** (0.000299)		-0.00178*** (0.000346)
Industry-Year FE	YES	YES	YES	YES	YES	YES
Observations	38,872	38,872	85,230	85,230	49,223	49,223
# of firms	14,499	14,499	21,646	21,646	7,621	7,621
R^2	0.120	0.120	0.097	0.097	0.134	0.135

	Firm age class			
	Young (7)	**Young** (8)	**Old** (9)	**Old** (10)
$tfpr_{it}$	0.0383*** (0.00575)	2.435 (2.659)	0.0171*** (0.00124)	1.340** (0.559)
l_{it-1}	-0.0122*** (0.00124)	-0.0122*** (0.00125)	-0.00328*** (0.000359)	-0.00323*** (0.000359)
$tfpr_{it} * year_{it}$		-0.00119 (0.00132)		-0.000658** (0.000278)
Industry-Year FE	YES	YES	YES	YES
Observations	15,095	15,095	102,187	102,187
# of firms	7,178	7,178	23,113	23,113
R^2	0.159	0.159	0.082	0.082

Notes: results from estimating Equation (4) for separate firm groups and while controlling for industry-year fixed effects. Significance: *10 percent, **5 percent, ***1 percent. German manufacturing sector firm-product-level data.

6 Conclusions

In this paper, we presented novel evidence on business dynamism in Europe. We established that, similarly to the US, in the last decades there has been a widespread decline in business dynamism in most European countries. Job reallocation rates and share of young firms in total firm counts decline in almost all the 19 countries we study. This is accompanied by a decline in employment shares within young firms and high-growth young firms. The decline in business dynamism occurs through all economic sectors and is mainly a within-sector phenomenon. When studying the mechanisms behind this decline in business dynamism, we find that firms labor adjustments became less sensitive to productivity shocks. We rationalize these results with a simple theory that shows how market power and changing production technologies can drive for the decline in business dynamism. In future work, we are planning to test for the importance of market power and technology in determining business dynamism.

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Appendices

A Data

A.1 The CompNet Dataset

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

The dataset, in its 8th Vintage version (the version we use), includes the 19 countries listed in Table 1. The data covers the years 1999-2019 and the NACE rev. 2 industries 10-33 (manufacturing), 41-43 (construction), 45-47 (wholesale/retail trade and repair of motor vehicles and motorcycles), 49-53 (transportation/storage), 55-56 (accommodation/food services), 58-63 (ICT), 68 (real estate), 68-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities).

In addition to providing unweighted firm-level based micro-aggregates, the CompNet team produces a weighted version of its dataset to enhance representativeness. All the statistics available in the dataset are weighted using population weights from Eurostat Structural Business Statistics (SBS) to recover population figures when only a sample of firms in the underlying firm data is observed.

Table A1 shows coverage ratios for employment and number of firms available from the (cleaned) underlying sample in column (1) and (3), whereas columns (2) and (4) show the weighted figures for the same indicators. We benchmark CompNet statistics against the aggregate ones presented in Eurostat SBS.

In Panel A, columns (1) and (3) show a high coverage of both employment and number of firms, showing that the numerosity of the sample is able to cover for most of the employment: on average, CompNet is able to cover for 75% of employment and 72% of the number of firms present in Eurostat. In addition to this, columns (2) and (4) show that the weighting scheme applied to raw figures is successful in bringing sample statistics to respective population ones. Indeed, coverage ratios for weighted figures are always close to one. Turning to a sectoral analysis, Panel B shows more heterogeneity in terms of coverage across sectors, with coverage ratios ranging from 42 to 78% in employment and from 38 to 73% in the number of firms. Notwithstanding this fact, even here the weighting routine recovers population figures well, signaling the appropriateness of the underlying sample.

Table A1. Country and Sector coverage after weighting (20e sample).

Panel A. Country Coverage

Country	Years	Employment unweighted	Employment weighted	Number of firms unweighted	Number of firms weighted
		(1)	(2)	(3)	(4)
Belgium	2000-2018	0.76	1.05	0.74	1.03
Croatia	2002-2019	0.86	1.03	0.84	1.01
Czech Republic	2005-2019	0.71	1.04	0.49	1.00
Denmark	2001-2018	0.80	1.00	0.86	1.03
Finland	1999-2019	0.89	0.99	0.88	1.00
France	2009-2015	0.70	0.81	1.01	1.07
Germany*	2005-2018	-	1.05	-	1.00
Hungary	2003-2019	0.86	1.12	0.83	1.02
Italy	2006-2018	0.75	1.02	0.70	1.00
Lithuania	2000-2019	0.83	1.00	0.81	1.00
Netherlands	2007-2018	0.85	1.06	0.81	1.03
Poland	2002-2019	0.79	1.02	0.62	1.02
Portugal	2005-2018	0.91	1.01	0.90	1.00
Romania	2007-2019	0.85	0.98	0.86	1.00
Slovenia	2002-2019	0.89	1.03	0.82	1.03
Slovakia	2000-2019	0.88	1.04	0.79	1.01
Spain	2008-2018	0.68	1.08	0.62	1.00
Sweden	2008-2018	0.61	0.90	0.78	1.04
Switzerland	2009-2018	0.67	1.11	0.33	1.00
TOTAL	2009-2016	0.58	1.01	0.59	1.01
Cross-country simple average	2009-2016	0.75	1.02	0.72	1.01

Panel B: Macro – Sector Coverage (balanced sample excluding France)

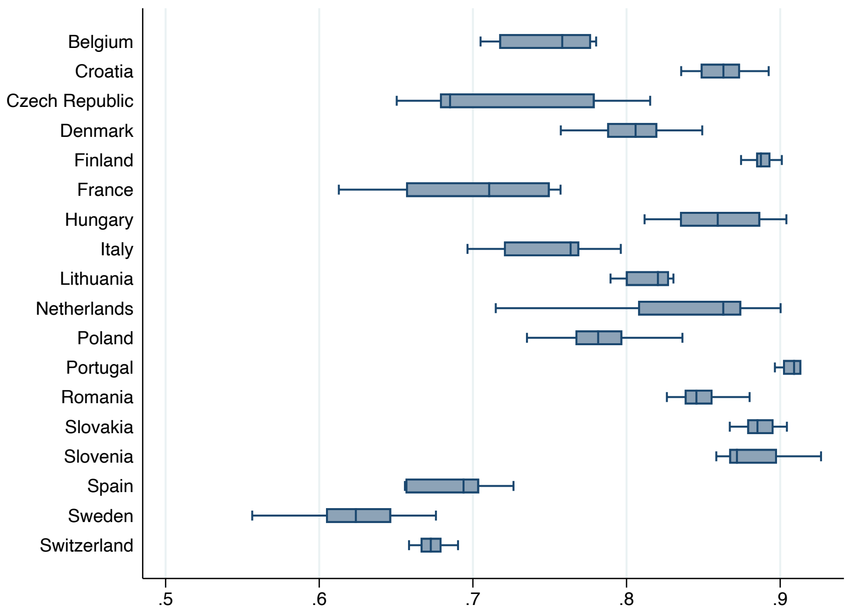
Macro-sector	Employment unweighted	Employment weighted	Number of firms unweighted	Number of firms weighted
	(1)	(2)	(3)	(4)
Manufacturing	0.53	1.03	0.56	1.00
Construction	0.57	1.03	0.51	1.00
Wholesale and retail trade	0.78	1.01	0.73	1.00
Transportation and storage	0.49	1.05	0.42	1.00
Accommodation and food service activities	0.76	1.05	0.70	1.04
ICT	0.55	1.01	0.50	1.01
Professional Activities	0.42	1.01	0.40	1.01
Administrative and service	0.49	1.06	0.38	1.00

Notes: Panel A displays country-level statistics using the first and last year of observation for each country. Panel B shows statistics for each sector using the balanced set of countries and sectors from 2009 to 2018 (excluding France, the Wholesale and retail trade and Accommodation and Food Service activities sector for Germany). * Germany does not contain sample number information for confidentiality reasons and hence it is excluded from all the unweighted computations.
Source: own calculations based on CompNet data. Firms with at least 20 employees.

