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

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Abstract

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

Keywords: *Business dynamism, job reallocation, productivity, responsiveness of labor demand, market power, technology, European cross-country data.*
JEL classification: *D24, D43, 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 business dynamism. The slowdown in the process of birth, expansion, and contraction of firms has been documented with a variety of measures and data sources for the US (e.g., Decker et al., 2014; Decker et al., 2016a; Dent et al., 2016; Guzman and Stern, 2020; Akcigit and Ates, 2023). This secular decline 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, 2024; 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. We document broad patterns of declining business dynamism over the past decades in Europe and analyze the microeconomic drivers underlying this decline. Our analysis draws inspiration from standard models of firm dynamics (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993). In these models, firms' employment changes, and ultimately economy-wide job reallocation, are tied to the decisions of individual firms to expand or contract in response to changes in their fundamentals and market conditions. We explore these firm decisions focusing on the role of changing productivity shocks (i.e., "shock hypothesis") versus changes in the pass-through of those shocks to labor demand (i.e., "responsiveness hypothesis") in explaining declining job reallocation (Decker et al., 2020). We then derive and apply a novel production-side framework that quantifies the contribution of changes in productivity, sales, markups, wage markdowns, wages, and technology to changes in firms' employment. Based on this framework, we provide new insights into the micro-level determinants that shape aggregate job reallocation.

Existing evidence on business dynamism in Europe is limited to a few country-specific studies (e.g., 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).[1] The main challenge researchers face in Europe is the lack of accessible firm-level data across countries. Combining administrative firm-level data from national statistical institutes and central banks across countries is not feasible under current legislation, and accessing any of these databases individually is often tied to high administrative costs. We solve these challenges and collect and *publish* new micro-aggregated data on key 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 are representative of the firm population in each country and harmonized across countries. Providing these data to the scientific community is our first contribution.[2]

We use our novel data to document new facts on business dynamism in Europe over the last two decades, which is our second key contribution. Our data covers the years from 1997 to 2021, although with heterogeneous time coverage across countries. As measures of interest, we first focus on aggregate job reallocation rates and young firm activity. Job reallocation rates capture the intensity of job flows between firms resulting from job creation and job destruction. We find a widespread and strong decline in job reallocation in all 19 countries under analysis that, on average, amounts to 21%, which is similar to the decline in US job reallocation during that period. This decline concerns most economic sectors and is mainly driven by dynamics within sectors, size, and age classes rather than by compositional changes. Large and mature firms, which account for most economic activity, show a relatively stronger reduction in job reallocation rates. Simultaneously, employment shares of young firms decline substantially, following similar patterns as in the US. While important, firm age composition effects account on average only for 18% of the overall decline in reallocation. Similarly to the US, the decline in startups and young-firm activity does not explain the bulk of the overall decline in job reallocation in Europe. Our results establish that the broad declines in business dynamism are not unique to the US but rather span geographies with very different labor

[1] Within the DynEmp project, the OECD runs harmonized codes on administrative firm-level databases located in statistical institutes across a number of OECD countries. Unfortunately, these data are not available to external researchers.

[2] Our data is part of the 9^{th} vintage of the CompNet database, which is now available to all researchers upon request at www.comp-net.org/data/9th-vintage/. Similar to our data collection, De Haas et al. (2022) cooperated with the CompNet team to study young firm activity in Europe.

market institutions.

Our analysis of the responsiveness versus shock hypotheses shows that the responsiveness of firms' employment changes to productivity shocks has declined in many European countries. In relative terms, the magnitudes of these declines are comparable to those in the US. An important novel result that we establish is that large firms are characterized by a lower responsiveness to productivity shocks than small firms. Concerning productivity shock dynamics, we find a notable difference between European countries and the US, particularly in the last decade. We document a generalized reduction in the dispersion of productivity changes, suggesting that both the shocks *and* the responsiveness hypotheses are relevant for explaining declining job reallocation in Europe. We confirm these results with another database on German manufacturing firms, which we can directly access, covers a longer time span (starting from 1995), and allows us to derive more accurate productivity estimates. Using these data, we quantify that 40% of the observed decline in job reallocation is explained by the decline in firms' responsiveness, which is a large share but significantly smaller than what has been documented for the US, where declining responsiveness accounts for almost the entire decline in job reallocation (Decker et al., 2020, henceforth DHJM).

To rationalize the observed patterns, we extend the framework employed by DHJM. While they focus on adjustment costs to explain the decline in job reallocation and responsiveness in the US, we derive a general production-side framework that connects changes in firms' market power, wages, and technology to firms' responsiveness and job reallocation.[3] Our approach is motivated by evidence that, while labor regulations are stricter in Europe, there has been a concerted effort of European economies to increase the labor market flexibility over the last decades (Eichhorst et al., 2017; Gehrke and Weber, 2018). With this new framework, our third contribution is to open the black box of firm responsiveness by providing alternative explanations for its changes that focus on firms' market power, wages, and technology.

We apply our framework to the rich German firm-product level 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; Mertens, 2022). The German manufacturing data are ideally suited for this analysis because, unlike the other country-specific firm-level

[3]DHJM acknowledge that their findings could also be interpreted in terms of "correlated wedges" that may capture, among others, changes in firms' market power.

data sources in this paper, we can directly access them and they contain firm-specific price information. This allows 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 show that the decline in firm responsiveness over the past decades has primarily resulted from weaker sales growth and higher markup increases in response to productivity shocks. Responsiveness has declined also because the pass-through of productivity to wages has increased, which suggests that firms shared a growing portion of their productivity gains with their workers. Although contributing to a lesser extent, technological change lowering the importance of labor in production and increasing the importance of intermediates has also played a role in reducing responsiveness.

Overall, our framework highlights the potential of market power, technology, and wages in shaping responsiveness and job reallocation. In this regard, our paper relates changing business dynamism to several recent studies that document changes in 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).[4] Applying our framework to other countries is an important next step that we leave open for future research due to the significant barriers in directly accessing granular firm-level data for multiple countries.

The remainder of this 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, wages, and technology shape firms' responsiveness. Section 6 concludes.

[4]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 novel data on European business dynamism through the Competitiveness Research Network (henceforth, CompNet).[5] 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 pan-European harmonized micro-aggregated database. In addition to the standard CompNet data collection routines, we added a series of 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.[6]

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] While this approach provides us with rich cross-country comparable data, it prevents us from directly inspecting the microdata.

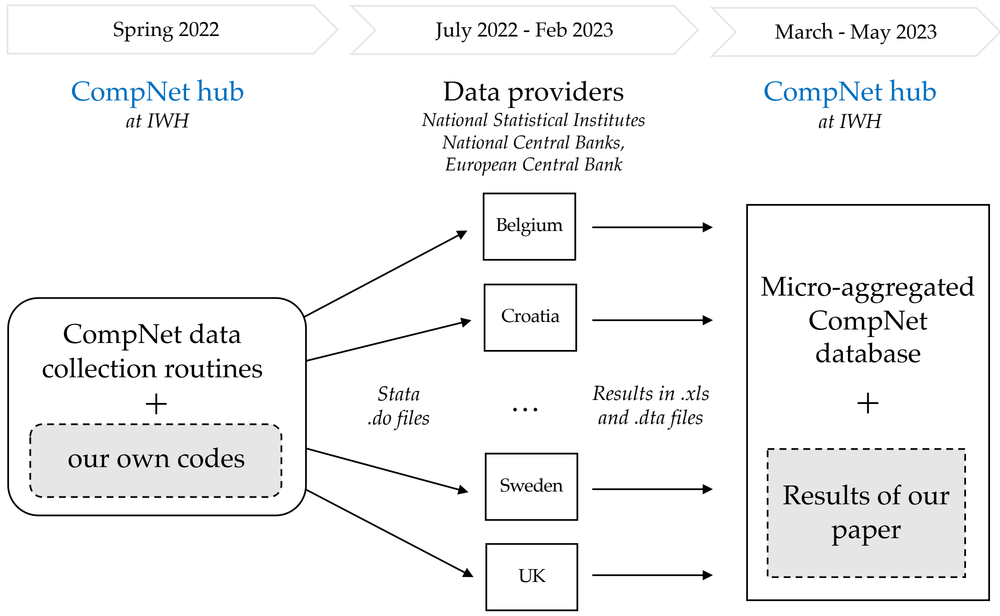
[5] CompNet is hosted by the Halle Institute for Economic Research (IWH) and includes several partner institutions: the European Commission, the European Central Bank, the European Bank for Reconstruction and Development, the European Investment Bank, the European Stability Mechanism, France Stratégie,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

[6] 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, the CompNet team assembled a pan-European database after a series of quality and consistency checks.

[7] In accompanying studies, Bighelli et al. (2023) use the 7$^{\text{th}}$ vintage to study European firm concentration, 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 is available at www.comp-net.org/data/.

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 key results for the set of countries where the "all sample" is available (online Appendix C.3). Table 1 provides an overview of time and sample coverage across countries.[11] The database covers the last two decades, although the time span differs across countries. The coverage of firms and employ-

[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.

[11]The CompNet database also includes the Netherlands, Switzerland, and Malta. We excluded the Netherlands and Switzerland as discussions with the data providers indicated that some of our business dynamism results were not representative due to unanticipated issues in the underlying firm-level data during our data collection. We excluded Malta as the number of firms was insufficient for several of our analyses.

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	2005-2018	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 are available since 2001.

ees is very high. Online Appendix Table A2 shows that the "20e sample" covers 75% of total employment and 73% of the total number of firms reported in Eurostat Structural Business Statistics. 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 is close to 100% in most countries after re-weighting (online Appendix Table A2). We refer to CompNet's User Guide (CompNet, 2023) for further details on the database.

Finally, it is important to note that due to country-specific disclosure rules, a few results in Section 3 do not contain information for certain individual country-sector-year combinations. This is a minor issue concerning only a handful of cases, which we list in online Appendix Table A3.

2.1.3 Measures of interest

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

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

$g_{it} = \dfrac{L_{it} - L_{it-1}}{\overline{L}_{it}}$ is the DHS employment growth rate of firm i between $t-1$ and t, where $\overline{L}_{it} = 0.5 \times (L_{it} + L_{it-1})$ is average employment over the two periods. 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 country ($n = c$) and sector ($n = j$) levels.[12] As we cannot precisely 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 and excludes entering and exiting firms.

Young firms' activity. While our primary focus is on job reallocation, we are also interested in documenting changes in the employment shares of 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. We can measure the share of young firms only for 14 countries where we have data on firms' registration years.

Firm-level productivity. In Section 4, we analyze how firm-level employment responds to productivity changes. In terms of measurement, we focus on 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.[13] All monetary values in our data are measured in thousands of euros and deflated using country-industry-year-specific deflators from EU-KLEMS for output, capital, and intermediate inputs. Labor is measured in number of employees, excluding

[12] 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.

[13] 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.

employed shareholders or owners. Depending on the data source, labor is either defined as the annual average or at a specific point in time.[14] All other variables pertain to the entire calendar year. In addition to labor productivity, CompNet provides various productivity measures estimated as a residual from firms' production functions.[15] We focus on the following Hicks-neutral Cobb-Douglas specification:

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

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 each firm's 2-digit NACE industry. We suppress this subscript for firm-specific variables. 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 expenditures over total costs.[16] 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 the log of total factor productivity as residual from the estimated industry-year-specific production function:

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

Lowercase letters indicate logs. A tilde indicates that the variable is not measured in quantities but in deflated monetary units. As in most empirical studies, we observe deflated revenues rather than physical output. For this reason, our productivity measure is a composite of technical efficiency and product appeal, both of which influence firms' growth (Foster et al., 2008). We denote this revenue-TFP measure by $TFPR_{it}$.

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

[15] We rely on labor productivity and cost-share-based TFP measures as they perform consistently well across our broad set of countries.

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

2.2 German manufacturing sector microdata

In the second part of the paper, we use more detailed data for the German manufacturing sector. These data are accessible at the Research Data Centres of the German Statistical Office and contain, among others, information on firms' employment, investment, and input expenditures.[17] Moreover, this dataset contains detailed information on the quantities and prices of the products sold by each firm at a very granular level (10-digit product classification).[18] 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, wages, and market power affect firms' labor demand and, thus, job reallocation rates. The firm-product-specific 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 is 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. We harmonize product and industry codes as in Mertens (2022). Online Appendix A.2 contains all variable definitions, provides relevant summary statistics, and explains our cleaning routine.

3 Facts on Business Dynamism in Europe

This section uses our novel data to document key facts on European business dynamism. We perform various decompositions at the sector, age-, and size-class levels to assess the underlying dynamics. We supplement our analyses with additional results in online Appendix C.

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

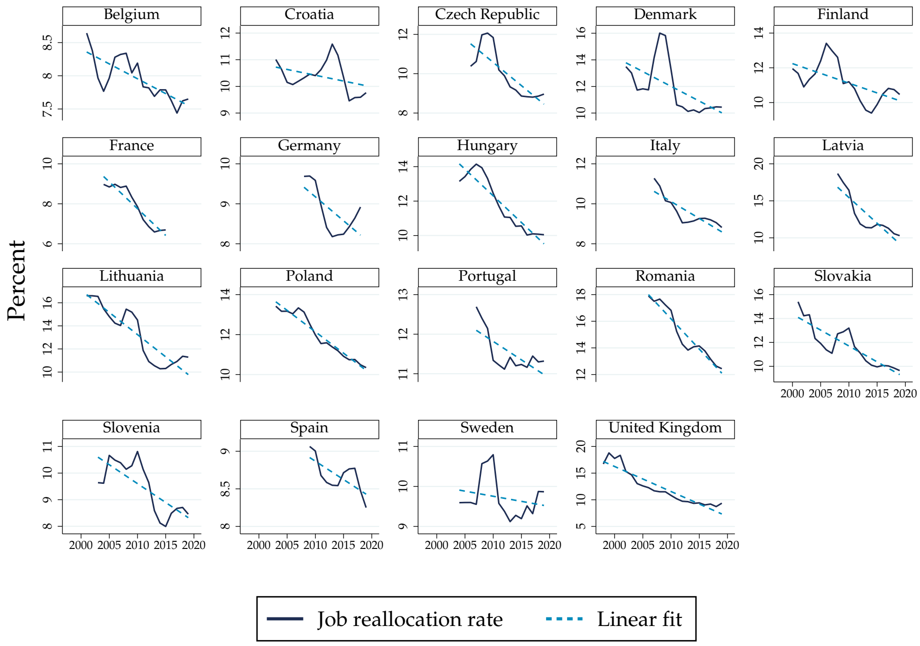
Figure 2 reports job reallocation rates for firms with at least 20 employees, showing a stark trend decline (dashed light-blue line) in job reallocation in all countries. While the decline is widespread, Eastern European countries display a higher initial level and more substantial decline in job reallocation rates. This likely reflects transition dynamics after their accession

[17] Access requests can be made here: https://www.forschungsdatenzentrum.de/en/request. The files (DOI) we use are: 10.21242/42131.2017.00.03.1.1.0, 10.21242/42221.2018.00.01.1.1.0, and 10.21242/42111.2018.00.01.1.1.0.

