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Declining Business Dynamism in Europe: The Role of Shocks, Market Power, and Technology

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Declining Business Dynamism in Europe: The Role of Shocks, Market Power, and Technology*

Abstract

We study the changing patterns of business dynamism in Europe after 2000 using novel micro-aggregated data that we collect for 19 European countries. In all of them, we document a decline in job reallocation rates that concerns most economic sectors. This is mainly driven by dynamics within sectors, size classes, and age classes rather than by compositional changes. Large and mature firms show the strongest decline in job reallocation rates. Simultaneously, the shares of employment and sales of young firms decline. Consistent with US evidence, firms' employment changes have become less responsive to productivity. However, the dispersion of firms' productivity shocks has decreased too. To enhance our understanding of these patterns, we derive a firm-level framework that relates changes in firms' productivity, market power, and technology to job reallocation and firms' responsiveness.

Keywords: business dynamism, European cross-country data, market power, productivity, responsiveness of labor demand

JEL classification: D24, J21, J23, J42, L11, L25

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1 Introduction

One of the most debated macroeconomic trends in the past decade has been the decline in US business dynamism. This secular decline has been documented with a variety of measures and data sources in the US (e.g., Decker et al., 2014; Decker et al., 2016a; Dent et al., 2016; Guzman and Stern, 2020; Akcigit and Ates, 2021).[1] The slowdown in the process of birth, expansion, and contraction of US firms has received ample attention because it has potentially far-reaching implications for innovation (Haltiwanger et al., 2014a; Acemoglu et al., 2018), aggregate productivity growth (Decker et al., 2017; Decker et al., 2020; Alon et al., 2018) and the pace of economic recoveries (Pugsley and Şahin, 2019).

Despite its importance, the economic factors driving this decline remain subjects of ongoing debate. Among others, the roles played by demographic shifts (Pugsley et al., 2015), declining knowledge diffusion (Akcigit and Ates, 2021), rising market power (De Loecker et al., 2021), technological change (De Ridder, 2019; Chiavari, 2023), or rising adjustment costs (Decker et al., 2020) have been recently explored for the US.

In this article, we bring European data to this debate. The main contributions of our study are (i) to collect and publish new data for 19 European countries on business dynamism, (ii) to document a widespread decline in business dynamism over the past decades also in Europe, (iii) to analyze the microeconomic drivers underlying this decline, and (iv) to derive a framework that connects changes in firms' productivity, market power, and technology to changing business dynamism.

The main challenge researchers face in Europe is the lack of comparable firm-level data across countries. The legal setting in Europe prohibits combining administrative firm-level data from national statistical institutes and central banks across countries, and accessing any of these databases is often tied to high administrative costs. Researchers are therefore forced to rely on aggregate data (e.g., Eurostat), administrative data for a single country, or non-administrative data sources like ORBIS, despite their well-known limitations in terms of cross-country comparability.[2] As a result, existing evidence on business dynamism in Europe is limited to a few country-specific studies (e.g.,

[1] Earlier work has analyzed worker reallocation also in the context of turnover costs (Douglas, 1918; Slichter, 1920; Oi, 1962) and the cyclicality of labor markets (Blanchard et al., 1990; Davis and Haltiwanger, 1992).

[2] See Bajgar et al. (2020) for a discussion on the limitations of ORBIS data in terms of representativeness and cross-country coverage.

Bijnens and Konings (2020) for Belgium and Citino et al. (2023) for Italy) or reports by the OECD for a sub-sample of European countries (Calvino and Criscuolo, 2019; Calvino et al., 2020).[3]

In this study, we provide a solution to this limitation by collecting and publishing new micro-aggregated data on various indicators of business dynamism for 19 European countries. We gather these data within the Competitiveness Research Network (CompNet) by distributing harmonized data collection protocols across national statistical institutes and central banks. These data collection protocols generate a series of relevant statistics that we can use to study business dynamism and related factors in Europe. Our indicators are based on firm-level administrative data and then aggregated at various levels (e.g., country, industry, size class) such that the disclosed information complies with the confidentiality rules set by national data providers. Our data covers the last two decades, from 1997 to 2021, although with heterogeneous time coverage across countries. Due to its administrative nature and a rigorous re-weighting procedure based on Eurostat Structural Business Statistics, our data is highly representative of the firm population in each country. Moreover, being generated with the same data collection routine and cleaning procedures, the data is highly comparable across countries. We publish our data as part of the 9^{th} vintage of the CompNet database, which is now available to all researchers upon request.[4] Providing this data on European business dynamism to the scientific community is our first major contribution.

Our second contribution is to use this novel data to document whether and how business dynamism changed in Europe over the last two decades. We focus on aggregate job reallocation rates and young firm activity. Job reallocation rates capture the intensity of job flows across firms resulting from job creation or job destruction. We find a widespread and strong decline in this measure in all 19 countries under analysis. This decline concerns most economic sectors and is mainly driven by dynamics within sectors, size classes, and age classes rather than by cross-sectoral reallocations. Large and mature firms, which account for most economic activity, show a relatively stronger reduction in job reallocation rates. Simultaneously, young firms' shares of aggregate employment and sales decline, which indicates that European countries are experiencing a structural aging of their economies.

3 Within the Dynemp project, the OECD runs harmonized codes on administrative firm-level databases located in statistical offices across a number of OECD countries. However, the data is not accessible to external researchers. The CompNet data collection approach described in Section 2.1.1 is similar, but the CompNet data covers more European countries and is accessible to researchers.

4 Requests can be made to https://www.comp-net.org/data/9th-vintage/.

The third key contribution of our paper is to analyze the microeconomic mechanisms underlying the decline in aggregate job reallocation. The job reallocation rate is defined as an employment-weighted sum of firms' employment changes and is therefore tied to the decisions of individual firms to expand or contract in response to changes in their fundamentals and market conditions. In standard models of firm dynamics (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993), firms change their production and employment in response to their productivity shocks. From this perspective, Decker et al. (2020) (henceforth DHJM) argue that a decline in the pace of job reallocation can be attributed to two potential mechanisms. First, the dispersion of firm-level productivity shocks could decline. This may reflect that the business environment has become less turbulent from a technological and/or competitive perspective. As a result, aggregate job reallocation would decline too. Second, the firm-level responsiveness to those productivity realizations could decline. In other words, firms expand or downsize less in response to a given productivity shock. In the US, DHJM provide evidence that the dispersion of shocks experienced by firms has, in fact, risen over the 1981-2013 period. At the same time, they find that firms' responsiveness to those shocks has declined.

We examine the same hypotheses in Europe, following closely their approach to ensure a straightforward comparison with the US. We show that the responsiveness of firms' employment changes to productivity has declined in many European countries. In relative terms, the magnitudes of these declines are comparable to the ones estimated for the US. An important novel result we establish is that large firms are generally characterized by a lower responsiveness to productivity shocks than small firms. Regarding the dynamics of productivity shocks, we find a notable difference between European countries and the US. We document a generalized reduction in the dispersion of productivity changes, suggesting that both the shocks *and* the responsiveness hypotheses appear relevant in Europe. We confirm these results with another database on German manufacturing firms, which we can directly access, covers an even longer time span, and allows us to derive more precise productivity estimates.

To rationalize the observed patterns, we extend the framework of DHJM. While DHJM focus on adjustment costs to explain the decline in job reallocation and responsiveness, they recognize that their findings could also be interpreted in terms of "correlated wedges" that may capture, among others, changes in firms' market power. We formalize this intuition with a general production-side framework based on firms' derived labor demand, where we link changes in firms' output and labor market power and technology to job reallocation and firms' responsiveness. Our framework relates to several recent studies that document increasing firm market power on product (De Loecker et al., 2020) and labor (Yeh et al., 2022) markets, as well as changes in firms' production technology that replace labor with other inputs (Hubmer and Restrepo, 2021; Autor et al., 2022).[5]

We apply our framework to our rich German data with which we can estimate market power and technology at the firm-year level using the production function approach (De Loecker and Warzynski, 2012; Yeh et al., 2022). The German manufacturing data is perfectly suited for this analysis because it contains firm-specific price information, allowing us to address common biases in the literature that usually plague estimates of output elasticities, markups, and markdowns (Klette and Griliches, 1996; De Loecker et al., 2016; Bond et al., 2021). Equipped with these estimates, we prove that productivity shocks have become more muted over time. However, subdued changes in market power, output, wages, and technology also matter for declining job reallocation. Turning to the analysis of responsiveness, we confirm empirically that higher market power and less labor-intensive production processes reduce firms' responsiveness to productivity. We further document that all firms experienced a substantial shift in their production technology from labor to intermediate inputs. In terms of market power, instead, we document a small increase only for large firms' markups. Given that we also find that responsiveness declined for firms of all sizes, our findings suggest that changes in firms' production technologies that substitute labor with other inputs play a key role in explaining the decline in responsiveness.

The remainder of the article is structured as follows. Section 2 describes the collection process and main features of our data. Section 3 presents stylized facts on European business dynamism. Section 4 shows how firms' responsiveness and the evolution of productivity shocks have changed over the past two decades. Section 5 presents and applies our firm-level framework to analyze how firms' market power and technology shape firm responsiveness and job reallocation. Section 6 concludes.

[5] Our analysis also relates to work studying firm growth in response to demand and productivity shocks (e.g., Pozzi and Schivardi, 2016; Foster et al., 2016; Arkolakis, 2016; Kaas and Kimasa, 2021).

2 Data

2.1 The CompNet data

2.1.1 Data collection process

We collect data on European business dynamism through the Competitiveness Research Network (henceforth, CompNet).[6] Together with the CompNet team, we designed and distributed harmonized data collection protocols (i.e., Stata codes) across administrative firm-level databases which are located within national statistical institutes and national central banks in 19 European countries. Online Appendix Table A1 provides more details on the data providers and data sources for each country. These datasets are among the most reliable and representative firm-level datasets in Europe. Importantly, we did not access the microdata in person but relied exclusively on the cooperation of data providers to run our codes. As illustrated in Figure 1, the outcome of this data collection procedure is a European harmonized micro-aggregated database. In addition to the standard CompNet data collection routines, we added a series of additional econometric analyses that are specific to our study.

We adopted this complex data collection approach because combining administrative firm-level data across multiple European countries is legally prohibited. The approach of distributing harmonized data collection protocols circumvents this restriction by aggregating firm-level information such that the disclosed information passes the confidentiality criteria of the data providers. The aggregation levels are the country, regional, sector, industry, sector-size-class, and age-class levels. From the micro-aggregated information collected in each country, we assembled a European database after a series of quality and consistency checks.

The entire data collection process took place over 2022-2023 and led to the 9$^{\text{th}}$ vintage of the CompNet database.[7] The database is accessible to researchers free of cost via a simple application form.[8]

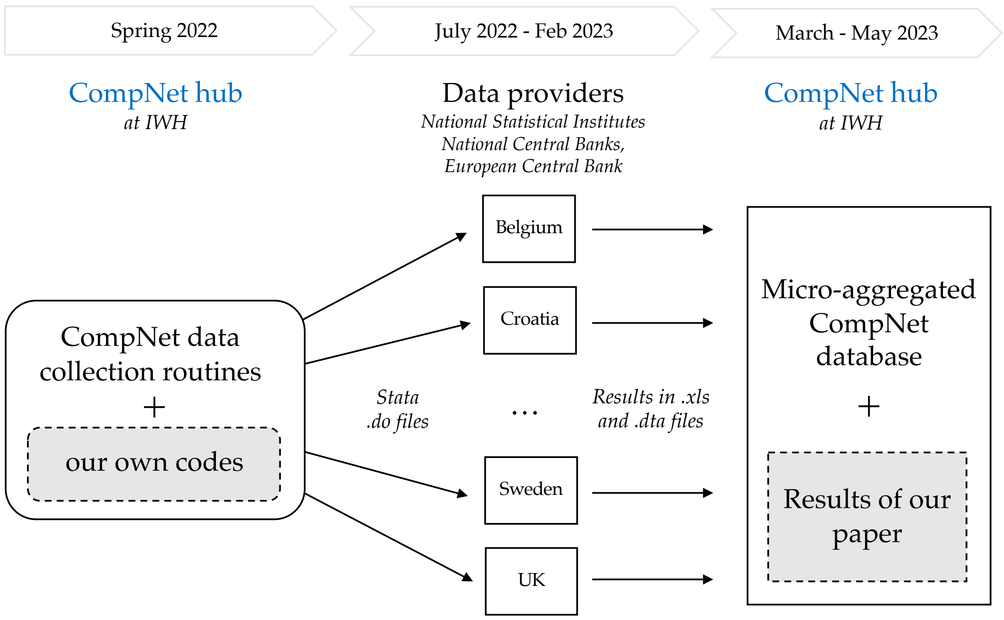
[6] CompNet is hosted by the Halle Institute for Economic Research (IWH) and includes several partner institutions: the European Commission, the European Central Bank (ECB), the European Bank for Reconstruction and Development (EBRD), the European Investment Bank (EIB), the European Stability Mechanism (ESM), France Stratégie, the German Council of Economic Experts, the German Federal Ministry for Economic Affairs and Climate Action, and the Tinbergen Institute.

[7] In accompanying studies, Bighelli et al. (2023) use the 7$^{\text{th}}$ vintage to study European firm concentration, while Mertens (2023) and Mertens and Mottironi (2023) use the 8$^{\text{th}}$ vintage data to study market power in Europe. Older vintages of CompNet data have been used, among others, in Autor et al. (2020) and Gutiérrez and Piton (2020).

[8] More information on accessing the database are available here. Importantly, although the CompNet data is an aggregated database, it contains rich statistics on the distribution of each variable (i.e., various percentiles and

While this approach provides us with uniquely rich data, it prevents us (and other researchers) from directly inspecting the microdata.

Figure 1. Data collection process and timeline.



2.1.2 Features and coverage of CompNet data

The data covers firms from the NACE (i.e., the Statistical Classification of Economic Activities in the European Community) 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 (information and communication technology), 68 (real estate), 69-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities).[9] We follow the literature and drop the real estate sector from our analysis (e.g., Decker et al., 2020). The CompNet micro-aggregated database comes in two versions: one is based on firms with at least 20 employees ("20e sample"). The other features all firms with at least one employee ("all sample").[10] Most of our analyses focus on the "20e sample", as this is available for all countries. However, we replicate our main results for the set of countries where the "all sample" is available (online Appendix C.3). Table 1 provides an overview on time and sample coverage across countries.

dispersion measures).

9 The firms are independent legal entities with at least one employee whose main activity is the production of goods and non-financial services.

10 The reason for having two samples is that in some countries firms are legally obliged to report their balance sheet data only when certain size thresholds are met.

Table 1. Coverage of CompNet data

Country	ISO Code	Years	Available sample
Belgium	BE	2000-2020	20e/all firms
Croatia	HR	2002-2021	20e/all firms
Czech Republic	CZ	2005-2020	20e/all firms
Denmark	DK	2001-2020	20e/all firms
Finland	FI	1999-2020	20e/all firms
France	FR	2003-2020	20e
Germany*	DE	2001-2018	20e
Hungary	HU	2003-2020	20e/all firms
Italy	IT	2006-2020	20e/all firms
Latvia	LV	2007-2019	20e/all firms
Lithuania	LT	2000-2020	20e/all firms
Poland	PL	2002-2020	20e
Portugal	PT	2004-2020	20e/all firms
Romania	RO	2005-2020	20e
Slovakia	SK	2000-2020	20e
Slovenia	SL	2002-2021	20e/all firms
Spain	ES	2008-2020	20e/all firms
Sweden	SE	2003-2020	20e/all firms
United Kingdom	GB	1997-2019	20e/all firms

Notes: *For Germany, the manufacturing sector data starts in 2001. Coverage on all sectors starts in 2005.

Overall, the database covers the last two decades, although the time span differs across countries. In terms of employment and number of firms, the coverage of the CompNet database is very high. As reported in online Appendix Table A2, the "20e sample" covers 75% of total employment relative to the Eurostat Structural Business Statistics. In terms of the total number of firms, the average coverage ratio is 73%. To iron out sampling differences within and across countries, CompNet applies an inverse probability re-weighting based on firm counts by industry-size-class cells from Eurostat. The coverage of employment becomes close to 100% after re-weighting (online Appendix Table A2). We provide summary statistics and further details about the database in online Appendix A.1, while referring to CompNet's User Guide (CompNet, 2023) for an in-depth exposition of the database.

Finally, due to country-specific disclosure rules, it is important to note that a few results in Section 3 do not contain information for a few individual country-sector-year combinations. This is a minor issue and concerns only a handful of cases, which we list in online Appendix Table A5.

2.1.3 Measures of interest

Job reallocation. Our main measure of business dynamism is the job reallocation rate. This widely applied indicator can easily be measured and compared across countries and sectors. Following Davis et al. (1996) (henceforth, DHS), the job reallocation rate equals the weighted sum of firm-level absolute employment growth rates:

$$JR_{nt} = \sum_i s_{it} \, |g_{it}|, \tag{1}$$

where $g_{it} = \dfrac{L_{it} - L_{it-1}}{\overline{L}_{it}}$ is the DHS employment growth rate of firm i between $t-1$ and t and $\overline{L}_{it} = 0.5 \times (L_{it} + L_{it-1})$. The weights are the employment shares of each firm $s_{it} = \dfrac{\overline{L}_{it}}{\sum_i \overline{L}_{it}}$. We measure the yearly job reallocation rate mainly at the the country ($n = c$) and sector ($n = j$) levels.[11] As we cannot identify firm entry and, in particular, exit in many countries, our measure of job reallocation is defined in terms of employment changes of expanding/downsizing firms, but it excludes entering and exiting ones.

Young firms' activity. While our primary focus is on job reallocation, we are also interested in documenting changes in the share of economic activity (both employment and sales) accounted for by young firms, given their relevance for business dynamism. We define a firm as "young" if its creation does not date back more than five years. Unfortunately, the share of young firms can only be defined for 14 countries for which we have data on firms' registration years.

Firm-level productivity. In Section 4, we analyze how firm-level employment responds to productivity changes. Regarding firm productivity, we focus on standard measures of labor productivity (LP) and revenue-based total factor productivity ($TFPR$). Labor productivity is computed as the log of value added over labor. Value added equals the difference between gross output and intermediate input expenditures.[12] All the monetary values in our data are measured in thousands of euros and deflated using country-industry-year-specific output, capital, and intermediate input deflators

11 As we are interested in studying long-run trends, we will not consider the years after 2019 due to the SARS-CoV-2 pandemic in our initial analyses on business dynamism. Moreover, we exclude the years (i) before 2005 for Germany due to changes in sector compositions, (ii) after 2015 for France due to some changes in firm definitions, and (iii) the year 2004 for Portugal due to the presence of some outliers.

12 As defined in CompNet (2023), gross output includes turnover at factor cost, changes in the stock/inventory of manufactured finished - or semi-finished products, and capitalized internal activities. Intermediate expenditures reflect raw materials and consumables, components, energy, goods intended for resale, and hired services.

from EU-KLEMS. Labor is measured in number of employees, excluding employed shareholders or owners. Depending on the data source, labor is either defined as the annual average or at a specific point in time.[13] All other variables pertain to the full calendar year. In addition to labor productivity, CompNet provides various productivity measures estimated as a residual from firms' production functions.[14] We focus on the following Hicks-neutral Cobb-Douglas specification:

$$Q_{it} = F(L_{it}, K_{it}, M_{it})\ TFP_{it} = L_{it}^{\theta_{jt}^{L}} K_{it}^{\theta_{jt}^{K}} M_{it}^{\theta_{jt}^{M}}\ TFP_{it}\ , \tag{2}$$

where Q_{it} is the quantity produced by the firm. K_{it} is the capital stock (both tangible and intangible assets), L_{it} is labor, M_{it} denotes intermediate inputs, and θ_{jt} denotes the output elasticity of each factor. The subscript j denotes firms' 2-digit NACE industry. To estimate the output elasticities, we rely on a cost-share approach. Under constant returns to scale, full adjustment of factors, and exogenous input prices, static cost minimization implies that an input's output elasticity equals the input's cost share, defined as input expenditure over total costs.[15] Following De Loecker and Syverson (2021), we take the median of the cost share by industry-year-cells to mitigate idiosyncratic misalignments between actual and optimal input levels due to adjustment costs and/or optimization errors.

Using our estimates of output elasticities, we compute total factor productivity as:

$$tfpr_{it} = \tilde{q}_{it} - \beta_{jt}^{l} l_{it} - \beta_{jt}^{k} \tilde{k}_{it} - \beta_{jt}^{m} \tilde{m}_{it}. \tag{3}$$

Lowercase letters indicate logs, and a tilde indicates that the variable is not measured in quantities but in deflated monetary units. As most empirical studies, we observe deflated revenues rather than physical output. Therefore, our productivity measure, $tfpr_{it} = log(TFPR_{it})$, contains firm-specific price variation and reflects firm-level output prices and demand shocks (Foster et al., 2008). As noted by DHJM, also the latter influences firms' growth.

[13] Labor is defined at a specific point in time for Denmark, Sweden, Germany, and the Czech Republic. Portugal reports employment at the end of the year. Otherwise, the labor variable refers to the annual average.

[14] We rely on labor productivity and cost-share-based TFP measures as they perform consistently well across our large set of countries. The more sophisticated TFP measures using control function approaches are characterized by large outliers in several country-industry pairs and are sometimes missing for small industry-country cells, due to being particularly demanding in the estimation process.

[15] While intermediate and labor expenditures are directly reported in most datasets, capital costs are computed as the sum of depreciation, interest paid, and imputed interest on equity. If this information is unavailable, capital costs are derived by setting the rental rate of capital to 0.08.

2.2 German manufacturing sector microdata

In the second part of the article, we use detailed firm-level data for the German manufacturing sector. The data are accessible at the Research Data Centres of the German Statistical Offices and contain, among other, information on firms' employment, investment, costs, and product quantities and prices at a ten-digit product classification. While employment refers to the September 30$^{\text{th}}$ value, all other variables pertain to the full calendar year. We use this rich firm-product-level data to (i) validate key findings based on the CompNet data, and (ii) to analyze how production technologies and market power affect firms' labor demand and thus job reallocation rates. The firm-specific product price information allows us to estimate quantity-based production functions, which is essential to properly estimate firms' markups, markdowns, and output elasticities (more details in Section 5.2). In terms of coverage, the German data are available from 1995 to 2017. The data are collected for a representative and periodically rotating sample, covering 40% of all manufacturing firms with at least 20 employees. Online Appendix A.2 contains all variable definitions, provides relevant summary statistics, and explains our cleaning routine, how to access these data, and how we harmonize industry classifications following Mertens (2022).

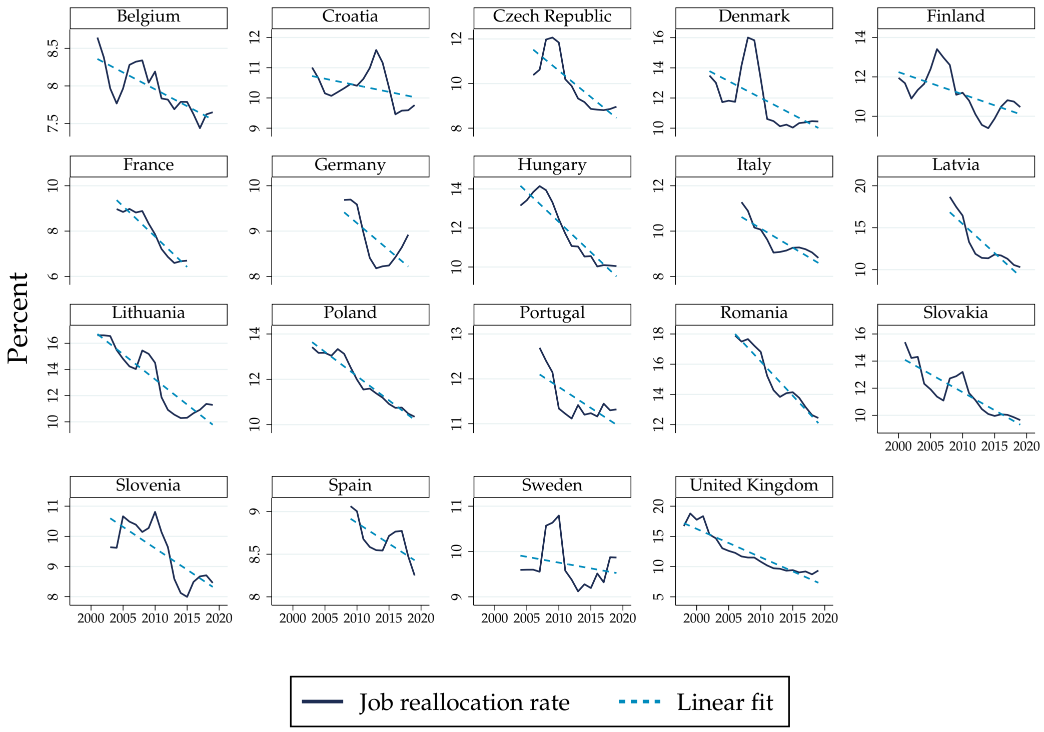
3 Facts on Business Dynamism in Europe

Fact 1. *There is a pervasive decline in job reallocation in Europe.*

Figure 2 reports job reallocation rates by country for firms with at least 20 employees, showing a striking decline in job reallocation in all countries. While the decline is widespread, Eastern European countries display a higher initial level and stronger decline in job reallocation rates. This likely reflects transition dynamics after their accession to the European Union. In the online Appendix, we show that the widespread decline in job reallocation rates is (i) present in manufacturing and non-manufacturing sectors alike (Figure C2), and (ii) robust to using data on firms of all size classes for the subset of countries that provide such data (Figure C9). Finally, Figure C3 documents that sales reallocation rates, which we define by replacing employment changes with sales changes in Equation (1), show a similar decline. This suggests a general reduction in the reallocation of economic activity between firms in Europe, which does not pertain only to employment.[16]

[16] As mentioned in Section 2.1.3, our job reallocation rates abstract from firm entry and exit. Therefore, in online

Figure 2. Job reallocation rates in European countries.



Notes: Three-year moving averages of the job reallocation rates defined in Equation (1). The light blue dashed lines report linear trends. Germany excludes the construction sector in 2009. CompNet data, firms with at least 20 employees.

Compared to US evidence, Europe shows a lower level of job reallocation.[17] For instance, calculations from the US Census Bureau's Business Dynamics Statistics series suggest an average job reallocation rate for continuing establishments in the US of approximately 15% between 2000 and 2020 when excluding firms with less than 20 employees.[18] By contrast, we find job reallocation rates in Western Europe ranging from 8% to 12%, with countries like Germany, Spain, and Belgium at the lower bound. Eastern European countries display rates closer to those of the US. However, an important difference to keep in mind is that job reallocation rates measured by the US Census reflect employment changes at the establishment level. In contrast, we measure it at the firm level (legal unit). As a result, our job reallocation measures are lower also because they do not account for within-firm reallocation.

Appendix Figure C1 we use Eurostat data to show that there is no systematic trend in firm entry or exit that could explain the decline in job reallocation among continuing firms as a result of excluding entering and exiting firms.

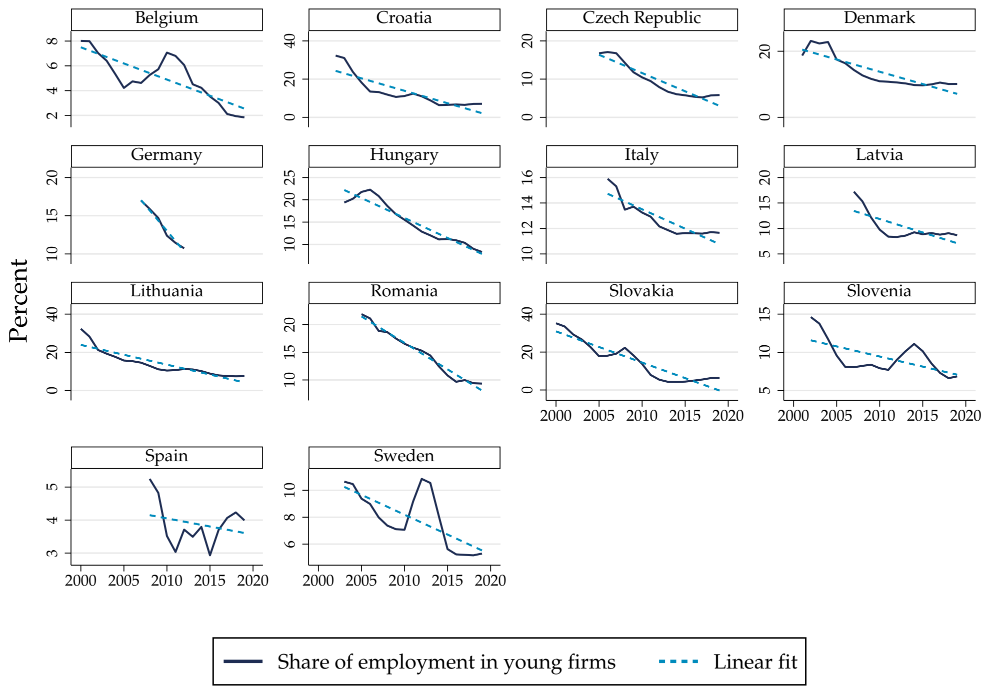
17 Our results confirm and extend previous findings by Haltiwanger et al. (2014b), which document lower job reallocation rates for a small set of European countries during the 80s and 90s without studying changes over time.