Finally, Figures A1 to A4 show the yearly distribution of the coverage ratios for employment and the number of firms, both in the weighted and unweighted versions. By doing so, we are able to understand whether the good coverage ratios are average results of dispersed figures across years, or whether coverage ratios cluster around a good percentage. For what concerns employment, this is the case for most of the countries, especially in the weighted version of the dataset (that is here used). Few exceptions arise, namely France, Sweden, and Switzerland. Looking at the sectoral aggregation, we see that all the ratios cluster around the value of one, pointing again at the quality of the dataset we are using. Qualitatively similar results are found when analyzing the number of firms in the dataset.

Figure A1. Employment coverage ratios by country: outcome of weighting.

(a) Unweighted.



(b) Weighted

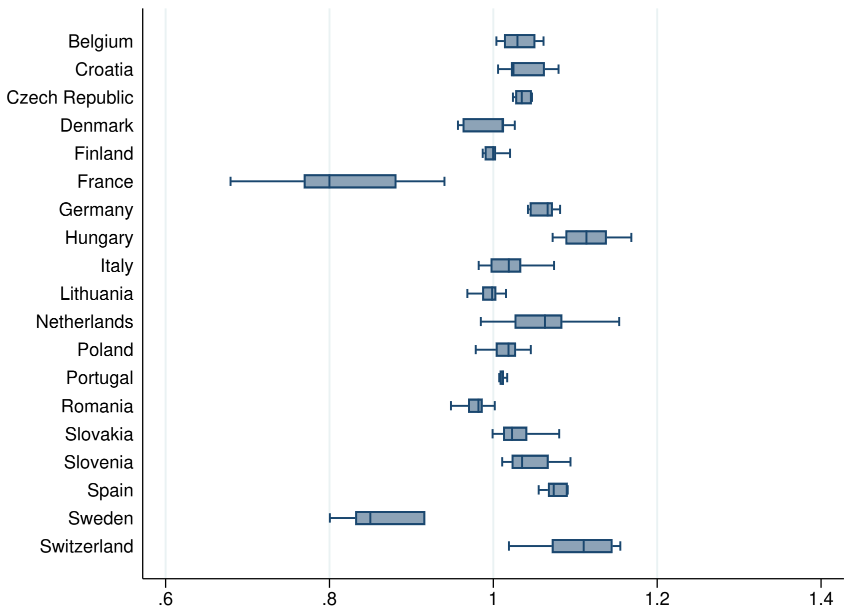
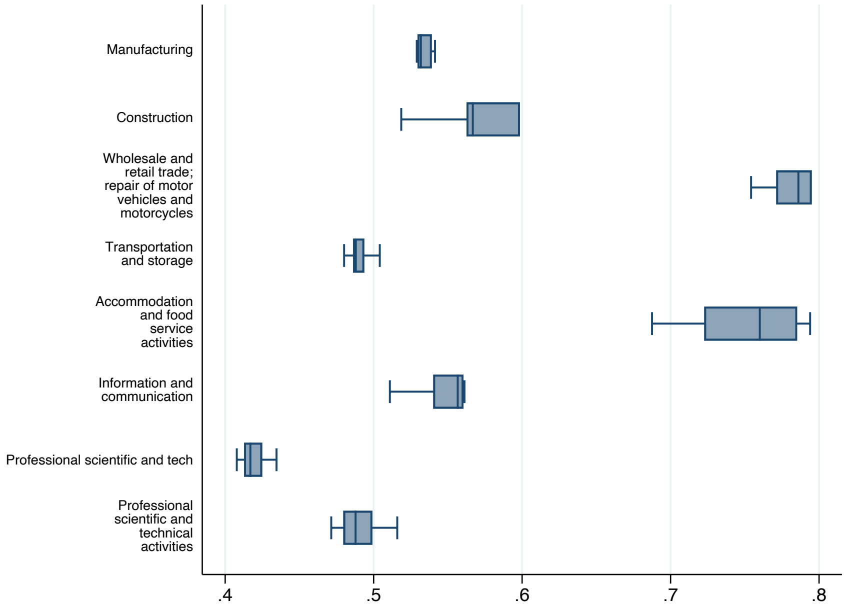


Figure A2. Employment coverage ratios by macro-sector: outcome of weighting.

(a) Unweighted.



(b) Weighted

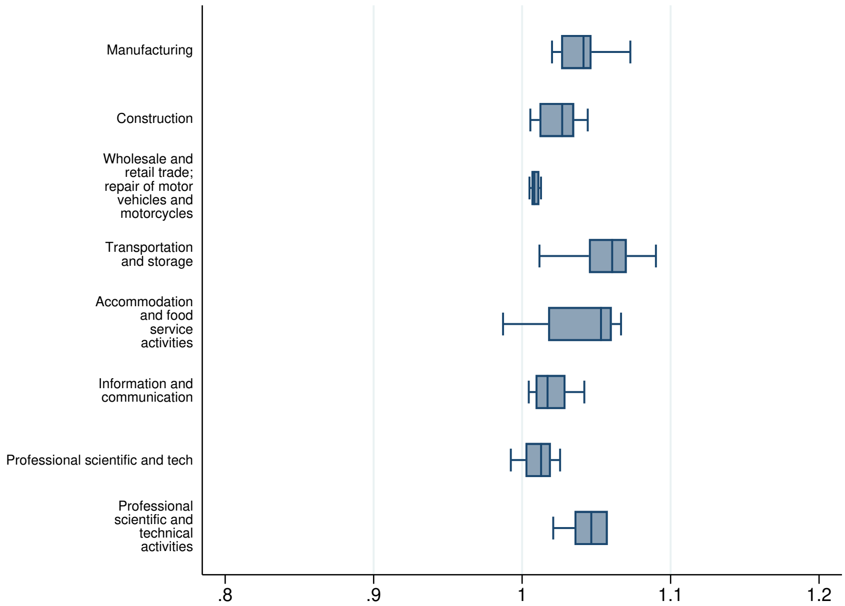
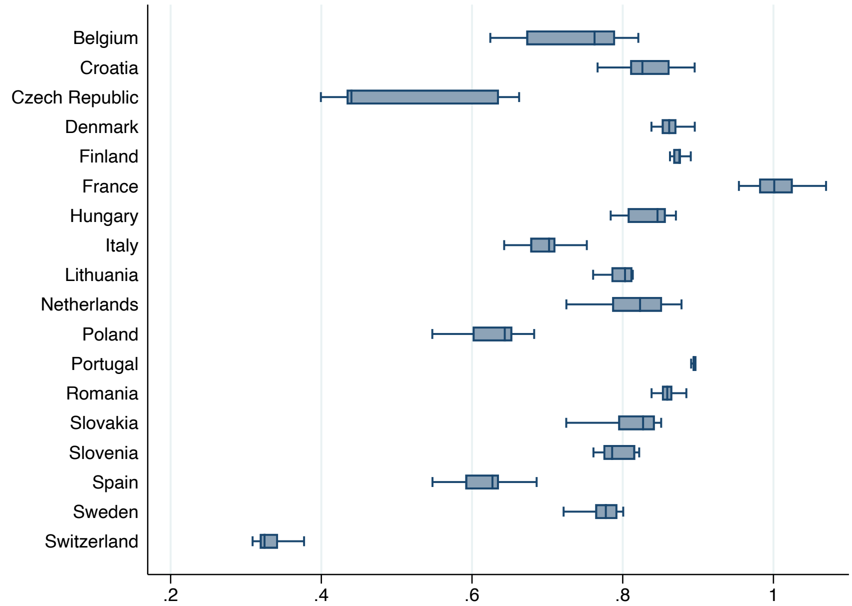


Figure A3. Number of firms coverage ratios by country: outcome of weighting.