[18] Examples of products are "Tin sheets and tapes, thicker than 0.2mm" or "Workwear - long trousers for men, cotton".

to the European Union. In the online Appendix, we show that the widespread decline in job reallocation rates is robust to using data on firms of all size classes for the subset of countries that provide such data (Figure C7). Additionally, Figure C2 documents that sales reallocation rates 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.[19]

Figure 2. Job reallocation rates in European countries.



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

Compared to US evidence, Europe shows a lower level of job reallocation.[20] 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 24% between 2000 and 2019 when excluding firms with less than 20 employees.[21] 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

[19]As mentioned in Section 2.1.3, our job reallocation rates abstract from firm entry and exit. Therefore, in online Appendix Figure C1, we use Eurostat data to show that there is no systematic trend in firm entry or exit that could offset the decline in job reallocation that we document.

[20]Our results confirm and extend previous findings by Haltiwanger et al. (2014b), who document lower job reallocation rates for a small set of European countries during the 80s and 90s.

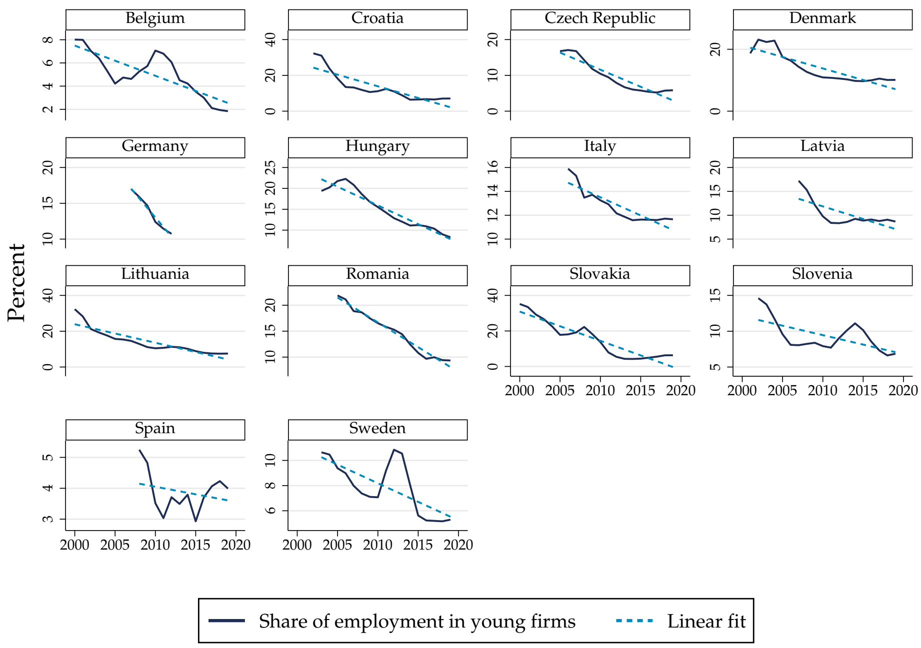
[21]For these calculations, we exclude the sum of job creation from entry and job destruction from exit. The Business Dynamics Statistics (BDS) series can be downloaded for firm-size classes here.

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. Trend declines should be less affected by these differences and are broadly comparable. The US displays declines of 24% between 2000 and 2019, while the average decline in job reallocation across all European countries equals 21% over our period of analysis.

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. Also with this measure, the decline is more substantial among Eastern European countries. Using data on firms of all size classes confirms the decline in young firm activity for almost all countries (Figure C8).

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



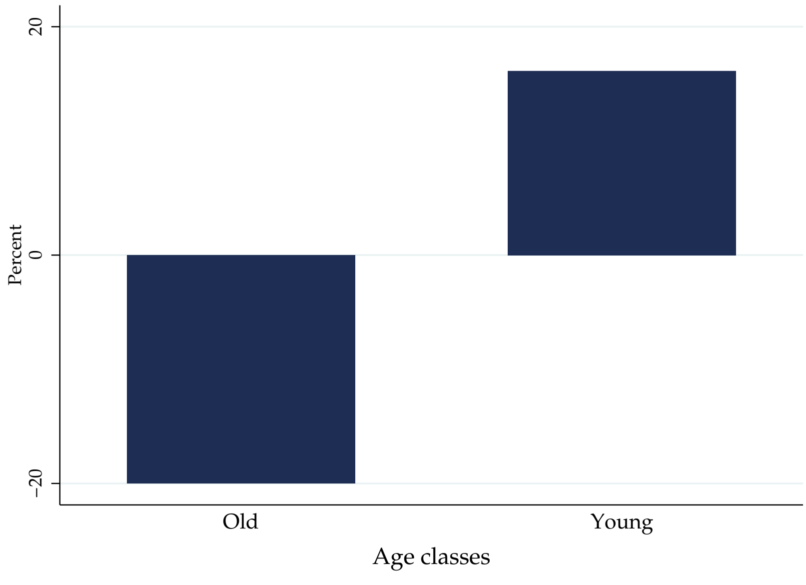
Notes: Three-year moving averages of the employment share of firms not older than five years. The dark-blue solid line shows country-level shares of employment in young firms. The light-blue dashed lines report linear trends. The underlying data are aggregated from sector-age-class data, resulting in a drop of a few sector-age-class cells due to country-specific disclosure rules (see online Table A3). CompNet data, firms with at least 20 employees.

While declines in the "20e sample" are particularly pronounced (ranging from one-third to more than half in some countries), declines in the "all sample" appear 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 five years of activity. Therefore, our findings imply that high-growth young firms exhibit a particularly strong decline in Europe.[22]

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. To provide a cross-country overview, 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.[23] The decline in job reallocation is concentrated among old firms. This also holds for the "all sample" (online Appendix Figure C9). The increase in job reallocation amongst the youngest firms is surprising and indicates that these firms have become more volatile over this time period. This development mitigates the overall decline in job reallocation. However, there is also a compositional effect on aggregate job reallocation as young firms, whose job reallocation rate increased, experienced a decrease in their employment shares.

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 Eq. (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 as we directly use age-class aggregated data. CompNet data, firms with at least 20 employees.

To assess the importance of such compositional changes, we apply a standard shift-share decomposition to the change in the job reallocation rate for each country c, defined as

[22] The US also exhibits large declines in high-growth young firm activity, as documented by Decker et al. (2016b), Guzman and Stern (2020), and Sterk et al. (2021).

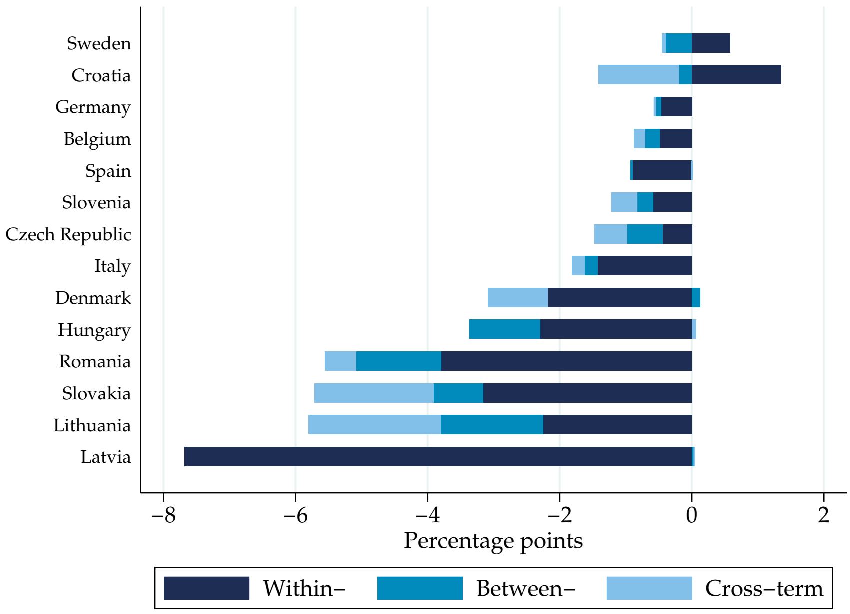
[23] Online Appendix Figure C3 shows the time series of the job reallocation rate for young and old firms.

$\Delta JR_{c(t-t_0)} = JR_{ct} - JR_{ct_0}$, in the following way:

$$\Delta JR_{c(t-t_0)} = \underbrace{\sum_h s_{cht_0}\, \Delta JR_{ch(t-t_0)}}_{\text{within-term}} + \underbrace{\sum_h \Delta s_{ch(t-t_0)}\, JR_{cht_0}}_{\text{between-term}} + \underbrace{\sum_h \Delta s_{ch(t-t_0)}\, \Delta JR_{ch(t-t_0)}}_{\text{cross-term}}, \tag{4}$$

where s_{cht} denotes the employment shares in each age class h, while t_0 represents the initial year.[24] 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.

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 Eq. (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 as we directly use age-class aggregated data. CompNet data, firms with at least 20 employees.

Although compositional effects (captured by the between-term) matter in many countries, most of the decline in job reallocation rates occurs within age classes. Overall, age composition effects account for an average of 18% of the decline in job reallocation across the countries in our sample.[25] As job reallocation increased among young firms (Figure 4), the large neg-

[24] This accounting decomposition is widely used in the literature. See Foster et al. (2001) for a detailed discussion.

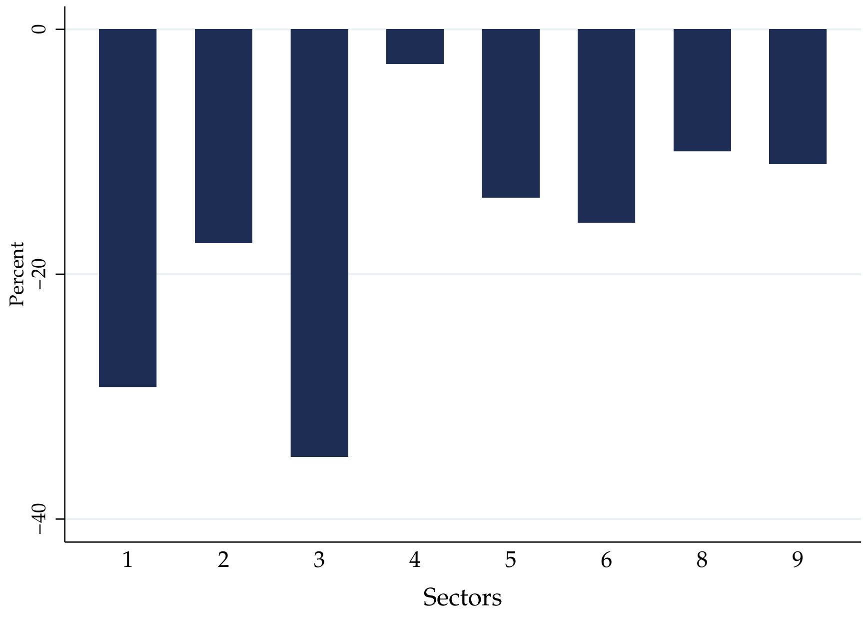
[25] By contrast Decker et al. (2016b) report firm age composition effects account for 26% of the decline in job reallocation in the US when considering the full population of businesses during the 90s and early 2000s.

ative contribution of the within-component underlies the importance of established firms in driving the trends in the European economy. Results for the "all sample" are similar (online Appendix Figure C10).

Fact 4. *The decline in reallocation is evident in most sectors.*

Figure 6 shows the percentage change in job reallocation rates by economic sector. To focus on the sectoral dynamics, we calculate the percentage change between the first and last two years in each country and then average these relative changes across countries. Using the "20e sample", we document a reduction in job reallocation rates in all sectors. The relative decline is notably pronounced in manufacturing (1) and wholesale/retail trade (3), which are the two largest sectors in the European economy. As shown in online Appendix Figure C11, with the exception of the construction (2) and ICT (6) sectors, this is also confirmed when using the "all sample".

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

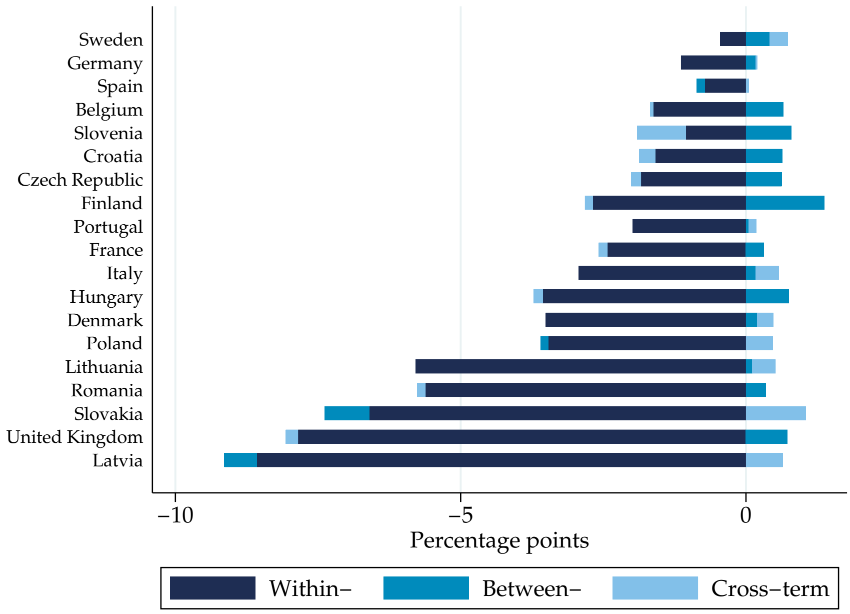


Note: Averages across countries in relative changes in job reallocation rates as computed in Eq. (1) by sectors. Changes are computed between the first and last two years for each country-sector pair. Sectors are numbered in the following way: manufacturing (1), construction (2), wholesale/retail trade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

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 shifts in employment shares toward sectors with lower job reallocation. To assess the relevance of these different dynamics, we apply a sector-level version of the decomposition in Eq. (4). Figure 7 presents our results. The main insight is that within-sector changes in job reallocation (the darkest bars) are negative in all countries and account for most of the decline in job reallocation. Interestingly, in most countries, between-sector shifts counteracted the decline in job reallocation.