18 For these calculations, we exclude the sum of job creation from entry and job destruction from exit. The US Bureau of the Census, Business Dynamics Statistics (BDS) series can be downloaded for firm-size classes here.

Fact 2. *The share of economic activity in young firms is declining in Europe.*

Figure 3 displays the share of employment captured by young firms for the 14 countries for which we have data on firms' registration years. The decline in job reallocation rates coincides with a decline in the share of young firms' activity. This indicates a shift of economic activity towards older firms. Again, this finding holds for manufacturing and non-manufacturing sectors alike (online Appendix Figure C4). Using data on firms of all size classes confirms the decline in young firm activity for almost all countries (Figure C11). Declines in the "20e sample" are particularly pronounced, ranging from one-third to more than a half in some countries. By contrast, declines in the full sample are less significant overall. High-growth young firms are, by definition, part of the 20-employee sample because most firms remain small and below this size threshold in their first 5 years of activity. Therefore, the implication of our results is that high-growth young firms exhibit a particularly strong decline in Europe.[19] Once again, the decline appears to be stronger for Eastern European countries.

Figure 3. Young firms' employment share in European countries.



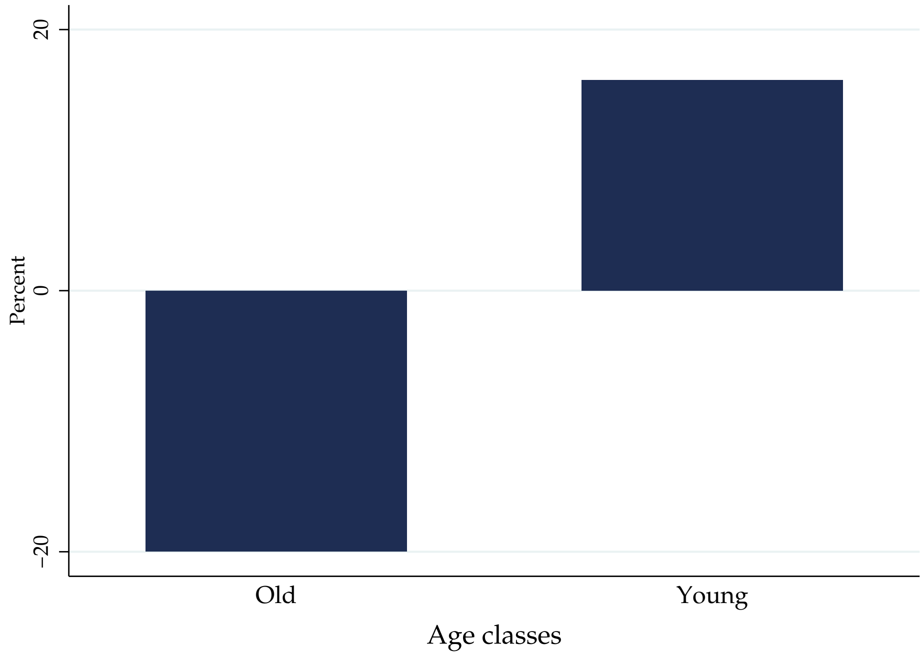
Notes: Three-year moving averages of the employment share of firms not older than five years. The dark blue solid line shows country-level shares of employment in young firms. The light blue dashed lines report linear trends. The underlying data are aggregated from sector-age-class data resulting in a drop of a few sector-age-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data, firms with at least 20 employees.

[19] The US also exhibits large declines in high-growth young firm activity, as documented in Decker et al. (2016b) and Guzman and Stern (2020).

Fact 3. *On average, job reallocation declined for mature firms but not for young firms.*

Figure 4 reports percentage changes in job reallocation rates for young and old firms. We first compute percentage changes between the first and last two years for the countries reported in Figure 3 and then report averages across them by age class. The decline in job reallocation is concentrated among old firms. This also holds for the "all firms" sample (online Appendix Figure C12) and implies that the reduction in young firms' economic activity (Figure 3) also reduces aggregate job reallocation.[20]

Figure 4. Relative changes in job reallocation rates by age classes.



Note: Averages across countries in relative changes in job reallocation rates as computed in Equation (1) by age class. Changes are computed between the first and last two years for each country-age-class cell. All countries except Romania additionally include the real estate sector. CompNet data, firms with at least 20 employees.

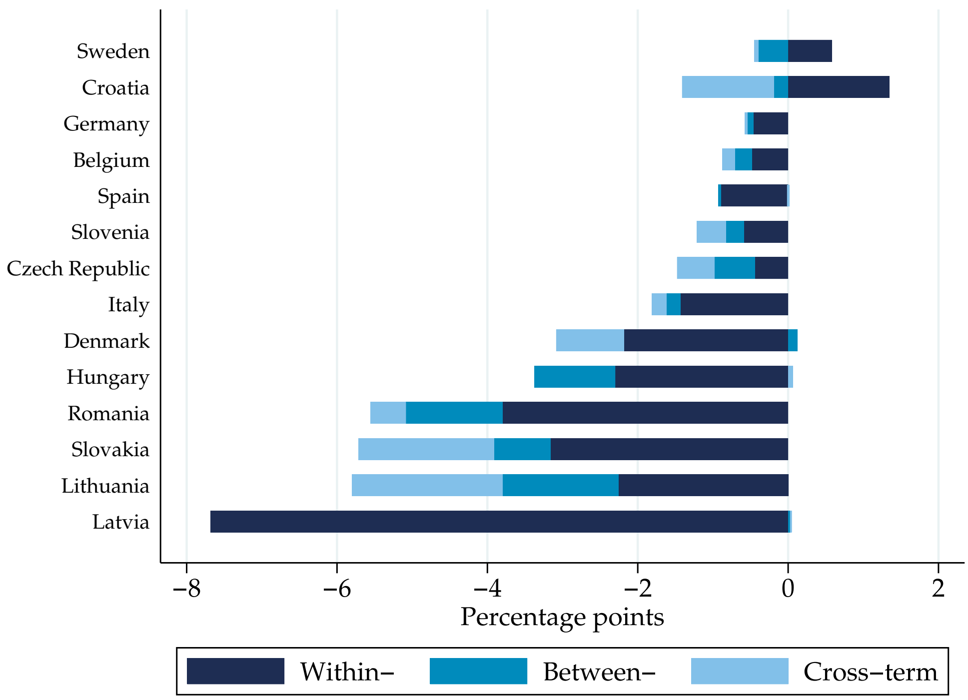
To assess the importance of such compositional changes with respect to firm age, we decompose the change in the job reallocation rate for each country c, defined as $\Delta JR_{c(t-t_0)} = JR_{ct} - JR_{ct_0}$, in the following way:

$$\Delta JR_{c(t-t_0)} = \underbrace{\sum_j s_{cjt_0}\, \Delta JR_{cj(t-t_0)}}_{\text{within-term}} + \underbrace{\sum_j \Delta s_{cj(t-t_0)}\, JR_{cjt_0}}_{\text{between-term}} + \underbrace{\sum_j \Delta s_{cj(t-t_0)}\, \Delta JR_{cj(t-t_0)}}_{\text{cross-term}}, \tag{4}$$

[20] Online Appendix Figure C5 shows the time series of the job reallocation rate for young and old firms.

where s_{cjt} denotes the employment shares in each age class j.[21] The first term on the right-hand side represents the contribution of within-age-class changes to the change in job reallocation, fixing the employment shares of young and old firms at their initial value. The second term captures the contribution of between-age-class changes in employment shares, keeping job reallocation constant. The last term captures joint changes in age-class shares and job reallocation rates. For each country, we study the changes over the entire period in our sample. Figure 5 shows the results from the decomposition. As expected, compositional effects (captured by the between-term) matter in many countries. However, the major part of the decline in job reallocation rates occurs within age classes.[22] As job reallocation increased among young firms (Figure 4), the large negative contribution of the within-component underlies the importance of old firms in the European economy. Results for the "all firms" sample are similar (online Appendix Figure C13). If anything, they highlight an even greater contribution of the within-age-class changes.

Figure 5. Decomposition of job reallocation changes across age classes.



Notes: Results of the decomposition of job reallocation rates across age classes as described in Equation (4). To define the start and end points for the decomposition, we average the first and last two years of job reallocation rates for every country-sector combination. All countries except Romania additionally include the real estate sector. CompNet data, firms with at least 20 employees.

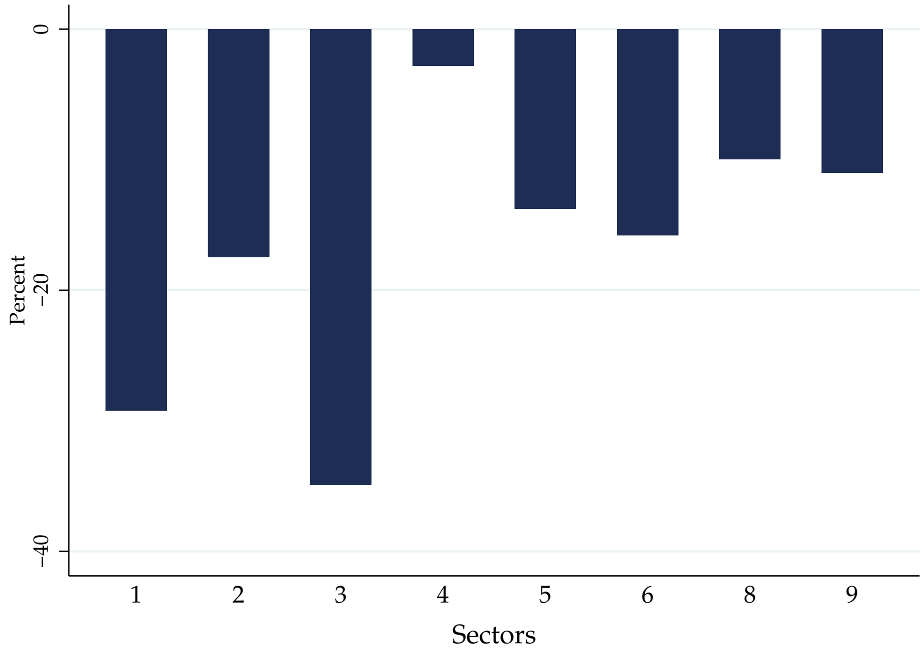
21 This accounting decomposition has been introduced by Foster et al. (2001) and is widely used in the literature on firm performance.

22 The cross-term jointly captures within-changes and compositional effects.

Fact 4. *The decline in reallocation is evident in almost all sectors.*

Figure 6 shows the percentage changes in job reallocation rates by macroeconomic sectors. To summarize the dynamics by sector, we calculate the percentage changes between the first and last two years in each country and then average these relative changes across countries. Using our "20e sample", we document a reduction in job reallocation rates in all economic sectors. The decline is particularly strong in (1) manufacturing and (3) wholesale/retail trade, which are also the two largest sectors in the European economy. As shown in online Appendix Figure C14, with exception of the sector 2 (construction) and 6 (ICT), this is also confirmed when using the "all firms" sample.

Figure 6. Relative changes in job reallocation rates by sectors.



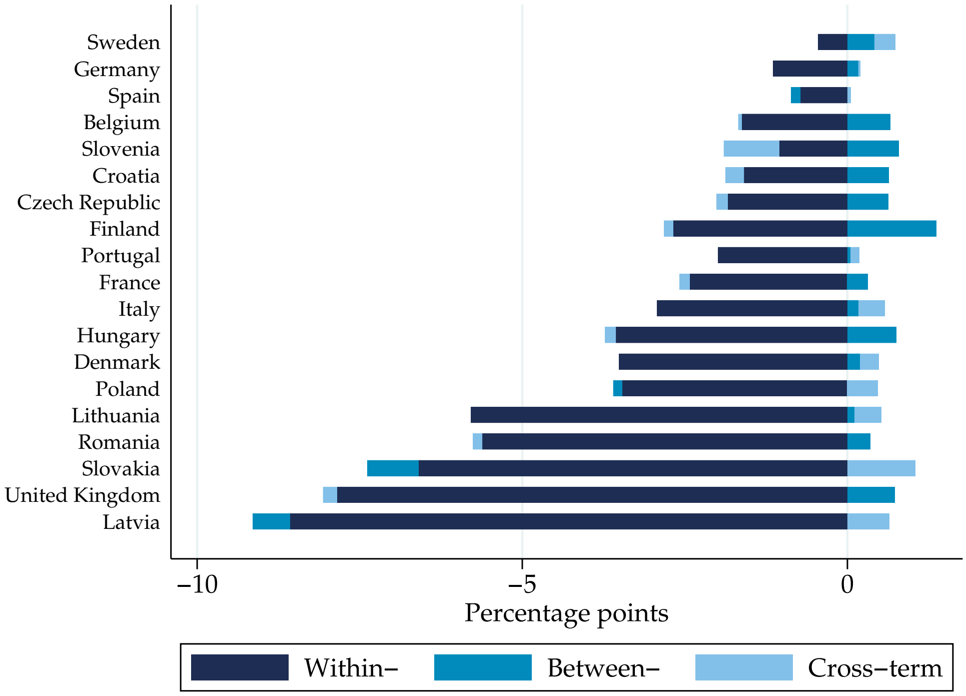
Note: Averages across countries in relative changes in job reallocation rates as computed in Eq. (1) by sectors. Changes are computed between the first and last two years for each country-sector. Sectors are numbered in the following way: manufacturing (1), construction (2), wholesale/retail trade and repair of motor vehicles and motorcycles (3), transportation/storage (4), accommodation/food services (5), information and communication technology (ICT) (6), professional/scientific/technical activities (8), administrative/support service activities (9). CompNet data, firms with at least 20 employee.

Fact 5. *The decline in reallocation is driven by within-sector dynamics.*

The observed decline in reallocation can be driven by changes within sectors or by shifts in employment shares towards sectors with lower job reallocation. To assess the relevance of these two different dynamics, we apply a sector-level version of the decomposition in Equation (4), where the j

now refers to sectors. Figure 7 presents the results. The main insight is that within-sector changes in job reallocation (the darkest bars) are negative in all countries and contribute to most of the decline in job reallocation in all European countries. Note also that in most countries between effects work against the decline in reallocation; put differently, industry composition effects work to increase not decrease reallocation. Broad declines across sectors and countries in Europe are consistent with broad declines in the US and point to economy-wide and possibly common underlying factors.

Figure 7. Decomposition of job reallocation changes across sectors.



Notes: Results of the decomposition of job reallocation rates across sectors using a sector-level version of Equation (4), where the j now refers to sectors. To define the start and end points for the decomposition, we average the first and last two years of job reallocation rates for every country-sector combination. CompNet data, firms with at least 20 employees.

Fact 6. *Job reallocation rates declined for firms of any size, but relatively more among the largest firms.*

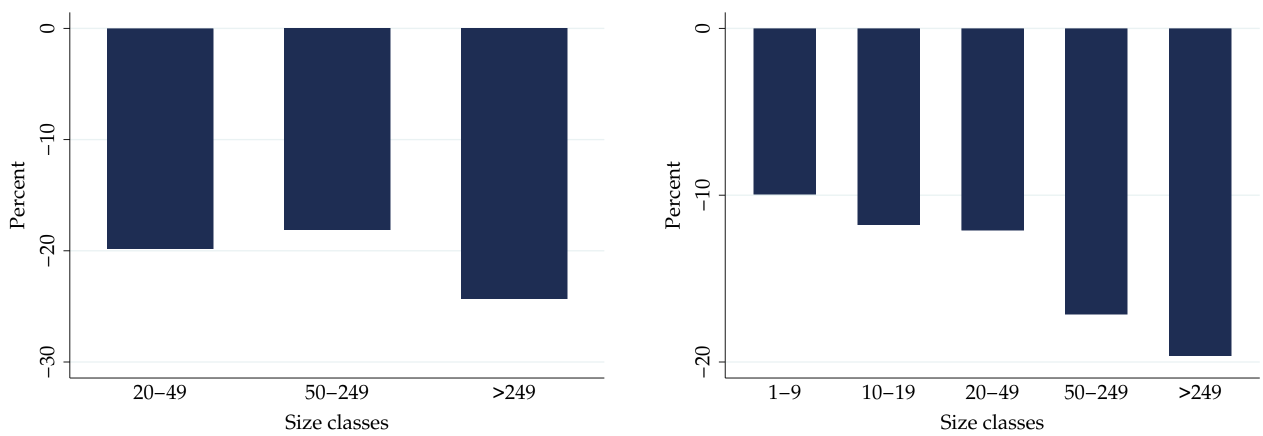
It has been documented that larger firms exhibit lower job reallocation rates and account for a major share of employment, which highlights their pivotal role in understanding aggregate job reallocation (Haltiwanger et al., 2014b; Haltiwanger, 2022). We confirm this finding in most European countries in online Appendix Figure C6. Motivated by this result, we delve deeper into the decline in aggregate job reallocation by examining the variation across firm size classes. We employ Eurostat's classification system and categorize firms with more than 20 employees into three groups:

small (20-49 employees), medium (50-249 employees), and large firms (250 or more employees).

Figure 8 shows changes in job reallocation rates by size class. Panel (a) is based on the "20e sample", while in Panel (b) we consider the "all sample" where we define two additional size classes for smaller firms (1-9 employees and 10-19 employees), following the Eurostat classification system. Both panels show that job reallocation declined throughout the entire firm size distribution. However, on average, it declined relatively more among the largest firms. This result highlights the importance of large firms in shaping the decline in job reallocation in Europe and serves as an important starting point for our theoretical discussion on its underlying mechanisms in Section 5.

Figure 8. Relative decline in job reallocation rates by size class.

(a) 20e sample **(b)** All sample

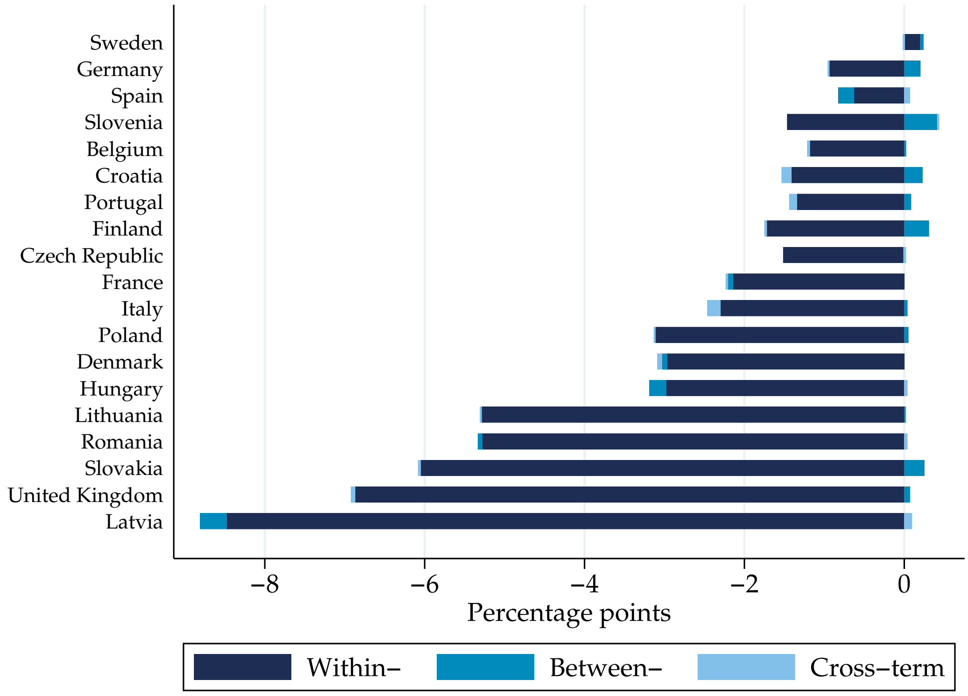


Notes: Averages across countries of relative changes in job reallocation rates by size classes. Changes between the first and last two years for every country-size-class combination. The underlying data are aggregated from sector-size-class data resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Appendix A.1.1). Panel (a) based on all 19 countries. Panel (b) on countries with the "all firms" sample. CompNet data. Firms with at least 20 employees in Panel (a); firms with at least one employee in Panel (b).

Figure 9 concludes this section by decomposing changes in job reallocation rates into within- and between-size-class changes using a size-class-level version of Equation (4). Again, we find that the within-term dominates, implying that within-size-classes declines in JR are the main drivers of the aggregate decline. On the contrary, reallocation between size classes does not contribute much to the declining job reallocation.[23]

[23] Using the "all sample" confirms this finding. If anything, reallocation between size classes contributes to a slight increase in job reallocation rates in some countries (online Appendix Figure C16).

Figure 9. Decomposition of job reallocation changes across size classes.



Notes: Decomposition of changes in job reallocation rates based on a version of Eq. (4) that decomposes aggregate changes in job reallocation into within- and between-size-class contributions. Underlying data are aggregated from sector-size-class data resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data, firms with at least 20 employees.

In summary, we document a widespread decline in job reallocation rates in Europe. This decline is common to most economic sectors. Large and mature firms show the strongest reduction in job reallocation rates. Simultaneously, high-growth young firms' employment shares are declining. Yet, the decline in job reallocation is mainly driven by changes within sectors, size classes, and age classes, rather than by compositional changes.

4 Responsiveness *and* shocks hypotheses

What can explain the widespread decline in reallocation in Europe? To start our analysis of the underlying mechanisms, we follow DHJM. They explore the changing patterns of job reallocation in the US, drawing inspiration from canonical models of firm dynamics (Hopenhayn, 1992, Hopenhayn and Rogerson, 1993). In this class of models, job reallocation between firms arises from firms' responses to changes in their productivity.[24] From this perspective, a decline in the pace of job reallocation can be attributed to two potential drivers. First, firms' responsiveness to productivity shocks could weaken; that is, firms may hire or downsize less in response to a given productivity shock. Second, the dispersion of firm-level productivity shocks could decline as a result of a less turbulent business environment. As a consequence, also job reallocation would decline.

DHJM show that, for the US and for the period covered by their analysis (1981-2013), the dispersion of shocks faced by individual businesses has, in fact, risen, contrary to what we might expect given the declining pace of reallocation. At the same time, they find that firms' responsiveness to those shocks has declined markedly. In the following, we examine these patterns for Europe and compare our findings to the US.

4.1 Responsiveness hypothesis

To examine whether firms' responsiveness to productivity has changed over time also in Europe, we closely follow the empirical approach of DHJM. In particular, we estimate a linear regression model to capture the relationship between a firm's employment growth, g_{it}, and its lagged productivity and employment levels. We provide more details about the derivations and assumptions leading to this model in online Appendix B.1. The dependent variable, g_{it}, is the DHS employment growth rate between $(t-1)$ and t of firm i. The responsiveness of g_{it} to productivity is estimated as follows:

$$g_{it} = \beta_0 + \beta_1 a_{it-1} + \beta_2 l_{it-1} + \delta_1 a_{it-1} T_t + \delta_2 l_{it-1} T_t + X_{jt} + \epsilon_{it}. \tag{5}$$

a and l denote the log values of productivity and employment, respectively. β_1 captures the marginal responsiveness of a firm's employment growth to its productivity, conditional on its initial employment l_{it-1}. The standard prediction of firm dynamics models is that $\beta_1 > 0$. In other words, firms with high productivity realizations grow, whereas those with low productivity realizations shrink (conditional on initial size).[25] The inclusion of the linear trend, $T_t = 0, 1, ...$, allows us to test if this relationship has changed over time. If the responsiveness to productivity declined over time, δ_1

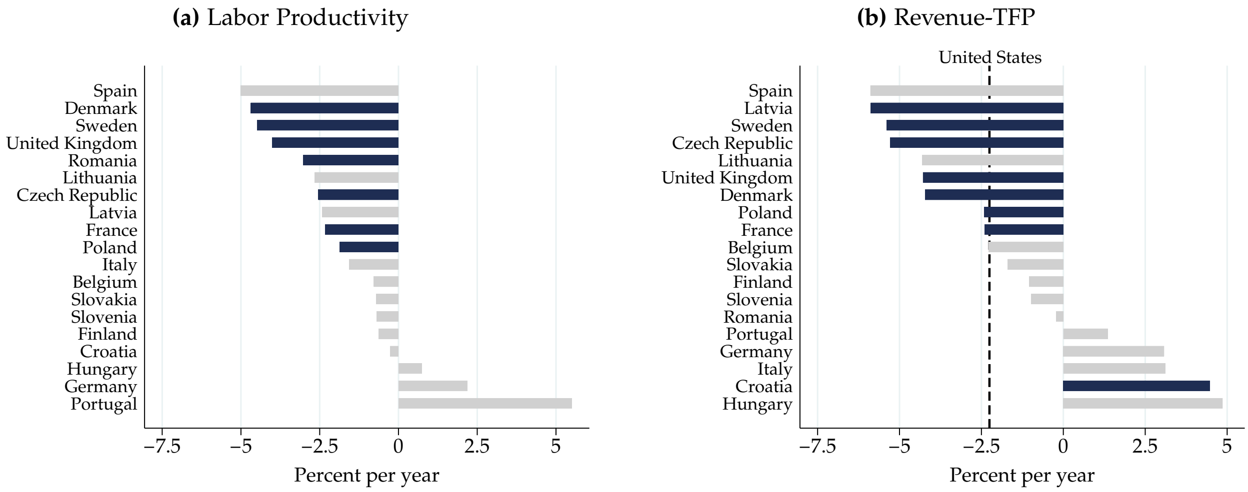
24 Unless stated differently, we refer to productivity shocks as the composite of idiosyncratic technical efficiency and demand shocks.

25 DHJM and online Appendix B show how this specification in levels corresponds to a transformation of a first-difference specification, where changes in labor are directly related to changes in productivity. With the German manufacturing data in Section 4.3, we estimate both specifications and find comparable results. As argued in DHJM, however, the specification in levels is less demanding in terms of data as only one year of productivity is required.

should be negative. We allow the effect of initial employment to vary over time in the same way. X_{jt} controls for industry-year fixed effects (at the NACE 2-digit level) to capture industry-specific shocks as our focus is on secular rather than cyclical changes. To relate our analysis to the decline in the job reallocation rate, which is the employment-weighted average of g_{it} (see Equation (1)), we weight our regression by firms' employment level, averaged between t and $t-1$. Finally, note that we follow DHJM in using lagged productivity on the right-hand side. As discussed in online Appendix B.1, this helps (i) to address differences in the data collection timing between labor and other variables, and (ii) to account for potential extra time to adjust which may be particularly relevant in Europe.

We report our estimates of the responsiveness coefficient, β_1, and and its trend over time, δ_1, for each country in online Appendix Table C1. To compare our results across countries, it is helpful to express the time trend relative to the initial level of responsiveness, which is given by the ratio δ_1/β_1. We plot these relative changes in Figure 10 for labor productivity in Panel (a) and total factor productivity in Panel (b).

Figure 10. Relative changes in responsiveness over time.



Notes: Estimated coefficient of the linear trend relative to the initial responsiveness, i.e., δ_1/β_1 in Equation (5). Underlying estimates are reported in Table C1. Countries are ranked in descending order. Bars are colored if both coefficients are statistically significant at least at the 10% level. The value for Portugal (25.3, resulting from a small β_1 coefficient) in (a) is truncated to allow comparison between productivity measures. The dashed blue line is the relative change estimated for the United States over 1981–2013 by DHJM. The Portuguese data starts in 2009 due to missing values in TFP. CompNet data, firms with at least 20 employees.

We estimate a declining responsiveness coefficient ($\delta_1 < 0$) in almost all countries. However, the negative δ_1 coefficient is statistically different from zero for seven countries, which are highlighted in blue: Czech Republic, Denmark, France, Latvia, Poland, Romania, Sweden, and the United

Kingdom. In Croatia, we estimate a statistically significant increase in responsiveness. However, this is the case only when using revenue-TFP as a productivity measure. Overall, relative changes in responsiveness range between 2 and 5 percent per year. This aligns well with US evidence. DHJM report an annual decline in responsiveness of approximately 2.25 percent over the 1981–2013 for the US using a similar specification.[26] These results are confirmed when we perform the same analysis in the group of countries where we also observe firms with less than 20 employees (online Appendix Figure C17). In fact, we find a significant decline in responsiveness in more countries, such as Italy, Spain, and Lithuania.[27]

As an alternative approach to capture a change in responsiveness, we also estimate a specification that allows responsiveness to vary by time windows (before 2009, 2009-2013, and after 2013), rather than a linear trend. As illustrated in online Appendix Figure C7, we find evidence of a clear downward trend in responsiveness also with this period-specific estimation approach.[28]

As large firms account for a substantial employment share and are characterized by lower job reallocation rates (Figure C6), they play a key role in shaping aggregate worker reallocation. To better understand job reallocation in Europe, we therefore examine whether large firms also exhibit lower responsiveness by estimating the following version of Equation (5):

$$g_{it} = \beta_0 + \sum_{z=1}^{3} \mathbb{I}_{zit-1} \left(\beta_{1z} a_{it-1} + \beta_{2z} l_{it-1}\right) + X_{jt} + \epsilon_{it} \tag{6}$$

$$\text{for } \; z = \begin{cases} 1, & L \in [20, 49] \\ 2, & L \in [50, 249] \\ 3, & L > 249, \end{cases}$$

where $\mathbb{I}_{zit}$ is an indicator for firms' employment size-class. Figure 11 presents the results from this specification.[29] Across most countries, we document a stark cross-sectional gradient over the size

[26] We added the relative changes in the US to our results on revenue-TFP because they are the only comparable ones. DHJM define labor productivity as revenue per worker, while we measure it in terms of value-added. We calculate the relative changes for the United States based on coefficient estimates reported by DHJM in Table 1 - Panel B. In particular, $\delta_1/\beta_1 = (-0.0046/0.2040) = -0.0225$.