(a) Unweighted.



(b) Weighted

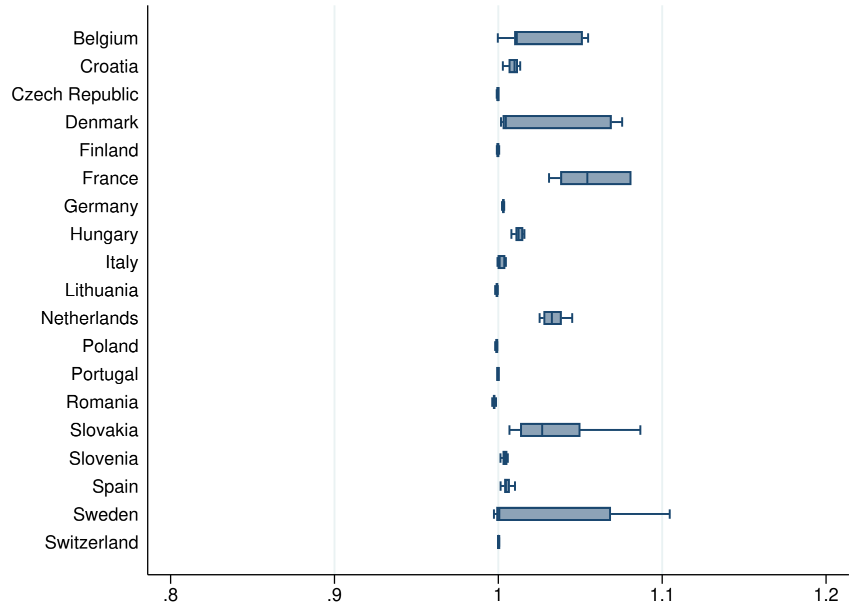
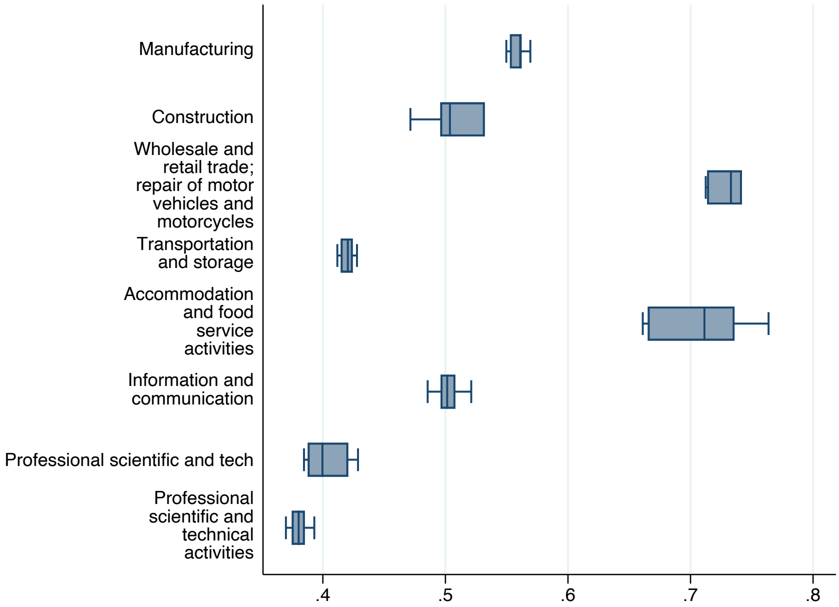
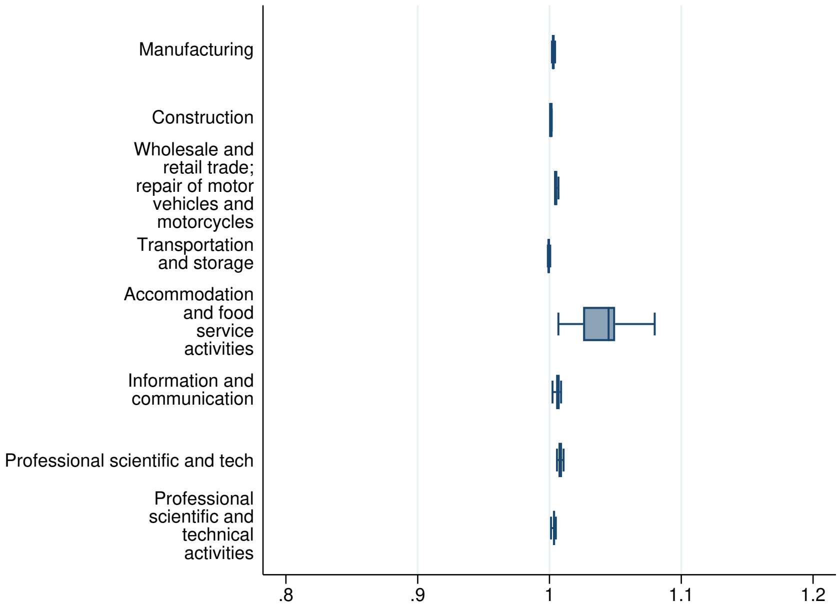


Figure A4. Number of firms coverage ratios by macro-sector: outcome of weighting.

(a) Unweighted.



(b) Weighted



A.2 German manufacturing sector firm-product-level data

Data access. The data can be accessed at the "Research Data Centres" of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Data request can be made at: https://www.forschungsdatenzentrum.de/en/request.

The statistics we used are: "AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen", "Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", "Panel der Kostenstrukturerhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden". The data are combined by the statistical offices and provided as a merged dataset.

Variable definitions. The following list presents an overview on the variable definitions of all variables used in this article. This includes variables used in other sections of the Appendix.

- $L_{i,t}$: Labor in headcounts.
- $w_{i,t}$: Firm wage (firm average), defined as gross salary + "other social expenses" (latter includes expenditures for company outings, advanced training, and similar costs) divided by the number of employees.
- $K_{i,t}$: Capital derived by a perpetual inventory method following Mertens (2020, 2022), who used the same data.
- $M_{i,t}$: Deflated total intermediate input expenditures, defined as expenditures for raw materials, energy, intermediate services, goods for resale, renting, temporary agency workers, repairs, and contracted work conducted by other firms. Nominal values are deflated by a 2-digit industry-level deflator supplied by the statistical office of Germany.
- $z_{i,t}\ M_{i,t}$: Nominal values of total intermediate input expenditures.
- $P_{i,t}\ Q_{i,t}$: Nominal output / nominal total revenue, defined as total gross output, including, among others, sales from own products, sales from intermediate goods, revenue from offered services, and revenue from commissions/brokerage.
- $Q_{i,t}$: Quasi-quantity measure of physical output, i.e. $P_{i,t}\ Q_{i,t}$ deflated by a firm-specific price index (denoted by $\Pi_{i,t}$, see the definition of $\Pi_{i,t}$ below).
- $\Pi_{i,t}$: Firm-specific Törnqvist price index, derived as in Eslava, Haltiwanger, Kugler, and Kugler (2004). See the Appendix B.1 for its construction.
- $p_{i,k,t}$: Price of a product k.
- $share_{i,k,t}$: Revenue share of a product k in total firm revenue.