Figure 7. Decomposition of job reallocation changes across sectors.

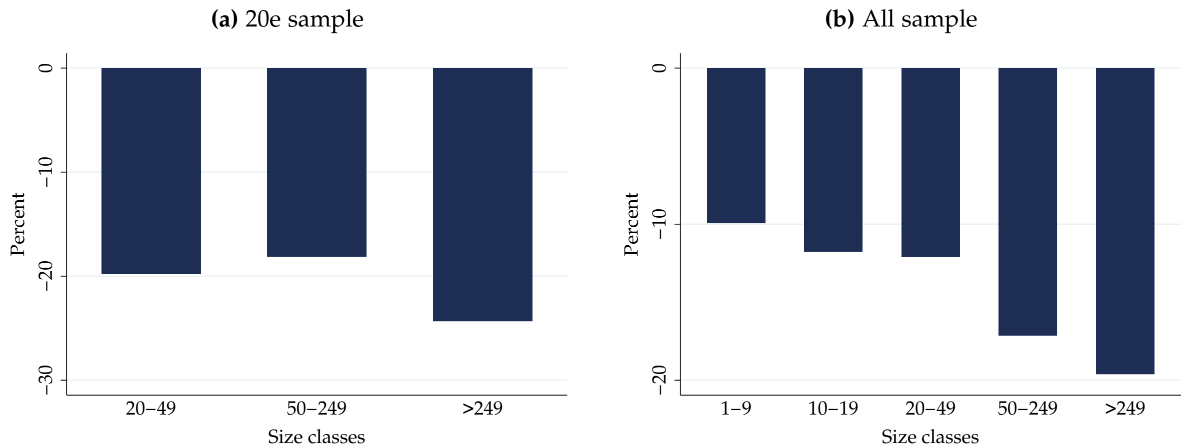


Notes: Results of the decomposition of job reallocation rates across sectors using a sector-level version of Eq. (4). To define the start and end points for the decomposition, we average the first and last two years of job reallocation rates for every country-sector combination. CompNet data, firms with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

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

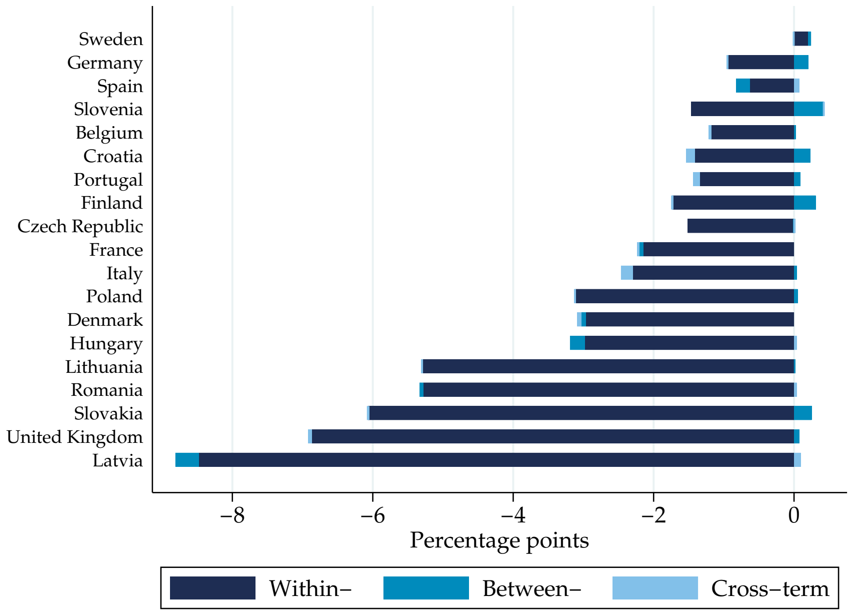
Larger firms exhibit lower job reallocation rates and account for a major share of employment, which highlights their pivotal role in understanding aggregate job reallocation (Haltiwanger et al., 2014b; Haltiwanger, 2022). We confirm this finding in most European countries in online Appendix Figure C4. We further dissect the decline in aggregate job reallocation by examining the dynamics by firm size classes. We follow the Eurostat classification system to 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). Both panels show that job reallocation declined throughout the entire firm size distribution. However, 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.

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



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 Table A3). Panel (a) is based on all 19 countries, while panel (b) on countries with the "all sample". CompNet data.

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 Table A3). CompNet data, firms with at least 20 employees.

We conclude this section by decomposing changes in job reallocation rates into within- and between-size-class changes using a size-class-level version of Eq. (4). As illustrated in Figure 9, most of the decline in job reallocation results from within-size-class changes (darker bars).[26]

In sum, we document a widespread decline in job reallocation rates in Europe. This is an economy-wide phenomenon occurring in most economic sectors. The decline is mainly driven by changes within sectors, size classes, and age classes, rather than by compositional changes. Large and mature firms experience the most substantial reduction in job reallocation rates. Simultaneously, the employment shares of young firms decline. Overall, the decline in European business dynamism is similar to US evidence.

4 Responsiveness *and* shocks hypotheses

To understand the underlying mechanisms of this widespread decline in reallocation in Europe, we explore changing patterns of job reallocation following DHJM. Specifically, we explore the relative importance of changes in productivity dynamics and firm behavior. The empirical approach draws 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. From this perspective, a decline in the pace of job reallocation can be attributed to two potential mechanisms. 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, firms' incentives to adjust their size would decline.[27]

For the US and the period covered by their analysis (1981-2013), DHJM show that 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' respon-

[26]Using the "all sample", we confirm this finding in online Appendix Figure C13.

[27]This framework provides a firm-side perspective on job reallocation, abstracting from labor supply-side factors discussed in the literature, such as population aging (e.g., Hopenhayn et al., 2022). We later expand this framework to examine the influence of firms' wages, market power, and technology on shaping responsiveness and job reallocation. By doing so, we implicitly take into account overall trends in wages and/or technology, which may be driven also by aggregate labor supply-side factors. For example, Acemoglu and Restrepo (2022) show that population aging also affects firms' technology choices through higher incentives for robotization. As we discuss in Section 5.1, such changes in firms' production technologies that reduce the output elasticity of labor can lead to a decline in firms' responsiveness.

siveness to those shocks has declined markedly. In the following, we examine these patterns for Europe and compare our findings to the US. As we estimate several regression models by 19 countries, we focus on a visual representation and publish the full regression tables in our data appendix (supplementary material).

4.1 Responsiveness hypothesis

To examine whether firms' responsiveness to productivity has changed over time also in Europe, we closely follow the empirical approach in 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 specification in online Appendix B.1. The dependent variable, g_{it}, is the DHS employment growth rate between $(t-1)$ and t of firm i. We estimate the responsiveness of g_{it} to productivity as follows:

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

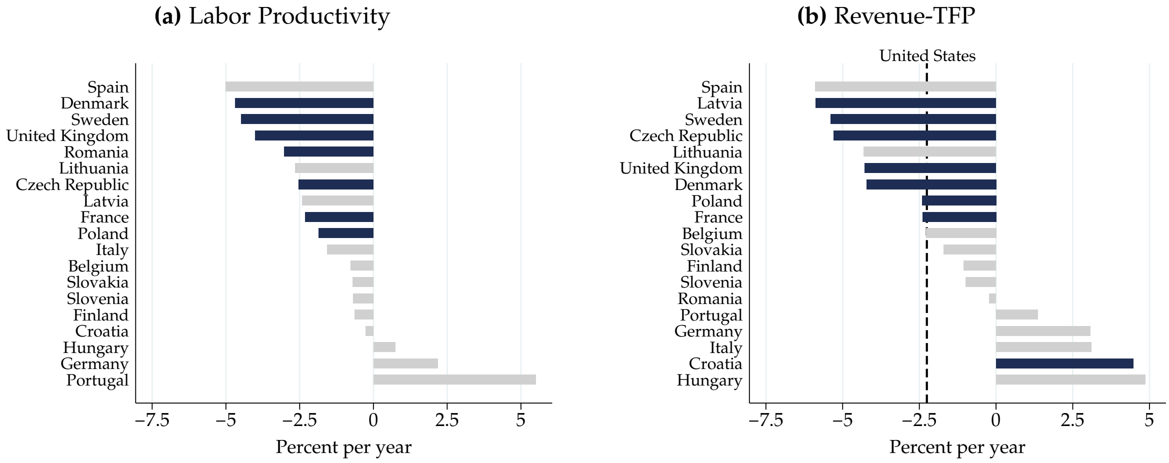
l and a denote the log values of employment and productivity, respectively. For our application with the CompNet data, we use labor productivity and total factor productivity measures. β_1 captures the marginal responsiveness of a firm's employment growth to its productivity, conditional on its initial 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).[28] Including 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, the coefficient of the linear trend, δ_1, should be negative. We allow the effect of initial employment to vary over time in the same way. As our focus is on secular rather than cyclical changes, we include industry-year fixed effects (X_{jt}) to control for industry-specific shocks. To relate our analysis to the decline in the job reallocation rate, which is the employment-weighted average of individual firms' g_{it}, we weight our regression by firms' employment level (we use the weight s_{it} as defined

[28]DHJM and online Appendix B show how this specification in levels corresponds to a transformation of a first-difference specification, where employment changes are directly related to productivity changes. 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. For this reason, it is also our preferred specification.

in ̧refeq: JR definition). Finally, note that we follow DHJM in using lagged productivity on the right-hand side. As discussed in online Appendix B.1, this (i) helps to address differences in the data collection timing between labor and other variables, and (ii) allows for potential extra time for employment to adjust.

We report the estimates of the responsiveness coefficient, β_1, and its trend over time, δ_1, for each country in our 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 yearly relative changes in Figure 10 for labor productivity in Panel (a) and revenue-TFP 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 Eq. (5). Underlying estimates are reported in Table C1 and overall regressions results are available in our data appendix. 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 estimate for β_1) in Panel (a) is truncated to allow for a better visual comparison. The dashed line reports the relative change estimated for the United States over 1981–2013 by DHJM. Portuguese data start in 2009 due to missing values in TFP. Most country data start in the early or mid 2000s (see Table 1). CompNet data, firms with at least 20 employees.

We estimate a declining responsiveness coefficient ($\delta_1 < 0$) in almost all countries. The negative δ_1 coefficient is statistically different from zero in around half of them, which are highlighted in blue. This is the case for the Czech Republic, Denmark, France, Latvia, Poland, Romania, Sweden, and the United Kingdom. In Croatia, we estimate a statistically significant increase in responsiveness when using revenue-TFP as a productivity measure.

Overall, relative changes in responsiveness range from 2 to 5 percent per year. This aligns well with US evidence. DHJM report an average annual decline in responsiveness of approximately 2.25 percent over the 1981–2013 period for the US.[29] These results are confirmed

[29]We added the relative changes for the US only to our revenue-TFP results because they are the only comparable ones. DHJM define labor productivity as revenue per worker. We measure it in terms of value-added. We

when performing the same analysis for the countries where we observe firms with less than 20 employees (online Appendix Figure C14). Using the "all sample", we find a statistically significant decline in responsiveness in additional countries, such as Italy, Spain, and Lithuania.[30]

As an alternative approach to capture changes in responsiveness, we estimate a specification that allows responsiveness to vary by time windows (before 2009, 2009-2013, and after 2013). As reported in online Appendix Figure C5, we find evidence of a downward trend in responsiveness also with this period-specific estimation approach.[31]

As large firms account for a substantial employment share and are characterized by lower job reallocation rates (Figure C4), they play a key role in shaping aggregate worker reallocation. To better understand job reallocation in Europe, we thus examine differences in responsiveness by firm size classes using the following version of Eq. (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.[32] In most countries, we document a stark cross-sectional gradient over the size 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 we find this gradient in all countries when using the "all sample". In Section 5.1, we develop a theoretical framework that can rationalize this gradient through larger firms having higher market power, paying higher wages, and/or operating with a different technology.[33]

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calculate the relative changes for the United States based on coefficient estimates reported by DHJM in Table 1 - Panel B.

[30]The fact that the coefficient δ_1 becomes statistically significant in these countries when using more observations (five times larger in the "all sample") suggests that statistical power may be an issue in our "20e sample".

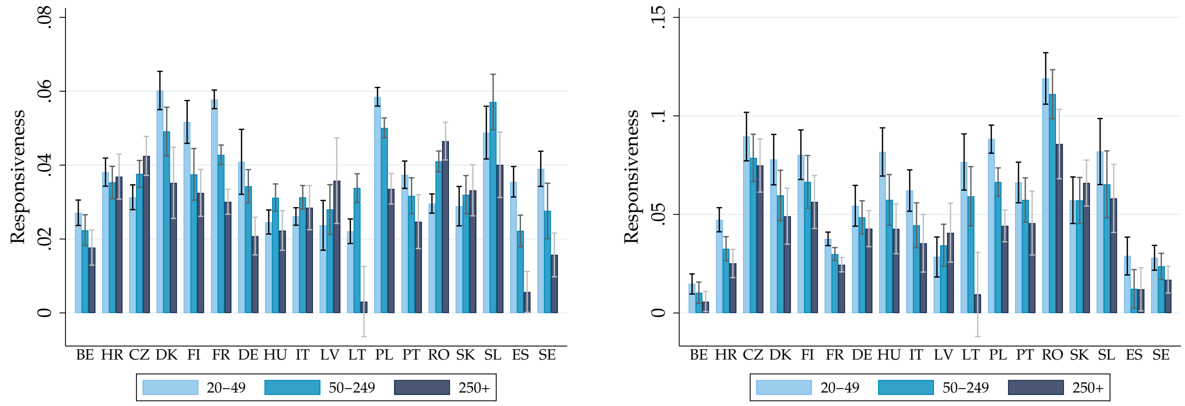
[31]These period-specific regressions also allow us to compare the size of the responsiveness coefficient (i.e., β_1) between the US and European countries for the only overlapping period (i.e., the 2000s). Using a comparable productivity definition, DHJM estimates a coefficient of 0.08 for the 2000s.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

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

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

Figure 11. Responsiveness levels by size class.