[27] The fact that in these countries the coefficient δ_1 becomes statistically significant with more observations (x5 larger in the "all sample") suggests that statistical power was probably an issue in our 20e sample.

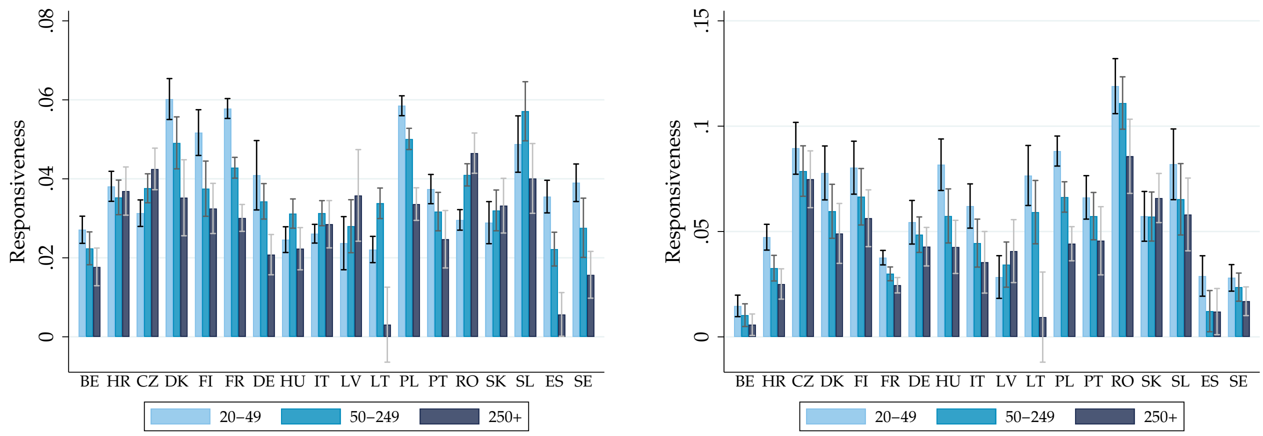
[28] These period-specific regressions allow us to compare the size of the firm responsiveness coefficient (i.e., β_1) between the US and European countries for the only overlapping period (i.e., the 2000s). Using a comparable productivity definition, DHJM estimates a coefficient of 0.08 for the 2000s. Our coefficients range from 0.01 to 0.15, which is broadly in line with DHJM.

[29] Unfortunately, we did not receive these results for the UK as the UK entered the data collection at a later stage.

distribution in the responsiveness of firms' employment changes to productivity. Larger firms have lower responsiveness. This gradient becomes particularly clear when using TFP as productivity measure (Panel (b)). Figure 12 shows that using the "all sample" countries strengthens the conclusions on the size gradient even further. In this case, we find this gradient in all countries. In Section 5.1, we develop a theoretical framework that can rationalize this gradient through larger firms having higher market power and/or operating with less labor-intensive technologies.[30]

Figure 11. Responsiveness levels by size class.

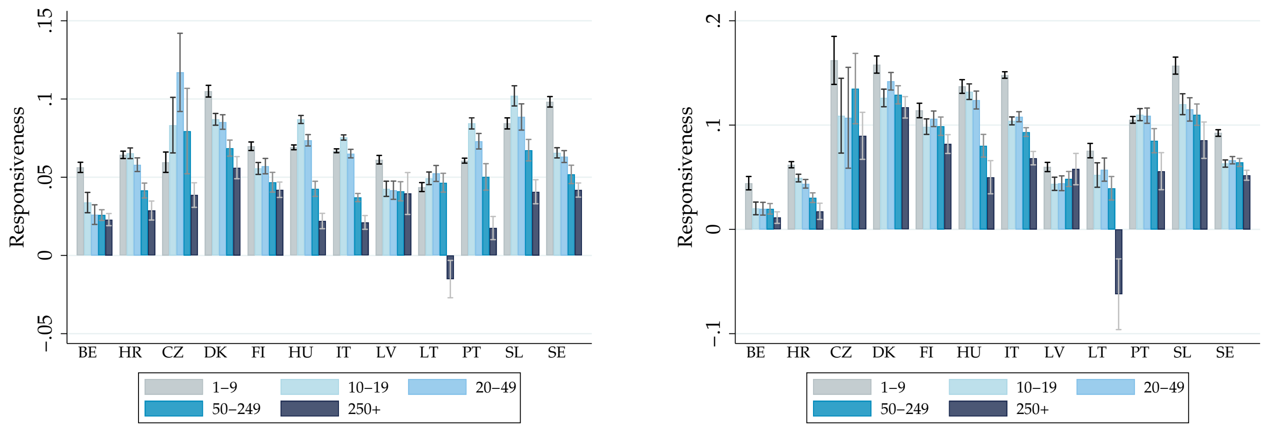
(a) Labor Productivity **(b)** Revenue-TFP



Notes: Size-class-specific responsiveness coefficients coefficient, i.e., β_{1z} in Equation (6). The full regression results are reported in Table C2 and Table C3. 90% confidence intervals are reported for each coefficient estimate. CompNet data, firms with at least 20 employees.

Figure 12. Responsiveness by size class ("all firms" sample).

(a) Labor Productivity **(b)** Revenue-TFP



Notes: Size-class-specific responsiveness coefficients coefficient, i.e., β_{1z} in Equation (6), but from a specification that uses the "all sample" and includes two additional size-classes for smaller firms. The full regression results are reported in Table C4 and Table C5. 90% confidence intervals are reported for each coefficient estimate. We did not receive results for Spain for this specification. CompNet data, firms with at least one employee.

[30] We analyze changes in large and small firms' responsiveness using the German microdata in Section 4.3.

Overall, our results suggest that firms' responsiveness to productivity shocks weakened in Europe over the last decades and that this decline is comparable to the US. A novel finding that we document is that larger firms have a lower responsiveness than smaller firms.

4.2 Shocks hypothesis

We now examine another potential driver of the decline in job reallocation, which is the change in the productivity dynamics. To examine whether productivity shocks have become more muted, we follow DHJM and analyze the productivity evolution with the following AR(1) model:

$$a_{ijt} = \rho_t \, a_{ijt-1} + X_{jt} + \eta_{ijt}, \tag{7}$$

where the coefficient ρ_t captures the persistence of the productivity evolution and the residual η_{it} represents productivity innovations. We again include industry-year fixed effects via X_{jt} to control for the fact that we pool different industries. In theory, a decline in the dispersion of productivity innovations leads to a decline in the dispersion of firm growth, ultimately reducing job reallocation. DHJM find that the US economy experienced an increase in the dispersion of productivity innovations between the 1980s and the 2000s. Based on this result, they conclude that changes in productivity shocks cannot explain the decline in US job reallocation.

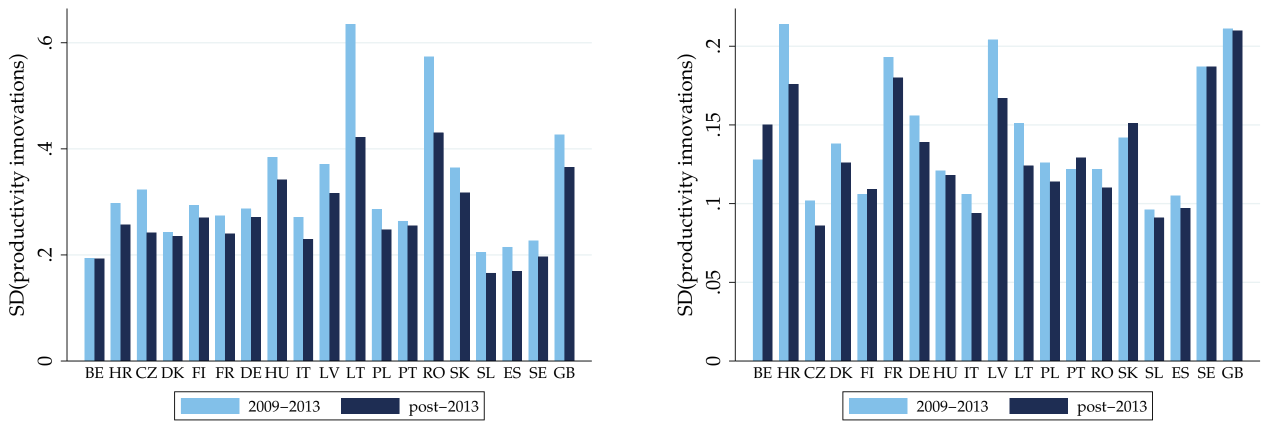
We report our estimates for the dispersion in productivity innovations, η_{it}, for the periods 2009-2013 and post-2013 in Figure 13. Similar results based on the "all sample" countries are reported in online Appendix C.3.3. For labor productivity, we find that the dispersion in productivity innovations declined across all countries. For the vast majority of countries, this is also confirmed using our revenue-TFP measure.[31] This decline in the dispersion of productivity shocks is a key difference between Europe and the US. In contrast to US evidence, our result suggests that the decline in job reallocation in Europe is - at least in part - the result of muted productivity dynamics.[32]

[31] Unfortunately, our data collection codes did not yield results before 2009. Therefore, we use additional results that we collected to directly study the standard deviation of productivity changes in online Appendix Figure C8. Note that the analysis in Figure C8 does also not impose any parametric assumptions on productivity dynamics. As Figure C8 shows, the dispersion of productivity changes decreased in almost all countries, and this declining trend was already in place before 2009.

[32] Analysis of the US Census Bureau, Productivity Dispersion Statistics (DISP) suggest the US may have experienced a change in dispersion dynamics post 2010. Approximately 47% of the 86 4-digit manufacturing industries in the US have experienced declines in dispersion post-2009. By contrast, 83% of the same 4-digit industries experienced increases between 1987 & 2009. The DISP can be downloaded here. The question of whether these patterns differ across Europe and the US, or whether indeed the US may have experienced a change in dispersion dynamics post-2010 merits further analysis that we do not pursue here.

Figure 13. Lower dispersion of productivity innovations.

(a) Labor Productivity **(b)** Revenue-TFP

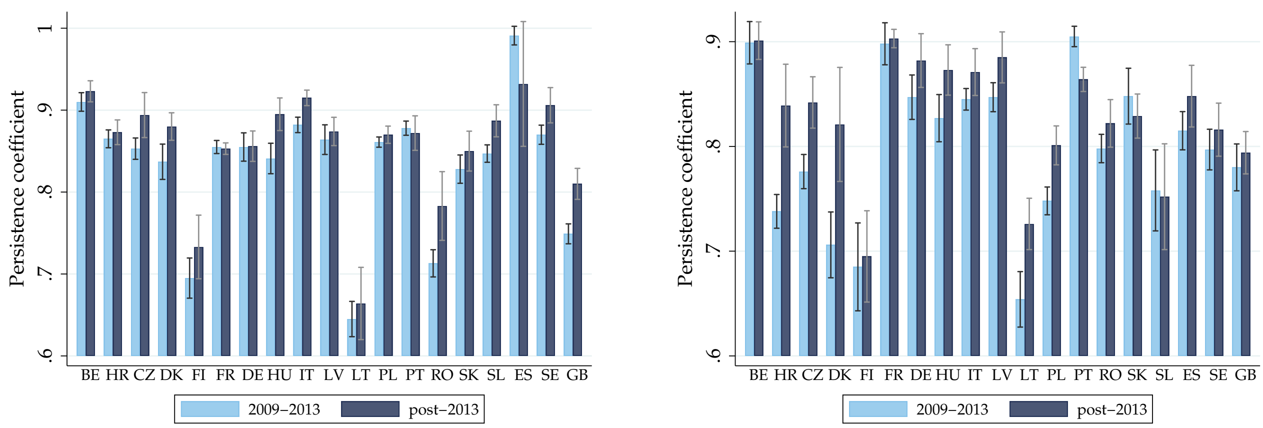


Notes: Standard deviation of the residuals of the AR(1) process in Equation (7) estimated over two consecutive periods. CompNet data, firms with at least 20 employees.

The estimation of the AR(1) process provides us also with information about the persistence of productivity shocks. In theory, a declining shock persistence reduces the incentives of firms to adjust to a given productivity shock if firms anticipate the lower permanence of productivity realizations. Therefore, a lower productivity persistence could provide one explanation for the declining responsiveness. However, Figure 13 illustrates that, if anything, persistence increased in many countries.[33]

Figure 14. Increasing persistence in productivity dynamics.

(a) Labor productivity **(b)** Revenue-TFP



Notes: Point estimates of the persistence coefficient ρ_t in the AR(1) in Equation (7) estimated over two consecutive periods. CompNet data, firms with at least 20 employees.

33 Again, these results are limited to post-2009. However, we replicate these results including earlier years with our German microdata in Section 4.3 and find similar results.

4.3 Replication with German manufacturing microdata

While rich in terms of its coverage and cross-country comparability, the CompNet data has a few limitations for our analyses. First, we cannot directly access the underlying firm-level data, limiting our ability to adjust our estimation methods and add additional analyses. Second, the time coverage is limited for some countries. Finally, our regression analyses using CompNet are based on basic estimates of firm-level productivity.

To address these concerns, we employ richer firm-level data on German manufacturing that we can directly access. The German manufacturing sector is one of the most important economic sectors in Europe. Moreover, as the data range from 1995 to 2017, we can analyze trends over a longer period. Finally, as the data contain firm-specific price information, we can estimate more flexible production functions that account for unobserved price variation.

4.3.1 Estimating productivity from firms' production functions

Using the German data, we derive revenue-productivity from estimating firms' production functions, relying on a flexible *translog* production function defined as:

$$\begin{aligned} q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \\ \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + tfp_{it} + \epsilon_{it}. \end{aligned} \tag{8}$$

q_{it}, l_{it}, m_{it}, and k_{it} denote the logs of output quantities, labor, intermediate, and capital inputs, respectively. tfp_{it} is the log of the Hicks-neutral (quantity-)productivity term. ϵ_{it} is an i.i.d. error term.

We estimate Equation (8) separately by NACE rev. 1.1 industries using a one-step approach as in Wooldridge (2009), which formulates a control function for unobserved productivity using information on firms' expenditures for raw materials and energy inputs. To account for unobserved input price variation, we leverage a firm-level adaption of the approach proposed by De Loecker et al. (2016). In a nutshell, we formulate a firm-specific input price control function based on observed firm-product-level output prices and market shares that we add to the production function. To account for firm-specific output price variation, we follow Eslava et al. (2004) and derive a firm-specific output price index from our firm-product-level price data. We describe the entire methodology in online Appendix E, which closely follows Mertens (2022). Having estimated the production function, we derive log revenue-productivity, $log(TFPR)$, as $tfpr_{it} = q_{it} + p_{it} - f_{it}(.)$, where $f_{it}(.)$ captures the production factors and their interactions from Equation (8). p_{it} is the log of a firm-level output price index as defined in Eslava et al. (2004) and described in online Appendix E.1.[34]

4.3.2 Core results using the German manufacturing microdata

The strong decline in job reallocation documented with CompNet is also confirmed with the German manufacturing sector firm-level data. Job reallocation rate decreased by one-third, from 8.3% in 1996 to less than 5.6% in 2017.[35] Table 2 reports our estimates of the responsiveness regressions using the German microdata. We estimate a version of Equation (5) with a period interaction instead of including a linear trend to allow for more flexibility (as in Figure C7). The periods are 1996-1998, 1999-2002, 2003-2006, 2007-2010, 2011-2014, and 2015-2017. Columns 1-3 of Table 2 show the estimation results of the specification using productivity levels on the right-hand side, as in DHJM and our previous results. In columns 4-6, we use a first-differences specification, which is more demanding in terms of data, but directly relates firm growth to productivity changes. This specification is defined as follows:

$$g_{it} = \beta_0 + \sum_{TW=1}^{6} \mathbb{I}_{TW}\, \delta_{TW} \Delta tfpr_{it-1} + X_{jt} + \epsilon_{it}\,,$$

where $\mathbb{I}_{TW}$ is a dummy variable for each time window. As discussed in DHJM, both specifications are theoretically valid. We estimate both specifications by splitting our sample into large (i.e., at least 100 employees) and small (i.e., less than 100 employees) firms.[36]

Consistent with our previous results at the European level, we find that (i) larger firms have lower responsiveness, and (ii) there is a strong decline in firms' responsiveness in the German manufacturing sector. The responsiveness coefficients in the last two periods are less than half the size of the responsiveness coefficients in the first periods. In absolute terms, the decline in responsiveness is similar for large and small firms. In relative terms, the decline in large firms' responsiveness is

[34] To ensure that our results are not driven by outliers, we drop the top and bottom one percent in industry-demeaned TFPR.

[35] Online Appendix Figure D1 compares the dynamics in job reallocation rates estimated with CompNet data and the German firm-level data, highlighting that both datasets lead to comparable results, both in levels and changes. See also Figure 16 of Section 5.3 for changes in the job reallocation rate in the German microdata.

[36] The data did not support a split into three size categories as in the CompNet data when estimating changes in responsiveness over time because the number of observations per period became too low.

Table 2. Responsiveness to productivity in the German manufacturing sector.

	Dependent variable: Employment growth rate (g_{ijt})					
	Productivity in levels ($tfpr_{ijt-1}$)			Productivity in first-differences ($\Delta tfpr_{ijt-1}$)		
	All firms	**Small firms**	**Large firms**	**All firms**	**Small firms**	**Large firms**
Period	(1)	(2)	(3)	(4)	(5)	(6)
1996-1998	0.048***	0.062***	0.051***	0.064***	0.095***	0.062***
	(0.011)	(0.009)	(0.013)	(0.021)	(0.032)	(0.022)
1999-2002	0.034***	0.043***	0.037***	0.034***	0.066***	0.031**
	(0.007)	(0.007)	(0.0076)	(0.013)	(0.021)	(0.015)
2003-2006	0.017***	0.033***	0.017**	0.052***	0.052***	0.053***
	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)	(0.013)
2007-2010	0.033***	0.031***	0.035***	0.078***	0.051***	0.082***
	(0.005)	(0.004)	(0.006)	(0.014)	(0.009)	(0.016)
2011-2014	0.016***	0.027***	0.016***	0.018*	0.035***	0.016
	(0.004)	(0.003)	(0.005)	(0.01)	(0.013)	(0.012)
2015-2017	0.016***	0.026***	0.015***	0.029	0.05***	0.027
	(0.005)	(0.004)	(0.005)	(0.02)	(0.013)	(0.022)
Lagged labor control	yes	yes	yes	no	no	no
Industry-Year FE	yes	yes	yes	yes	yes	yes
Observations	180,022	87,108	92,914	122,659	52,675	69,984
N of firms	38,721	25,785	16,533	27,480	16,847	12,602
R^2	0.053	0.039	0.057	0.048	0.038	0.052

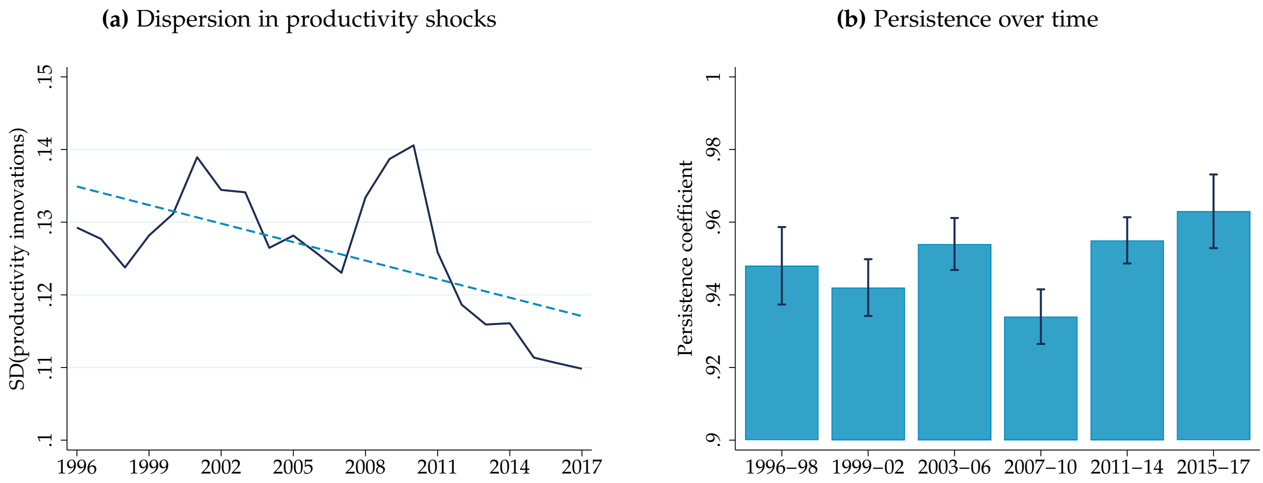
Notes: Results from estimating firms' responsiveness using productivity levels (columns 1-3) and differences (4-6) on the right-hand side. Productivity variables are interacted with a full set of period dummies. All regressions include industry-year fixed effects. The specifications in levels also include a full set of interactions between period dummies and lagged labor. In columns (1) and (4), we report results for all firms, while in (2) and (5) for small firms (less than 100 employees), and in (3) and (6) for firms with more than 100 employees. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

much larger, given their initial lower responsiveness. Overall, the level of the estimated coefficients is comparable to our results from the CompNet data and consistent with findings in DHJM.[37]

Regarding the shock hypothesis, Figure 15 shows the results derived from estimating the AR(1) process of our TFPR measure for our six periods while controlling for industry-year fixed effects as in Equation (7). The dark blue solid line in Panel (a) shows the evolution of the standard deviation of the productivity innovations (η_{ijt}), while the bars in Panel (b) display our estimates of the persistence coefficients (ρ_t). In line with previous results in Figure 13, we find a decline in the dispersion of productivity shocks also with our more sophisticated productivity estimates. If anything, productivity persistence slightly increased in the German data during this period.

[37] We compare our coefficients with manufacturing "TFPP" (proxy method) estimates for the 90s and 2000s reported by DHJM (Table 1). They show somewhat larger estimates for the 90s and 2000s periods (approximately 0.10). However, it is important to stress that they focus on plant-level data, including information on exit margins and plants with less than 20 employees.

Figure 15. Productivity dynamics in the German manufacturing sector.



Notes: Estimates based on an AR(1) process for $TFPR_{it}$ that controls for industry-year fixed effects and is estimated separately for six periods (1996-1998, 1999-2002, 2003-2006, 2007-2010, 2011-2014, 2015-2017). The regressions feature 180,022 observations. In sub-figure (a), the solid line indicates the standard deviation (SD) of the residuals. The dashed line is a linear trend. In sub-figure (b), the bars indicate the persistence coefficients with 90% confidence intervals. German microdata.

5 The role of market power and technology

In this section, we develop a firm-level framework to understand the role of market power and technology in the observed decline in job reallocation and responsiveness. While DHJM focus on adjustment costs to rationalize this decline, they highlight that their findings could also be interpreted in terms of "correlated wedges" that may capture, among others, variation in firms' market power. Our contribution is to formalize this intuition and to unpack the black box of firm responsiveness and job reallocation. In particular, we rationalize declining responsiveness via changes in firms' market power in output and labor markets, factor costs, and production technologies.[38] Compared to changes in adjustments costs, these factors provide a more natural explanation for declining job reallocation as many European countries have significantly increased their labor market flexibility in the past 20 years (Eichhorst et al., 2017; Gehrke and Weber, 2018). Section 5.1 derives our framework showing how changes in firms' labor demand are influenced by technology and market power in output and labor markets. Section 5.2 describes how we estimate these variables at the firm-year

[38] Our approach is thus related to work by De Loecker et al. (2021). Whereas their analysis of job reallocation rates is based on an industry equilibrium model and focuses on firms' product market power, our approach also considers firms' monopsony power and labor output elasticity and can be implemented directly from firm-level estimates of markups, markdowns, and output elasticities. However, this prevents us from studying counterfactual changes in market primitives.

level with our German manufacturing data. Section 5.3 and Section 5.4 provide empirical evidence that changes in firms' market power, wages, and production technologies quantitatively matter for the decline in job reallocation and responsiveness.

5.1 Theory

Consider a firm i at time t that combines labor (L_{it}), materials (M_{it}), and capital (K_{it}) to produce output (Q_{it}) according to a Hicks-neutral production function defined as:

$$Q_{it} = F_{it}(L_{it}, M_{it}, K_{it})\, TFP_{it} = F_{it}(\cdot)\, TFP_{it},$$

where TFP_{it} denotes the firm's total factor productivity level. We do not restrict the production function to any specific parametric form but only require that it is continuous and twice differentiable. Firms' operating profits are given by:

$$\Pi_{it} = P_{it}(Q_{it})Q_{it} - W_{it}(L_{it})L_{it} - V_{it}M_{it} - R_{it}K_{it},$$

where W_{it}, V_{it}, and R_{it} denote unit costs for labor, intermediates, and capital. Note that we express output prices and wages as functions of quantities and labor inputs. This allows for firm market power in product and labor markets. Under profit maximization, the first-order condition for labor implies that the marginal revenue product of labor ($MRPL_{it}$) must be equated to the marginal factor cost (MFC_{it}) of hiring an additional worker:

$$\frac{\partial \Pi_{it}}{\partial L_{it}} = 0 \quad \Rightarrow \quad \overbrace{\underbrace{\left(P_{it} + \frac{\partial P_{it}}{\partial Q_{it}} Q_{it}\right)}_{MR_{it}} \underbrace{\frac{\partial Q_{it}}{\partial L_{it}}}_{MPL_{it}}}^{MRPL_{it}} = \overbrace{W_{it}\,(1+\xi_{it})}^{MFC_{it}}, \tag{9}$$

where $\xi \equiv \dfrac{\partial W_{it}}{\partial L_{it}} \dfrac{L_{it}}{W_{it}}$ is the firm-specific (inverse) labor supply elasticity faced by the firm. Reformulating Equation (9) yields the following expression for labor demand:

$$L_{it} = \frac{P_{it}Q_{it}}{\gamma_{it}\mu_{it}} \frac{\theta^L_{it}}{W_{it}} = F_{it}(\cdot)\frac{TFPR_{it}}{\gamma_{it}\mu_{it}} \frac{\theta^L_{it}}{W_{it}}, \tag{10}$$

where $\mu_{it} \equiv \dfrac{P_{it}}{MC_{it}}$ is the price over marginal cost markup set by the firm, $\gamma_{it} \equiv 1 + \xi$ is a measure of the firm's monopsony power. Finally, $\theta^L_{it} \equiv \dfrac{\partial Q_{it}}{\partial L_{it}} \dfrac{L_{it}}{Q_{it}}$ is the output elasticity of labor, which reflects the technological importance of labor in the firm's production process. If we further decompose revenue ($P_{it}Q_{it}$), we can express labor demand in terms of $TFPR_{it}$. This is the productivity measure that we use in our regressions, which is a composite of firms' technical efficiency and demand conditions. The term $F_{it}(\cdot)$, which is the the production function, (i.e., output) net of the productivity term, depends on the specification of the production function and captures firms' production technology in a broader sense.[39]

By taking logs and first differences of Equation (10), the employment growth between $t-1$ and t can be decomposed as follows:

$$\begin{aligned} g_{it} \approx \Delta l_{it} &= l_{it} - l_{it-1} \\ &= p_{it} + q_{it} + log(\theta^L_{it}) - log(\gamma_{it}) - log(\mu_{it}) - log(W_{it}) - l_{it-1} \\ &= tfpr_{it} + f_{it}(\cdot) + log(\theta^L_{it}) - log(\gamma_{it}) - log(\mu_{it}) - w_{it} - l_{it-1}, \end{aligned} \tag{11}$$

where smaller letters denote logs. Compared to the stylized model of DHJM (see online Appendix B.1), Equation (11) sheds light on the role of firms' productivity, markups, markdowns, wages, and technology in driving changes in firms' employment. To make this apparent, we rewrite Equation (11) in first-differences:

$$g_{it} \approx \Delta l_{it} = \Delta tfpr_{it} + \Delta f_{it}(\cdot) + \Delta log(\theta^L_{it}) - \Delta log(\gamma_{it}) - \Delta log(\mu_{it}) - \Delta w_{it}. \tag{12}$$

Equation (11) provides a general decomposition of employment growth at the firm level. In the following sections, we estimate the components of this equation and apply it to study the determinants of job reallocation and responsiveness.

5.2 Estimating markups, markdowns, and output elasticities

In addition to estimating TFPR and firms' production function, $f_{it}(\cdot)$, we can use the production function approach described in Equation (8) and online Appendix E to recover estimates of output elasticities, markups, and markdowns for each firm and year in the German manufacturing data.