- $ms_{i,t}$: Weighted average of firms' product market shares in terms of revenues. The weights are the sales of each product in firms' total product market sales.

- $G_{i,t}$: Headquarter location of the firm. 90% of firms in my sample are single-plant firms.

- $D_{i,t}$: A four-digit industry indicator variable. The industry of each firm is defined as the industry in which the firm generates most of its sales.

- $E_{i,t}$ (or in logs, $e_{i,t}$): Deflated expenditures for raw materials and energy inputs. Nominal values are deflated by a 2-digit industry-level deflator for intermediate inputs and which is supplied by the statistical office of Germany. $E_{i,t}$ is part of $M_{i,t}$.

- $Exp_{i,t}$: Dummy-variable being one, if firms generate export market sales.

- $NumP_{i,t}$: The number of products a firm produces.

Table A2. Summary statistics of our German manufacturing sample.

Variables	**Mean** (1)	**Sd** (2)	**P25** (3)	**Median** (4)	**P75** (5)	**Observations** (6)
Average real wage	33,560	11,091	25,666	33,211	40,646	242,982
Labor market power parameter	1.03	0.51	.069	0.93	1.25	242,982
MRPL	35,348	23,301	19,787	29,650	44,440	242,982
Product market power parameter	1.09	0.18	0.97	1.05	1.17	242,982
Number of employees	303.74	2,220.89	47	94	223	242,982
Deflated capital stock in thousands	39,900	408,000	2,384	6,673	21,100	242,982
Deflated intermediate input expenditures in thousands	49,200	743,000	2,649	7,047	22,400	242,982
Deflated capital per employee in thousands	95.97	96.04	38.03	68.54	119.88	242,982
Value-added over revenue	0.40	0.13	0.30	0.40	0.49	242,982
Value-added labor share	0.78	0.26	0.63	0.76	0.88	242,982
Nominal revenue in thousands	74,200	1,000,000	5,097	12,400	37,100	242,982
Log of real value-added per employee	10.55	0.87	10.12	10.61	11.06	222,215
Number of products	3.60	6.72	1	2	4	242,982
Export status dummy	0.78	0.42	1	1	1	242,982
Revenue weighted product market shares (euro-based, in percent)	10.79	17.65	0.77	3.23	12.28	242,982
Average real wage	33,560	11,091	25,666	33,211	40,646	242,982

Deriving a time consistent industry classification. During our long time series of data, the NACE classification of industry sectors (and thus firms into industries) changed twice. Once in 2002 and once in 2008. Because our estimation of the production function relies on having a time-consistent industry classification at the firm level (as we allow for sector-specific production functions) it is crucial to recover a time-consistent NACE industry classification. Recovering such a time-consistent industry classification from official concordance tables is, however, problematic as they contain many ambiguous sector reclassifications. To address this issue, we follow the procedure described in Mertens (2020) and use information on firms' product mix to classify firms into NACE rev 1.1 sectors based on their main production activities. This procedure exploits that the first four digits of the ten-digit GP product classification reported in the German data are identical to the NACE sector classification (i.e. they indicate the industry of the product). Applying this method demands a consistent reclassification of all products into the GP2002 scheme (which corresponds to the NACE rev 1.1 scheme). Reclassifying products is, however, due to the granularity of the ten-digit classification, less ambiguous than reclassifying industries. In the few ambiguous cases, we can follow the firms' product mix over the reclassification periods and unambiguously reclassify most products (i.e. we observe what firms produce before and after reclassification years). Having constructed a time-consistent product-industry classification according to the GP2002 scheme, we attribute every firm to the NACE rev 1.1 industry in which it generates most of its revenue. When comparing our classification with the one of the statistical offices for the years 2002-2008 (years in which industries are already reported in NACE rev 1.1), we find that my two-digit and four-digit classification of firms into industries matches the classification of the statistical offices in 95% and 86% of all cases, respectively. Table A3 provides a few examples on the product classifications within the product-level data used to calculate firm-specific price indices as described in Appendix B.

Table A3. Examples of industry and product classifications.

NACE rev. 1.1	Product code	Description
18		**Manufacture of wearing apparel; dressing and dyeing of fur**
1821		Manufacture of workwear
		Products
	182112410(0)	Long trousers for men, cotton (not contracted)
	182112510(0)	Overalls for men, cotton (not contracted)
	182112510(2)	Overalls for men, cotton (contracted production)
	182121350(2)	Coats for women, chemical fiber (contracted production)
27		**Manufacture of basic metals**
2743		Lead, zinc, and tin production
		Products
	274312300(0)	Zinc, unwrought, refined (not contracted)
	274311300(0)	Lead, unwrought, refined (not contracted)
	274311500(0)	Lead, unwrought, with antimony (not contracted)
	274328300(0)	Tin sheets and tapes, thicker than 0.2mm (not contracted)
	274328600(0)	Tin sheets and tapes, not thicker than 0.2mm (not contracted)

Notes: the reported GP2002 product codes define 6,500 distinct products at the nine-digit level from which we find 5,927 in our database and 4,194 in our final sample of firms. The last number of each product code (10th position) indicates whether the product was manufactured as contracted work (2).
Source: Mertens and Müller (2020).

B Estimating production functions, TFPR, and market power terms

B.1 Production function estimation

We follow Mertens (2020) in estimating the production function, by apply a time-varying approach. We discuss how we introduce time variation in the estimated parameters by estimating the production function for specific time-intervals after discussing the identification of the production function. Specifically, we assume the following translog production function:

$$q_{i,t} = \boldsymbol{\phi}'_{i,t}\,\boldsymbol{\beta} + \omega_{i,t} + \epsilon_{i,t}\,. \tag{B1}$$

$q_{i,t}$ denotes the log of produced quantities and $\boldsymbol{\phi}'_{i,t}$ captures the production inputs Capital ($K_{i,t}$), labor ($L_{i,t}$), and intermediates ($M_{i,t}$) and its interactions. The production function is specified in logs as

$$\begin{aligned} q_{i,t} =& ,\beta_l l_{i,t} + \beta_m m_{i,t} + \beta_k k_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{mm} m_{i,t}^2 + \beta_{kk} k_{i,t}^2 \\ &+ \beta_{lk} l_{i,t} k_{i,t} + \beta_{lm} l_{i,t} m_{i,t} + \beta_{km} k_{i,t} m_{i,t} + \beta_{lkm} l_{i,t} k_{i,t} m_{i,t} + \omega_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{B2}$$

where smaller letter denote logs. The output elasticity of labor is

$$\frac{\partial q_{i,t}}{\partial l_{i,t}} = \beta_l + 2\beta_{ll} l_{i,t} + \beta_{lm} m_{i,t} + \beta_{lk} k_{i,t} + \beta_{lkm} k_{i,t} m_{i,t}\,.$$

$\epsilon_{i,t}$ is an i.i.d. error term and $\omega_{i,t}$ denotes Hicks-neutral productivity and follows a Markov process. $\omega_{i,t}$ is unobserved to the econometrician, yet firms know $\omega_{i,t}$ before making input decisions for flexible inputs (intermediates in our case). We assume that only firms' input decision for intermediates depends on productivity shocks. Labor and capital do not respond to contemporary productivity shocks (our results are similar when allowing labor to respond to productivity innovations).