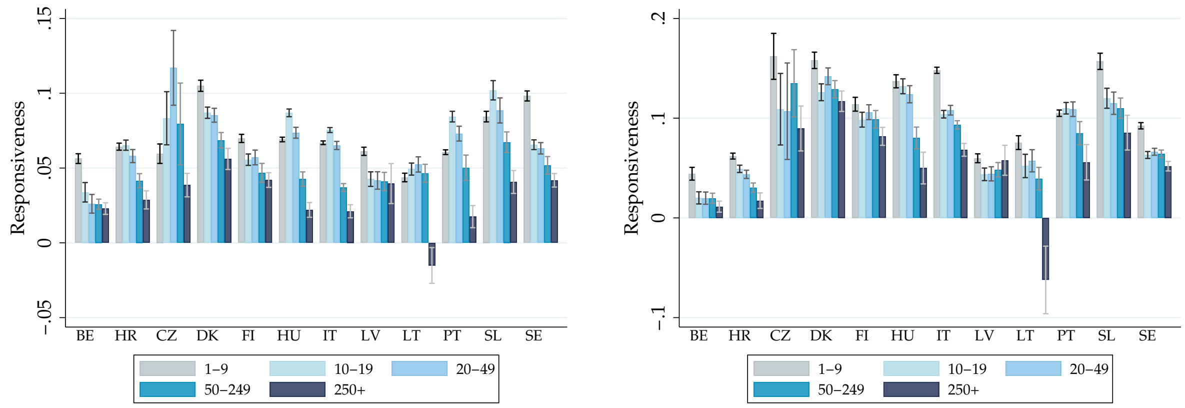
(a) Labor Productivity **(b)** Revenue-TFP



Notes: Size-class-specific responsiveness coefficients, i.e., β_{1z} in Eq. (6). The overall regression results are available in our data appendix. 90% confidence intervals are reported for each coefficient estimate. CompNet data, firms with at least 20 employees.

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

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



Notes: Size-class-specific responsiveness coefficients, i.e., β_{1z} in Eq. (6), but from a specification that uses the "all sample" and includes two additional size-classes for smaller firms. The overall regression results are available in our data appendix. 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.

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. In addition, we find that larger firms tend to have a lower responsiveness than smaller firms.

4.2 Shocks hypothesis

We now examine changes in productivity dynamics as another potential driver of the decline in job reallocation. To understand whether productivity shocks have induced less reallocation, we analyze the productivity evolution with an AR(1) model:

$$a_{it} = \rho \, a_{it-1} + X_{jt} + \eta_{it}. \tag{7}$$

The coefficient ρ captures the persistence of the productivity evolution, and the residual η_{it} represents productivity innovations. We again include industry-year fixed effects (X_{jt}) as 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 2000s.

We report our estimates for the dispersion in productivity innovations, η_{it}, for the periods 2009-2013 and post-2013 in Figure 13. Online Appendix C.3.3 reports similar results based on the "all sample" countries. For labor productivity, the dispersion in productivity innovations declined across all countries. For most countries, this is also confirmed using our revenue-TFP measure.[34] This decline in the dispersion of productivity shocks is a key difference between Europe and the US, where DHJM document a substantial increase in the dispersion of productivity innovations in the 2000s.[35]

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.[36]

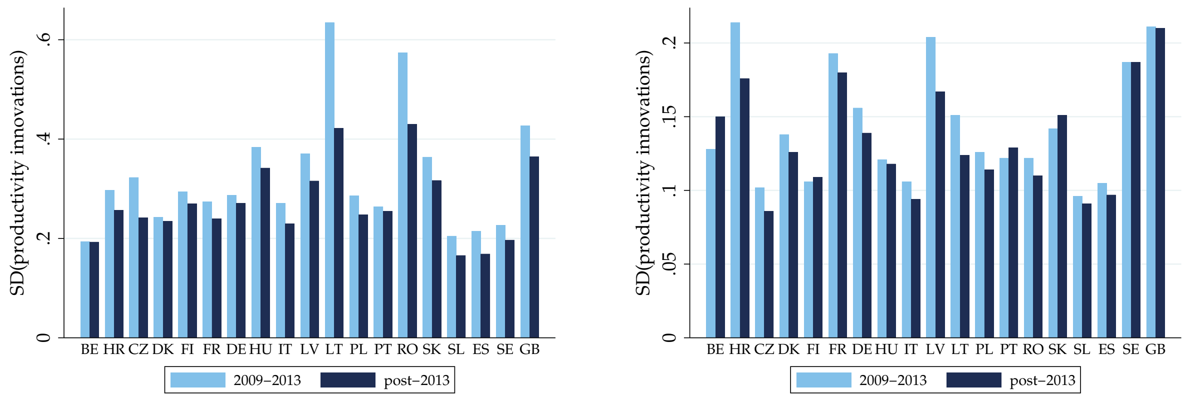
[34] Unfortunately, our data collection codes did not yield results before 2009. Therefore, we use additional results that we collected to directly study the standard deviation of productivity growth in online Appendix Figure C6. We observe that, for most countries, the dispersion of productivity changes post-2013 is below its pre-2009 level. This suggests that excluding the 2009-2013 period would not alter our conclusions. Notably, the analysis in Figure C6 does not impose any parametric assumptions on productivity dynamics.

[35] We cannot measure productivity shock dispersion after 2009 for the US. Yet, available statistics from the US Census Bureau Productivity Dispersion Statistics (DISP) show that the US may have experienced a change in the dispersion of productivity levels after 2009. Approximately 47% of the 86 4-digit manufacturing industries in the US have experienced declines in productivity *level* dispersion post-2009. By contrast, 83% of these same 4-digit industries experienced increases between 1987 and 2009. In unreported results, we find that the evolution in the dispersion of productivity *levels* varies across Europe, with many countries experiencing an increase in dispersion up to 2009 and a decline thereafter. The question of whether productivity shock dynamics continue to differ between Europe and the US or have instead converged after 2009 merits further analysis in future research.

[36] Explaining the reasons behind the European productivity shock dynamics exceeds the scope of this study. Studying innovation processes might be particularly important in this context. For instance, Bloom et al. (2020) show that returns from innovation activities become smaller as "ideas are getting harder to find". Additionally, Akcigit et al. (2023) document how firms' political connections also dampen incentives for market leaders to invest in product and process innovations, while Akcigit and Ates (2023) argue that knowledge diffusion between leader

Figure 13. Lower dispersion of productivity innovations.

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

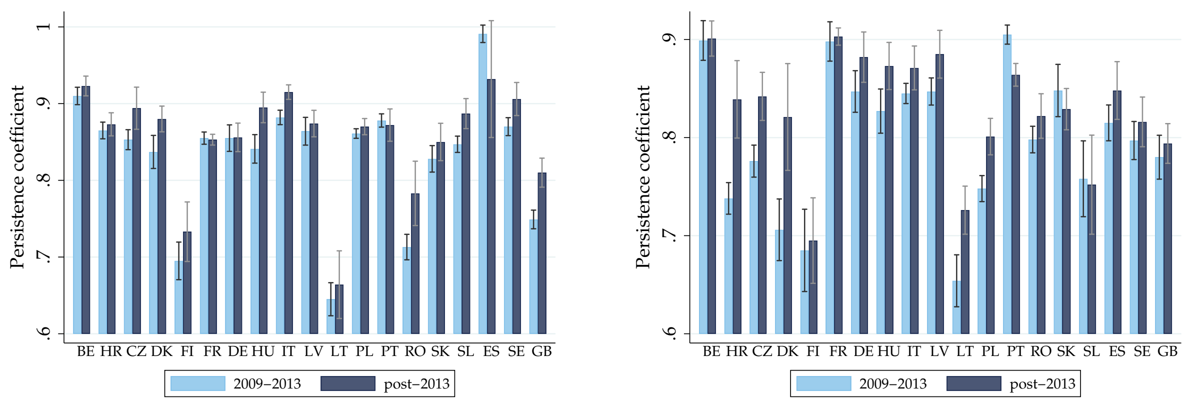


Notes: Standard deviation of the residuals of the AR(1) process in Eq. (7) estimated over two consecutive periods. Overall regressions results are available in our data appendix. CompNet data, firms with at least 20 employees.

The estimation of the AR(1) process provides us also with information about the persistence of productivity shocks. In theory, declining shock persistence reduces firms' incentives to adjust to a given productivity shock if firms anticipate the lower permanence of productivity realizations. Therefore, a lower productivity persistence could provide another explanation for the declining responsiveness. However, Figure 14 illustrates that, if anything, persistence increased in most countries.[37]

Figure 14. Increasing persistence in productivity dynamics.

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



Notes: Point estimates of the persistence coefficient ρ in the AR(1) in Eq. (7) estimated over two consecutive periods. Complete regression results are available in our data appendix. CompNet data, firms with at least 20 employees.

and follower firms declined.

[37] We replicate these results, including earlier years, with our German microdata in Section 4.3 and find similar results.

4.3 Evidence from German Manufacturing

While unique in terms of its coverage and cross-country comparability, the CompNet data has nonetheless 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 relatively basic estimates of firm-level productivity.

Therefore, we now employ richer firm-product-level data on German manufacturing that we can access directly. 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 account for unobserved price variation when estimating production functions (and firms' market power in Section 5). We first confirm our results on the responsiveness and shock hypotheses with these richer data. Subsequently, we use them to quantify the importance of both hypotheses in explaining declining aggregate job reallocation - something that we could not do with the aggregated CompNet data.

4.3.1 Estimating productivity from firms' production functions

Using the German data, we derive productivity from estimating more flexible production functions. In particular, we rely on a *translog* production function that allows for firm- and time-specific output elasticities:

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

where 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 Eq. (8) separately by NACE rev. 1.1 industries using a one-step approach as in Wooldridge (2009), which defines 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 adaptation 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 Eq. (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.[38]

4.3.2 Responsiveness versus shocks

The strong decline in job reallocation documented with CompNet is also confirmed with the German manufacturing sector microdata. The job reallocation rate decreased by one-third, from 8.3% in 1996 to less than 5.6% in 2017.[39]

Online Appendix Table D1 estimates the responsiveness regression (Eq. (5)) and reports a declining linear trend in responsiveness. In Figure 15, Panel (a), we estimate a version of Eq. (5) with a period interaction instead of a linear trend, which allows for more flexibility (as in Figure C5). The periods are 1996-1998, 1999-2002, 2003-2006, 2007-2010, 2011-2014, and 2015-2017. Panel (b) reports results from an alternative specification in first-differences, which is more demanding in terms of data but directly relates firm growth to productivity changes. This specification is defined as follows:

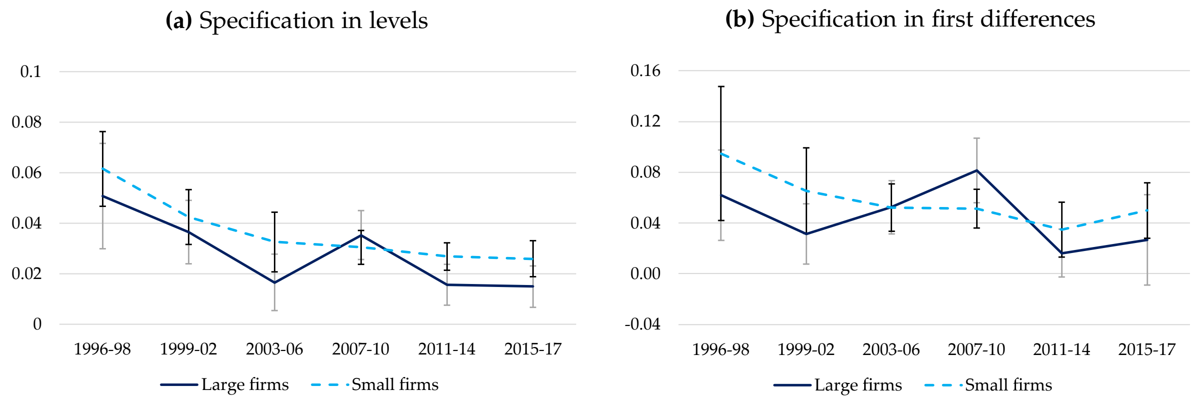
$$g_{it} = \beta_0 + \sum_{TW=1}^{6} \mathbb{I}_{TW}\, \delta_{TW} \Delta tfpr_{it-1} + X_{jt} + \epsilon_{it}\,,$$

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.

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

[39] 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. Figure D2 further shows that the decline in job reallocation in the German microdata is primarily driven by changes within industries, size classes, and age classes, confirming our European results.

Figure 15. Responsiveness in the German manufacturing sector.

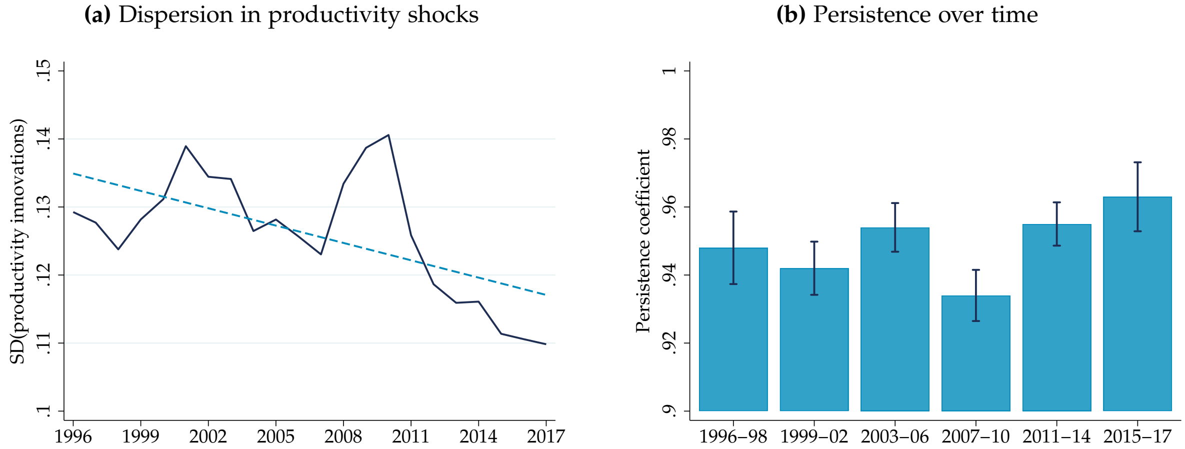


Notes: Results from estimating firms' responsiveness using productivity levels (Panel (a)) and differences (Panel (b)). Productivity variables are interacted with a full set of period dummies. All regressions include industry-year fixed effects. The specifications in levels also includes a full set of interactions between period dummies and lagged labor. We report results for firms with less than 100 employees and firms with more than 100 employees. German microdata.