The output elasticity of labor is derived as the derivative of the logged production function: $\theta^L_{it} = \frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$. We estimate markups using the firm's first-order

[39] For instance, under a Cobb-Douglas production function, $F_{it} = L_{it}^{\theta^L_{it}} M_{it}^{\theta^M_{it}} K_{it}^{\theta^K_{it}}$, Equation (10) becomes $L_{it} = \left(K_{it}^{\theta^K_{it}} M_{it}^{\theta^M_{it}} \frac{TFPR_{it}}{\gamma_{it}\mu_{it}} \frac{\theta^L_{it}}{W_{it}} \right)^{\frac{1}{1-\theta^L_{it}}}$.

condition for intermediates following the approach of De Loecker and Warzynski (2012):

$$V_{it} = MRPM_{it} \;\Rightarrow\; \mu_{it} = \frac{P_{it}}{MC_{it}} = \theta^M_{it}\frac{P_{it}Q_{it}}{V_{it}M_{it}}, \tag{13}$$

where $MRPM_{it}$ is the marginal revenue product of intermediates and $\theta^M_{it} = \frac{\partial q_{it}}{\partial m_{it}}$ is the firm-year specific output elasticity of intermediates.[40] Combining the first-order condition of labor from our framework (Equation (9)) with Equation (13) yields an expression for markdowns:

$$\gamma_{it} = 1 + \xi_{it} = \frac{MRPL_{it}}{W_{it}} = \frac{\theta^L_{it}}{\theta^M_{it}}\frac{V_{it}M_{it}}{W_{it}L_{it}}, \tag{14}$$

where $MRPL_{it}$ is the marginal revenue product of labor. This approach to estimating wage markdowns has been recently used in several studies (Dobbelaere and Mairesse, 2013; Caselli et al., 2021; Mertens, 2022; Yeh et al., 2022).[41] We present summary statistics on estimated markups, markdowns, and output elasticities in online Appendix Table A6. The estimates are meaningful and well in line with previous work. The average markup, markdown, and labor output elasticity equal 1.07, 1.08, and 0.30, respectively. These results indicate that the average firm sets a price 7% higher than its marginal costs and pays its workers 93% of their marginal revenue product. The estimated value of θ^L implies that a 100 percent increase in a firm's employment results in 30 percent more output, all else equal. Underlying these averages, we find evidence of a substantial heterogeneity across firms.

5.3 Direct influence on job reallocation

Equipped with these estimates at the firm-year level, we can analyze whether and to what extent changes in market power and technology affect the aggregate job reallocation rate through their effect on individual firms' labor demand. By summing over employment changes as defined in

[40] As in De Loecker and Warzynski (2012), we assume that intermediate inputs are flexible and that intermediate input prices are exogenous to firms to recover markups using Equation (13).

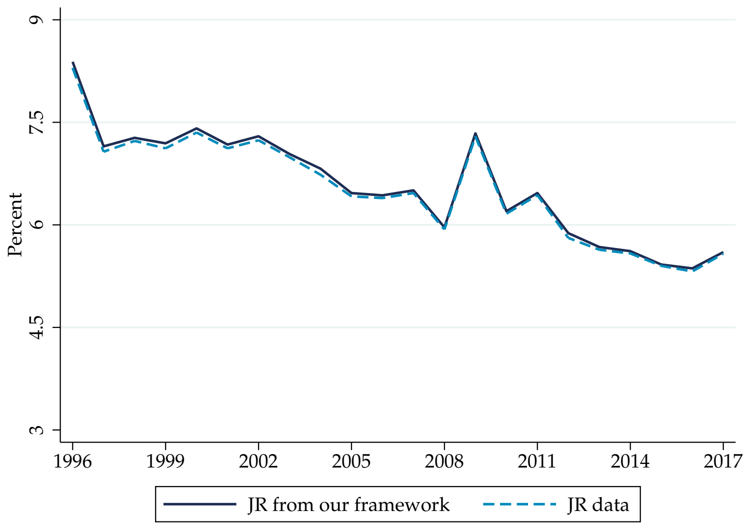
[41] Equation (14) leads to an unbiased estimate of firms' wage markdown in the absence of adjustment frictions. Particularly in the European/German context, labor adjustment frictions might be a relevant concern, and indeed, we estimate that a large share of firms has values of $\gamma_{it} < 1$. This signals the presence of adjustment costs that could cause worker-side labor market power, as mentioned in Mertens (2020) and Garin and Silvério (2019). We highlight this limitation that we share with all studies estimating firm-specific wage markdowns using a production function approach. Note, however, that our previous responsiveness regressions account for adjustment frictions by using lagged productivity values.

Equation (12), we can relate aggregate job reallocation rate to changes in productivity, market power, output, technology, and wages as follows:

$$JR_t = \sum_i s_{it} \, |g_{it}| \approx \sum_i s_{it} \left| \left[\Delta f(\cdot)_{it} + \Delta tfpr_{it} + \Delta log(\theta^L_{it}) - \Delta log(\gamma_{it}) - \Delta log(\mu_{it}) - \Delta w_{it} \right] \right|. \tag{15}$$

As both the expansion and contraction of firms contribute to job reallocation, the employment changes (and its determinants) are written in absolute values. Importantly, this absolute value is taken over a sum of terms that positively and negatively affect changes in labor demand. Consequently, the observed changes in job reallocation are the net results of changes in productivity, technology, output, market power, and wages that influence firm growth in different directions. Figure 16 shows that the implied job reallocation rate based on Equation (15) (dark blue solid line) closely mimics the job reallocation rate measured from observed employment changes (dashed line), both in levels and trends over time. This result validates our theoretical approach.

Figure 16. Implied job reallocation *vs.* data.



Notes: The dark blue solid line depicts the job reallocation rate as derived from the sum of the right-hand side terms of Equation (15). The dashed light blue line depicts the job reallocation rate as directly measured in the data based on employment changes. German microdata.

To study the relationship between job reallocation and changes in market power, technology, output, and wages, we analyze each factor of Equation (15) in isolation. In particular, we look at the weighted sum across firms of the absolute changes in each term. These changes provide an intuitive link between job reallocation and its components. If only one factor changes, holding everything else fixed in Equation (15), the hypothetical job reallocation rate would be equal to the employment-weighted average of the absolute changes in that factor. Undoubtedly, this is an extreme thought experiment because changes in each component are endogenous and depend on each other. However, the aim of this exercise is not to quantify the net influence of these changes on the job reallocation rate. Instead, it helps us assess the importance of each factor with a partial effect perspective. Holding everything else fixed, we ask which factors have a larger direct effect on the job reallocation rate.

As reported in Table 3, we find evidence that the (weighted sum of absolute) changes in market power, technology, and wages are different from zero. This indicates that these factors played an important role in shaping job reallocation, in addition to productivity changes. Comparing the changes between the beginning and end of our sample (Columns 1-2), we find that absolute changes in productivity and output net of productivity, $f(\cdot)$, decreased by more than 20%.[42] At the same time, the dynamics of all the other components related to market power, wages, and technology became more muted over time. We conclude that the subdued changes in market power, technology, wages, output, and productivity all contributed to declining job reallocation.

Table 3. Changing dynamics of productivity, market power, technology, and wages

Sum of absolute changes in......	1995-1996 (1)	2016-2017 (2)	Percentage change (3)
TFPR ($\sum_i s_{it}\,\lvert\Delta tfpr_{it}\rvert$)	0.087	0.069	–20.9%
Markups ($\sum_i s_{it}\,\lvert\Delta log(\mu_{it})\rvert$)	0.053	0.045	–14.9%
Markdowns ($\sum_i s_{it}\,\lvert\Delta log(\gamma_{it})\rvert$)	0.084	0.074	–11.5%
Labor output elasticities ($\sum_i s_{it}\,\lvert\Delta log(\theta_{it})\rvert$)	0.046	0.043	–5.8%
Wages ($\sum_i s_{it}\,\lvert\Delta w_{it}\rvert$)	0.063	0.057	–8.9%
Output net of productivity ($\sum_i s_{it}\,\lvert\Delta f(.)_{it}\rvert$)	0.115	0.087	–24.13%

Notes: This table reports the individual components of Equation (15) for the first and last year in our data. German microdata.

5.4 The influence on responsiveness

Our theoretical framework emphasizes that changes in markups, markdowns, technological importance of labor, and wages not only *directly* reduce job reallocation, as just demonstrated, but also *indirectly* affect it through their effect on firms' responsiveness. We now turn our attention to the latter. We first theoretically describe how changes in markups, technology, and wages that are correlated with productivity changes influence responsiveness. Subsequently, we show how the levels

[42] According to Equation (15), these employment-weighted averages of changes are the relevant aggregation metric determining job reallocation.

of these factors affect responsiveness.

5.4.1 Correlated *changes* in market power, technology, and wages

Note that dividing Equation (12) by $\Delta tfpr_{it}$ decomposes the responsiveness of employment to productivity (now expressed as an elasticity) into its drivers:

$$\frac{\Delta l_{it}}{\Delta tfpr_{it}} = 1 + \frac{\Delta f_{it}(\cdot)}{\Delta tfpr_{it}} + \frac{\Delta log(\theta^L_{it})}{\Delta tfpr_{it}} - \frac{\Delta log(\gamma_{it})}{\Delta tfpr_{it}} - \frac{\Delta log(\mu_{it})}{\Delta tfpr_{it}} - \frac{\Delta w_{it}}{\Delta tfpr_{it}}. \tag{16}$$

This decomposition shows how the pass-through of productivity shocks to employment adjustments is shaped by market power, technology, and wages. Equation (12) suggests that the more a firm increases its markup and/or markdown in *relative* terms, the smaller will be the changes in its employment after a productivity shock. The same reasoning applies to technology and wages. Employment responsiveness to a productivity shock weakens as the output elasticity of labor declines or wages increase.

Clearly, all these predictions are based on partial adjustments of each component of Equation (12). In fact, any of these changes are likely to coincide with simultaneous changes in other components and output as well. Nonetheless, Equation (16) provides a formal interpretation of the "correlated wedges" discussed by DHJM, which enhances our understanding of the potential factors that can explain the documented changes in firms' responsiveness. The key takeaway is that joint changes in productivity and the other components of Equation (16) matter for responsiveness.

5.4.2 Responsiveness and *levels* of market power, technology, and wages

One subtle but crucial point in our analysis is that firms' output changes are determined by the levels of firms' market power, wages, and output elasticities. As proved in very general terms in Biondi (2022), firms with higher product and/or labor market power adjust output to a lesser extent in response to a productivity shock, because they operate on steeper product demand and/or marginal cost of labor curves. Similarly, firms with lower output elasticities generate less output from a given increase in productivity. Formally, the second derivatives of firms' labor demand (Equation (10)) with respect to market power, technology, and wages are non-zero:

$$\frac{\partial^2 L_{it}}{\partial TFPR_{it} \partial \kappa_{it}} \neq 0, \text{ with } \kappa_{it} = \{\theta^L_{it}, \mu_{it}, \gamma_{it}, W_{it}\}. \tag{17}$$

Consequently, also the levels of firms' market power, wages, and technology shape firms' responsiveness. We demonstrate this through simulations and an empirical extension of our previous responsiveness regressions in the next sections.

5.4.3 Simulations and the role of firm size

We now perform a series of numerical simulations that use our framework to analyze how market power, technology, and factor cost affect firms' responsiveness. We also connect this analysis to the documented size gradient in firm responsiveness. Our simulation shows that differences in market power and technology that are correlated with firm size provide an intuitive rationale for why larger firms are less responsive than smaller firms.

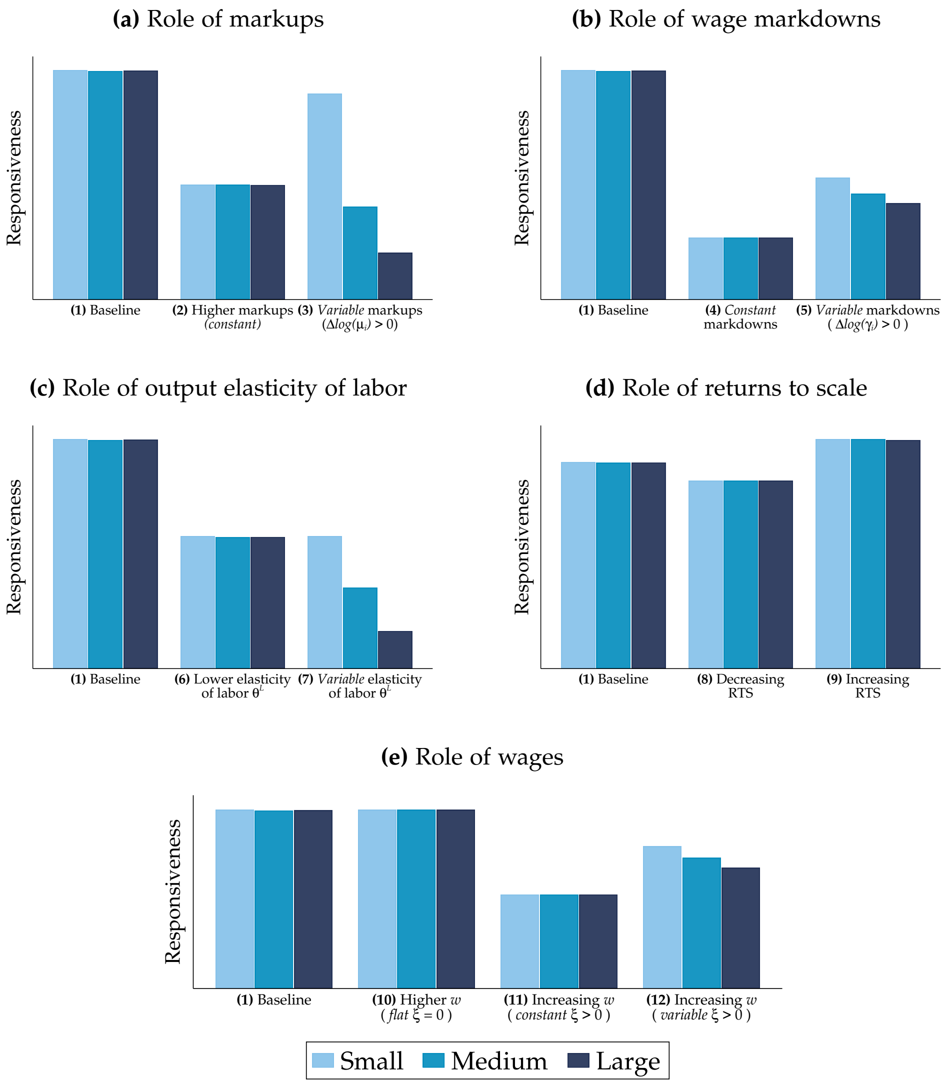
Figure 17 illustrates the predicted responsiveness of a firm's employment to a 1% productivity increase under different scenarios. Each bar represents the responsiveness of a small (lightest blue), a medium, and a large monopolist (darkest blue). To model the role of technology, we allow for two production factors, labor and one other flexible factor (e.g., intermediates). We provide more details about our simulations in online Appendix B.2.

In the baseline scenario (1), we consider a setting where markups, markdowns, labor output elasticities, returns to scale, and wages are constant over time and identical across firms. In this case, firms of different sizes respond identically to a 1% productivity shock. In scenario (2) in Figure 17a, we show the responsiveness of labor to productivity when all firms set a higher markup. This represents a situation where consumers are less price elastic, and firms can exert higher market power. We graphically compare the first-order conditions in scenarios (1) and (2) in online Appendix Figure B1. Responsiveness is lower for all firms compared to the baseline scenario. Scenario (3) illustrates how differences in responsiveness across size classes arise if firms producing more set higher markups. As shown, larger firms have a lower responsiveness whenever the price elasticity of demand decreases along the demand curve.[43] A firm that produces more has a lower responsiveness to productivity because, as output levels increase, consumers become less willing to pay for each additional unit.[44] As a result, a growing part of the firm's productivity gains is converted into

[43] This is the case for any demand function that satisfies Marshall's second law of demand.

[44] This is because demand gets closer to a point of near satiation. In this situation, a highly productive firm finds it unprofitable to continually expand its output at the same rate as this would result in a rapid decline in its marginal revenue. Its profit-maximizing strategy, instead, is to take its "foot off the gas" after a productivity shock and expand

Figure 17. Simulated responsiveness to productivity shocks by size class.



Notes: Different scenarios for the responsiveness of labor to productivity changes, i.e., $\frac{\Delta l_{it}}{\Delta tfp_{it}}$, as described in online Appendix B.2.

higher markups. This represents a first mechanism that can explain why larger firms have a lower responsiveness as reported in Figure 11 and Figure 12. Moreover, a rise in markups can therefore also explain the decline in responsiveness.

A similar logic applies to wage markdowns. In Figure 17b scenario (4), firms have a lower responsiveness to productivity if they exert monopsonistic power in the labor market. This is because the firm faces an additional trade-off in maximizing its profit, this time on the cost side. Compared to scenario (1), where a firm is a *wage-taker*, the firm's marginal factor costs become upward-sloping if

output - and thus employment - at a decreasing rate.

it exerts monopsony power. Mirroring the case of markups, a more productive firm refrains from expanding output and thus labor demand. We graphically illustrate this in online Appendix Figure B2. If larger firms increase their markdown relatively more, their responsiveness to productivity becomes relatively weaker. We consider this in scenario (5). This occurs whenever the conditions in the labor market are such that the markdowns are heterogeneous and increasing in firm size. For instance, if the elasticity of inverse supply increases with firm size.

We analyze the role of technology in Figure 17c and Figure 17d. In scenario (6), we reduce the labor output elasticity compared to the baseline (1), such that technology is less labor-intensive. We increase the output elasticity of our second production input such that returns to scale remain constant. As labor is less relevant in the production process, also its responsiveness to productivity is lower. A gradient of responsiveness across firms of different sizes emerges when the labor output elasticity declines faster at a higher output level. For instance, this tends to occur when larger firms become better integrated into global value chains and are more likely to offshore parts of their labor-intensive production. This is the scenario we consider in Panel (7).

While the previous scenarios relate to input substitution, we highlight the role of returns to scale in scenarios (8) and (9). If the production technology of the firm exhibits decreasing returns to scale, responsiveness is lower. The opposite occurs with increasing returns to scale. Returns to scale influence the incentive to expand output (and thus employment) after a productivity shock because they affect how marginal cost changes with output.

Finally, we illustrate the role of wages in Figure 17e. In scenario (10), we consider a higher wage than the baseline under a perfectly elastic labor supply curve. For a given productivity level, firms are smaller in terms of output and employment. However, their responsiveness to a productivity shock remains unchanged. This is because wages influence responsiveness only when the inverse supply elasticity (i.e., ξ) differs from zero.[45] In scenario (11), we consider a setting where firms remain wage-takers but face an upward-sloping inverse supply curve with a constant but positive elasticity (i.e., $\xi > 0$). The responsiveness to productivity is lower compared to the baseline because the wage increases as a firm produces more. The rate at which this occurs, which is reflected by ξ, is constant in scenario (11), while it increases with size in scenario (12).

45 To see that, note that the term related to wages in Equation (16), $\frac{\Delta w_{it}}{\Delta tfpr_{it}}$, can be further decomposed as $\frac{\Delta w_{it}}{\Delta l_{it}} \frac{\Delta l_{it}}{\Delta q_{it}} \frac{\Delta q_{it}}{\Delta tfpr_{it}}$. The first component $\frac{\Delta w_{it}}{\Delta l_{it}}$ is precisely the inverse supply elasticity ξ.

In summary, our framework rationalizes declining responsiveness through rising firm market power and/or wages or a reduction in firms' labor output elasticity or returns to scale. At the same time, it provides a clear connection between differences in responsiveness and differences in market power, factor costs, and technology between firms. If larger firms exert greater market power, employ less labor-intensive technologies, or pay higher wages, our framework can rationalize the size gradient of firm responsiveness observed in most European countries. A framework with adjustment costs could not do that unless one assumes that adjustment costs are increasing with firm size.

5.4.4 Empirical evidence on responsiveness, market power, technology and wages

Our previous results are based on simulations. As these results depend on the features of product demand, labor supply, and production functions, we now assess their empirical relevance by estimating an extension of the empirical model in DHJM that allows firms' responsiveness to differ by the level of firms' market power, technology, and wages. Specifically, we estimate the following extended responsiveness regressions:

$$g_{it} = \beta_0 + \beta_{tfpr} tfpr_{it-1} + \beta_l l_{it-1} + (\boldsymbol{\beta}'_{tfpr \times \Lambda} \boldsymbol{\Lambda}_{it-1}) \times tfpr_{it-1} + \boldsymbol{\beta}'_{\Lambda} \boldsymbol{\Lambda}_{it-1} + X_{jt} + \epsilon_{it}, \tag{18}$$

where the vector $\boldsymbol{\Lambda}'_{it-1} = (log(\mu_{it-1}), log(\gamma_{it-1}), log(\theta_{it-1}), w_{it-1}, f(.)_{it-1})$ captures the components of our firm growth decomposition (Equation (11)). We write the model as a level specification but we also estimate a first difference version that substitutes $tfpr_{it-1}$ with $\Delta tfpr_{it-1}$ and omits the lagged labor control (the other variables remain in lagged levels). Consistent with our previous regressions, we control for industry-year fixed effects in X_{jt}.

The results in Table 4 are in line with our theoretical discussion and simulations. On average, higher markups, higher markdowns, higher wages, and lower output elasticities of labor are associated with lower responsiveness of employment to productivity. A ten percent higher markup decreases responsiveness by 0.8 (1.9) percentage points in the levels (first difference) specification. Markdowns have a smaller but highly statistically significant impact: A ten percent increase is associated with a 0.13 (0.44) percentage points reduction in responsiveness in the levels (first difference) specification. As predicted by our simulation, a higher labor output elasticity increases responsiveness (coefficient of 0.023). Regarding wages, we find a negative coefficient, although with a lower statistical signif-

Table 4. Extended responsiveness regressions.

	Dep. variable: Employment growth rate (g_{ijt})	
	Levels	First differences
Lagged variables	(1)	(2)
$TFPR$	0.207**	0.388**
	(0.0954)	(0.176)
$TFPR \times markup$	-0.0836***	-0.192***
	(0.0185)	(0.0414)
$TFPR \times markdown$	-0.0129**	-0.0437***
	(0.00625)	(0.0144)
$TFPR \times labor\ output\ elasticity$	0.0234***	0.0231*
	(0.00862)	(0.0131)
$TFPR \times wage$	-0.00484	-0.0310*
	(0.00905)	(0.0170)
$TFPR \times\ prod.\ function\ net\ of\ productivity$	0.000113	0.000120
	(0.000515)	(0.00115)
Lagged labor control	yes	no
Control for main effects	yes	yes
Industry-Year FE	yes	yes
Observations	180,022	122,659
N of firms	38,721	27,480
R^2	0.067	0.070

Notes: This table presents results from running a levels and a first difference specification of Equation (18). All regressions control for lagged markups, markdowns, labor output elasticities, wages, and production function terms net of productivity (i.e., "main effects"). All regressions include industry-year fixed effects. The level specification controls for lagged levels of labor. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

icance. This weak evidence possibly reflects that the effect of wages on responsiveness depends on the shape of the labor supply curve, as highlighted in our simulation. Finally, changes in the term capturing the production function net of productivity ($f(\cdot)$) have no explanatory power after conditioning on firms' market power, wages, and labor output elasticities. This is not surprising because output changes are determined by differences in firms' technology, factor costs, and market power.

After demonstrating that firms' market power and technology are important for determining firms' responsiveness, it is now key to understand how these factors can rationalize the observed differences between large and small firms and the general decline over time. Table 5 therefore reports average firms' markups, markdowns, technology, and wages overall and for large and small firms. We also present changes in market shares to document potential reallocation processes.

Panel (a) of Table 5 shows that markups are generally low in the German manufacturing sector.

Table 5. Changes in average market power, technology, and wages.

Panel a: Market Power	*All firms*		*Small firms*		*Large firms*	
	1996	2017	1996	2017	1996	2017
Markups ($\overline{\mu}_t$)	1.01	1.07	1.09	1.10	1.00	1.06
Markdowns ($\overline{\gamma}_t$)	1.32	1.31	0.89	0.87	1.37	1.36
Combined ($\overline{\mu_t \gamma_t}$)	1.38	1.56	0.99	1.02	1.41	1.60
Panel b: Technology and wages	*All firms*		*Small firms*		*Large firms*	
	1996	2017	1996	2017	1996	2017
Labor output elasticity ($\overline{\theta_t^L}$)	0.38	0.33	0.29	0.27	0.39	0.34
Capital output elasticity ($\overline{\theta_t^K}$)	0.17	0.15	0.10	0.09	0.18	0.16
Intermediate output elasticity ($\overline{\theta_t^M}$)	0.60	0.66	0.61	0.64	0.60	0.66
Returns to scale ($\overline{\theta_t^L + \theta_t^K + \theta_t^M}$)	1.15	1.14	1.00	0.99	1.17	1.15
Real wages ($\overline{W_t}$)	40,060€	43,046€	30,969€	31,079€	41,102€	44,473€
Panel c: Market shares	*All firms*		*Small firms*		*Large firms*	
	1996	2017	1996	2017	1996	2017
Employment share	1	1	0.10	0.11	0.90	0.89
Sales share	1	1	0.08	0.07	0.92	0.93

Notes: Firms are split into small (less than 100 employees) and large (at least 100 employees) firms. In Panel (a), we report the employment-weighted average of markups and markdowns for each size class at the beginning and the end of our sample. In Panel (b), we report the employment-weighted output elasticities, returns to scale, and real wages for each size class at the beginning and the end of our sample. Wages are deflated and expressed in terms of 1995 values. Panel (c) reports the shares of aggregate employment and sales of each size class. German microdata.

Small and large firms have similar markups.[46] However, large firms exert, on average, more market power on workers than small firms. This difference in wage markdowns can thus be an important factor in explaining the lower responsiveness of large firms. The last row presents statistics on an overall market power measure that combines firms' product and labor market power.[47] We find that larger firms have higher and increasing overall market power. As only their markups increased, our findings suggest that this rise in overall market power results from higher markups.

Panel (b) shows the results for technology. Except for the output elasticity of intermediates, larger firms have higher output elasticities than smaller firms, reflecting higher returns to scale. Also the ratio of the labor output elasticity to the output elasticities of other inputs is higher for large firms. According to our framework, this does not rationalize large firms' lower responsiveness. Concerning changes over time, we find that the importance of labor vis-à-vis other production factors declined

[46] If anything, small firms tend to have higher (employment-weighted) markups. This is consistent with recent evidence in Mertens and Mottironi (2023), who document a negative correlation between firm size and markups for 19 European countries.

[47] This combined term equals the wedge between the labor output elasticity and the inverse labor expenditure shares in sales: $\mu_{it}\gamma_{it} = \theta_{it}^L \frac{P_{it}Q_{it}}{W_{it}L_{it}}$.

for all firms, while intermediates became more important. This decline is stronger among large firms (-17%) than small ones (-9%).[48] These changes in firms' production technology are consistent with the rise in off-shoring of German firms' production processes over the last decades (Sinn, 2007) and drag down firm responsiveness for all firms.

In addition, Panel (b) shows that large firms pay higher wages. As discussed in our simulation, the effect of higher wages on responsiveness depends on whether higher wages reflect that larger firms face different wages or operate on a steeper labor supply curve. If the latter is true, higher wages reduce large firms' responsiveness relative to small firms. Over time, wages only increased among large firms.

Finally, as summarized in Panel (c), we do not find evidence of employment reallocation toward large firms. As the aggregate job reallocation rate is an employment-weighted average, reallocation toward large firms, which tend to have a lower responsiveness, cannot explain the overall decline in responsiveness.

In summary, our analysis shows a decline in responsiveness for small and large firms (Table 2) that coincides with a generalized reduction in output elasticities of labor. While changes in market power and wages cannot explain the decline in responsiveness among small firms, the increase in large firms' markups (+6%) and wages (+8%) rationalizes the decrease in large firms' responsiveness. We conclude that market power and wage differences are important in explaining the differences in responsiveness between large and small firms and that changes in firms' output elasticities are the only factors that can rationalize the joint decline in large and small firms' responsiveness. Changes in market power, particularly for large firms, can further explain the percentage-wise stronger decline in responsiveness for the larger firms.

6 Conclusions

This article documents novel facts on European business dynamism using a combination of administrative firm-level databases we collected through our Competitive Research Network (CompNet). Similarly to the US, job reallocation rates have declined in Europe. This decline is broad. It is com-

[48] We compute this using $1 - \left(\frac{\overline{\theta^L_{2017}}}{\overline{\theta^K_{2017}} + \overline{\theta^M_{2017}}} \right) / \left(\frac{\overline{\theta^L_{1996}}}{\overline{\theta^K_{1996}} + \overline{\theta^M_{1996}}} \right)$.

mon to all sectors and prevalent in all 19 countries we analyze. It is mostly driven by dynamics within sectors, size classes, and age classes. Job reallocation decreased particularly strongly among large and mature firms. Concurrently, the European economy is experiencing a structural aging reflected in a reduction in young firms' economic activity. Compositional changes away from young firms explains a relatively small share of the overall decline. We find firms' responsiveness has experienced sharp declines in Europe similar in relative terms to those in the US. Unlike the US, the decline in job reallocation in Europe coincides with a decrease in the dispersion of productivity shocks. An important novel finding that we document is that larger firms have lower responsiveness.

To enhance our understanding of these patterns, we derive a firm-level framework that shows how job reallocation and firms' responsiveness are shaped by productivity, market power, production technologies, and wages. We apply our framework to the German manufacturing sector. We find that the economic environment has become less dynamic over the past decades due to subdued changes in firms' productivity, market power, wages, output, and technology. This directly lowers job reallocation. Regarding firms' responsiveness, we empirically confirm that higher firm market power and lower technological importance of labor reduce responsiveness and, thus, job reallocation. We show that larger firms have higher labor market power while paying higher wages, which can explain their lower responsiveness. We document stark changes in firms' production technologies that are increasingly less dependent on labor but more on other inputs. Our findings suggest a key role for changing production technologies in explaining declining firm responsiveness among all firms. Additionally, rising markups and wages contribute to the reduction in large firms' responsiveness.