There are three issues preventing an estimation of the production function (B1) using OLS:

1. We need to estimate a physical production model to recover the relevant output elasticities. Although we observe product quantities, quantities cannot be aggregated across the various products of multi-product firms. Relying on the standard practice to apply sector-specific output deflators does not solve this issue if output prices vary within industries.

2. We do not observe firm-specific input prices for capital and intermediate inputs. If input prices are correlated with input decisions and output levels, this creates an endogeneity issue.

3. The facts that productivity is unobserved and that firms' flexible input decisions depend on productivity shocks create another endogeneity problem.

We now discuss we solve these three identification problems.

B.1.1 Solving identification problem 1: Deriving a firm-specific output price index as in Eslava et al. (2004).

As we cannot aggregate output quantities across different products of a firm (a common problem), we follow Eslava et al. (2004) and construct a firm-specific price index from observed output prices. We use this price index to purged observed firm revenue from price variation by deflating firm revenues with this price index.[21] We construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products in the following way:

$$\Pi_{i,t} = \prod_{g=1}^{n} \frac{p_{i,k,t}}{p_{i,k,t-1}}^{1/2(share_{i,k,t}+share_{i,k,t-1})} \Pi_{i,t-1} \,. \tag{B3}$$

$\Pi_{i,t}$ is the price index, $p_{i,k,t}$ is the price of good k, and $share_{i,k,t}$ is the share of this good in total product market sales of firm i in period t. The growth of the index value is the product of the individual products' price growths, weighted with the average sales share of that product over the current and the last year. The first year available in the data is the base year, i.e. $\Pi_{i,1995} = 100$. If firms enter after 1995, we follow Eslava et al. (2004) and use an industry average of the computed firm price indices as a starting value. Similarly, we impute missing product price growth information in other cases with an average of product price changes within the same industry.[22] After deflating firm revenue with this price index, we end up with a quasi-quantity measure of output, for which, with slightly abusing notation, we keep using $q_{i,t}$.[23]

B.1.2 Solving identification problem 2: Accounting for unobserved input price variation.

While the recent literature stresses the so-called "output-price-bias" when estimating production functions, previous work has also highlighted that unobserved input prices introduce another identification problem. To control for input price variation across firms, we use a firm-level analogue of De Loecker et al. (2016) and define a price-control function from firm-product-level output price information that we add to the production function (B1):

$$q_{i,t} = \boldsymbol{\phi}'_{i,t}\boldsymbol{\beta} + B_{i,t}((\pi_{i,t}, ms_{i,t}, G_{i,t}, D_{i,t}) \times \boldsymbol{\phi}^c_{i,t}) + \omega_{i,t} + \epsilon_{i,t} \,. \tag{B4}$$

$B_{i,t}(.) = B_{i,t}((\pi_{i,t}, ms_{i,t}, G_{i,t}, D_{i,t}) \times \boldsymbol{\phi}^c_{i,t})$ is the price control function consisting of our logged firm-specific output price index ($\pi_{i,t}$), a logged sales-weighted average of firms' product market sales shares ($ms_{i,t}$), a head-quarter location dummy ($G_{i,t}$) and a four-digit industry dummy ($D_{i,t}$). $\boldsymbol{\phi}^c_{i,t}) = [1; \boldsymbol{\phi}_{i,t}]$, where $\boldsymbol{\phi}_{i,t}$ includes

[21] This approach has also been applied in various other studies, e.g. Smeets and Warzynski (2013).

[22] For roughly 30% of all product observations in the data, firms do not have to report quantities as the statistical office views them as not being meaningful.

[23] Note that, as discussed in Bond, Hashemi, Kaplan, and Zoch (2021), using an output price index does not fully purge firm-specific price variation. There remains a base year difference in prices. Yet, using a firm-specific price index follows the usual practice of using price indices to deflate nominal values, we are thus following the best practice. Moreover, it is the only available approach when pooling multi- and single-product firms. Estimating the production unction separately by single-plant firms requires other strong assumptions like perfect input divisibility of all inputs across all products. Finally, our result are also robust to using cost-share approaches to estimate the production function, which requires other strong assumptions.

the production function input terms as specified in (B2). These are either in monetary terms and deflated by an industry-level deflator (capital and intermediates) or already reported in quantities (labor). The constant entering $\phi^c_{i,t}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\phi_{i,t}$ (a consequence of the translog production function). The idea behind the price-control function $B(.)$ is that output prices, product market shares, firm location, and firms' industry affiliation are informative about input prices of firms. Particularly, we assume that product prices and market shares contain information about product quality and that producing high-quality products requires expensive high-quality inputs. As De Loecker et al. (2016) discuss, this motivates to add a control function containing output price and market share information to the right-hand side of the production function to control for unobserved input price variation emerging form input quality differences across firms. We also include location and four-digit industry dummies into $B(.)$ To additionally absorb remaining differences in local and four-digit industry-specific input prices. Conditional on elements in $B(.)$, we assume that there are no remaining input price differences across firms. Although restrictive, this assumption is more general than the ones employed in most other studies estimating production functions without having access to firm-specific price data and which implicitly assume that firms face identical input and output prices within industries. A notable difference between the original approach of De Loecker et al. (2016) and our version is that they estimate product-level production functions, whereas we transfer their framework to the firm-level. For that we use firm-product-specific sales shares in firms' total product market sales to aggregate firm-product-level information to the firm-level. This implicitly assume that i) such firm aggregates of product quality increase in firm aggregates of product prices and input quality, ii) firm-level input costs for inputs entering as deflated expenditures increase in firm-level input quality, and iii) product price elasticities are equal across the various products of a firm. These or even stricter assumptions are always implicitly invoked when estimating firm-level production functions. Finally, note that even if some of the above assumptions do not hold, including the price control function is still preferable to omitting it. This is because the price control function can nevertheless absorb some of the unobserved price variation and does not require that input prices vary between firms with respect to all elements of $B_{i,t}(.)$. The estimation can regularly result in coefficients implying that there is no price variation at all. The attractiveness of a price control function lies in its agnostic view about existence and degree of input price variation.

B.1.3 Solving identification problem 3: Controlling for unobserved productivity.

To address the dependence of firms' intermediate input decision on unobserved productivity, we follow Olley and Pakes (1996) and Levinsohn and Petrin (2003) and employ a control function approach. We base our control function on firms' consumption of energy and raw materials, which we denote with $e_{i,t}$ and which are components of total intermediate inputs. Inverting the demand function for $e_{i,t}$ defines an expression for productivity:

$$\omega_{i,t} \equiv g_{i,t}(.) = g_{i,t}(e_{i,t}, k_{i,t}, l_{i,t}, \mathbf{\Gamma}_{i,t}). \tag{B5}$$

$\mathbf{\Gamma}_{i,t}$ captures state variables of the firm, that in addition to $k_{i,t}$ and $l_{i,t}$ affect firms demand for $e_{i,t}$. Ideally, $\mathbf{\Gamma}_{i,t}$ should include a wide set of variables affecting productivity and demand for $e_{i,t}$. We include dummy variables for export ($EX_{i,t}$) activities, the log of the number of products a firm produces ($NumP_{i,t}$) and the average wage a firm pays ($w_{i,t}$) into $\mathbf{\Gamma}_{i,t}$. The latter absorbs unobserved quality and price differences that shift input demand for $e_{i,t}$. As discussed in De Loecker and Scott (2016), this accounts for the criticism of Gandhi, Navarro, and Rivers (2020). Recap that productivity follows a first order Markov process. We allow that firms can shift this Markov process as described in Doraszelski and Jaumandreu (2013) and De Loecker (2013), giving rise to the following law of motion for productivity: $\omega_{i,t} = h_{i,t}(\omega_{i,t-1}, \mathbf{T}_{i,t-1}) + \xi_{i,t} = h_{i,t}(.) + \xi_{i,t}$, where $\xi_{i,t}$ denotes the innovation in productivity and $\mathbf{T}_{i,t} = (EX_{i,t}, NumP_{i,t})$ reflects that we allow for learning effects from export market participation and (dis)economies of scope through adding and dropping products to influence firm productivity.[24] Plugging (B5) and the law of motion for productivity into (B4) gives

$$q_{i,t} = \boldsymbol{\phi}'_{i,t}\boldsymbol{\beta} + B_{i,t}(.) + h_{i,t}(.) + \epsilon_{i,t} + \xi_{i,t}\,, \tag{B6}$$

which constitutes the basis of our estimation.