Consistent with our European results, we find evidence of a strong decline in firms' responsiveness in the German manufacturing sector. The responsiveness coefficients in the last two periods are less than half of those estimated in the first periods. The decline is similar for large and small firms. However, consistent with our European results, large firms have a lower responsiveness during most periods. Online Appendix Table D1 shows that this difference in responsiveness is statistically significant at the 5% level when considering all years collectively. Overall, the level of the estimated coefficients is comparable to our previous results from the CompNet data.

Regarding the shock hypothesis, Figure 16 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 Eq. (7). The dark-blue solid line in Panel (a) shows the evolution of the standard deviation of the productivity innovations (η_{it}), while the bars in Panel (b) display our estimates of the persistence coefficients (ρ). In line with previous European results, the dispersion of productivity shocks declined while productivity persistence slightly increased.

Figure 16. 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.

4.3.3 Quantification of the responsiveness and shock hypotheses

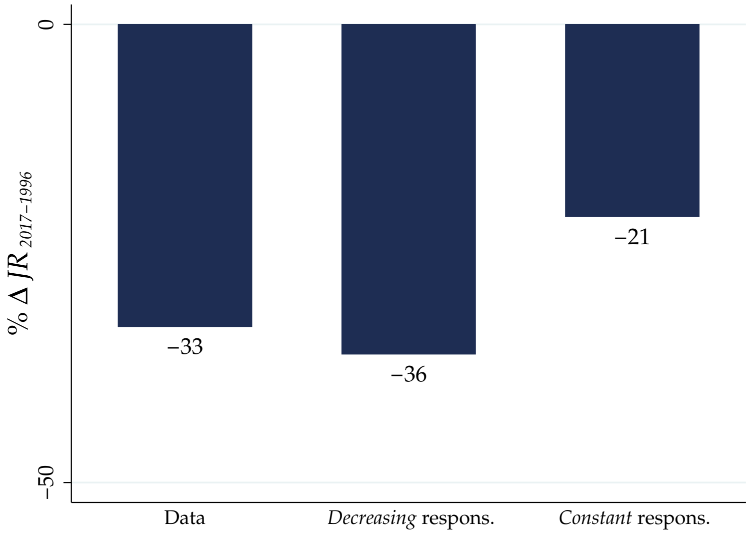
With direct access to the German microdata, we can quantify the importance of the responsiveness and shock hypotheses. To this end, we predict job reallocation rates from our responsiveness regressions in two scenarios: one allows for declining responsiveness, while the other holds responsiveness constant at its initial period value.[40] To allow for maximum flexibility, we estimate period- and firm-size-specific responsiveness coefficients, akin to Panel (a) in Figure 15, but using size quintiles.[41] To recover predictions of aggregate job reallocation rates, we first predict firm-level growth rates from our regressions. $\widehat{g}_{it}^{DR}$ denotes the predicted growth rate that uses the period-specific coefficients (i.e., declining responsiveness scenario), whereas $\widehat{g}_{it}^{CR}$ is the predicted growth rate that imposes the first-period coefficients for all periods (i.e., constant responsiveness scenario). Using these predicted employment growth rates and firms' initial employment, we calculate firms' predicted employment in each period t. Subsequently, we obtain the job reallocation rate for the declining-responsiveness scenario, $\widehat{JR}_t^{DR}$, considering predicted employment growth rates and employment shares based on the specification with varying responsiveness coefficients. Similarly, the job reallocation rate for the constant-responsiveness counterfactual, $\widehat{JR}_t^{CR}$, is derived from predicted growth rates and employment shares under the assumption that responsiveness has remained at its initial

[40] See DHJM for details.

[41] Regression results are reported in online Appendix Table D2.

level. Comparing the evolution of $\widehat{JR}_t^{DR}$ and $\widehat{JR}_t^{CR}$ yields an estimate of the importance of the declining responsiveness vs. shock hypotheses in explaining the overall declines.

Figure 17. Quantification of responsiveness vs. shock hypotheses.



Notes: Counterfactual changes in job reallocation rates using predicted employment growth rates from firm-level responsiveness regressions that estimate period-specific responsiveness coefficients. The left bar shows the relative changes in the job reallocation rate observed in the data. The middle bar reports the predicted job reallocation, allowing for time-varying responsiveness ($\widehat{JR}_t^{DR}$). The right bar is based on predicted changes in job reallocation, assuming that responsiveness remains constant over time at the initial period value ($\widehat{JR}_t^{CR}$). The underlying regression results are reported in Table D2. German microdata.

Figure 17 shows the results from this counterfactual analysis, where we compare the first (1996) and last (2017) years of our data. The left bar indicates the percentage decline in observed job reallocation in the German microdata, equaling 33%. The middle bar reports the decline in the predicted job reallocation rate under the declining responsiveness scenario ($\widehat{JR}_t^{DR}$). Reassuringly, the predicted decline of 36% is similar to the decline of job reallocation in the data. The right bar indicates the decline in job reallocation in the constant-responsiveness counterfactual ($\widehat{JR}_t^{CR}$), which, as expected, is smaller, equaling 21%.

Using these estimates, we can infer that $(1 - \frac{21}{36})100 = 42\%$ of the decline in job reallocation within the German manufacturing sector is explained by the reduction in responsiveness. The remaining 58% can be attributed to changing productivity shock dynamics. While declining responsiveness accounts for a significant portion in our case, our results differ from the US, where DHJM find that it accounts for almost the entire decline in job reallocation. The remainder of our study will focus on studying the factors driving firm responsiveness.

5 Drivers of declining responsiveness

This section develops a firm-level framework to understand declining responsiveness and applies this framework to the German microdata. While DHJM focus on adjustment costs to rationalize this decline, the authors 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 into a new framework that unpacks the black box of firms' responsiveness. In particular, we rationalize declining responsiveness via endogenous changes in firms' sales, market power in output and labor markets, wages, and production technologies.[42] Compared to an increase in adjustments costs, these factors provide a more natural explanation for declining firm responsiveness in Europe as many European countries have significantly increased their labor market flexibility in the past 20 years (Eichhorst et al., 2017; Gehrke and Weber, 2018). In this context, online Appendix Figure F1 shows that the OECD employment protection index, which is a widely used indicator of labor market flexibility, declined in most European countries.

Section 5.1 introduces our framework. Section 5.2 describes how we estimate markups, markdowns, and technology at the firm-year level with our German manufacturing data. Section 5.3 empirically validates our approach and Section 5.4 provides empirical evidence that changes in firms' sales, market power, wages, and production technologies quantitatively matter for the decline in responsiveness.

5.1 A firm-level framework

Consider a firm i 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:

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

[42]Our approach is thus related to De Loecker et al. (2021). Whereas their analysis of job reallocation rates is based on an industry equilibrium model and focuses on the evolution of firms' product market power, our approach additionally considers firms' monopsony power, wages, and labor output elasticities and can be implemented directly from firm-level estimates of markups, markdowns, and output elasticities. While our approach has the advantage of not imposing any structural assumption, it does not allow us to study counterfactual changes in market primitives.

where TFP_{it} denotes the firm's total factor productivity. 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:

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

where W_{it}, V^M_{it}, and V^K_{it} denote unit costs for labor, intermediates, and capital. We express output prices and wages as functions of quantities and labor inputs to allow for firm market power in product and labor markets.[43] Under profit maximization, the first-order condition for labor implies that the marginal revenue product of labor ($MRPL_{it}$) equals 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 Eq. (9) yields an 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 $\mu_{it} \equiv \frac{P_{it}}{MC_{it}}$ is the firm's price over marginal cost markup. $\gamma_{it} \equiv 1 + \xi$ 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 ($P_{it}Q_{it} = R_{it}$), we can express labor demand in terms of $TFPR_{it}$. This is the productivity measure we use in our regressions, which is a composite of firms' technical efficiency and demand conditions. $F_{it}(\cdot)$ captures output net of the productivity term and depends on the specification of the production function.[44]

[43] Our framework takes a "firms'-eye perspective" which nests different market structures in output and input markets. The values of markups and markdowns are endogenous outcomes of the equilibrium.

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

By taking logs and first differences of Eq. (10), we can decompose employment growth:

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

where lowercase letters denote logs. Eq. (11) sheds light on the role of firms' productivity, markups, markdowns, wages, and technology in driving changes in firms' employment.[45] To make this apparent, we rewrite Eq. (11) in first-differences:

$$\Delta l_{it} = \Delta r_{it} + \Delta log(\theta^L_{it}) - \Delta log(\gamma_{it}) - \Delta log(\mu_{it}) - \Delta w_{it}. \tag{12}$$

Eq. (12) provides a general decomposition of employment growth at the firm level. By dividing Eq. (12) by $\Delta tfpr_{it}$, we can decompose firms' responsiveness, expressed as a pass-through rate, into its drivers:

$$\frac{\Delta l_{it}}{\Delta tfpr_{it}} = \frac{\Delta r_{it}}{\Delta tfpr_{it}} + \frac{\Delta log(\theta^L_{it})}{\Delta tfpr_{it}} - \frac{\Delta log(\gamma_{it})}{\Delta tfpr_{it}} - \frac{\Delta log(\mu_{it})}{\Delta tfpr_{it}} - \frac{\Delta w_{it}}{\Delta tfpr_{it}}. \tag{13}$$

This result highlights that responsiveness is equal to the sum of the pass-through of productivity shocks to sales, market power, technology, and wages. The first term on the right-hand side shows that changes in a firm's employment in response to a productivity shock depend on how much its sales increase in *relative* terms. The smaller the increase in sales, the lower the responsiveness of labor to productivity. Similarly, the more a firm increases its markup and/or wage markdown, the smaller the changes in its employment in response to a positive productivity change. The same reasoning applies to technology and wages.[46]

A subtle but important point is that all these pass-through terms also depend on the initial levels of firms' market power, technology, and wages. To fix ideas, consider a scenario where markups, markdowns, technology, and wages remain constant. The responsiveness of employment to productivity is therefore fully determined by the pass-through of productivity to sales ($\frac{\Delta r_{it}}{\Delta tfpr_{it}}$). In this scenario, a firm that charges a high markup expands its sales after a productivity shock to a smaller extent than a firm with a lower markup. In other words, the higher a firm's markup, the lower its pass-through of productivity to sales and, thus,

[45] Eq. (11) nests the expression derived by DHJM in their framework (see online Appendix B.1).

[46] Clearly, all these predictions are based on partial adjustments of each component of Eq. (12). Any of these changes are likely to coincide with simultaneous changes in other components as well.

employment. Similar predictions hold for labor market power and technology.[47] In online Appendix D.2, we illustrate the roles of market power, technology, and wage *levels* in shaping firms' responsiveness using a set of stylized simulations.

The main takeaway of our stylized framework is that both the levels (in an indirect way) and the changes (in a direct way) in markups, markdowns, technology, and wages influence the responsiveness of employment to productivity. In the following, we estimate these components at the firm-year level to empirically assess their role in declining responsiveness.

5.2 Estimation of markups, markdowns, and output elasticities

In addition to estimating TFPR, our production function estimation allows us to recover estimates of output elasticities, markups, and markdowns for each firm and year. The output elasticity of labor is the derivative of the logged production function: $\theta_{it}^{L} = \frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$. We estimate markups using the firm's first-order condition for intermediates following De Loecker and Warzynski (2012):

$$V_{it} = MRPM_{it} \;\Rightarrow\; \mu_{it} = \frac{P_{it}}{MC_{it}} = \theta_{it}^{M} \frac{P_{it} Q_{it}}{V_{it}^{M} M_{it}}, \tag{14}$$

where $MRPM_{it}$ is the marginal revenue product of intermediates and $\theta_{it}^{M} = \frac{\partial q_{it}}{\partial m_{it}}$ is the firm-year specific output elasticity of intermediates.[48] Combining the first-order condition of labor from our framework (Eq. (9)) with Eq. (14) yields an expression for markdowns:

$$\gamma_{it} = 1 + \xi_{it} = \frac{MRPL_{it}}{W_{it}} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{V_{it}^{M} M_{it}}{W_{it} L_{it}}, \tag{15}$$

where $MRPL_{it}$ is the marginal revenue product of labor. This approach to estimating wage markdowns has been used in several recent studies (Dobbelaere and Mairesse, 2013; Caselli et al., 2021; Mertens, 2022; Yeh et al., 2022).[49] We present summary statistics on estimated markups, markdowns, and output elasticities in online Appendix Table A5. The estimates are meaningful and in line with previous work. The average markup, markdown, and labor

[47] In more general scenarios, where firms have the incentive to vary their markups, markdowns, output elasticities, and wages, the pass-through of productivity to these components also depends on their initial levels and the characteristics of demand, the inverse supply curve, and technology (see Biondi, 2022 and online Appendix D.2).

[48] 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 Eq. (14).

[49] Although not explicitly discussed in our setting, this empirical measure of wage markdowns also nests rent-sharing models and, more generally, cases in which the wage exceeds the MRPL. Rent-sharing can also rationalize why some firms have wage markdowns below unity. For more extensive discussions on this issue, we refer to Mertens (2023), Treuren (2022), and Garin and Silvério (2023).

output elasticity equal 1.07, 1.08, and 0.3, respectively. These results indicate that the average firm sets a price 7% above its marginal costs and pays its workers 93% of their marginal revenue product. The estimated value of θ^L implies that a 1% increase in a firm's employment results in 0.3% more output, all else equal.

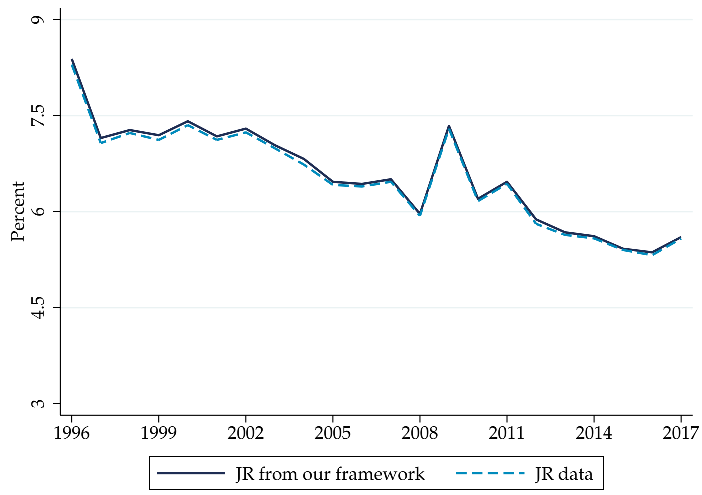
5.3 Empirical validation

As a first empirical validation of our framework, we use Eq. (12) to predict firms' employment changes by summing up estimated changes in sales, output elasticities, markdowns, markups and wages. Using these predicted employment changes, we estimate the implied job reallocation rate as follows:

$$\widehat{JR_t} = \sum_i s_{it} \, |\widehat{g_{it}}| \approx \sum_i s_{it} \left| [\Delta r_{it} + \Delta log(\widehat{\theta^L_{it}}) - \Delta log(\widehat{\gamma_{it}}) - \Delta log(\widehat{\mu_{it}}) - \Delta w_{it}] \right|. \tag{16}$$

Figure 18 compares our estimated job reallocation (solid line) with the job reallocation in the data (dashed line). Both time series align closely, which provides a strong validation of our decomposition approach and empirical implementation.