Our findings have important implications. Firstly, we demonstrate that the differences in technology and market power across firms *and* over time influence job reallocation. This offers additional explanations for declining job reallocation rates (alternative to rising adjustment costs) which are closely related to recent work documenting increasing firm market power in product (De Loecker et al., 2020) and labor markets (Yeh et al., 2022) and a decreasing importance of labor compared to other inputs in firms' production processes (Hubmer and Restrepo, 2021; Autor et al., 2022). In particular, we highlight the mechanisms through which these structural changes can contribute to a decline in firms' labor growth responsiveness to productivity shocks and job reallocation. Secondly, our work emphasizes the necessity for researchers to simultaneously consider the levels and changes in technology, wages, and market power when analyzing the drivers of job reallocation. Levels in these variables affect firms' responsiveness, while changes directly affect job reallocation through firms' labor demand. Lastly, our study highlights that declining job reallocation and firm responsiveness can also result from technological change. A technology-driven explanation may offer a more nuanced perspective on the declining responsiveness and job reallocation compared to explanations rooted in rising market power or increasing adjustment costs. Assessing the relevance of these different drivers of the decline in job reallocation represents an important avenue for future research. We hope that the findings of our study and the data collection efforts behind it can foster fruitful work on this and related questions.

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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 9$^{\text{th}}$ Vintage version (the version we use), includes the 19 countries listed in Table 1 in addition to Malta, Netherlands, and Switzerland. We dropped Netherlands and Switzerland as discussions with the data providers indicated that some of our business dynamism results where not representative and/or distorted by issues in the underlying microdata. We excluded Malta as the number of firms where not sufficient for several of our analyses. Table A1 shows information on the data sources for each country.

Table A2 and Table A3 shows information on the country and sector coverage, before and after weighting the data (we use the weighted version). Column (1) and (4) show the total employment and number of firms available in our sample; column (2) and (5) show the unweighted sample coverage ratios for these statistics; column (3) shows the coverage ratio for employment after weighting. We benchmark CompNet statistics against the aggregates from Eurostat's structurel business statistics (SBS). In Table A2, columns (2) and (5) show a high coverage of both employment and the number of firms. On average, CompNet data covers 75% of employment and 73% of the number of firms present in Eurostat. In addition to this, column (3) shows that after weighting the data, the coverage becomes close to 100% for most countries. Turning to the sector-level analysis, Table A3 shows unweighted sample coverage ratios ranging from 73% to 83% for employment and from 65% to 79% for the number of firms. Again, after weighting, we recover population figures well, which is reassuring.

Finally, Table A4 shows summary statistics for the CompNet dataset. As CompNet is aggregated at the country-industry-year level, we cannot provide firm-level summary statistics for each indicator at the European level. Instead, we summarize the industry-country-level averages of each indicator. For instance, the column p25 for the labor variable shows the 25^{th} percentile of the distribution of industry-level average employment across countries and years in our data.

Table A1. Data sources for the CompNet dataset

Country	Data source	Institute	Data provider
Belgium	European Central Bank - Bank for the Accounts of Companies Harmonized	Nationale Bank van België	European Central Bank
Croatia	The Croatian Business Registry (Annual financial statements), Court Registry	Financial Agency Croatia	Croatian National Bank
Czech Republic	P5-01 survey, Register of Economic Subjects, foreign trade dataset	Czech Statistical Office	Czech National Bank
Denmark	Account statistics, general enterprise statistics	Statistics Denmark	Central Bank of Denmark
Finland	Structural business and financial statement statistics, international trade statistics data, Employment statistics data	Tax administration, Finnish Customs, Finnish Centre for Pensions	Statistics Finland
France	Élaboration des statistiques annuelles d'entreprises, Système Unifié de Statistiques d'Entreprises, Base Tous Salariés	Statistics France (INSEE)	Statistics France (INSEE)
Germany	Amtliche Firmendaten in Deutschland, Kostenstrukturerhebung im Bauhaupt- und Ausbaugewerbe, Jahreserhebung der Gastgewerbestatistik, Jahreserhebung der Handelsstatistik, Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden	Destatis	Federal Statistical Office of Germany and Federal Statistical Offices of the German Länder
Hungary	Tax registry database of National Tax and Customs Administration, Business Registry, Pension Payment data, including the work history	National Tax and Customs Authority, Central Statistica Office, Pension Payment Directorate	Central Bank of Hungary
Italy	European Central Bank - Bank for the Accounts of Companies Harmonized	Bank of Italy/Cerved	European Central Bank
Latvia	Central Statistical Bureau of Latvia	Central Statistical Bureau of Latvia	Central Statistical Bureau of Latvia
Lithuania	Statistical Survey on the Business Structure (Annual questionnaire F-01), Business Register, Customs Declaration	Statistics Lithuania, Centre of Register, Customs of the Republic of Lithuania	Central Bank of Lithuania
Poland	Report on revenues, costs and financial result as well as on expenditure on fixed assets, Annual enterprise survey	Statistics Poland	Central Bank of Poland
Portugal	Integrated Business Accounts System	Statistics Portugal	GEE - Office for Strategy and Studies - Ministry of Economy.
Romania	Balance sheet information on non-financial enterprises	Ministry of Public Finances	National Bank of Romania
Slovakia	Annual report on production industries, Statistical register of organizations, Foreign trade statistics, Bisnode database	Statistics Slovakia, Bisnode Slovakia	National Bank of Slovakia
Slovenia	Agency of the Republic of Slovenia for Public Legal Records and Related Services	IMAD	IMAD
Spain	European Central Bank - Bank for the Accounts of Companies Harmonized	Banco de España / Mercantile Registries	European Central Bank
Sweden	Structured business statistics, International trade in goods, Business register, Labor statistics based on administrative sources	Statistics Sweden/Tax Authority	Statistics Sweden/Tax Authority
UK	Structural business survey (ABS), business registry (IDBR)	Office for National Statistics	Office for National Statistics

Table A2. Country coverage before and after weighting.

Country	Years	Total Employment sample (*thousand*) (1)	Employment coverage ratio sample (2)	Employment Coverage ratio weighted (3)	Firm count sample (4)	Firm count coverage ratio sample (5)
Belgium	2008-2019	967.3	70%	101%	9,577.3	73%
Croatia	2008-2019	471.9	90%	104%	4,479.1	88%
Czech Republic	2008-2019	1,472.4	76%	105%	9,541.4	54%
Denmark	2008-2019	856.5	83%	101%	8,081.2	79%
Finland	2008-2019	781.3	95%	100%	7,135.9	95%
France	2010-2019	7,544.8	82%	85%	73,004.4	116%
Germany*	2008-2018	-	-	106%	-	-
Hungary	2008-2019	1,176.6	93%	109%	10,648.3	89%
Italy	2008-2019	4,817.4	81%	101%	52,370.7	79%
Lithuania	2008-2019	468.3	94%	101%	5,487.8	92%
Poland	2008-2019	3,896.2	91%	102%	27,591.5	77%
Portugal	2008-2019	1,459.7	96%	100%	16,929.9	95%
Romania	2008-2019	2,052.3	90%	99%	20,481.8	92%
Slovakia	2008-2019	639.1	92%	103%	4,900.6	86%
Slovenia	2008-2019	277.1	91%	104%	2,514.2	84%
Spain	2008-2019	2,486.6	46%	115%	21,289.6	38%
Sweden	2008-2019	1,341.6	74%	91%	12,967.9	86%
UK*	2008-2019	-	-	105%	-	-
All countries	2008-2019	1,706.1	75%	102%	15,944.5	73%

Notes: The table displays country-level coverage information for a subset of years. The selection of years is shorter than in the CompNet data, and determined by the data availability of the Eurostat data. All columns report averages values across all years. Sample coverage ratios in columns 2 and 5 are computed as the ratio of the total employment or number of firms in the microdata underlying CompNet to the respective totals in Eurostat data. The weighted employment coverage ratio in column 3 is computed as the weighted total employment in CompNet divided by the total employment as reported in Eurostat data. CompNet and Eurostat data (file *sbs_sc_sca_r2*). Firms with at least 20 employees.

* The German and UK data providers do not disclose unweighted data files with sample information.

Table A3. Sector coverage (balanced sample of sectors excluding France, Germany, and the United Kingdom).

Macro-sector	Total Employment sample (*thousand*) (1)	Employment coverage ratio sample (2)	Employment Coverage ratio weighted (3)	Firm count sample (4)	Firm count coverage ratio sample (5)
Manufacturing	9,165.84	81%	101%	82,573.42	76%
Construction	1,363.159	78%	100%	21,463.33	75%
Wholesale and retail trade	3,860.063	83%	102%	39,851.08	79%
Transportation and storage	2,505.888	77%	104%	17,463.67	71%
Accommodation and food service activities	1,040.906	73%	108%	14,877.25	67%
Information and communication	1,312.086	79%	104%	9921	77%
Professional, scientific and technical activities	1,072.18	74%	106%	12,427.83	69%
Administrative and support service activities	2,883.182	73%	109%	15,905.67	65%

Notes: The table shows coverage information for each sector using a balanced set of countries and sectors from 2008 to 2019 (excluding France as data as Eurostat data starts in 2010 and Germany and the United Kingdom as the data providers did not diclose the unweighted data files). All columns report averages values across all years. Sample coverage ratios in columns 2 and 5 are computed as the ratio of the total employment or number of firms in the microdata underlying CompNet to the respective totals in Eurostat data. The weighted employment coverage ratio in column 3 is computed as the weighted total employment in CompNet divided by the total employment as reported in Eurostat data. CompNet and Eurostat data (file *sbs_sc_sca_r2*). Firms with at least 20 employees.

* The German and UK data providers do not disclose unweighted data files with sample information.

Table A4. Summary statistics at the country-industry-year level (20e sample).

	Mean	p25	Median	p75	St.Dev.	Number of firms
Labor ($\bar{L}_{cjt}$)	136.37	67.12	94.37	137.31	217.66	571,991
Real Revenues ($\overline{R}_{cjt}$)	23957.88	4780.09	10159.98	22544.92	48121.89	571,991
Real Value Added ($\overline{VA}_{cjt}$)	10795.85	1735.607	3723.141	8231.117	30787.43	571,991
Labor growth (DHS) ($\overline{g}_{cjt}$)	0.008	-0.004	0.011	0.026	0.036	571,991
Job Reallocation Rate ($\overline{JR}_{cjt}$)	0.097	0.069	0.087	0.115	0.044	571,991

Notes: The table reports summary statistics of country-industry-year average values, i.e., the unit of observation are country-industry-year cell averages. Values for labor, revenues, and value-added have been weighted by the number of firms in each country-industry-year cell. The labor growth rate (DHS) and job reallocation rate have been weighted by total employment in each country-industry-year cell. The number of firms refers to the population count. The table exclude the United Kingdom, as the 2-digits industry-level data has not been disclosed by the relevant data provider. CompNet data. Firms with at least 20 employees. Years 2008-2018.

A.1.1 Disclosure rules and missing data

The statistical institutes and central banks participating to the CompNet project require our data collection protocols to meet country-specific disclosure criteria. This is ensured through an automatic routine that combines dominance rules for certain variables (e.g., employment and sales) with requirements on the minimum observation count per cell. As a result of these routines, some cells with low observation counts and/or too dominant firms are not disclosed. In the data, this is marked as a missing value. For some of our results from the CompNet data, this leads to the exclusion of certain cells, e.g., certain sector-year or sector-size-class-year combinations (particularly when we aggregate the data from a lower aggregation level). Table A5 provides an overview of the missing information for each figure and table where this issue is relevant. As shown, only a negligible amount of cells drop out due to disclosure rules.

Table A5. Detailed information on undisclosed information leading to missing data points.

Figure	Missing information
Figures 2 and C2	German Construction sector in 2009.
Figures 3, C4	40/5,685 country-age-category-sector cells, mostly from the sectors ICT and transportation and storage, for the countries Belgium, Czech Republic, Denmark, Italy, Romania, Slovenia, and Sweden.
Figure C11	17/5,504 country-age-category-sector-year cells, mostly from the sectors ICT and transportation and storage, for the countries Belgium, Denmark, Slovenia, and Sweden.
Figure C3	German construction sector in 2009, Danish transportation and storage sector.
Figure C6, 8 (a), and 9	17/451 country-sector-size-class combinations for the countries Belgium, Germany, Latvia, Romania, Slovakia, Slovenia, and United Kingdom
Figure C11	17/5,504 country-age-category-sector cells from the sectors ICT and transportation and storage for the countries Belgium, Denmark, Slovenia, and Sweden
Figure 8 (b)	The largest country-sector-size-class combination for the sectors transportation and storage (Belgium), accommodation and food services (Belgium, Latvia), and administration and support service activities (Slovenia).
Figure C16	UK is completely missing, due to non-disclosed data files. The largest country-sector-size-class combination for the sectors Transportation and Storage (Belgium), Accommodation and Food Services (Belgium, Latvia), and Administration and support service activities (Slovenia).

Notes: The table summarizes the missing cell-level information in our figures and tables due to country-specific disclosure routines.

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 online Appendix.

- L_{it}: Labor in headcounts.
- W_{it}: Firm wage (firm average), defined as gross salary before taxes (including mandatory social costs) + "other social expenses" (including expenditures for company outings, advanced training, and similar costs) divided by the number of employees.
- K_{it}: Capital derived by a perpetual inventory method following Mertens (2022), who used the same data.
- M_{it}: 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.
- $V_{it}M_{it}$: Nominal values of total intermediate input expenditures.
- $P_{it}Q_{it}$: 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_{it}: Quasi-quantity measure of physical output, i.e., $P_{it}Q_{it}$ deflated by a firm-specific price index (denoted by PI_{it}, see the definition of PI_{it} in Appendix E).

- PI_{it}: Firm-specific Törnqvist price index, derived as in Eslava et al., 2004. See the Appendix E.1 for its construction.

- $P_{i,o,t}$: Price of a product o.

- $share_{i,o,t}$: Revenue share of a product o in total firm revenue.

- ms_{it}: 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_{it}: Headquarter location of the firm. 90% of firms in our sample are single-plant firms.

- D_{it}: 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_{it} (or in logs, e_{it}): 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 federal statistical office of Germany. E_{it} is part of M_{it}.

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

- $NumP_{it}$: The number of products a firm produces.

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 price in the top and bottom one percent tails. We also drop the sectors 16 (tobacco), 23 (mineral oil and coke), and 37 (recycling) as the observation count is insufficient to derive estimates of firms' production function in these industries.

Table A6. Summary statistics of our German manufacturing sample.

	Mean (1)	p25 (2)	Median (3)	p75 (4)	St.Dev. (5)	Observations (6)
Number of employees	279.70	51	105	259	795.04	180,022
DHS growth rate	0.004	-0.043	0.00	0.053	0.122	180,022
TFPR (industry demeaned)	-0.013	-0.186	-0.003	0.171	0.290	180,022
Real wage (1995 values)	33976.72	25964.82	33646.61	41164.77	11205.28	180,022
Markup	1.07	0.95	1.04	1.15	0.17	180,022
Wage markdown	1.08	0.72	0.98	1.32	0.52	180,022
Combined market power (markup $\times$ markdown)	1.11	0.80	1.04	1.33	0.45	180,022
Output elasticity of labor	0.30	0.24	0.31	0.38	0.10	180,022
Output elasticity of capital	0.12	0.08	0.11	0.15	0.06	180,022
Output elasticity of intermediates	0.63	0.57	0.63	0.69	0.09	180,022
Returns to scale	1.05	0.97	1.05	1.12	0.11	180,022

Notes: This table presents summary statistics for selected variables from the German manufacturing sector firm-level data. Columns 1-5 show the mean, 25th percentile, median, 75th, and standard deviation, respectively. Column 6 reports the number of non-missing observations. German microdata.

Deriving a time-consistent industry classification. During our long time-series, the NACE classification of industries (and thus firms into industries) changed twice. Once in 2002 and once in 2008. Because our estimation of the production function requires a time-consistent industry classification at the firm level (as we allow for industry-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 (2022) and use information on firms' product mix to classify firms into NACE rev 1.1 industries 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 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, 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 our 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 A7 provides a few examples on the product codes within the product-level data.

Table A7. 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)
34		**Manufacture of motor vehicles, trailers, and semi-trailers**
3410		Manufacture of motor vehicles
		Products
	341021330(0)	Passenger car, petrol engine $\leq 1,000$ cm^3 (not contracted)
	341022302(0)	Passenger car, petrol engine $\geq 2,500$ cm^3 (not contracted)
	341023100(0)	Passenger car, diesel or semi-diesel engine $\leq 1,500$ cm^3 (not contracted)
	341023550((0)	Camper, diesel or semi-diesel engine $\geq 2,500$ cm^3 (not contracted)
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 approximately 6,500 distinct products at the nine-digit level, from which we find approximately 6,000 in our database and 4,200 in our final sample of firms. The last number of each product code (10^{th} position) indicates whether the product was manufactured as contracted work. Source: Mertens and Müller (2022)

B Additional theoretical results

B.1 Derivation of the responsiveness regression (Equation (5))

DHJM specify a one-factor (labor) model of firm dynamics to describe the relationship of firm-level employment growth and firm-level productivity realizations. In particular, they consider that the employment growth policy function of a firm i can be generally represented by:

$$g_{it} = f_t(A_{it}, L_{it-1}), \tag{B1}$$

where g_{it} is employment growth from $(t-1)$ to t, A_{it} is the productivity realization in time t, and L_{it-1} is initial/lagged employment. The standard prediction of these types of models is that, among any two firms, the one with higher A_{it}, holding initial employment constant, will have higher growth. The formulation in which A_{it} is specified in levels, as in Equation (B1), is quite general since the inclusion of L_{it-1} along with A_{it} in the policy function fully incorporates information contained in A_{it-1} and, therefore, the difference between A_{it} and A_{it-1}. Note that the time subscript, t, in $f_t(\cdot)$ allows the relationship between employment growth and the state variables to vary over time. In practice, DHJM consider a log-linear approximation of Equation (B1) defined as:

$$g_{it} = \beta_0 + \beta_{1t}a_{it} + \beta_{2t}l_{it-1} + \epsilon_{it}, \tag{B2}$$

where a and l denote the logs of productivity and employment, respectively. The parameter β_{1t} describes the marginal response of firm employment growth to firm productivity. In the typical model setting, $\beta_{1t} > 0$. However, the magnitude of this relationship depends on model parameters, distortions, adjustment frictions, and potentially firm characteristics. DHJM refer to a change in β_{1t} as a change in responsiveness.

They show that the Equation (B2) follows (among others) from a one-factor model without adjustment costs where a firm's revenue can be expressed as $R_{it} = (L_{it}A_{it})^{\phi}$. The parameter $\phi < 1$ reflects the revenue function curvature arising from imperfect competition due to horizontal product differentiation.[49] In this setting, the firm's first-order condition (in logs) is:

$$l_{it} = \frac{1}{1-\phi}\left(log\left(\frac{\phi}{W_{jt}}\right) + a_{it}\right),$$

[49] This is equivalent to assuming that firms face a CES demand with parameter $\sigma > 1$. In this case, $\phi = \frac{\sigma-1}{\sigma}$.

where W_{jt} is the wage rate in industry j. Taking time differences (indicated by Δ) and sweeping out year and industry effects yields the following firm-level growth rate:

$$\Delta l_{it} = \frac{1}{1-\phi}\Delta a_{it}, \tag{B3}$$

which is a function of relative changes in productivity. Equation (B3) highlights the link between productivity and employment changes. The prediction of this frictionless model is that the lower the productivity changes, the lower will be the employment changes, and thus job reallocation rates.

DHJM show that this relationship can also be expressed in terms of productivity levels by inverting the lagged employment such that $a_{it-1} = (1-\phi)l_{it-1} - log\left(\frac{\phi}{W_{j,t}}\right)$. Substituting this back into Equation (B3) yields (net of industry and year fixed effects):

$$\Delta l_{it} = \frac{1}{1-\phi}a_{it} - l_{it-1}\,. \tag{B4}$$

DHJM opted for this expression in levels mainly for empirical purposes. Their sample is representative in any specific year but is not designed to be longitudinally representative.

In practice, however, they bring to the data a slightly different specification to account for the fact that the employment data is reported with a delay of a few months in their data. In particular, the empirical analog of Equation (B1) that DHJM estimate is:

$$g_{it} = \beta_0 + \beta_{1t}a_{it-1} + \beta_{2t}l_{it-1} + \epsilon_{it}\,. \tag{B5}$$

To allow for a direct comparison between our European results and their results for the US, we estimate exactly the same specification. Similar to the US data, the timing of the employment and output variables often differ in the European data. For instance, in Germany, employment is collected as the September value, whereas output refers to the entire calendar year. Using the lagged specification addresses these timing features of the data. In addition, using a lagged specification is a parsimonious way of accounting for extra time to adjust.

B.2 Simulation: Responsiveness by size class

This section describes the different scenarios considered in Figure 17 and which illustrate the level of responsiveness for three firms of different sizes. Their difference in size is due to a different initial level of productivity. This difference is hold constant throughout all our simulations. In particular, we set $A_i = 0.5, 1, 2$ for the small, medium, and large firm, respectively. These firms are profit-maximizing monopolists and produce a certain level of output (Q_i) with labor (L_i) and a second input that we call materials but which can capture also other inputs (M_i) according to a Cobb-Douglas production function, $Q_i = L_i^{\theta^L} M_{it}^{\theta^M} A_i$. In our baseline scenario (1), we set the output elasticities $\theta^L = 0.4$ and $\theta^M = 0.6$, so that returns to scale are constant. Each firm is assumed to be *price-taker* in both input markets, and the wage rate and the material costs are set to $W^b = V^b = 0.5$, where superscript b stands for baseline.

In scenario

(2) we assume that firms face a lower price elasticity of demand, i.e. $\sigma = 2$, so that their markup $\mu_i = \dfrac{\sigma}{\sigma - 1}$ is higher.

(3) we assume that firms face a demand with a variable elasticity of demand. As a firm produces more, it will face a lower elasticity and an incentive to set a higher markup. In particular, we assume a constant proportional pass-through demand defined as $P_i(Q_i) = b/Q_i * (Q_i^{(\chi-1)/\chi} + \tau)^{\chi/(\chi-1)}$ with $\chi = 0.7$, $b = 5$, and $\tau = 0.2$. Such demand leads to a proportional pass-through of cost to prices of 70% (compared to 100% under CES demand) and heterogeneity in markups across firms. Similar predictions hold with any demand that satisfies Marshall's Second Law of Demand.

(4) we assume that firms exert some market power also in the labor market. However, we assume that the inverse supply curve is isoelastic, such that firms face the same elasticity ξ^W and thus set the same markdowns $\gamma = (1 + \xi^W) > 0$, irrespective of their size. In particular, we assume $W_i(L_i) = 0.1 * L_i^{(0.5)}$ such that $\xi^W = 0.5$.

(5) we allow for heterogeneous markdowns, emerging from the fact that the elasticity ξ^W varies along the supply curve. This is simply obtained by adding an intercept to the previous inverse supply curve. In particular, we add $W^b = 0.5$ so that $W_i(L_i) = 0.5 + 0.1 * L_i^{(0.5)}$. This implies that larger firms set higher markdowns γ_i.

(6) we shift the relevance in the production process of labor toward materials, compared to the baseline scenario (1). In particular, we reduce the output elasticity of labor by 0.01 so that $\theta^L = 0.39$ and increase θ^M likewise to 0.61.

(7) we shift the relevance of labor in the production process towards materials at different rates. In particular, we set $\Delta\theta_i^L = 0.01$ for the largest firm, while 0.0075 and 0.005 for the medium and small firm, respectively. This is a very stylized way to illustrate what a more flexible (e.g., *translog*) production function may imply in terms of variable/firm-specific output elasticities of labor. Importantly, we hold firms' returns to scale constant.

(8) we decrease returns to scale compared to the baseline to 0.95, by reducing proportionally both θ^L and θ^M.

(9) we increase returns to scale to $\theta^L + \theta^M = 1.05$.

(10) we increase wages by $w = 0.2$ compared to the baseline scenario.

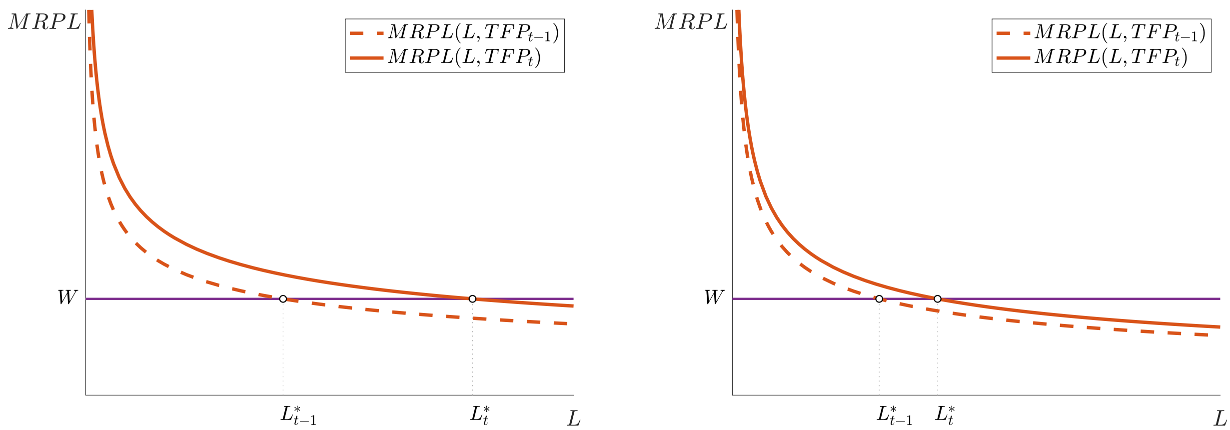
(11) we assume that the firm faces an isoelastic upward-sloping inverse supply curve defined as $W_i(L_i) = 0.1 * L_i^{(0.5)}$.

(12) we assume that the firm faces an upward-sloping inverse supply curve where ξ^W increases in L by adding an intercept exactly as in scenario (5).

B.3 Comparative statics of responsiveness

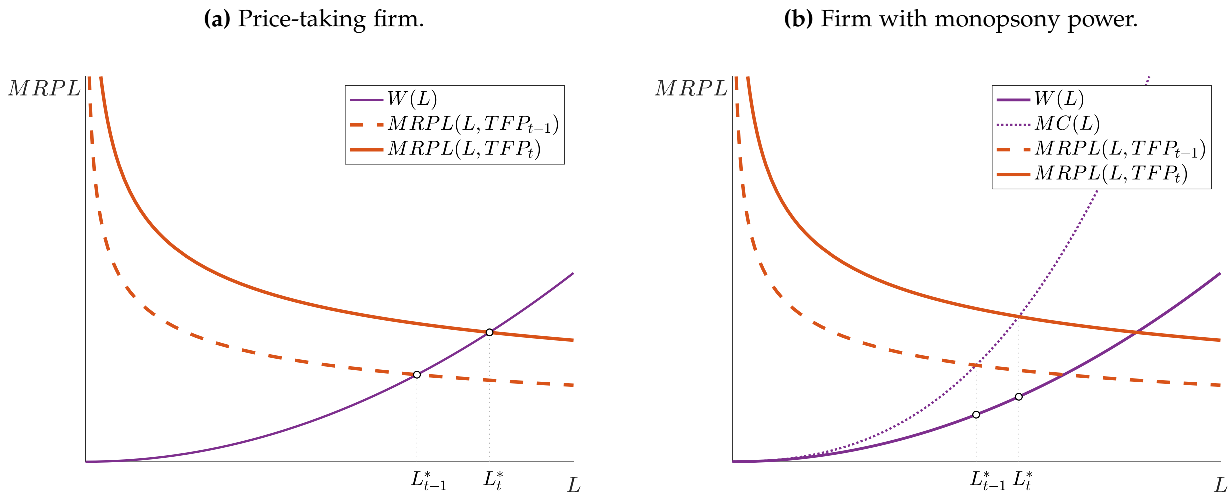
Figure B1. Responsiveness with higher markups.

(a) Baseline. **(b)** Less elastic demand.



Notes: Optimal labor demand for a monopolist facing a CES demand. In t, the firm experience a +50% productivity increase. In Panel (a), the price elasticity of demand is $\sigma = 3$, while in Panel (b) the firm faces a less elastic demand with $\sigma = 2$. In this setting, the firm sets a higher markup and expands less its labor demand.

Figure B2. Responsiveness and market power in the labor market.