B.1.4 Introducing time-variation and identifying moments

We estimate Equation (B6) separately by two-digit NACE rev. 1.1 industries and 5-year moving averages using a one-step estimator as in Wooldridge (2009).[25] Our estimator uses lagged values of flexible inputs (i.e. intermediates) as instruments for their contemporary values to address the dependence of firms' flexible input decisions on realizations of $\xi_{i,t}$. Similarly, we use lagged values of terms including firms' market share and output price index as instruments for their contemporary values as we consider these to be flexible variables.[26] We define identifying moments jointly on $\epsilon_{i,t}$ and $\xi_{i,t}$:

$$E[(\epsilon_{i,t} + \xi_{i,t})\mathbf{Y}_{i,t}] = 0. \tag{B7}$$

$\mathbf{Y}_{i,t}$ includes lagged interactions of intermediate inputs with labor and capital, contemporary interactions of labor and capital, contemporary location and industry dummies, the lagged output price index, lagged market shares, lagged elements of $h_{i,t}(.)$, and lagged interactions of the output price index with production inputs.

[24] Doraszelski and Jaumandreu (2013) also highlight the role of RD investment in shifting firms' productivity process. We would also like to add this information to the productivity model, but do not observe RD expenditures for the early years in our data.

[25] We approximate $h_{i,t}(.)$ by a third order polynomial in all of its elements, except for the variables in $\mathbf{\Gamma}_{i,t}$. Those we add linearly. $B_{i,t}(.)$ is approximated by a flexible polynomial where we interact the output price index with elements in $\boldsymbol{\phi}_{i,t}$ and add the vector of market shares, the output price index, and the location and industry dummies linearly. Interacting further elements of $B_{i,t}(.)$ with $\boldsymbol{\phi}_{i,t}$ creates too many parameters to be estimated. This implementation is similar to De Loecker et al. (2016).

[26] This also addresses any simultaneity concerns with respect to the price variables entering the right-hand side of my estimation.

Formally this implies

$$\mathbf{Y}'_{i,t} = (J_{i,t}(.), A_{i,t-1}(.), T_{i,t-1}(.), \Psi_{i,t}(.), \boldsymbol{\nu}_{i,t-1}) \ , \tag{B8}$$

where for convenience we defined:

$J_{i,t}(.) = (l_{i,t},\, k_{i,t},\, l^2_{i,t},\, k^2_{i,t},\, l_{i,t}k_{i,t},\, G_{i,t},\, D_{i,t})$,

$A_{i,t}(.) = (m_{i,t},\, m^2_{i,t},\, l_{i,t}m_{i,t},\, k_{i,t}m_{i,t},\, l_{i,t}k_{i,t}m_{i,t},\, ms_{i,t},\, \pi_{i,t})$,

$T_{i,t}(.) = \big((l_{i,t},\, k_{i,t},\, l^2_{i,t},\, k^2_{i,t},\, l_{i,t}k_{i,t},\, m_{i,t},\, m^2_{i,t},\, l_{i,t}m_{i,t},\, k_{i,t}m_{i,t},\, l_{i,t}k_{i,t}m_{i,t}) \times \pi_{i,t}\big)$,

$\Psi_{i,t}(.) = \sum_{n=0}^{3} \sum_{w=0}^{3-b} \sum_{h=0}^{3-n-b} \; l^n_{i,t-1}\, k^b_{i,t-1}\, e^h_{i,t-1}$, and

$\boldsymbol{\nu}_{i,t-1} = (Exp_{i,t-1},\, NumP_{i,t-1},\, w_{i,t-1})$,

with $w_{i,t}$ denoting the average wage a firm pays.

As we estimate the production function separately by 5-year moving averages, we drop the two first and last years (1995,1996,2016,2017) from our estimation sample. Our routine recovers time-specific production function coefficients, which, as mentioned in De Loecker, Eeckhout, and Unger (2020), is a parsimonious way of allowing for biased technological change without resorting to additional assumptions on the competitiveness of labor markets. The latter is key for us, as we are interested in studying the effect of labor market power on business dynamism. Since the production function routine is demanding in terms of data requirements, we estimate the production only by two-digit industries. We also tested alternative estimates using cost-shares approaches where we define cost-shares based on four-digit industry data. The results are unchanged.

B.2 Calculating TFPR, output elasticities and market power parameters

We calculate revenue productivity $TFPR$ directly from the estimate from our production function. Note that we estimate a quantity-based production function. $TFPR$ is defined as quantity-productivity ($TFPQ$) times output prices (Foster, Haltiwanger, & Syverson, 2008): $TFPR_{i,t} = TFPQ_{i,t} * P_{i,t}$, where $TFPQ_{i,t} = \omega_{i,t}$. Using Eq. (B6) we can calculate $TFPR$ as:

$$TFPR_{i,t} = q_{i,t} - \boldsymbol{\phi}'_{i,t}\,\boldsymbol{\beta} - B_{i,t}(.) + \pi_{i,t}, \tag{B9}$$

where $\pi_{i,t}$ is the log of our firm-specific price index and $q_{i,t}$ are quasi-quantities as described in the previous section (sales divided by our firm-specific price index). We calculate the output elasticity of input $X = K, L, M$ as $\frac{\partial q_{i,t}}{\partial x_{i,t}} = \theta^X_{i,t}$, where $x = log(X)$. To recover the quantity-based output elasticity we use the estimate of our price control function to purge input price variation from deflated production inputs (capital and intermediates) as described in De Loecker et al. (2016). We derive the markup ($\mu_{i,t}$) using the approach by De Loecker and Warzynski (2012), relying on firms' first order condition for intermediate input:

$$\mu_{i,t} = \theta^M_{i,t} \frac{P_{i,t}Q_{i,t}}{z_{i,t}M_{i,t}}\,, \tag{B10}$$

where $\theta^M_{i,t}$ is the output elasticity of intermediate inputs. $P_{i,t}Q_{i,t}$ are sales, $z_{i,t}M_{i,t}$ are intermediate input expenditures. For Equation (B10) to hold, we must assume that intermediate input price are exogenous to firms and that intermediate inputs are a flexible input. Finally, we derive firms' labor market power ($\gamma_{i,t}$) following a series of recent papers (Morlacco (2019); Mertens (2020, 2022); Hershbein, Macaluso, and Yeh (2020)) by combining firms input decision for intermediates and labor

$$\gamma_{i,t} = \frac{\theta^L_{i,t}}{\theta^M_{i,t}} \frac{z_{i,t}M_{i,t}}{w_{i,t}L_{i,t}} = \frac{MRPL_{i,t}}{w_{i,t}}\,. \tag{B11}$$

where $w_{i,t}L_{i,t}$ are labor expenditures. $MRPL_{i,t}$ is the marginal revenue product of labor. Equation (B11) relies on the same assumptions as the approach of De Loecker and Warzynski (2012) to estimate markups. In addition, for Equation (B11) to perfectly measure firms' monopsony power, it requires that there are no adjustment costs to labor. If this holds, Equation (B11) is also informative on the labor supply elasticity: $\gamma_{i,t} \equiv 1 + \frac{1}{\varepsilon^L_{i,t}}$, where $\varepsilon^L_{i,t}$ is the labor supply elasticity. As $\gamma_{i,t}$ is defined as the wedge between the marginal revenue product of labor and the wage, it will also capture any worker-side labor market power (e.g. rent-sharing) and unobserved adjustment costs (see Mertens (2022) for a detailed discussion).