Figure 18. 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 Eq. (16). The dashed light-blue line depicts the job reallocation rate as directly measured in the data based on employment changes. German microdata.

Online Appendix D.2.3 provides further validation of our framework. In a series of econometric analyses, we test whether the levels of market power, technology, and wages influence responsiveness in our data. In line with our predictions, we find evidence that higher markups, markdowns, and wages are associated with lower responsiveness, while the opposite holds for returns to scale.

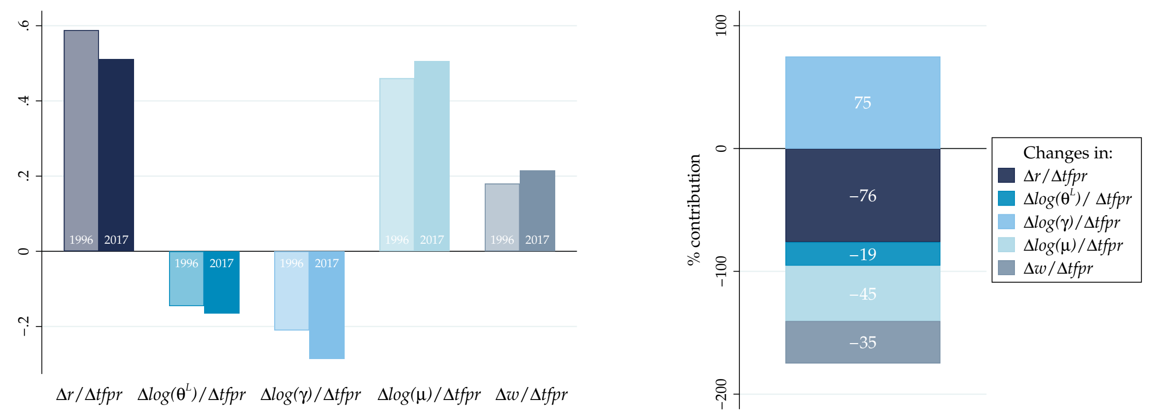
5.4 Correlated changes in sales, market power, technology, and wages

Using our estimates of markups, markdowns, output elasticities, wages, and productivity and Eq. (13), we now quantify the contribution of each component of responsiveness to its decline documented in Figure 15.

Figure 19. Results of the responsiveness decomposition.

(a) Changes in pass-through rates

(b) Contributions to changes in responsiveness



Notes: Changes in the components of responsiveness, i.e., the right-hand side terms of Eq. (13) (Panel (a)) and their contribution to the decline in responsiveness between 1996 and 2017 (Panel (b)). In Panel (b), a negative number refers to a contribution of that term to the (negative) changes in responsiveness (set to -100%). Employment-weighted averages across firms with a productivity change (positive or negative) of at least 1%, i.e., with $|\Delta tfpr_{it}| \geq 0.01$. German microdata.

We illustrate the results of this exercise in Figure 19. Panel (a) reports the average pass-through terms at the beginning (light bars) and end (dark bars) of our data. We first focus on the sign of each term. Firms that become more productive tend to expand their sales ($\frac{\Delta r_{it}}{\Delta tfpr_{it}} > 0$) and increase their markups ($\frac{\Delta log(\mu_{it})}{\Delta tfpr_{it}}) > 0$) and wages ($\frac{\Delta w_{it}}{\Delta tfpr_{it}} > 0$). Concurrently, their markdowns ($\frac{\Delta log(\gamma_{it})}{\Delta tfpr_{it}} < 0$) and output elasticities of labor ($\frac{\Delta log(\theta^L_{it})}{\Delta tfpr_{it}} < 0$) decrease. While the direction of these responses has remained unchanged over the past two decades, their magnitudes have not. In particular, the pass-through of productivity shocks to sales weakened, whereas labor output elasticities and markdowns declined relatively more in response to productivity. Moreover, the pass-through of productivity to markups and wages increased. Put differently, in recent years firms have grown less in terms of sales and extracted higher rents from consumers when experiencing a positive productivity shock. However, the increase in wage pass-through indicates that firms have shared a growing part of their rents with their workers, which is consistent with a stronger reduction in wage markdowns in response to a productivity shock.[50] Finally, a more negative pass-through to labor output elasticity changes indicates that firms have substituted labor with other production inputs more intensely after a productivity shock.

In Panel (b), we illustrate the relative contribution of each term to the overall change in responsiveness. Our decomposition shows that the decline in firm responsiveness over the past decades has been predominantly driven by weaker sales growth and higher markup growth in response to productivity. These factors account for 76% and 45% of the overall decline in labor responsiveness, respectively. Although to a lesser extent, changes in the pass-through of productivity to wages (35%) and output elasticities of labor (19%) contributed to lowering responsiveness too. In contrast, the evolution of the pass-through of productivity to markdowns counteracted the decline in responsiveness.[51]

Taken together, our results highlight that changes in sales growth after productivity shocks are crucial to understanding the decline in responsiveness. In online Appendix D.2, we provide evidence that rising markup *levels*, especially among larger firms that are less responsive to begin with (Figure 12), can rationalize these changes in the pass-through of productivity to sales. Our finding that the pass-through of productivity to output has become more incomplete over time, as firms translate a growing part of productivity into higher markups, is in line with findings for the US by De Loecker et al. (2021). However, we also find that firms share some of these additional rents with their workers. This is consistent with Chan et al. (2023), who, in a different context, report a negative pass-through of productivity to markdowns. While beyond the scope of our study, understanding whether all workers or only some benefit from these higher firm rents remains an important open question. In this regard, Bao et al. (2023) recently documented that top managers' pay is closely connected to firms' markup changes.

In addition to changes in firms' market power, also technological changes have contributed to lowering responsiveness. In Table D5, we show that the output elasticity of labor has declined

[50]The term $\frac{\Delta w_{it}}{\Delta tfpr_{it}}$ can be interpreted as the rent-sharing elasticity. Our estimate of this elasticity is in line with recent work that causally identifies it (Mertens et al., 2022; Acemoglu et al., 2022).

[51]Note that our markdown estimates are based on a static framework. In a dynamic model with adjustment costs, our markdown expressions also capture labor adjustment costs (Hall, 2004; Doraszelski and Jaumandreu, 2019). Our results thus also suggest that labor adjustment costs are unlikely to have an important role in explaining declining responsiveness in Europe, consistent with the documented increase in Europe's labor market flexibility.

in the German manufacturing sector for all firms, indicating a generalized tendency of firms to replace labor with other production factors. This is consistent with evidence by Mertens and Schoefer (2024) showing that output growth is associated with declining labor output elasticities in many European countries. Table D5 also shows large increases in intermediate output elasticities, particularly for large firms, which is consistent with greater intermediate goods outsourcing as discussed in Goldschmidt and Schmieder (2017). In broader terms, this also relates to evidence by Autor et al. (2022) showing that new technologies have become increasingly labor-replacing. Taken together, all these findings suggest that if productivity gains become increasingly connected to labor-replacing technologies (be it through robotization, AI, or offshoring), such technological advances will further reduce responsiveness and job reallocation by reducing firms' labor demand.

While we focus on the German manufacturing sector, for which we can directly access rich firm-product-level data, we believe that our results speak to the evidence suggesting that European countries and the US are experiencing considerable changes in concentration (Bighelli et al., 2023; Bajgar et al., 2023), market power (De Loecker and Eeckhout, 2018), and production technologies (Autor et al., 2022; Mertens and Schoefer, 2024). More broadly, we believe that our results also speak to evidence on the rise of high-markup superstar firms (Autor et al., 2020). The contribution of our framework is to provide a direct link between these aggregate trends, job reallocation, and firms' responsiveness. Our application is a first case study that sheds light on overlooked mechanisms driving the decline in firms' responsiveness, and we leave it open to future research to apply such an analysis to other countries and datasets.

6 Conclusions

This article documents novel facts on European business dynamism using a combination of administrative firm-level databases we collected and published within the Competitiveness Research Network. Similarly to the US, job reallocation rates declined in Europe. This decline is a broad-based phenomenon, common to most sectors and countries that we analyze. It is mainly driven by dynamics within sectors, size, and age classes. Concurrently, the European economy is experiencing a structural aging reflected in a reduction in young firms' economic activity. However, compositional changes away from young firms explain a relatively small share of the overall decline. Instead, job reallocation declines are relatively stronger among large and mature firms. Firms' responsiveness has decreased in many European countries at similar rates to the US. Unlike the US, the decline in job reallocation in Europe coincides with a decrease in the dispersion of productivity shocks, particularly post 2010. 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, where we show that the decline in responsiveness is predominantly driven by a weaker output response to productivity and a higher pass-through of productivity to markups. Although to a lesser extent, higher wage pass-through and labor-substituting technological changes also contributed to lowering firm responsiveness.

Our results have important implications. Firstly, the widespread decline in business dynamism across 19 European countries, combined with existing evidence from the US, highlights that declining business dynamism is a general phenomenon present in many advanced economies with very different labor institutions. Secondly, we show that declining job reallocation in Europe results from declines in productivity shock dynamics that induce less reallocation *as well as* a lower responsiveness of firms to those productivity shocks. To our knowledge, we are first to document the less dynamic productivity shock environment that induces less reallocation. Understanding the root drivers of this development (including changes in knowledge flows and incentives to invest in productivity improvements) is an important task for future research, given its implications for productivity growth and reallocation. Finally, our novel framework highlights that changes in firms' responsiveness can be explained by changes in the pass-through of productivity shocks to sales, wages, market power, and technology. This offers additional explanations for declining job reallocation rates (alternative to rising adjustment costs) that are related to, among others, increasing firm market power and a declining importance of labor compared to other production inputs. Understanding whether declining responsiveness and job reallocation result from firms' market power or from technological change has first-order priority, and we believe that our framework, or extensions of it, can be applied by other researchers and to other datasets to shed further light on the drivers of declining business dynamism around the world.

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Online Appendix

A Data

A.1 The CompNet Dataset

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	National Bank van Belgium	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

Source: CompNet (2023).

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 the 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. Detailed information on undisclosed information leading to missing data points.

Figure	Missing information
Figure 2	German Construction sector in 2009.
Figure 3	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 C8	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 C2	German construction sector in 2009, Danish transportation and storage sector.
Figures 8 (a), 9, and C4	17/451 country-sector-size-class combinations for the countries Belgium, Germany, Latvia, Romania, Slovakia, Slovenia, and the United Kingdom
Figure C8	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 C13	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, such as minimum requirements on the number of firms within a cell or dominance rules.

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

Table A4 presents an overview of the variable definitions of all variables used in this article. This includes variables used in other sections of the online Appendix. 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 industries 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 A5 presents summary statistics on key variables for the German microdata.

Table A4. Variable definition in the German microdata.

Variable	Definition
L_{it}	Labor in headcounts.
W_{it}	Firm wage (firm average), 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 Bräuer et al. (2023), 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.
$V_{it}^{M} M_{it}$	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 for its construction.
P_{iot}	Price of a product o.
$share_{iot}$	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} (e_{it} in logs)	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.

Notes: The table summarizes the missing cell-level information in our figures and tables due to country-specific disclosure routines, such as minimum requirements on the number of firms within a cell or dominance rules.

Table A5. Summary statistics of our German manufacturing sample.

	Mean (1)	**p25** (2)	**Median** (3)	**p75** (4)	**St.Dev.** (5)	**Observations** (6)
Number of employees, L_{it}	279.70	51	105	259	795.04	180,022
DHS growth rate, g_{it}	0.004	-0.043	0.00	0.053	0.122	180,022
Log 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, μ_{it}	1.07	0.95	1.04	1.15	0.17	180,022
Wage markdown, γ_{it}	1.08	0.72	0.98	1.32	0.52	180,022
Combined market power, $\mu_{it} \times \gamma_{it}$	1.11	0.80	1.04	1.33	0.45	180,022
Output elasticity of labor, θ_{it}^{L}	0.30	0.24	0.31	0.38	0.10	180,022
Output elasticity of capital, θ_{it}^{K}	0.12	0.08	0.11	0.15	0.06	180,022
Output elasticity of intermediates , θ_{it}^{M}	0.63	0.57	0.63	0.69	0.09	180,022
Returns to scale, $\theta_{it}^{L} + \theta_{it}^{K} + \theta_{it}^{M}$	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.

B Additional theoretical results

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

DHJM specify a one-factor (labor) model of firm dynamics to describe the relationship between firms' employment growth and productivity realizations. In particular, they consider that the employment growth policy function of a firm i can be 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 at 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 as 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 firm characteristics. DHJM refer to a change in β_{1t} as a change in responsiveness.