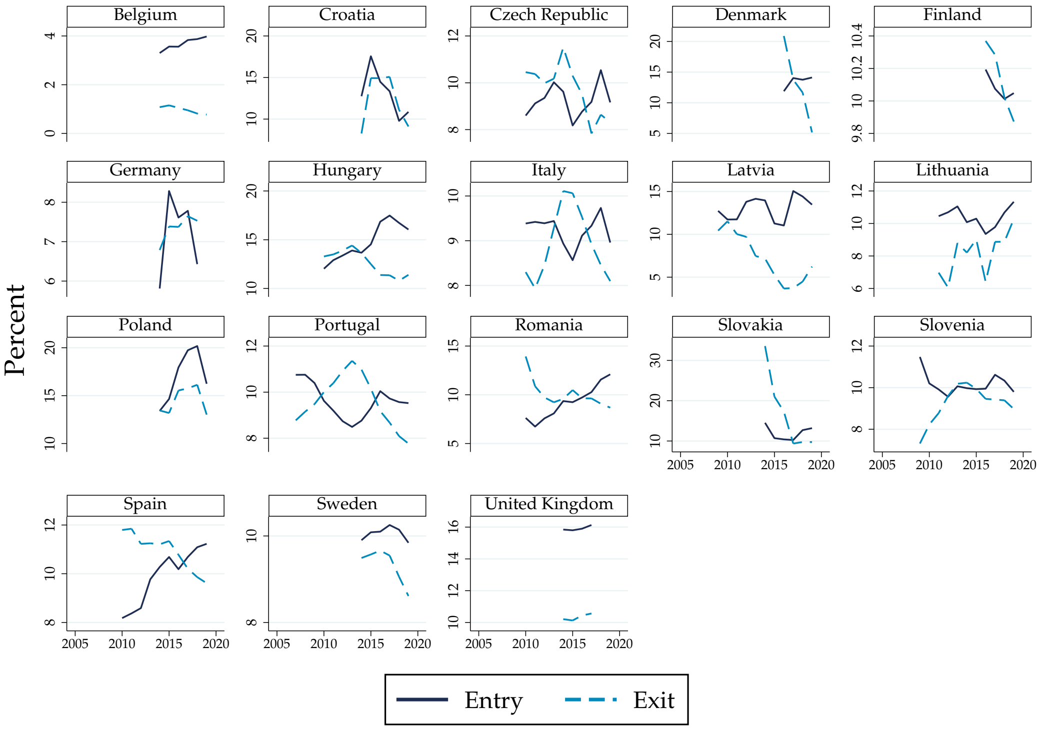


Notes: Optimal labor demand for a monopolist facing a CES demand. In t, the firm experience a +50% productivity increase. In Panel (a), the firm is a price-taker in the labor market, while in Panel (b) the firm faces the same inverse supply curve but acts as a monopsonist. In this setting, the firm sets a markdown to the wage paid to the workers and expands less its labor demand.

C Additional empirical results from the CompNet data

C.1 Further evidence on reallocation dynamics

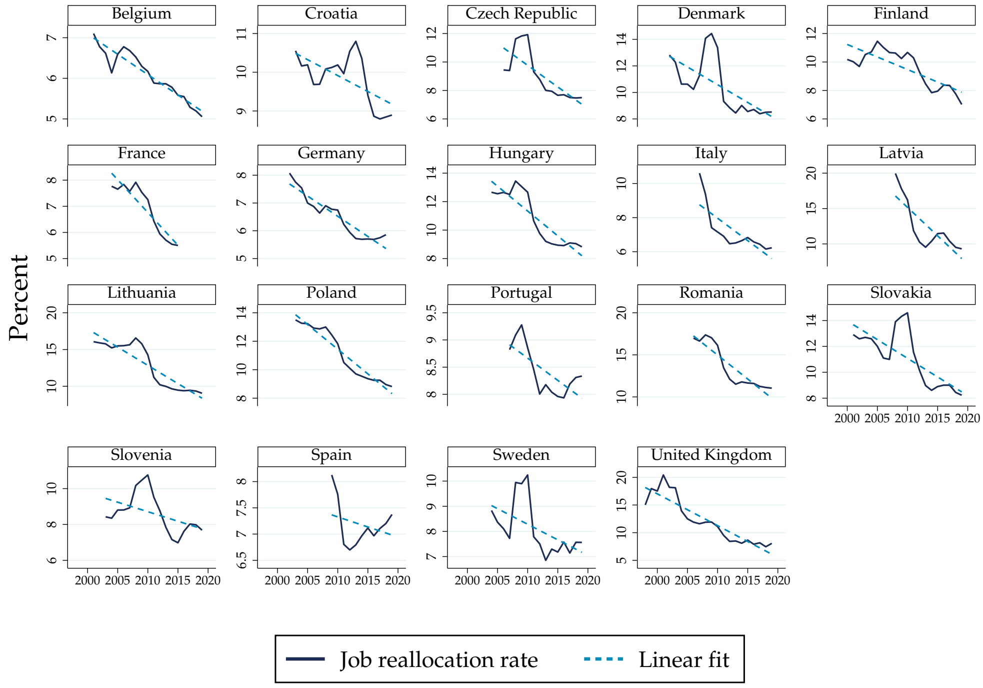
Figure C1. Entry and exit rates in a subset of European countries



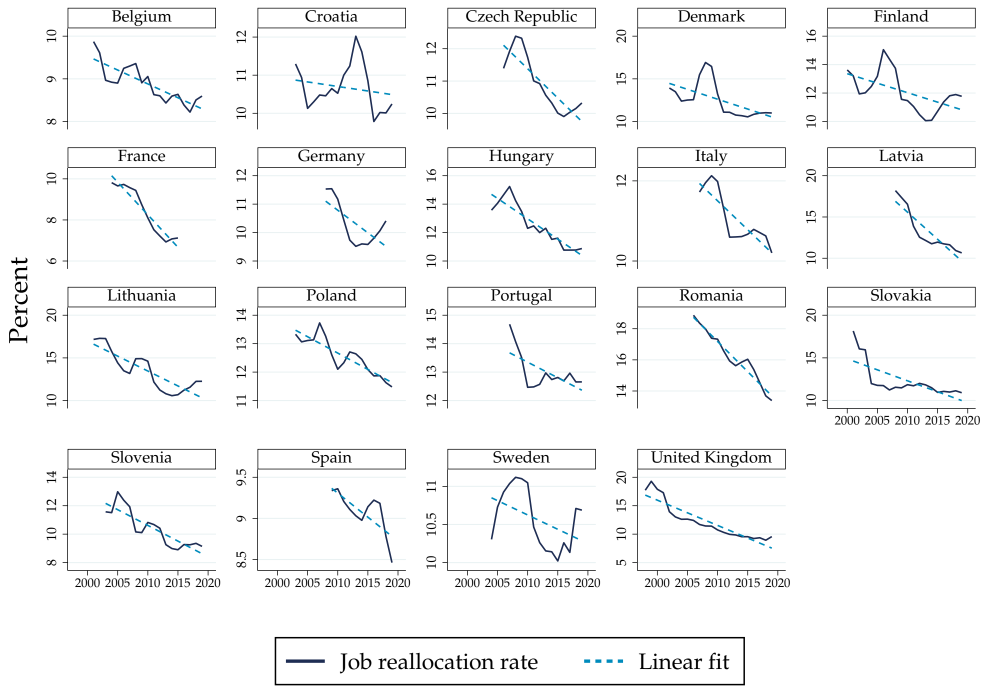
Notes: Three-years moving averages. The rate is computed as the ratio between the number of entering or exiting firms in year t to the average number of firms present in the economy in t and $t-1$. We can only report these results for countries for which Eurostat reports entry and exit counts. Firms from the agricultural, financial, or real estate sectors are excluded for comparability purposes. Eurostat data (file *bd_9fh_sz_cl_r2*).

Figure C2. Job reallocation rates in European countries by type of sector.

(a) Manufacturing sector.

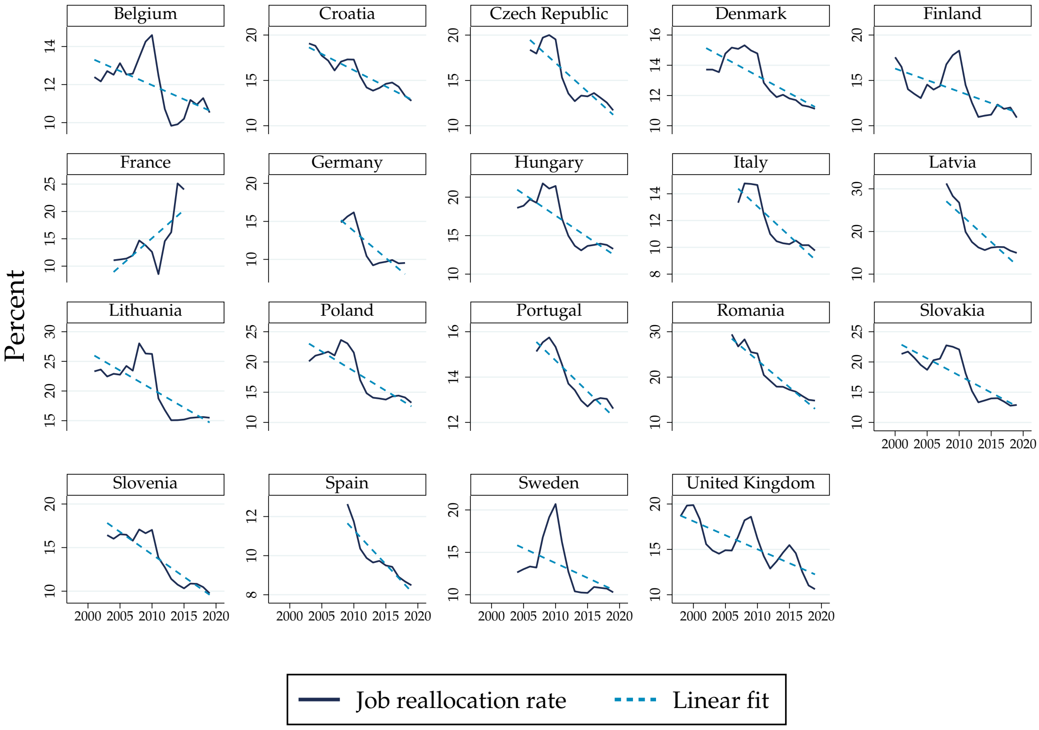


(b) Non-manufacturing sectors.



Notes: Three-year moving averages of job reallocation rates defined in Equation (1). The light blue dashed lines report the linear trends. Germany excludes the construction sector in 2009. CompNet data. Firms with at least 20 employees.

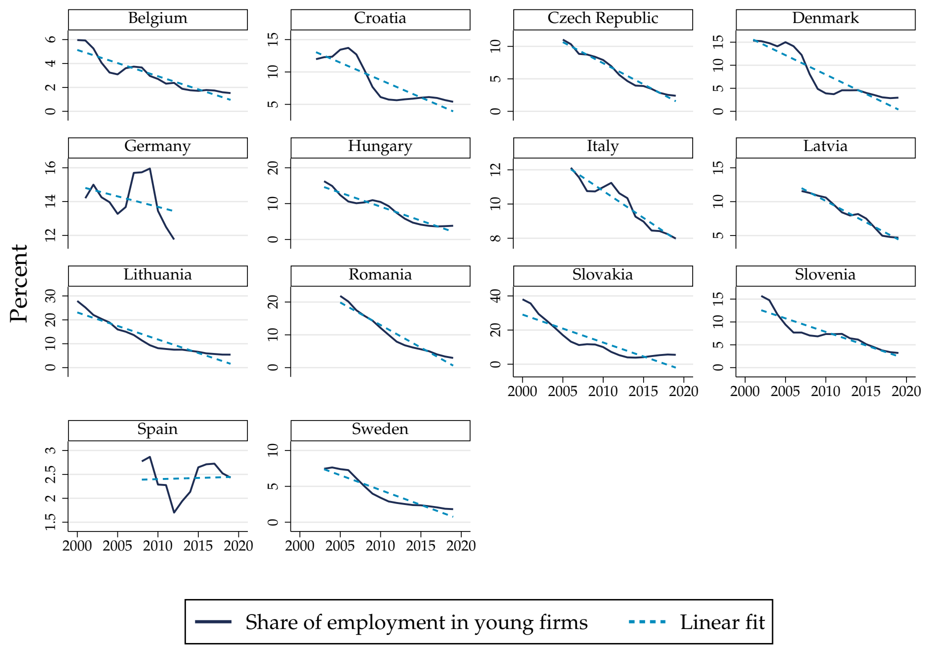
Figure C3. Sales reallocation rates in European countries.



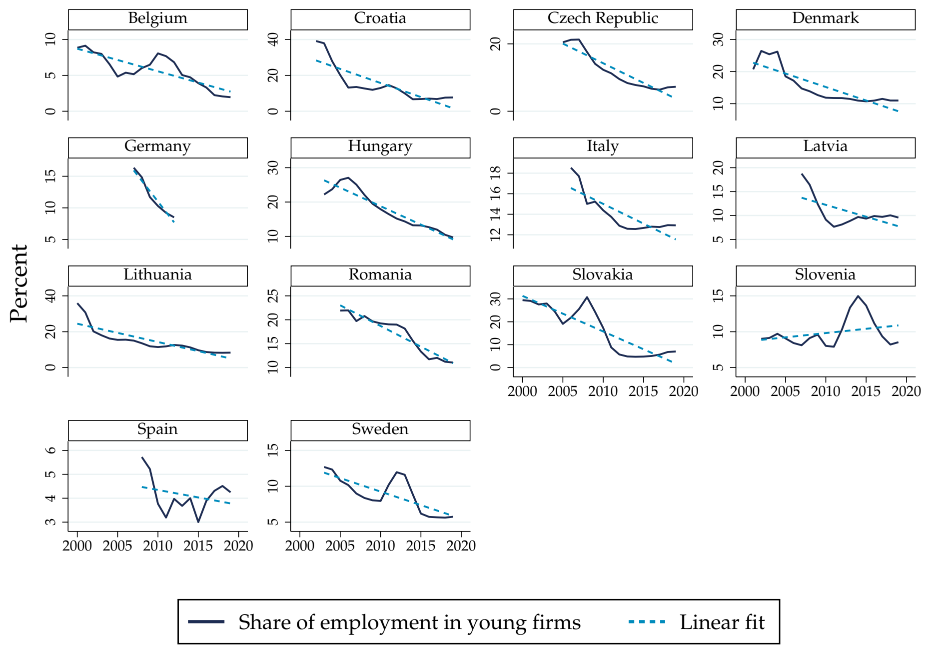
Notes: Three-year moving averages of sales reallocation rates, which we define as job reallocation rates in Equation (1) but for which we use sales instead of employment. The light blue dashed lines report the linear trends. Germany excludes the construction sector in 2009, Denmark excludes the transportation and storage sector. CompNet data, firms with at least 20 employees.

Figure C4. Young firms' employment share in European countries by type of sector.

(a) Manufacturing sector.



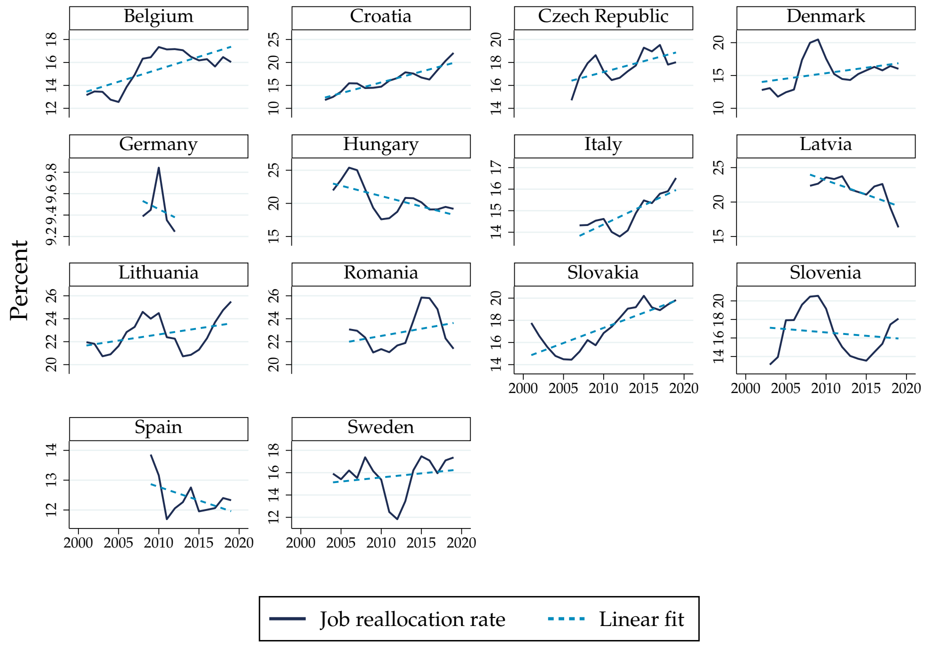
(b) Non-manufacturing sectors.



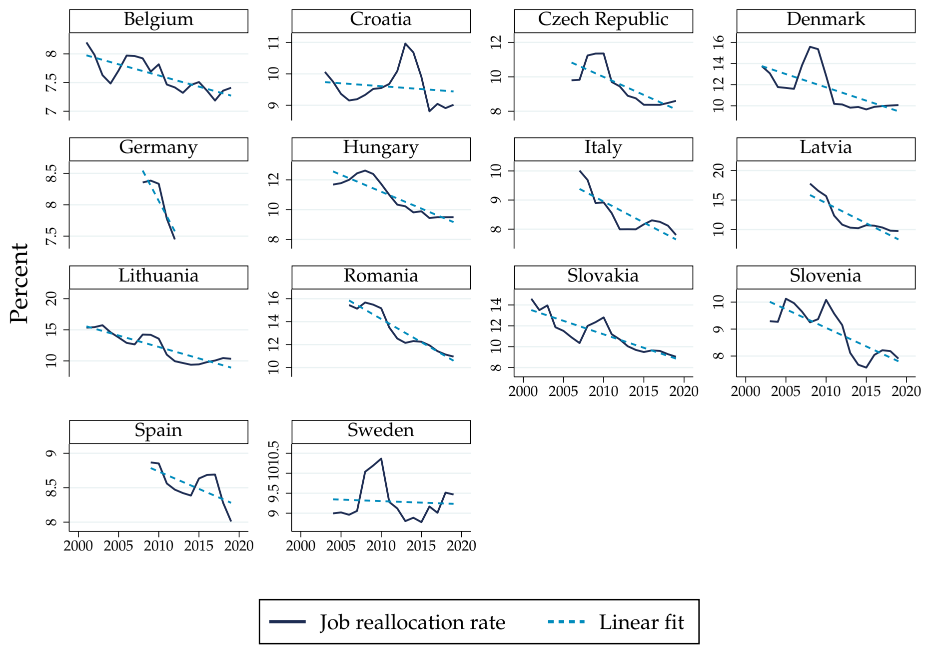
Notes: Three-year moving averages of the employment share of firms not older than five years. The dark blue solid lines shows country-level shares of employment in young firms. The light blue dashed lines report the linear trends. The underlying data are aggregated from sector-age-class data resulting in a drop of a few sector-age-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data, firms with at least 20 employees.

Figure C5. Job reallocation rate in European countries by age-class.

(a) Young firms.

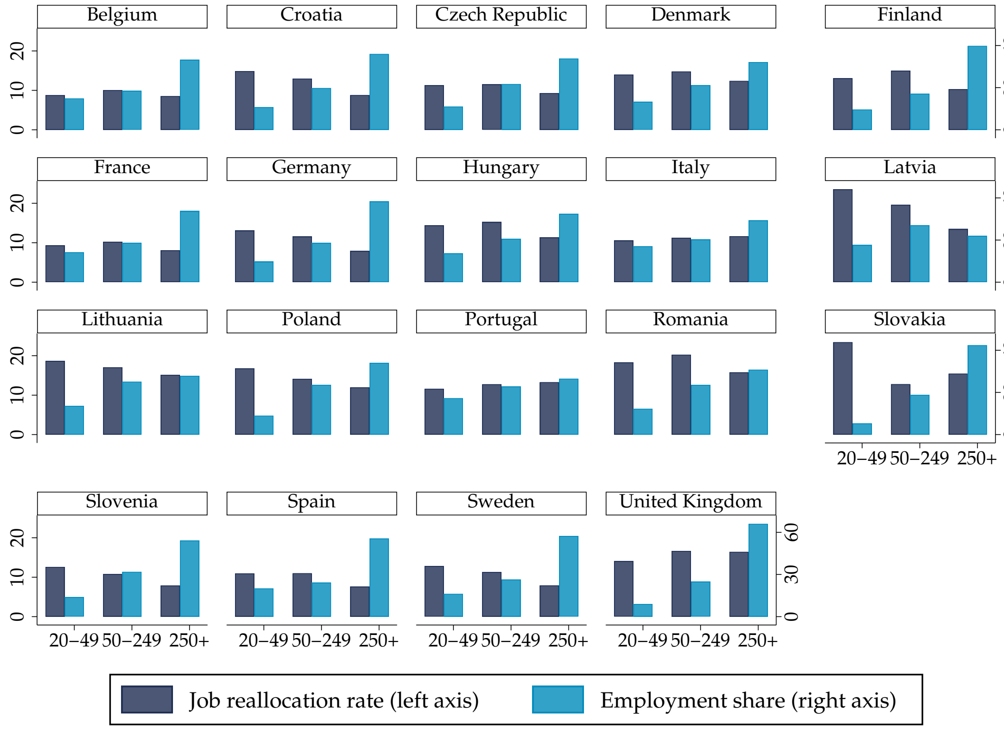


(b) Old firms.



Notes: Three-year moving averages of job reallocation rates defined in Equation (1). The light blue dashed lines report the linear trends. All countries except Romania additionally include the real estate sector. CompNet data. Firms with at least 20 employees.

Figure C6. Initial job reallocation rates and employment shares by size class.

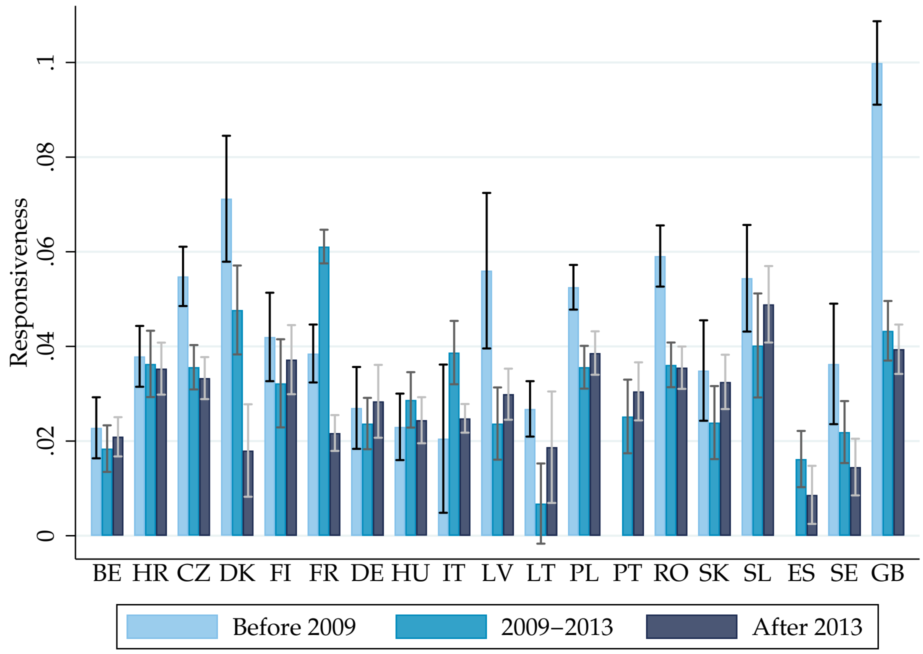


Notes: Average of the first two years for every country-size-class. The underlying data are aggregated from sector-size-class data resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data, firms with at least 20 employees.

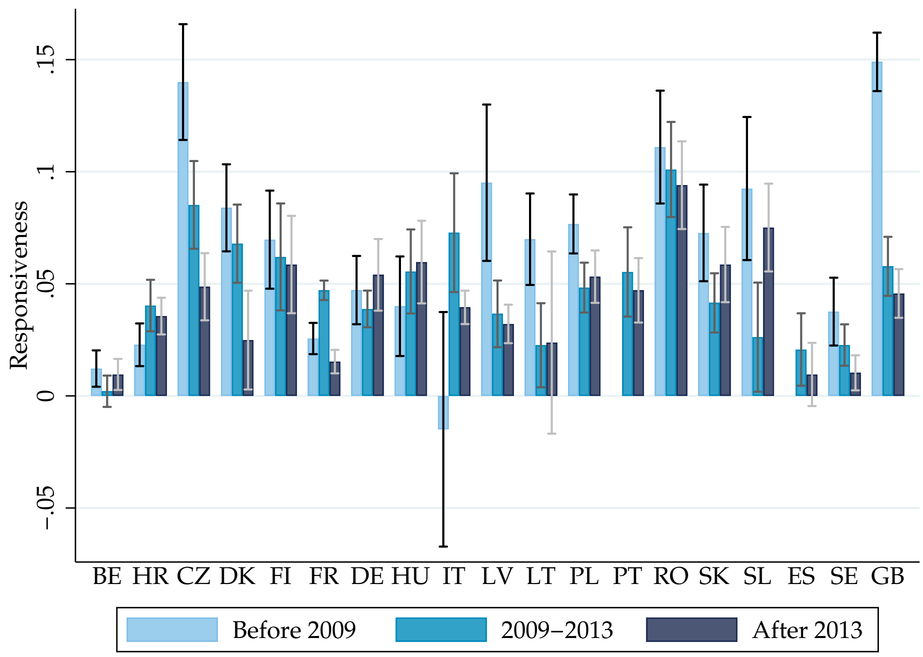
C.2 Responsiveness and shocks hypotheses

Figure C7. Responsiveness to productivity over different time windows.

(a) Labor Productivity



(b) Revenue-TFP



Notes: Estimated coefficients of period-specific responsiveness regressions where we omitted the linear trend and instead included interactions with three time-period dummies. 90% confidence intervals are reported for each coefficient estimate. CompNet data, firms with at least 20 employees.

Table C1. Responsiveness of employment growth to productivity across countries.

Country	β_1	(S.E.)	δ_1	(S.E.)	N	R^2
(a) Labor productivity						
Belgium	0.023***	(0.0052)	0.000	(0.0004)	91,165	0.13
Croatia	0.038***	(0.0046)	0.000	(0.0004)	79,582	0.12
Czech Republic	0.048***	(0.0034)	–0.001***	(0.0004)	119,048	0.13
Denmark	0.086***	(0.0107)	–0.004***	(0.0008)	135,271	0.16
Finland	0.041***	(0.0078)	0.000	(0.0006)	131,152	0.12
France	0.048***	(0.0038)	–0.001***	(0.0003)	871,405	0.12
Germany	0.021***	(0.0078)	0.000	(0.0007)	119,805	0.12
Hungary	0.024***	(0.0045)	0.000	(0.0004)	160,810	0.09
Italy	0.033***	(0.0066)	–0.001	(0.0006)	616,979	0.11
Latvia	0.036***	(0.0063)	–0.001	(0.0008)	30,123	0.17
Lithuania	0.025***	(0.0060)	–0.001	(0.0007)	83,831	0.14
Poland	0.052***	(0.0034)	–0.001***	(0.0003)	447,960	0.07
Portugal*	0.007	(0.0112)	0.002*	(0.0010)	140,963	0.08
Romania	0.054***	(0.0038)	–0.002***	(0.0004)	174,113	0.12
Slovakia	0.034***	(0.0088)	0.000	(0.0006)	64,484	0.22
Slovenia	0.052***	(0.0081)	0.000	(0.0007)	46,129	0.15
Spain	0.018***	(0.0052)	–0.001	(0.0008)	177,543	0.16
Sweden	0.039***	(0.0088)	–0.002**	(0.0007)	141,266	0.15
United Kingdom	0.130***	(0.007)	–0.005***	(0.0004)	228,460	0.11
(b) Revenue-TFP						
Belgium	0.012*	(0.0063)	0.000	(0.0005)	91,208	0.13
Croatia	0.023***	(0.0069)	0.001*	(0.0006)	79,583	0.11
Czech Republic	0.135***	(0.0147)	–0.007***	(0.0015)	119,537	0.12
Denmark	0.100***	(0.0160)	–0.004***	(0.0015)	135,463	0.15
Finland	0.073***	(0.0185)	–0.001	(0.0014)	131,423	0.12
France	0.035***	(0.0049)	–0.001*	(0.0004)	871,445	0.12
Germany	0.035***	(0.0127)	0.001	(0.0012)	120,062	0.12
Hungary	0.036**	(0.0144)	0.002	(0.0014)	162,600	0.09
Italy	0.035	(0.0230)	0.001	(0.0021)	618,749	0.10
Latvia	0.065***	(0.0130)	–0.004**	(0.0015)	30,189	0.16
Lithuania	0.076***	(0.0219)	–0.003	(0.0024)	85,721	0.14
Poland	0.077***	(0.0094)	–0.002**	(0.0009)	448,021	0.06
Portugal*	0.043	(0.0272)	0.001	(0.0023)	141,087	0.08
Romania	0.103***	(0.0155)	0.000	(0.0017)	185,362	0.10
Slovakia	0.074***	(0.0178)	–0.001	(0.0013)	64,728	0.22
Slovenia	0.074***	(0.0220)	–0.001	(0.0017)	46,148	0.14
Spain	0.024	(0.0144)	–0.001	(0.0020)	177,712	0.16
Sweden	0.043***	(0.0102)	–0.002***	(0.0009)	141,282	0.15
United Kingdom	0.200***	(0.0119)	–0.009***	(0.0008)	230,106	0.09

Notes: The table reports the results of estimating Equation (5) with OLS. Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' average employment levels between t and $t-1$. All regressions include industry-year fixed effects. *The Portuguese data starts in 2009 due to missing values in TFP. CompNet data, firms with at least 20 employees.