C Additional results

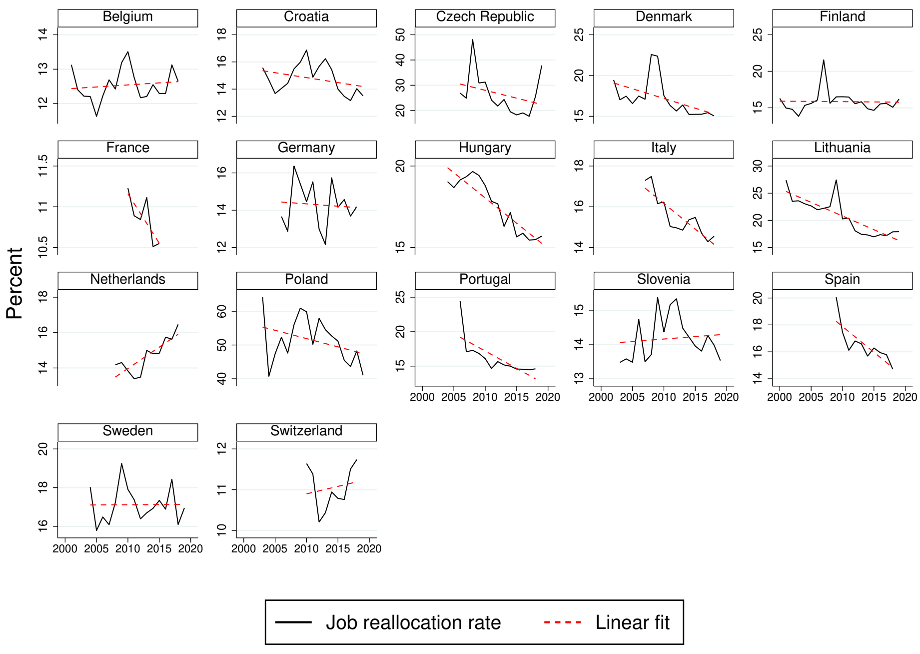
C.1 Appendix C.1: replication of the CompNet results with the full sample

In this section we will replicate the results obtained with CompNet using the sample with firms employing at least one worker. In the main analysis we used the sample of firms with at least 20 employees: checking whether our main results hold even employing a dataset in which the whole spectrum of firms is observed is an important robustness exercise.

Fact C.1: *There is a pervasive decline in job reallocation rates and young firm activity in Europe.*

For the full sample of firms, in Figure C1 we witness a decline in job reallocation rates across European countries, too. Clearly, the rate of reallocation is larger for this wider sample. Qualitatively, we observe only one discrepancy from the results presented for the truncated sample: Belgium is now characterized by a slightly growing trend in job reallocation, whereas all the other countries show similar trends.

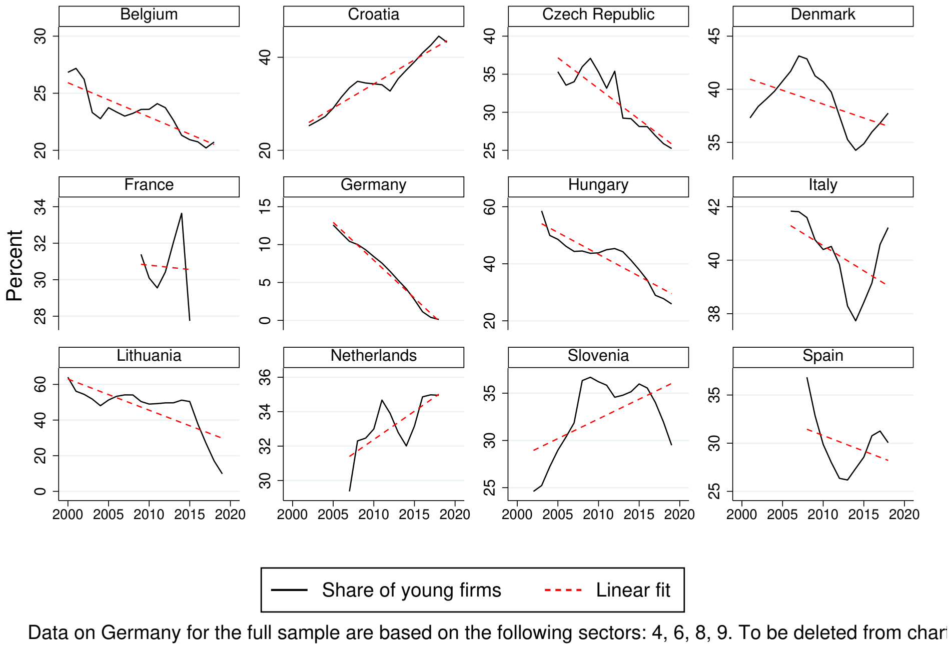
Figure C1. Job Reallocation rate in the Full Sample (CompNet)



Note: Data for Germany include only the following industries: Transportation and Storage; Information and Communication; Professional, scientific and technical activities; Administrative and support service activities.
Source: own calculations based on CompNet data. Firms with at least one employee.

On the other hand, for what concerns the share of young firms in the economy, we find reversed trends only for Croatia, Spain, and Slovenia (Figure C2). In addition to this, it is worth mentioning that the (already) increasing trend present in the Netherlands is amplified when studying the full sample.

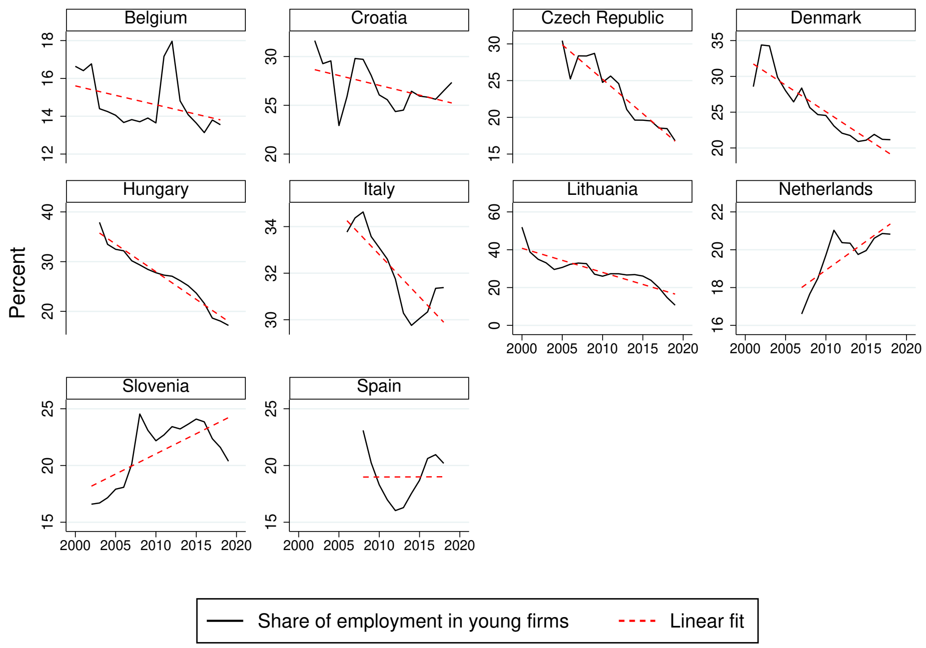
Figure C2. Share of young firms in the Full Sample (CompNet)



Note: Data for Germany include only the following industries: Transportation and Storage; Information and Communication; Professional, scientific and technical activities; Administrative and support service activities.
Source: own calculations based on CompNet data. Firms with at least one employee.