They show that Eq. (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.[52] In this setting, the firm's first-order condition (in logs) is:

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

where W_{jt} is the wage rate in industry j. Taking time differences (indicated by Δ) and sweep-

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

ing out year and industry effects yields the following firm-level growth rate:

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

which is a function of relative changes in productivity. Eq. (B3) highlights the link between productivity and employment changes. The prediction of this frictionless model is that the lower the productivity changes, the lower 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 $a_{it-1} = \frac{1-\phi}{\phi} l_{it-1} - \phi log\left(\frac{\phi}{W_{j,t}}\right)$. Substituting this back into Equation (B3) yields (net of industry and year fixed effects):

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

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 Eq. (B1) that DHJM estimate is:

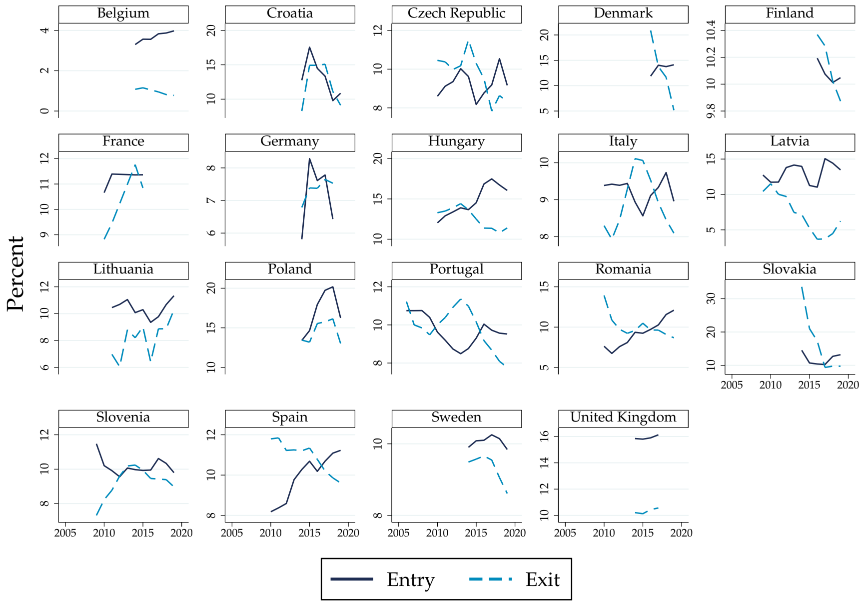
$$g_{it} = \beta_0 + \beta_{1t} a_{it-1} + \beta_{2t} l_{it-1} + \epsilon_{it}\,. \tag{B5}$$

We estimate the same specification to allow for a direct comparison between our European results and their results. 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.

C Additional empirical results from the CompNet data

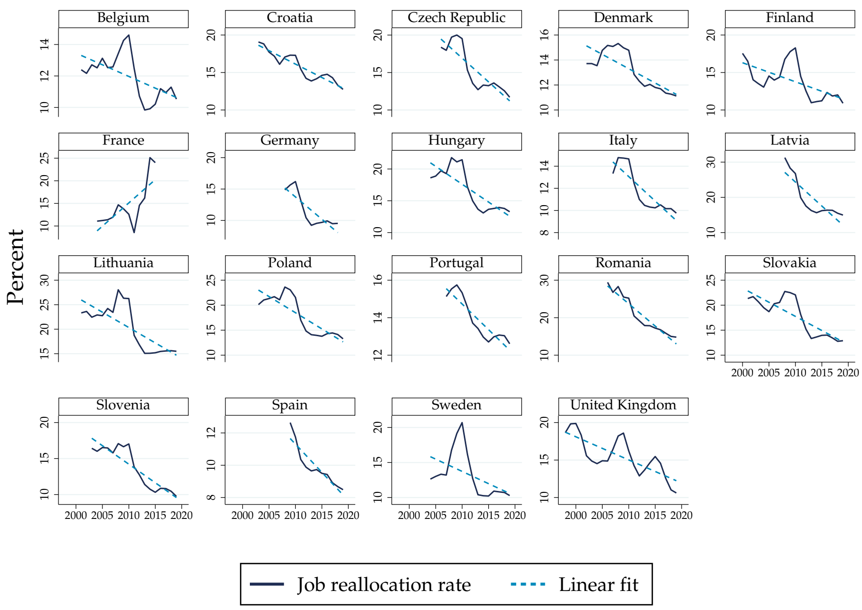
C.1 Further evidence on reallocation dynamics

Figure C1. Entry and exit rates in European countries



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

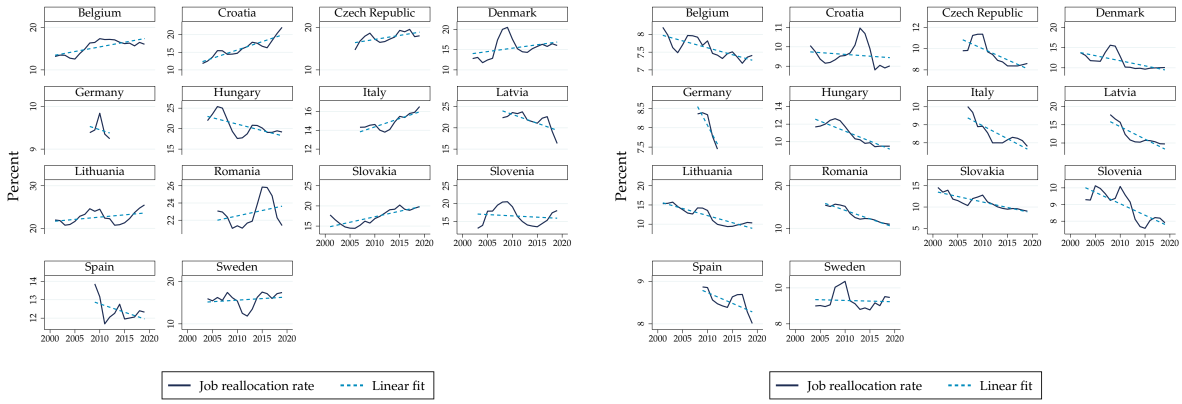
Figure C2. Sales reallocation rates in European countries.



Notes: Three-year moving averages of sales reallocation rates, which we define as job reallocation rates in Equation (1) but using sales instead of employment. The light blue dashed lines report linear trends. CompNet data, firms with at least 20 employees.

Figure C3. Job reallocation rate in European countries by age-class.

(a) Young firms. **(b)** Old firms.



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

Figure C4. 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 Table A3). CompNet data, firms with at least 20 employees.

C.2 Responsiveness and shocks hypotheses

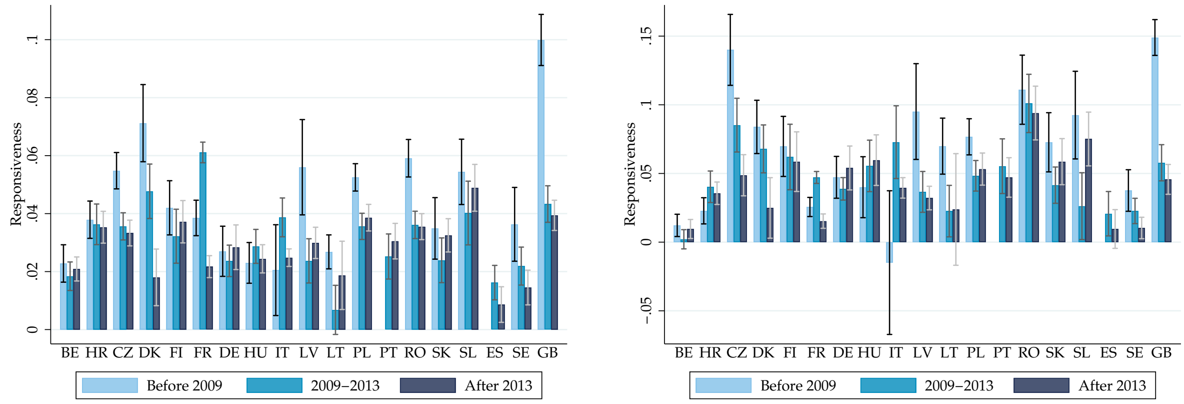
Table C1. Responsiveness of employment growth to productivity across countries.

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.

Figure C5. Responsiveness to productivity over different time windows.

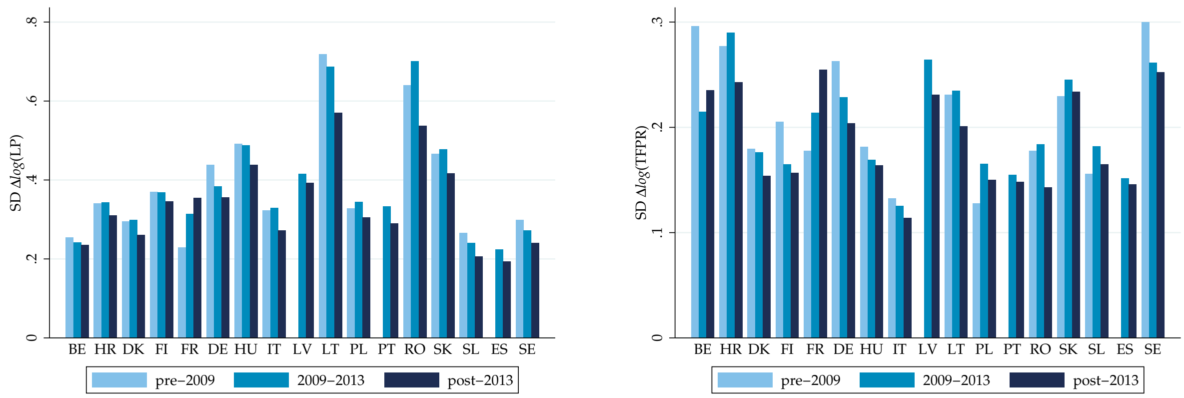
(a) Labor Productivity **(b)** Revenue-TFP



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

Figure C6. Evolution of the standard deviation of productivity changes.

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

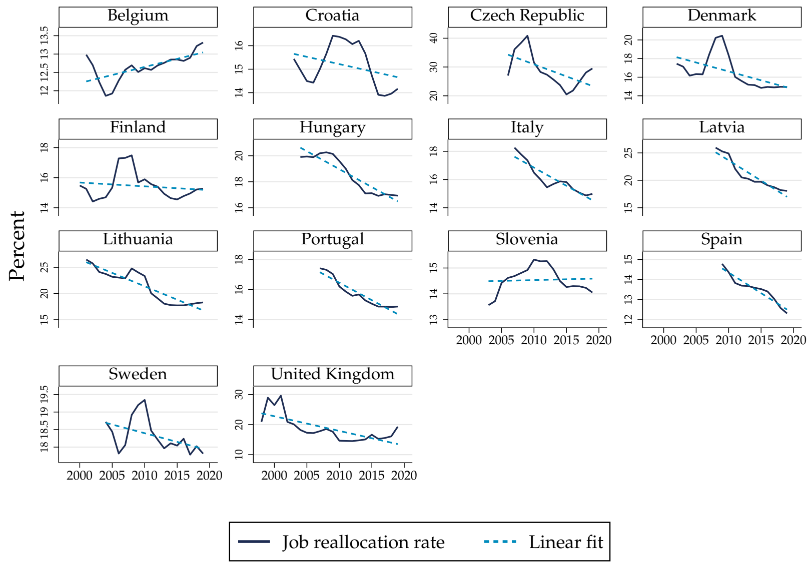


Notes: Standard deviation of productivity log-changes, i.e. $log(A_{it}) - log(A_{i(t-1)})$. Averages over three periods (pre-2009, 2009-2013, post-2013). CompNet data, firms with at least 20 employees.

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

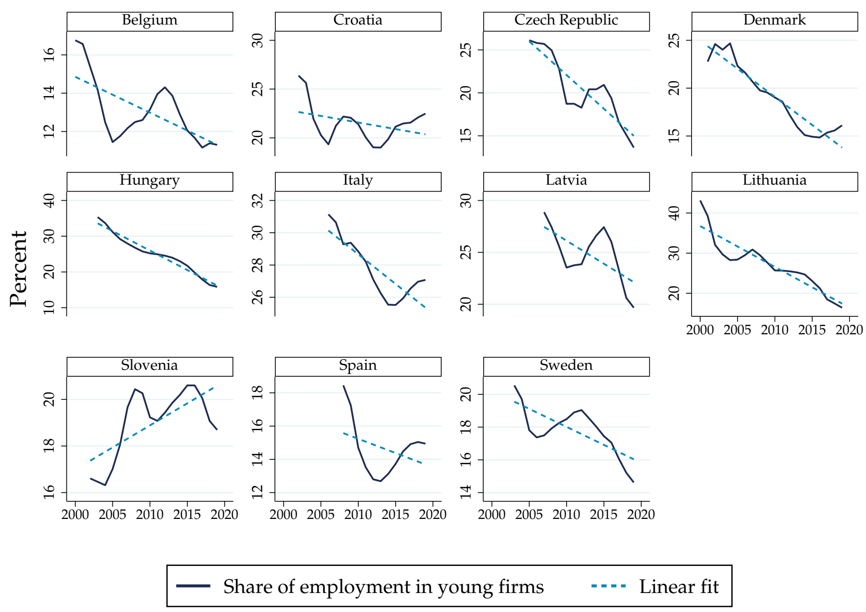
C.3.1 Stylized facts

Figure C7. Job reallocation rate in the "all sample".



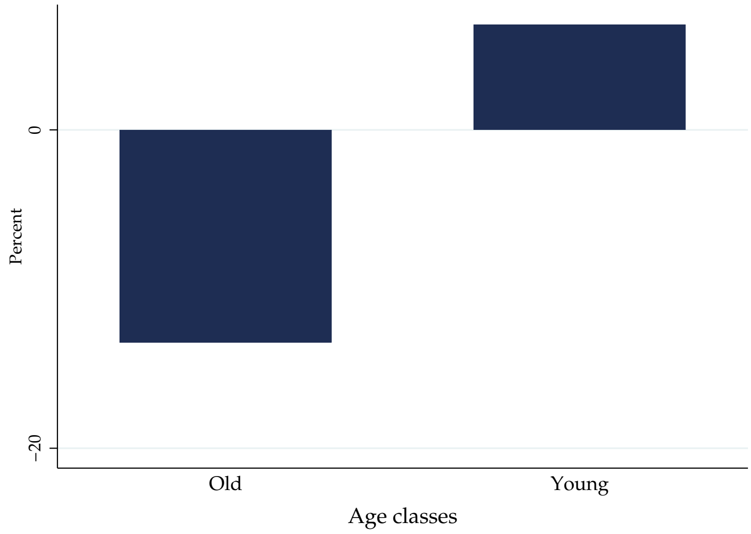
Notes: Three-year moving averages of job reallocation rates defined in Equation (1). The light blue dashed lines report linear trends. CompNet data. Firms with at least one employee.