Table C2. Responsiveness to labor productivity by size class across countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
variables	BE	HR	CZ	DK	FI	FR	DE	HU	IT	LV	LT	PL	PT	RO	SK	SL	ES	SE
l_{ijt-1} (20-49): $\beta_{2,z=3}$	−0.02***	−0.01**	−0.01*	−0.04***	−0.03***	−0.04***	−0.02***	−0.01***	−0.02***	0.00	−0.02***	−0.02***	−0.02***	0.00	−0.01***	−0.01*	−0.03***	−0.03***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.006)	(0.005)	(0.004)	(0.006)	(0.008)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
l_{ijt-1} (50-249): $\beta_{2,z=4}$	−0.01***	−0.01***	−0.01***	−0.03***	−0.02***	−0.02***	−0.01***	−0.02***	−0.02***	−0.01**	−0.03***	−0.01***	−0.02***	−0.01***	−0.02***	−0.02***	−0.02***	−0.02***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
l_{ijt-1} (250+): $\beta_{2,z=5}$	−0.01**	−0.01***	−0.02***	−0.01***	−0.01***	0.00***	0.00*	−0.01***	−0.02***	−0.01***	−0.01***	0.00	−0.01***	−0.01***	−0.01***	−0.01***	0.00**	−0.01***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
a_{ijt-1} (20-49): $\beta_{1,z=3}$	0.027***	0.038***	0.031***	0.060***	0.052***	0.058***	0.041***	0.025***	0.026***	0.024***	0.022***	0.059***	0.037***	0.030***	0.029***	0.049***	0.035***	0.039***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
a_{ijt-1} (50-249): $\beta_{1,z=4}$	0.022***	0.035***	0.038***	0.049***	0.038***	0.043***	0.034***	0.031***	0.031***	0.028***	0.034***	0.050***	0.032***	0.041***	0.032***	0.057***	0.022***	0.028***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)
a_{ijt-1} (250+): $\beta_{1,z=5}$	0.018***	0.037***	0.043***	0.035***	0.033***	0.030***	0.021***	0.022***	0.029***	0.036***	0.003	0.034***	0.025***	0.047***	0.033***	0.040***	0.006*	0.016***
	(0.003)	(0.004)	(0.003)	(0.006)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
Observations	91,165	79,582	119,048	135,271	131,152	871,405	119,805	160,810	616,979	14,547	83,831	447,960	141,323	174,113	64,484	46,129	177,543	141,266
R2	0.134	0.123	0.126	0.157	0.119	0.128	0.126	0.094	0.105	0.085	0.146	0.076	0.081	0.122	0.222	0.155	0.165	0.155

Notes: The table reports the results from estimating Equation (6) using OLS. Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. All regressions include industry-year fixed effects. Observations are weighted by firms' employment levels. CompNet data, firms with at least 20 employees.

Table C3. Responsiveness to revenue-TFP by size class across countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
variables	BE	HR	CZ	DK	FI	FR	DE	HU	IT	LV	LT	PL	PT	RO	SK	SL	ES	SE
l_{ijt-1} (20-49): $\beta_{2,z=3}$	−0.01***	−0.02***	−0.02***	−0.03***	−0.03***	−0.02***	−0.01	−0.03***	−0.03***	0.00	−0.04***	−0.02***	−0.02***	−0.01*	−0.01**	−0.02***	−0.02***	−0.02***
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
l_{ijt-1} (50-249): $\beta_{2,z=4}$	−0.01***	−0.01***	−0.02***	−0.02***	−0.02***	−0.01***	0.00**	−0.02***	−0.02***	−0.01**	−0.03***	−0.01***	−0.02***	−0.01***	−0.01***	−0.02***	−0.01***	−0.01***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
l_{ijt-1} (250+): $\beta_{2,z=5}$	−0.01***	−0.01***	−0.01***	−0.02***	−0.01***	−0.01***	0.00***	−0.01***	−0.01***	−0.01***	−0.01***	0.00	−0.01***	−0.01**	−0.01***	−0.01***	0.00**	−0.01***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
a_{ijt-1} (20-49): $\beta_{1,z=3}$	0.015***	0.047***	0.090***	0.078***	0.080***	0.038***	0.054***	0.082***	0.062***	0.028***	0.077***	0.088***	0.066***	0.119***	0.057***	0.082***	0.029***	0.028***
	(0.003)	(0.004)	(0.007)	(0.008)	(0.008)	(0.002)	(0.006)	(0.007)	(0.006)	(0.006)	(0.009)	(0.004)	(0.006)	(0.008)	(0.007)	(0.010)	(0.006)	(0.004)
a_{ijt-1} (50-249): $\beta_{1,z=4}$	0.010***	0.033***	0.079***	0.060***	0.067***	0.030***	0.049***	0.057***	0.045***	0.034***	0.059***	0.066***	0.057***	0.111***	0.057***	0.065***	0.012**	0.024***
	(0.003)	(0.004)	(0.007)	(0.008)	(0.008)	(0.002)	(0.005)	(0.008)	(0.007)	(0.007)	(0.009)	(0.004)	(0.007)	(0.008)	(0.007)	(0.010)	(0.006)	(0.004)
a_{ijt-1} (250+): $\beta_{1,z=5}$	0.006*	0.025***	0.075***	0.049***	0.056***	0.025***	0.043***	0.043***	0.035***	0.041***	0.009	0.044***	0.046***	0.086***	0.066***	0.058***	0.012*	0.017***
	(0.003)	(0.004)	(0.008)	(0.009)	(0.008)	(0.002)	(0.006)	(0.008)	(0.009)	(0.009)	(0.013)	(0.005)	(0.010)	(0.011)	(0.007)	(0.011)	(0.007)	(0.004)
Observations	91,208	79,583	119,537	135,463	131,423	871,445	120,062	162,600	618,749	14,585	85,721	448,021	141,468	185,362	64,728	46,148	177,712	141,282
R2	0.129	0.115	0.114	0.152	0.117	0.117	0.124	0.091	0.102	0.081	0.141	0.065	0.080	0.104	0.217	0.146	0.161	0.152

Notes: The table reports the results from estimating Equation (6) using OLS. Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' employment levels. All regressions include industry-year fixed effects. CompNet data, firms with at least 20 employees.

Table C4. Responsiveness to labor productivity by size class across countries (all sample).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
variables	BE	HR	CZ	DK	FI	HU	IT	LV	LT	PT	SL	SE
l_{ijt-1} (1-9): $\beta_{2,z=3}$	−0.090***	−0.104***	−0.073***	−0.114***	−0.081***	−0.131***	−0.133***	−0.171***	−0.156***	−0.094***	−0.087***	−0.143***
	(0.002)	(0.001)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
l_{ijt-1} (10-19): $\beta_{2,z=4}$	−0.031***	−0.087***	−0.171***	−0.060***	−0.042***	−0.121***	−0.137***	−0.106***	−0.148***	−0.106***	−0.099***	−0.057***
	(0.007)	(0.003)	(0.014)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.005)	(0.004)
l_{ijt-1} (20-49): $\beta_{2,z=3}$	−0.008	−0.052***	−0.135***	−0.033***	−0.025***	−0.074***	−0.076***	−0.082***	−0.105***	−0.064***	−0.054***	−0.020***
	(0.005)	(0.003)	(0.015)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)
l_{ijt-1} (50-249): $\beta_{2,z=4}$	−0.005**	−0.024***	−0.047***	−0.012***	−0.011***	−0.037***	−0.031***	−0.063***	−0.071***	−0.033***	−0.026***	−0.004
	(0.002)	(0.002)	(0.011)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
l_{ijt-1} (250+): $\beta_{2,z=5}$	−0.004**	−0.012***	−0.014***	−0.003	−0.008***	−0.018***	−0.013***	−0.041***	−0.028***	−0.007**	−0.008**	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)
a_{ijt-1} (1-9): $\beta_{1,z=3}$	0.056***	0.064***	0.060***	0.105***	0.070***	0.069***	0.067***	0.061***	0.044***	0.061***	0.084***	0.098***
	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
a_{ijt-1} (10-19): $\beta_{1,z=4}$	0.034***	0.065***	0.083***	0.087***	0.056***	0.087***	0.075***	0.043***	0.049***	0.084***	0.102***	0.066***
	(0.004)	(0.002)	(0.011)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
a_{ijt-1} (20-49): $\beta_{1,z=3}$	0.026***	0.058***	0.117***	0.085***	0.057***	0.074***	0.065***	0.042***	0.052***	0.073***	0.089***	0.063***
	(0.004)	(0.003)	(0.015)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.002)
a_{ijt-1} (50-249): $\beta_{1,z=4}$	0.026***	0.042***	0.080***	0.069***	0.047***	0.043***	0.037***	0.041***	0.047***	0.050***	0.067***	0.052***
	(0.002)	(0.003)	(0.017)	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
a_{ijt-1} (250+): $\beta_{1,z=5}$	0.023***	0.029***	0.039***	0.056***	0.042***	0.022***	0.021***	0.040***	−0.015**	0.018***	0.041***	0.042***
	(0.002)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)
Observations	290,755	784,502	153,466	801,800	1,291,005	2,063,525	4,352,753	145,374	365,622	1,708,418	427,327	1,216,893
R2	0.088	0.079	0.192	0.110	0.072	0.082	0.108	0.094	0.103	0.073	0.089	0.106

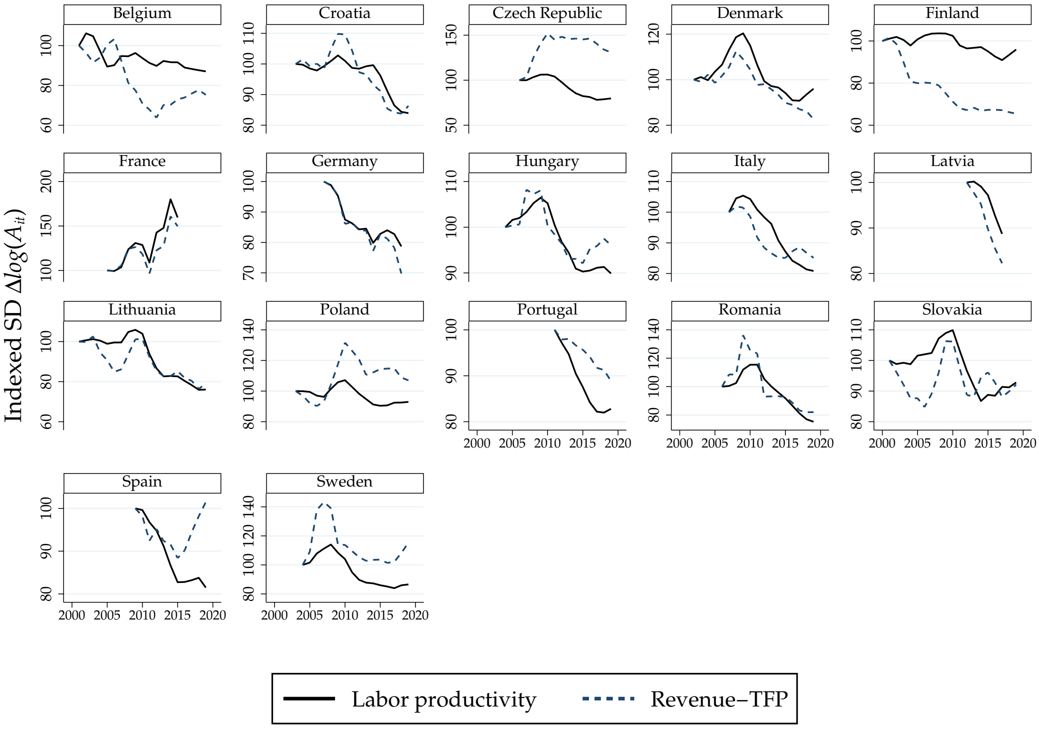
Notes: The table reports the results from estimating Equation (6) using OLS but with two additional size-classes to account for the smaller firms in the "all sample". Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' employment levels. All regressions include industry-year fixed effects. CompNet data, firms with at least one employee.

Table C5. Responsiveness to revenue-TFP by size class across countries (all sample).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
variables	BE	HR	CZ	DK	FI	HU	IT	LV	LT	PT	SL	SE
l_{ijt-1} (1-9): $\beta_{2,z=3}$	−0.079***	−0.101***	−0.090***	−0.111***	−0.079***	−0.135***	−0.135***	−0.174***	−0.200***	−0.100***	−0.085***	−0.143***
	(0.002)	(0.001)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)
l_{ijt-1} (10-19): $\beta_{2,z=4}$	−0.041***	−0.072***	−0.137***	−0.059***	−0.049***	−0.105***	−0.101***	−0.107***	−0.166***	−0.088***	−0.053***	−0.073***
	(0.003)	(0.002)	(0.012)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
l_{ijt-1} (20-49): $\beta_{2,z=3}$	−0.024***	−0.043***	−0.083***	−0.043***	−0.033***	−0.067***	−0.060***	−0.083***	−0.117***	−0.058***	−0.029***	−0.039***
	(0.002)	(0.002)	(0.012)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
l_{ijt-1} (50-249): $\beta_{2,z=4}$	−0.017***	−0.022***	−0.037***	−0.027***	−0.023***	−0.035***	−0.036***	−0.065***	−0.076***	−0.033***	−0.020***	−0.026***
	(0.001)	(0.001)	(0.008)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
l_{ijt-1} (250+): $\beta_{2,z=5}$	−0.011***	−0.012***	−0.013***	−0.017***	−0.013***	−0.018***	−0.019***	−0.047***	−0.030***	−0.012***	−0.011***	−0.014***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.006)	(0.004)	(0.003)	(0.001)
a_{ijt-1} (1-9): $\beta_{1,z=3}$	0.044***	0.062***	0.162***	0.158***	0.114***	0.137***	0.148***	0.060***	0.076***	0.105***	0.157***	0.092***
	(0.004)	(0.002)	(0.014)	(0.005)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)
a_{ijt-1} (10-19): $\beta_{1,z=4}$	0.020***	0.049***	0.109***	0.126***	0.099***	0.132***	0.104***	0.044***	0.052***	0.110***	0.120***	0.063***
	(0.004)	(0.002)	(0.022)	(0.005)	(0.005)	(0.005)	(0.002)	(0.004)	(0.007)	(0.004)	(0.006)	(0.002)
a_{ijt-1} (20-49): $\beta_{1,z=3}$	0.020***	0.044***	0.107***	0.142***	0.106***	0.124***	0.108***	0.044***	0.057***	0.109***	0.115***	0.066***
	(0.004)	(0.003)	(0.029)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.007)	(0.004)	(0.007)	(0.002)
a_{ijt-1} (50-249): $\beta_{1,z=4}$	0.020***	0.030***	0.135***	0.129***	0.099***	0.080***	0.093***	0.048***	0.039***	0.085***	0.110***	0.064***
	(0.003)	(0.003)	(0.021)	(0.005)	(0.005)	(0.007)	(0.003)	(0.004)	(0.007)	(0.007)	(0.006)	(0.002)
a_{ijt-1} (250+): $\beta_{1,z=5}$	0.011***	0.017***	0.090***	0.117***	0.082***	0.050***	0.068***	0.058***	−0.062***	0.056***	0.086***	0.052***
	(0.003)	(0.005)	(0.014)	(0.006)	(0.005)	(0.010)	(0.004)	(0.009)	(0.021)	(0.011)	(0.011)	(0.003)
Observations	292,083	786,443	155,587	802,407	1,297,264	2,198,831	4,454,703	157,011	410,731	1,809,778	430,276	1,217,233
R2	0.075	0.067	0.177	0.098	0.067	0.067	0.098	0.079	0.102	0.066	0.076	0.095

Notes: The table reports the results from estimating Equation (6) using OLS but with two additional size-classes to account for the smaller firms in the "all sample". Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' employment levels. All regressions include industry-year fixed effects. CompNet data, firms with at least one employee.

Figure C8. Overall trend in the standard deviation of productivity changes.

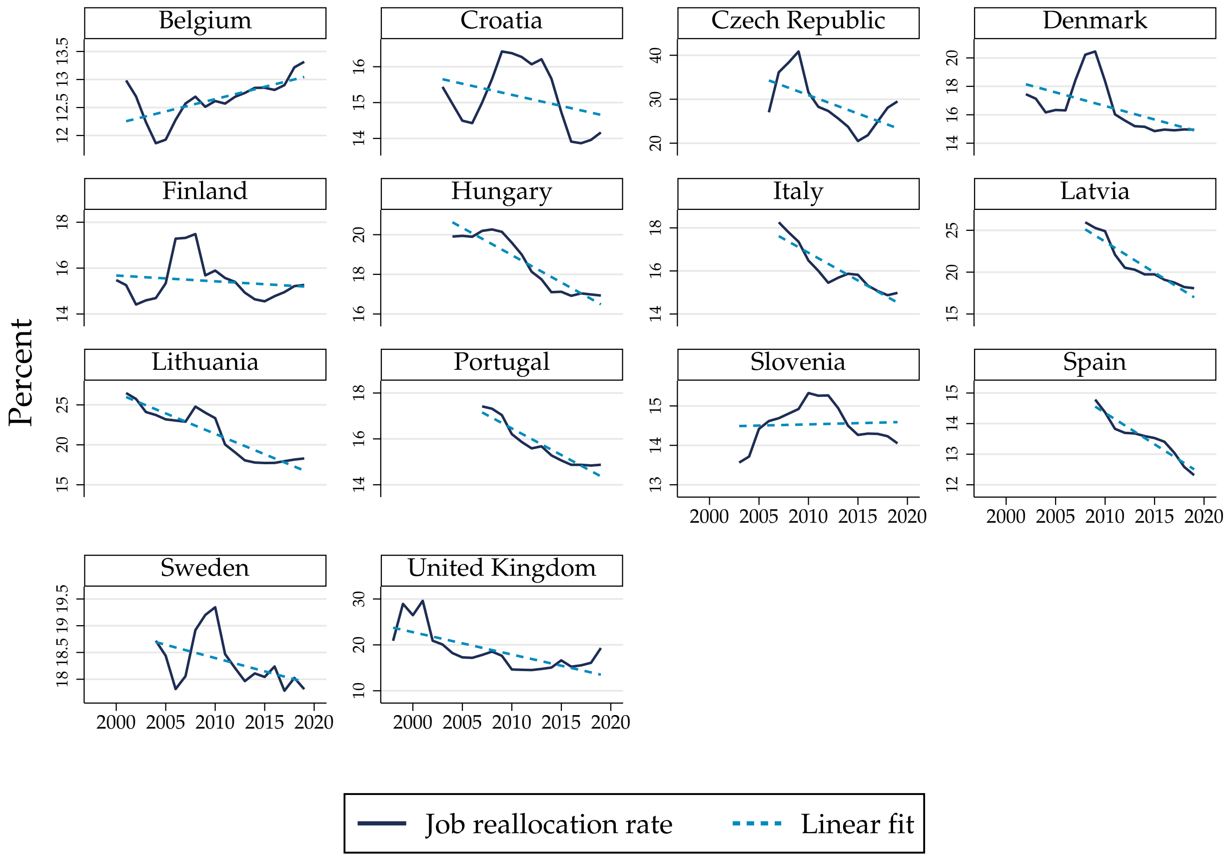


Notes: Standard deviation of productivity log-changes, i.e. $log(A_{it}) - log(A_{i(t-1)})$, indexed at the value of the first year for each country. CompNet data, firms with at least 20 employees.

C.3 Replication of key results with the all firms sample

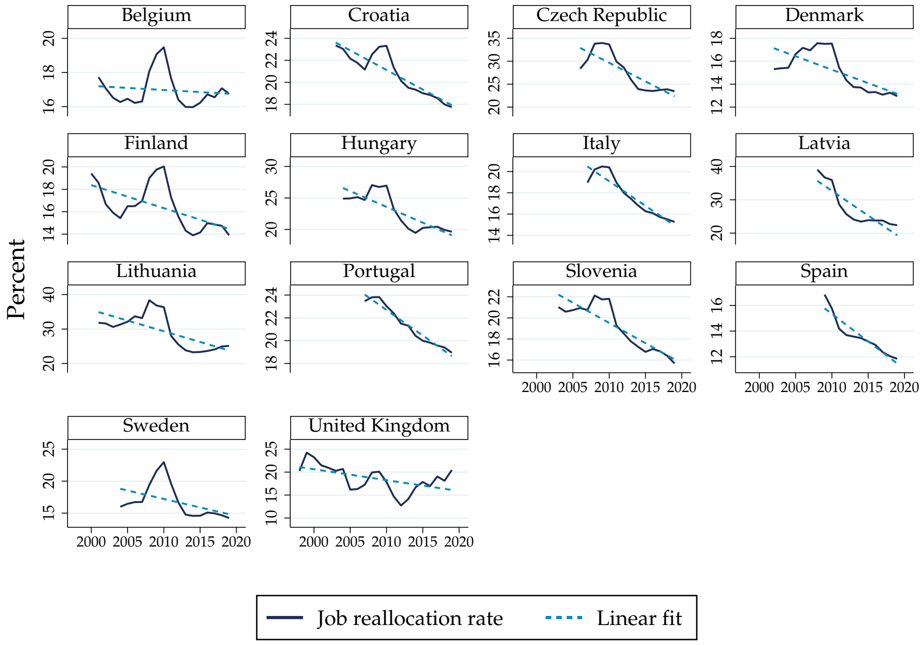
C.3.1 Stylized facts

Figure C9. Job reallocation rate in the all sample.



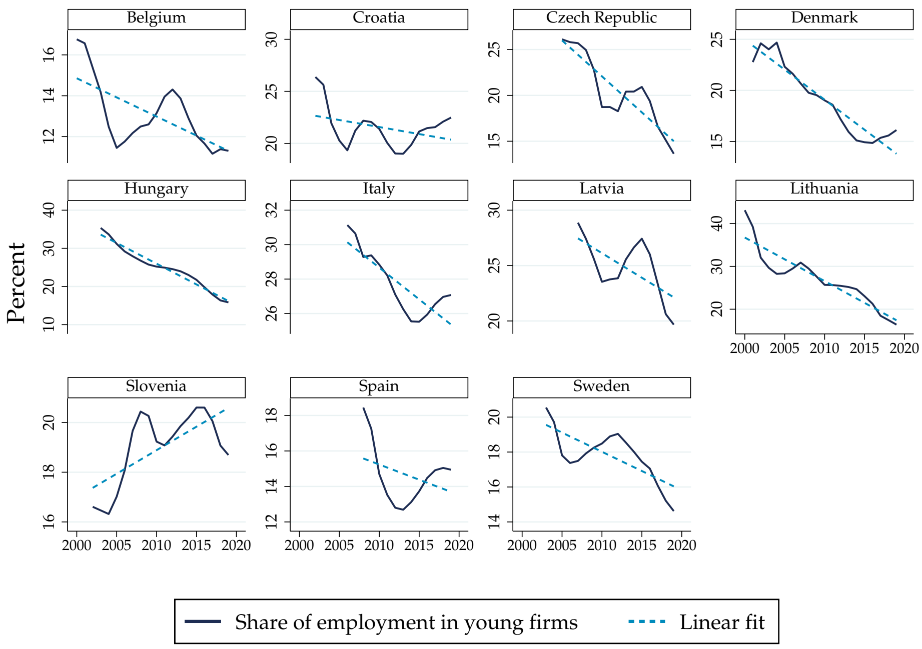
Notes: Three-year moving averages of job reallocation rates defined in Equation (1). The light blue dashed lines report linear trends. CompNet data. Firms with at least one employee.

Figure C10. Sales reallocation rate in the all sample.



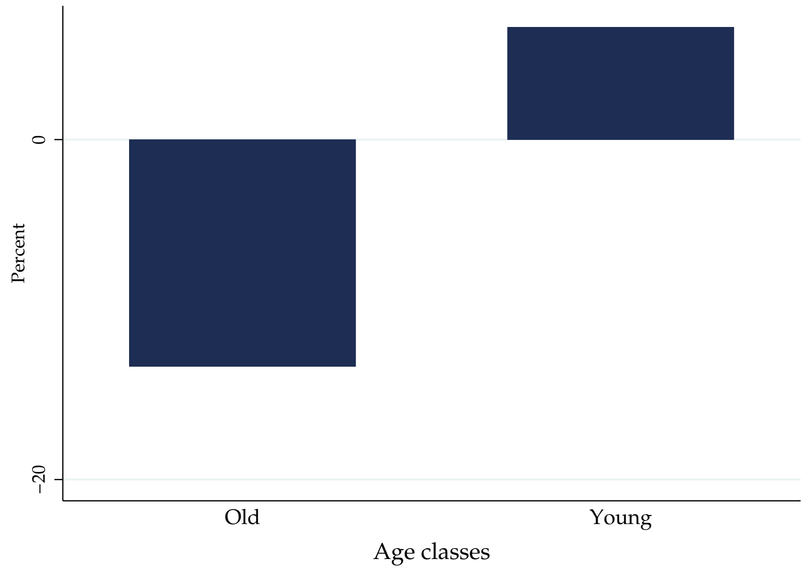
Notes: Three-year moving averages of the sales share of firms not older than five years. The dark blue solid lines shows country-level shares of sales in young firms. The light blue dashed lines report the linear trends. CompNet data. Firms with at least one employee.

Figure C11. Share of employment in young firms in the all sample



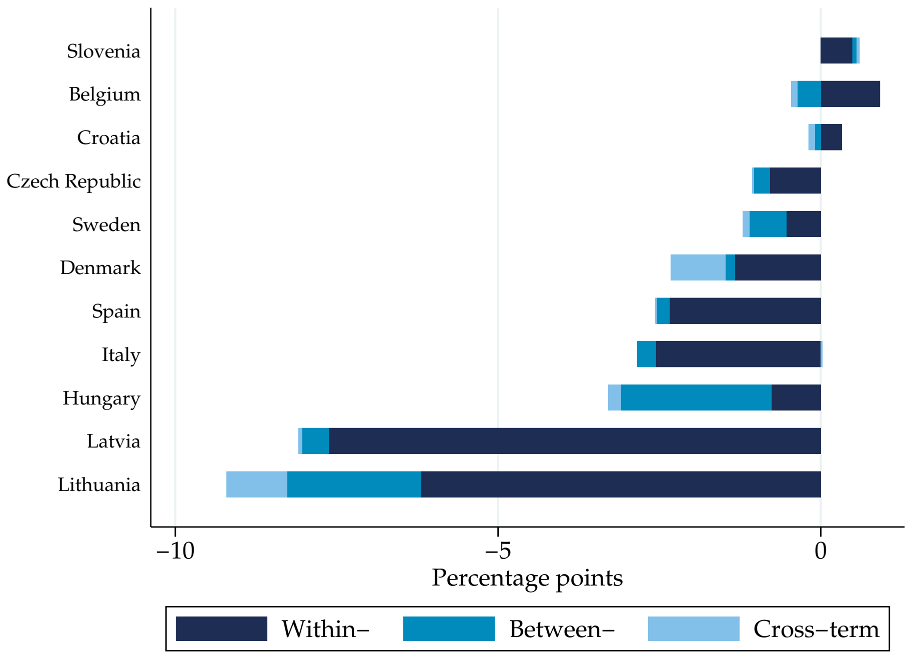
Notes: Three-year moving averages of the employment share of firms not older than five years. The dark blue solid lines shows country-level shares of employment in young firms. The light blue dashed lines report linear trends. The underlying data are aggregated from sector-age-class data resulting in a drop of a few sector-age-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data. Firms with at least one employee.

Figure C12. Relative changes in job reallocation rates by age-class in the all sample.



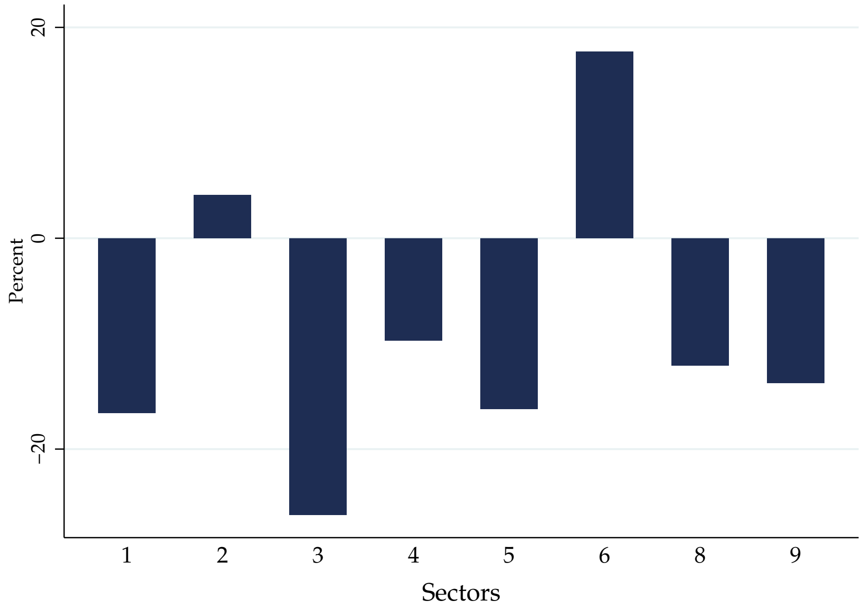
Note: Averages across countries in relative changes in job reallocation rates as computed in Equation (1) by age-class. Changes are computed between the first and last two years for each country-age-class cell. All countries additionally include the real estate sector. CompNet data, firms with at least one employee.

Figure C13. Decomposition of job reallocation changes across age classes in the all sample.