Finally, we look at the share of people employed in young firms, defined as firms not older than 5 years. Even here, the results look qualitatively equivalent with the sole exception of Netherlands, that shows an inverted trend.

Figure C3. Share of employment in young firms in the Full Sample (CompNet)

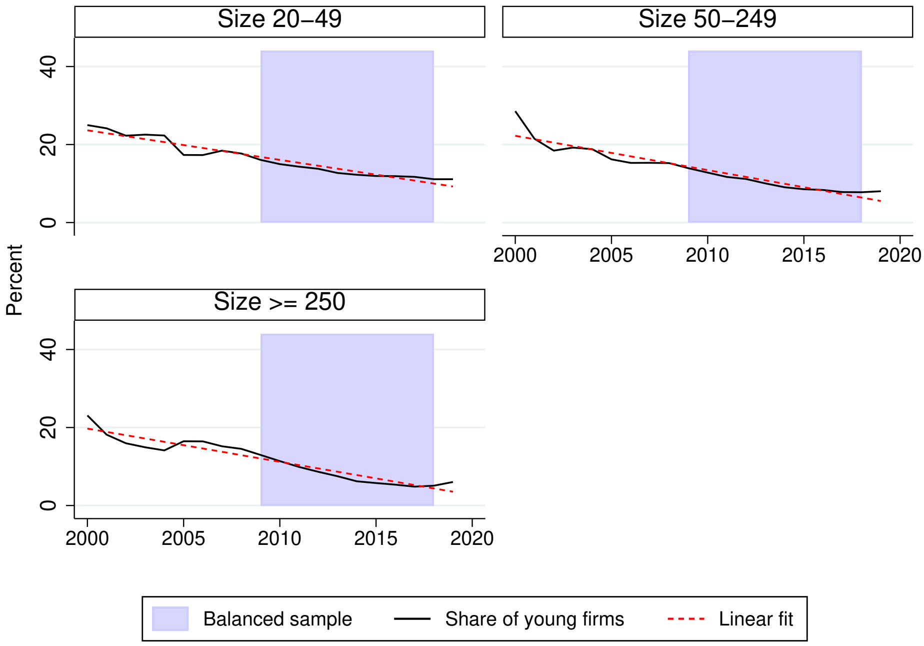


Note: Data for Germany include only the following industries: Transportation and Storage; Information and Communication; Professional, scientific and technical activities; Administrative and support service activities.
Source: own calculations based on CompNet data. Firms with at least one employee.

Fact C.2: *The decline in business dynamism is accompanied by a decline in high-growth young firms.*

As detailed in Figure 4, the share of young firms in each size class is declining over time, becoming extremely small in the most recent years. This stylized fact is confirmed by Figure C4, that plots the share of young firms in three different size classes. This figure is different from Figure 4 because it includes information for more countries, but finds the same identical results. Indeed, for some countries the CompNet dataset is available only including companies with at least 20 employees. Whereas Figure 4 augmented the number of size classes available in the chart, providing evidence related to a decline in the presence of young firms even in the smallest size classes, Figure C4 enlarges the set of countries for which such result holds true. Most notably, we add Germany, Romania, and Again, as a byproduct of this figure, we find that firms are becoming on average older in the countries analyzed, and that the presence of high-growth young firms is declining, too.

Figure C4. Young firm share by size-class

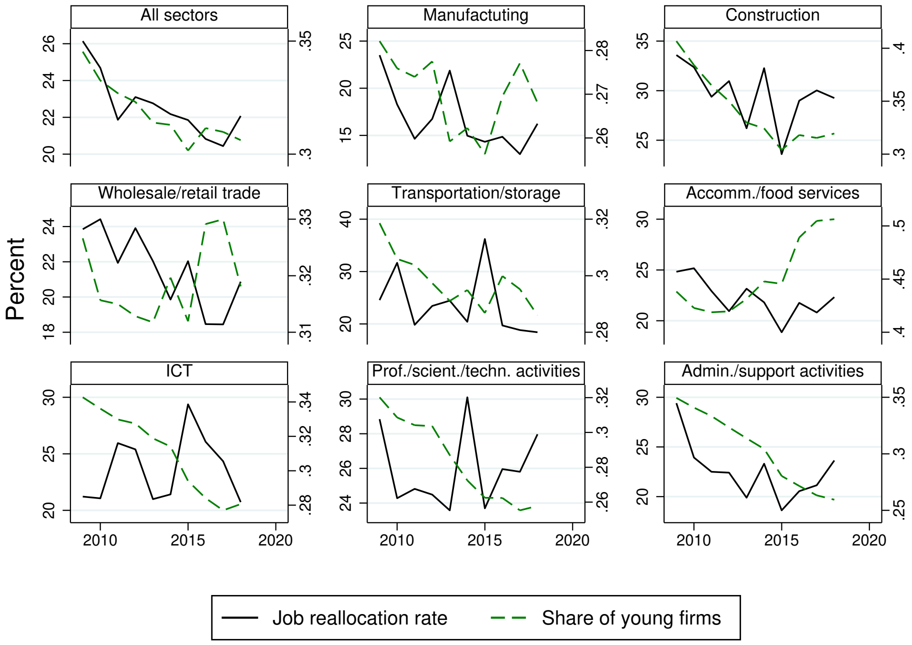


Note: the black solid line shows European-level shares of young firms in total firm counts by size classes. Young firms are firms not older than 5 years and not defined for Finland, Poland, Switzerland, Portugal, and Sweden. Real estate sector excluded.
Source: own calculations based on CompNet data. Firms with at least 20 employees.

***Fact C.3:** The decline in business dynamism is evident across all economic sectors in Europe*

We document whether the decline in business dynamism is pervasive of the whole economy or driven by any particular sector in this sample, too, as we did for Figure 5. In Figure A.8 we plot the job reallocation rate as a solid line, and the share of young firms as the dashed one. We find that both measures are declining over time in the whole economy. However, the decline is more evident in some sectors: Construction, Manufacturing, Transportation and Storage. Administrative and support activities all show declining trends in both constructs. A non-increasing trend for job reallocation is present for the ICT sector and for Professional, Scientific, and technical activities. The share of young firms increases in the Accommodation and food services industry, and in later years in the Wholesale and Retail trade one. All these trends are broadly in line with the results for the truncated sample, showing the robustness of our results. Summing up, the documented widespread and strong decline in business dynamism across countries in our truncated dataset is confirmed in the one in which small and micro firms (with at least one employee) are observed. The fall in European business dynamism is accompanied by a decline in high-growth young firms and it occurs in all economic sectors.

Figure C5. Job reallocation rate and share of young firms in the full sample in the full sample, by sector (CompNet)



Notes: the black solid (green dashed) line shows European-level job reallocation rates (shares of young firms in total firm counts) by sectors. Young firms are firms not older than 5 years and not defined for Finland, Poland, Switzerland, Portugal, and Sweden. Real estate sector excluded.

Source: own calculations based on CompNet data. Firms with at least one employee.