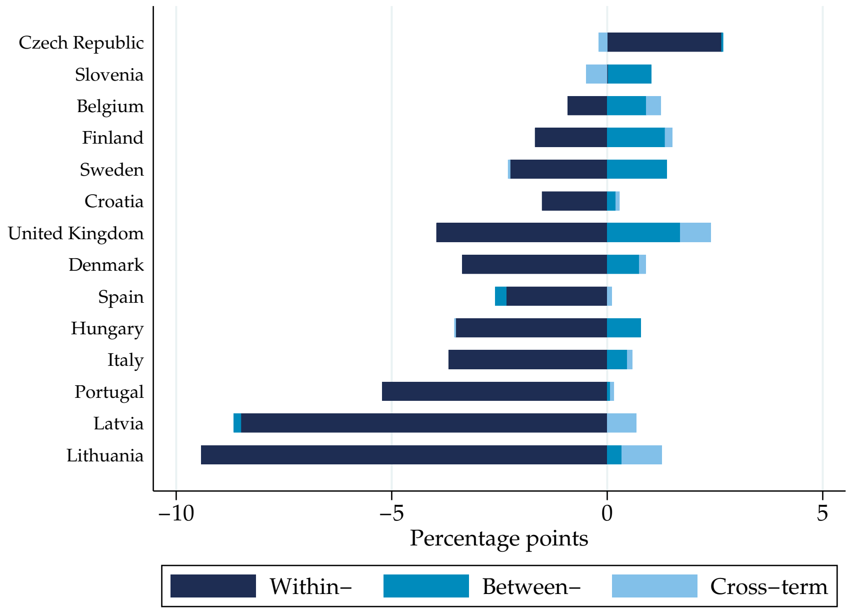
Notes: Results of the decomposition of job reallocation rates across age-classes as described in Equation (4). To define the start and end points for the decomposition, we average the first and last two years of job reallocation rates for every country-sector combination. All countries additionally include the real estate sector. CompNet data, firms with at least one employee.

Figure C14. Relative changes in job reallocation rate by sector in the all sample.



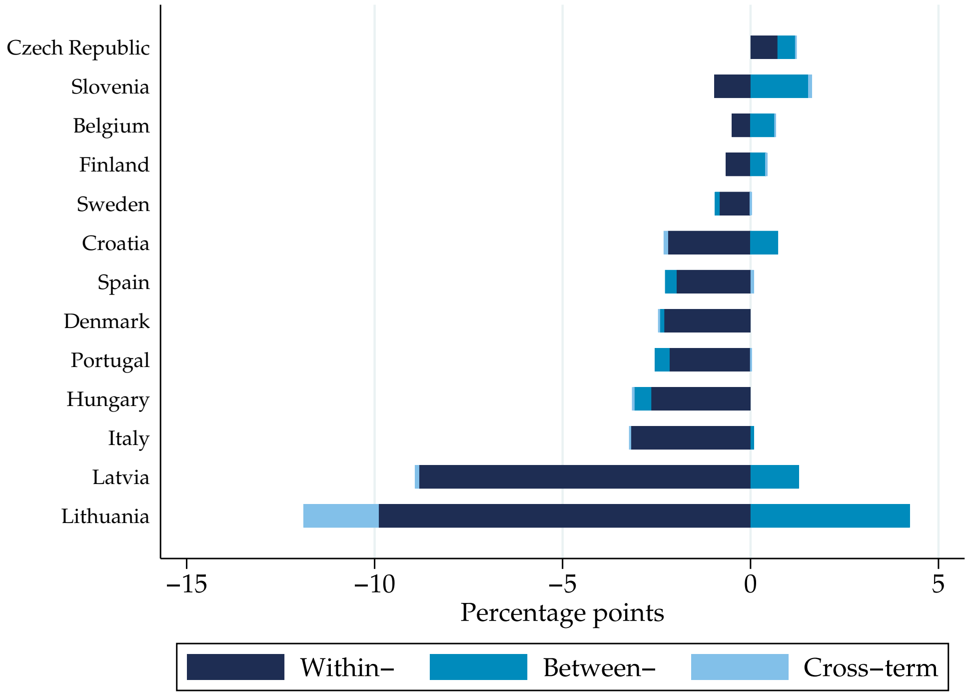
Notes: Averages across countries in relative changes in job reallocation rates as computed in Eq. (1) by sectors. Changes are computed between the first and last two years for each country-sector. Sectors are numbered in the following way: manufacturing (1), construction (2), wholesale/retail trade and repair of motor vehicles and motorcycles (3), transportation/storage (4), accommodation/food services (5), Information and Communication Technology (ICT) (6), professional/scientific/technical activities (8), administrative/support service activities (9). CompNet data, firms with at least one employee.

Figure C15. Decomposition across sectors in the all sample.



Notes: Results of the decomposition of job reallocation rates across sectors as described in Eq. (4). To define the start and end points for the decompositions, we average the first and last two years of job reallocation rates for every country-sector combination. CompNet data. Firms with at least one employee.

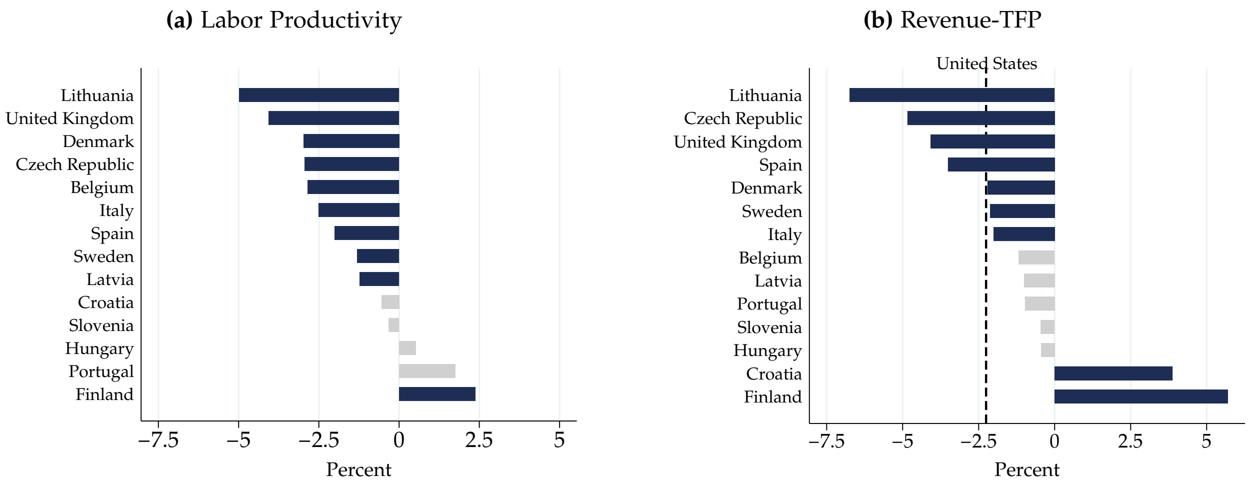
Figure C16. Decomposition of job reallocation changes across size classes in the all sample.



Notes: Decomposition of changes in job reallocation rates based on a version of Eq. (4) that decomposes aggregate changes in job reallocation into within- and between-size-class contributions. To define the start and end points for the decomposition, we average the first and last two years for every country-size-class combination. The underlying data are aggregated from sector-size-class data resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Appendix A.1.1). CompNet data, firms with at least one employee.

C.3.2 Responsiveness hypothesis

Figure C17. Relative changes in responsiveness over time (all sample).



Notes: Estimated coefficient of the linear trend relative to the initial responsiveness, i.e. δ_1/β_1 in Equation (5). Countries are ranked in descending order. Underlying results reported in Table C6 and Table C7. Bars are colored if both coefficients are statistically significant at least at the 10% level. The dashed blue line is the relative change estimated for the United States over 1981–2013 by DHJM (own calculations based on Table 1, Panel B). CompNet data, firms with at least 1 employee.

Table C6. Overall results of responsiveness regression to labor productivity across countries (all sample).

Country	β_1	(S.E.)	δ_1	(S.E.)	β_2	(S.E.)	δ_2	(S.E.)	N	R^2
Belgium	0.048***	(0.0035)	–0.001***	(0.0003)	–0.012***	(0.0012)	0.000***	(0.0001)	290,755	0.07
Croatia	0.055***	(0.0029)	0.000	(0.0002)	–0.010***	(0.0025)	0.000	(0.0002)	784,502	0.06
Czech Republic	0.092***	(0.0111)	–0.003**	(0.0011)	0.000	(0.0033)	0.000	(0.0003)	153,466	0.14
Denmark	0.127***	(0.0061)	–0.004***	(0.0005)	–0.009***	(0.0015)	0.000	(0.0001)	801,800	0.09
Finland	0.047***	(0.0044)	0.001***	(0.0003)	–0.007***	(0.0012)	0.000*	(0.0001)	1,291,005	0.06
Hungary	0.051***	(0.0032)	0.000	(0.0003)	–0.016***	(0.0025)	0.000	(0.0002)	2,063,525	0.05
Italy	0.078***	(0.0021)	–0.002***	(0.0002)	–0.026***	(0.0025)	0.001***	(0.0002)	4,352,753	0.06
Latvia	0.050***	(0.0031)	–0.001*	(0.0004)	–0.030***	(0.0043)	0.001***	(0.0004)	290,939	0.09
Lithuania	0.063***	(0.0047)	–0.003***	(0.0004)	–0.019***	(0.0064)	0.001*	(0.0004)	365,622	0.07
Portugal	0.041***	(0.0054)	0.001	(0.0004)	–0.013***	(0.0037)	0.000	(0.0002)	1,709,050	0.05
Slovenia	0.075***	(0.0041)	0.000	(0.0003)	–0.012***	(0.0027)	0.000**	(0.0002)	427,327	0.07
Spain	0.064***	(0.0044)	–0.001**	(0.0005)	–0.002*	(0.0012)	0.000**	(0.0002)	2,252,233	0.09
Sweden	0.101***	(0.0049)	–0.001***	(0.0004)	–0.015***	(0.0013)	0.000	(0.0001)	1,216,893	0.06

Notes: The table reports the results from estimating Equation (5) using OLS. Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' employment levels. All regressions include industry-year fixed effects. CompNet data, firms with at least one employee.

Table C7. Overall results of responsiveness regression to revenue-TFP across countries (all sample).

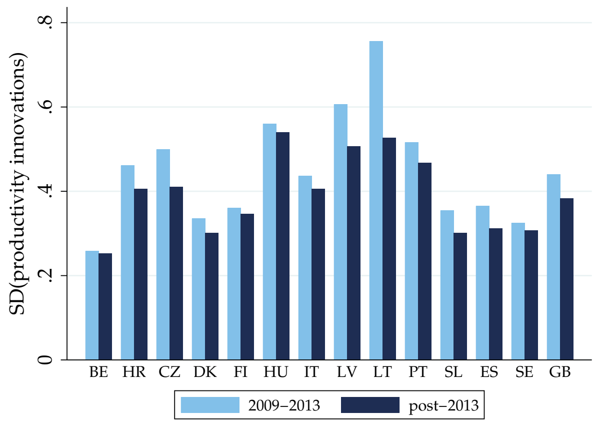
Country	β_1	(S.E.)	δ_1	(S.E.)	β_2	(S.E.)	δ_2	(S.E.)	N	R^2
Belgium	0.018***	(0.0057)	0.000	(0.0004)	–0.010***	(0.0013)	0.000***	(0.0001)	292,083	0.06
Croatia	0.030***	(0.0047)	0.001***	(0.0004)	–0.007***	(0.0029)	0.000	(0.0002)	786,443	0.04
Czech Republic	0.225***	(0.0321)	–0.011***	(0.0030)	0.001	(0.0034)	0.000	(0.0003)	155,587	0.12
Denmark	0.190***	(0.0113)	–0.004***	(0.0010)	–0.010***	(0.0015)	0.000	(0.0001)	802,407	0.08
Finland	0.066***	(0.0104)	0.004***	(0.0008)	–0.008***	(0.0012)	0.000**	(0.0001)	1,297,264	0.06
Hungary	0.096***	(0.0118)	0.000	(0.0013)	–0.018***	(0.0031)	0.000	(0.0003)	2,198,831	0.03
Italy	0.143***	(0.0044)	–0.003***	(0.0005)	–0.027***	(0.0024)	0.001***	(0.0002)	4,454,703	0.04
Latvia	0.057***	(0.0053)	–0.001	(0.0006)	–0.030***	(0.0038)	0.001***	(0.0004)	311,924	0.08
Lithuania	0.076***	(0.0149)	–0.005***	(0.0012)	–0.018**	(0.0076)	0.001	(0.0005)	410,731	0.06
Portugal	0.092***	(0.0104)	–0.001	(0.0009)	–0.020***	(0.0036)	0.000*	(0.0003)	1,808,029	0.04
Slovenia	0.127***	(0.0117)	–0.001	(0.0009)	–0.013***	(0.0032)	0.000	(0.0002)	430,276	0.06
Spain	0.135***	(0.0075)	–0.005***	(0.0010)	–0.004***	(0.0013)	0.000	(0.0002)	2,294,839	0.08
Sweden	0.111***	(0.0051)	–0.002***	(0.0004)	–0.015***	(0.0011)	0.000	(0.0001)	1,217,233	0.05

Notes: The table reports the results from estimating Equation (5) using OLS. Standard errors (in parentheses) are clustered at the firm level, and ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Observations are weighted by firms' employment levels. All regressions include industry-year fixed effects. CompNet data, firms with at least one employee.

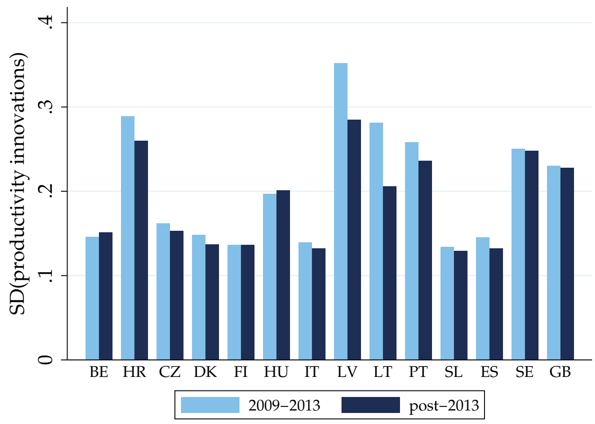
C.3.3 Shocks hypothesis

Figure C18. Standard deviation of productivity innovations η_{it} in the all sample.

(a) Labor Productivity



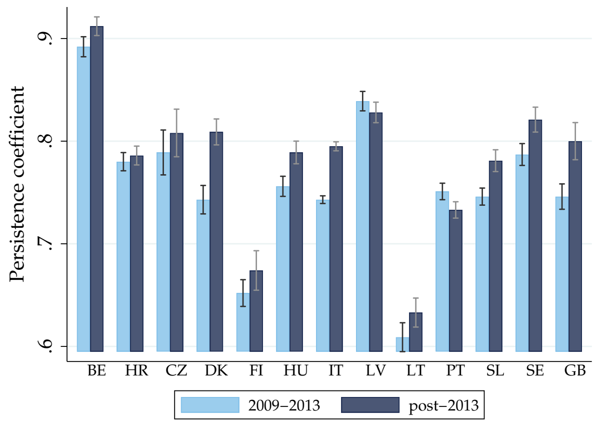
(b) Revenue TFP



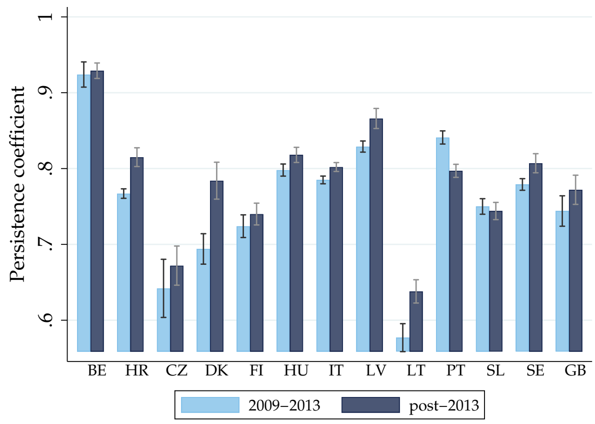
Notes: Standard deviation of the residuals of the AR(1) process in Equation (7) estimated over two different periods. CompNet data, firms with at least one employee.

Figure C19. Increasing persistence in productivity dynamics in the all sample.

(a) Labor productivity



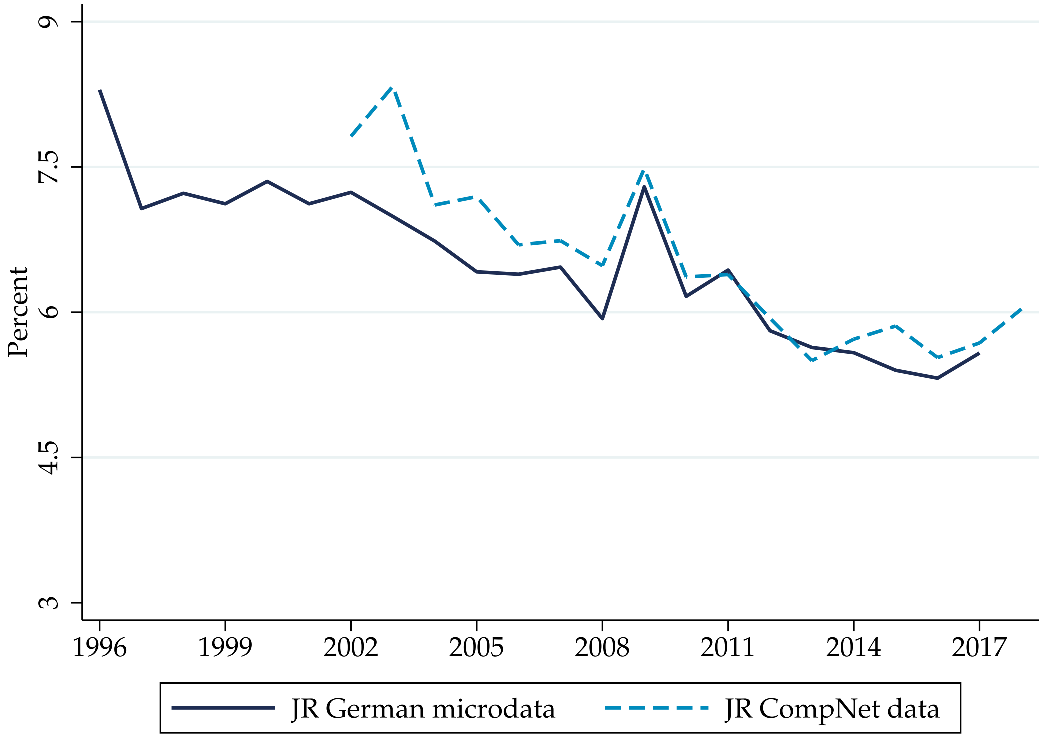
(b) Revenue-TFP



Notes: Point estimates of the persistence coefficient, ρ_t, in the AR(1) in Equation (7) estimated over two consecutive periods. CompNet data, firms with at least one employee.

D Additional results on the German manufacturing sector

Figure D1. Job reallocation in the German manufacturing sector.



Notes: The dark blue solid line represents the job reallocation rate based on the German microdata, while the light blue dashed line those for the German manufacturing sector from CompNet (firms with at least 20 employees). German microdata and CompNet data with at least 20 employees.

E Estimating production functions with the German data

E.1 Production function estimation

We model firms' production function as a translog production function:

$$q_{it} = \phi'_{it}\boldsymbol{\beta} + \omega_{it} + \epsilon_{it}\,. \tag{E1}$$

q_{it} denotes the log of produced quantities and ϕ'_{it} captures the production inputs Capital (K_{it}), labor (L_{it}), and intermediates (M_{it}) and its interactions. The production function is specified in logs as:

$$\begin{aligned} q_{it} =& \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \\ & \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \epsilon_{it}, \end{aligned} \tag{E2}$$

where smaller letter denote logs. ϵ_{it} is an i.i.d. error term and ω_{it} denotes Hicks-neutral productivity and follows a Markov process. ω_{it} is unobserved to the econometrician, yet firms know ω_{it} 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).[50] The output elasticity of labor is:

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

There are three identification issues preventing us from estimating the production function (E1) 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 industry-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, an endogeneity issue arises.

[50] The timing assumption on labor is consistent with Germany's rigid labor market and with the timing of the data collection. Whereas the labor information pertains to a fixed date (September 30$^{\text{th}}$), all other variables refer to the entire year.

(3) The fact that productivity is unobserved and that firms' flexible input decisions depend on productivity shocks creates another endogeneity problem.

We now discuss how we solve these three identification problems.

E.1.1 Solving (1) by deriving a firm-specific output price index

As one cannot aggregate output quantities across the different products of a firm, we follow Eslava et al. (2004) and construct a firm-specific price index from observed output prices. We use this price index to purge observed firm revenue from price variation by deflating firm revenue with this price index.[51] We construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products in the following way:

$$PI_{it} = \prod_{o=1}^{n} \frac{p_{iot}}{p_{iot-1}}^{1/2(share_{iot}+share_{iot-1})} PI_{it-1} \,. \tag{E3}$$

PI_{it} is the price index, p_{iot} is the price of good o, and $share_{iot}$ 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., $PI_{i1995} = 100$). 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.[52] 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_{it}.[53]

[51] This approach has also been applied in various other studies (e.g., Smeets and Warzynski, 2013, Carlsson et al., 2021.)

[52] 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.

[53] Note that, as discussed in Bond et al. (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 function separately by single-product firms requires other strong assumptions like perfect input divisibility of all inputs across all products. Finally, our results are also robust to using cost-share approaches to estimate the production function, which requires other assumptions (constant returns to scale, exogenous input prices for all inputs, and the absence of adjustment costs in all inputs).

E.1.2 Solving (2) by accounting for unobserved input price variation.

To control for input price variation across firms, we use a firm-level adaptation of the approach in 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 (Eq. (E1)):

$$q_{it} = \tilde{\phi}_{it}'\boldsymbol{\beta} + B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\phi}_{it}^{c}) + \omega_{it} + \epsilon_{it}\,. \tag{E4}$$

$B(.) = B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\phi}_{it}^{c})$ is the price control function consisting of our logged firm-specific output price index (pi_{it}), a logged sales-weighted average of firms' product market sales shares (ms_{it}), a headquarter location dummy (G_{it}), and a four-digit industry dummy (D_{it}). $\tilde{\phi}_{it}^{c} = [1; \tilde{\phi}_{it}]$, where $\tilde{\phi}_{it}$ includes the production function input terms as specified in Equation (E2). The tilde indicates that some of these inputs enter in monetary terms and are deflated by an industry-level deflator (capital and intermediates) while other inputs enter in quantities (labor). The constant entering $\tilde{\phi}_{it}^{c}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\tilde{\phi}_{it}$ (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 firms' input prices. 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 the addition of 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 from input quality differences across firms. We also include location and four-digit industry dummies into $B(.)$ to further absorb the 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 assumes 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 variations and does not require that input prices vary between firms with respect to all elements of $B(.)$. 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 the existence and degree of input price variation.

E.1.3 Solving (3) by 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_{it} and which are components of total intermediate inputs. Inverting the demand function for e_{it} defines an expression for productivity:

$$\omega_{it} \equiv g(.) = g(e_{it}, k_{it}, l_{it}, \mathbf{\Gamma}_{it}). \tag{E5}$$

$\mathbf{\Gamma}_{it}$ captures state variables of the firm, that in addition to k_{it} and l_{it} affect firms demand for e_{it}. Ideally, $\mathbf{\Gamma}_{it}$ should include a wide set of variables affecting productivity and demand for e_{it}. We include dummy variables for export (EX_{it}) activities, the log of the number of products a firm produces ($NumP_{it}$), and the log of the average wage a firm pays (w_{it}) into $\mathbf{\Gamma}_{it}$. The latter absorbs unobserved quality and price differences that shift input demand for e_{it}.

Remember that productivity follows a first-order Markov process. We allow firms to 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: $\omega_{it} = h(\omega_{it-1}, \mathbf{Z}_{it-1}) + \xi_{it}^{\omega} = h_{(.)} + \xi_{it}^{\omega}$, where ξ_{it}^{ω} denotes the innovation in productivity and $\mathbf{Z}_{it} = (EX_{it}, NumP_{it})$ 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.[54] Plugging Equation (E5) and the law of motion for productivity into Equation (E4) yields:

$$q_{it} = \tilde{\phi}'_{it}\boldsymbol{\beta} + B(.) + h(.) + \epsilon_{it} + \xi^{\omega}_{it} \, , \tag{E6}$$

which constitutes the basis of our estimation.

E.1.4 Identifying moments and results

We estimate Equation (E6) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[55] 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 ξ^{ω}_{it}. 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.[56] We define identifying moments jointly on ϵ_{it} and ξ^{ω}_{it}:

$$E[(\epsilon_{it} + \xi^{\omega}_{it})\mathbf{O}_{it}] = 0. \tag{E7}$$

$\mathbf{O}_{it}$ 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 $h(.)$, and lagged interactions of the output price index with production inputs. Formally this implies

$$\mathbf{O}'_{it} = (J(.), A(.), T(.), \Theta(.), \Psi(.), \boldsymbol{\nu}(.)) \, , \tag{E8}$$

where for convenience, we defined:

$J(.) = (l_{it},\, k_{it},\, l^2_{it},\, k^2_{it},\, l_{it}k_{it},\, G_{it},\, D_{it}) \, ,$

$A(.) = (m_{it-1},\, m^2_{it-1},\, l_{it-1}m_{it-1},\, k_{it-1}m_{it-1},\, l_{it-1}k_{it-1}m_{it-1},\, ms_{it-1},\, \pi_{it-1}) \, ,$

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

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

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

$\Theta(.) = \big((l_{it-1},\, k_{it-1},\, l^2_{it-1},\, k^2_{it-1},\, l_{it-1}k_{it-1},\, m_{it-1},\, m^2_{it-1},\, l_{it-1}m_{it-1},\, k_{it-1}m_{it-1},\, l_{it-1}k_{it-1}m_{it-1}) \times \pi_{it-1}\big),$

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

$\boldsymbol{\nu}(.) = (Exp_{it-1},\, NumP_{it-1},\, w_{it-1}).$

Table E1 summarizes the results of the production function estimation by reporting average output elasticities and associated standard deviations for each production factor after we drop observations with negative output elasticities from the data as these observations are inconsistent with our underlying production model. We drop 2% of observations due to negative output elasticities.

Table E1. Production function estimation: average output elasticities by industry.

Industry	Observations (1)	Capital (2)	Intermediates (3)	Labor (4)	Returns to Scale (5)
15 Food and beverages	30,570	0.13	0.64	0.18	0.95
		(0.05)	(0.11)	(0.08)	(0.06)
17 Textiles	8,581	0.17	0.65	0.32	1.15
		(0.08)	(0.10)	(0.09)	(0.10)
18 Apparel, dressing, dyeing of fur	3,234	0.12	0.71	0.24	1.07
		(0.05)	(0.11)	(0.11)	(0.08)
19 Leather, leather products	1,871	0.19	0.64	0.28	1.11
		(0.10)	(0.11)	(0.12)	(0.16)
20 Wood, wood products	7,010	0.09	0.65	0.26	1.00
		(0.04)	(0.08)	(0.10)	(0.09)
21 Pulp, paper, paper products	6,881	0.09	0.68	0.28	1.05
		(0.05)	(0.08)	(0.08)	(0.07)
22 Publishing, printing	6,111	0.08	0.57	0.25	0.90
		(0.03)	(0.09)	(0.07)	(0.07)
24 Chemicals, chemical products	15,748	0.12	0.69	0.27	1.07
		(0.05)	(0.08)	(0.05)	(0.09)
25 Rubber and plastic products	16,489	0.12	0.65	0.26	1.03
		(0.05)	(0.08)	(0.09)	(0.10)
26 Other non-metallic mineral products	13,696	0.14	0.61	0.30	1.05
		(0.06)	(0.08)	(0.06)	(0.08)
27 Basic metals	9,841	0.07	0.66	0.34	1.06
		(0.03)	(0.09)	(0.06)	(0.06)
28 Fabricated metal products	34,378	0.10	0.60	0.31	1.01
		(0.04)	(0.09)	(0.10)	(0.10)
29 Machinery and equipment	41,765	0.11	0.62	0.38	1.10
		(0.04)	(0.08)	(0.08)	(0.09)
30 Electrical and optical equipment	1,968	0.12	0.61	0.34	1.07
		(0.03)	(0.05)	(0.10)	(0.05)
31 Electrical machinery and apparatus	15,436	0.12	0.62	0.33	1.07
		(0.06)	(0.06)	(0.07)	(0.11)
32 Radio, television, communication	4,541	0.16	0.58	0.39	1.13
		(0.07)	(0.06)	(0.12)	(0.16)
33 Medical and precision instruments	11,010	0.14	0.55	0.39	1.08
		(0.02)	(0.05)	(0.04)	(0.08)
34 Motor vehicles and trailers	8,836	0.11	0.67	0.33	1.11
		(0.06)	(0.11)	(0.10)	(0.09)
35 Transport equipment	3,421	0.05	0.60	0.33	0.98
		(0.03)	(0.06)	(0.07)	(0.05)
36 Furniture	12,165	0.15	0.64	0.32	1.11
		(0.08)	(0.11)	(0.11)	(0.14)
Across all industries	253,552	0.12	0.63	0.30	1.05
		(0.06)	(0.09)	(0.10)	(0.11)

Notes: This table reports average output elasticities and associated standard deviations for each production factor. Standard deviations are reported in parentheses. We excluded observations with negative output elasticities. German microdata.

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