Figure C8. Share of employment in young firms in the "all sample"



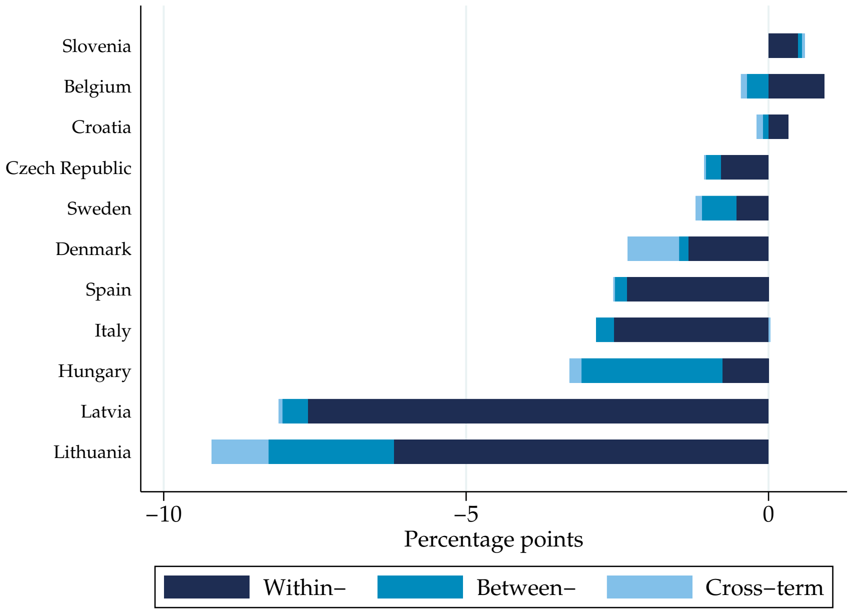
Notes: Three-year moving averages of the employment share of firms not older than five years. The dark blue solid lines show country-level shares of employment in young firms. The light blue dashed lines report linear trends. The underlying data are aggregated from sector-age-class data resulting in a drop of a few sector-age-class cells due to country-specific disclosure rules (see online Table A3). CompNet data. Firms with at least one employee.

Figure C9. Relative changes in job reallocation rates by age-class in the "all sample".



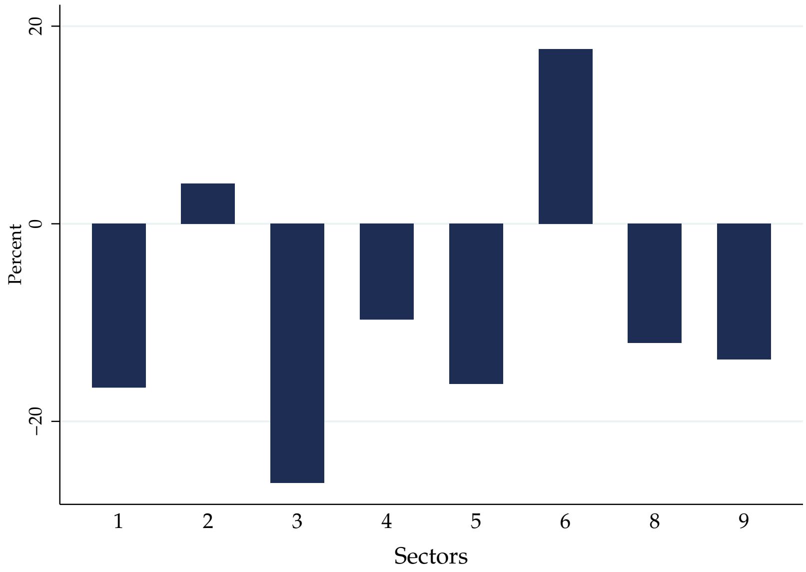
Note: Averages across countries in relative changes in job reallocation rates as computed in Equation (1) by age-class. Changes are computed between the first and last two years for each country-age-class cell. All countries additionally include the real estate sector as we directly use age-class aggregated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

Figure C10. Decomposition of job reallocation changes across age classes in the "all sample".



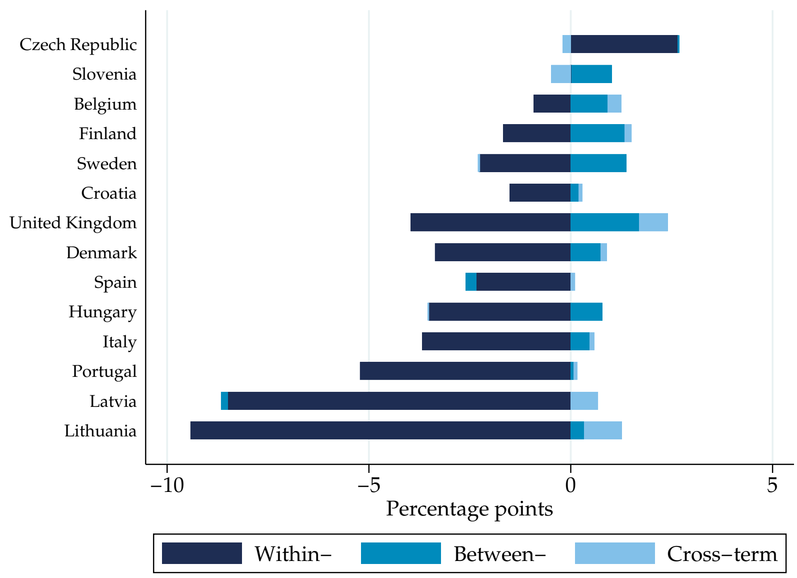
Notes: Results of the decomposition of job reallocation rates across age-classes as described in Equation (4). To define the start and end points for the decomposition, we average the first and last two years of job reallocation rates for every country-sector combination. All countries additionally include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

Figure C11. Relative changes in job reallocation rate by sector in the "all sample".



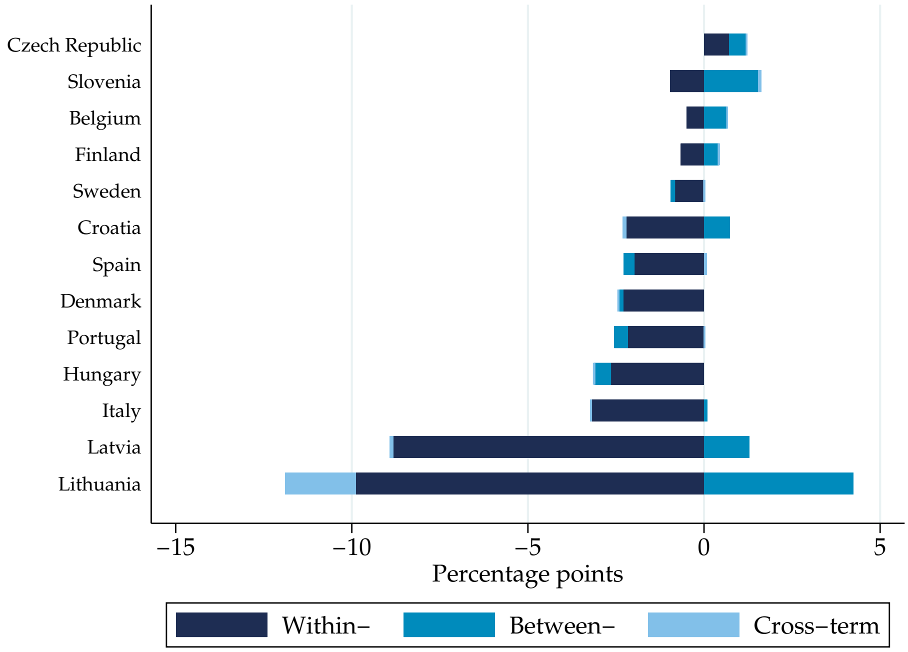
Notes: Averages across countries in relative changes in job reallocation rates as computed in Eq. (1) by sectors. Changes are computed between the first and last two years for each country-sector. Sectors are numbered in the following way: manufacturing (1), construction (2), wholesale/retail trade and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

Figure C12. 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.

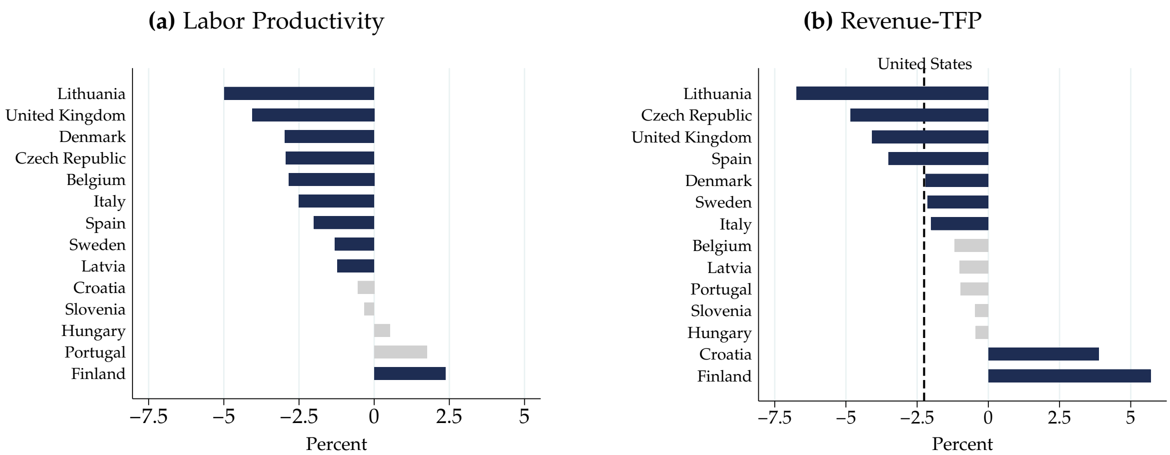
Figure C13. Decomposition of job reallocation changes across size classes in the "all sample".



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 Table A3). CompNet data, firms with at least one employee.

C.3.2 Responsiveness hypothesis

Figure C14. Relative changes in responsiveness over time ("all sample").

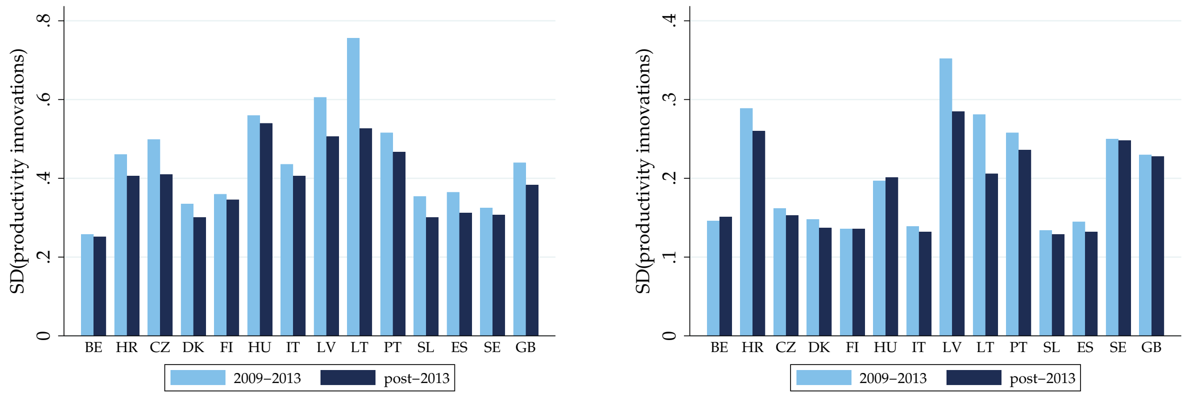


Notes: Estimated coefficients of the linear trend relative to the initial responsiveness, i.e., δ_1/β_1 in Equation (5). Countries are ranked in descending order. The underlying results are reported in our data appendix. Bars are colored if both coefficients are statistically significant (at least) at the 10% level. The dashed line reports 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 one employee.

C.3.3 Shocks hypothesis

Figure C15. Standard deviation of productivity innovations η_{it} in the "all sample".

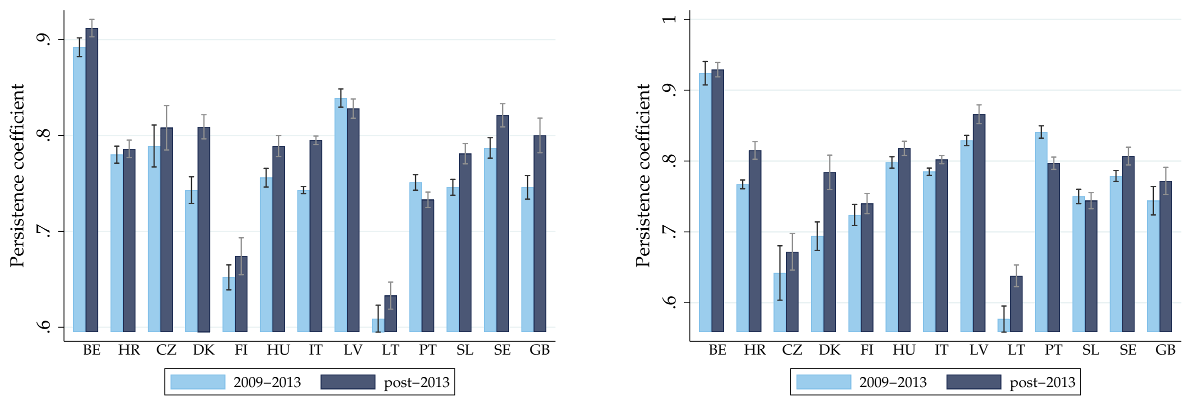
(a) Labor Productivity **(b)** Revenue-TFP



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

Figure C16. Increasing persistence in productivity dynamics in the "all sample".

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

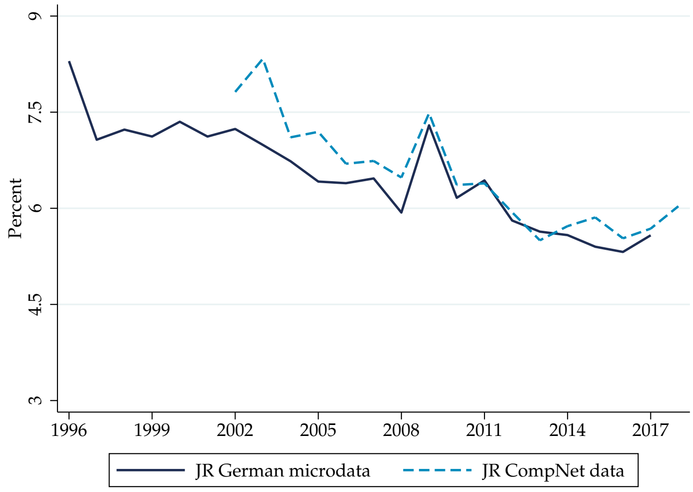


Notes: Point estimates of the persistence coefficient, ρ_t, in the AR(1) in Equation (7) estimated over two consecutive periods. Complete results of the regressions are available in our data appendix. CompNet data, firms with at least one employee.

D Additional results on the German manufacturing sector

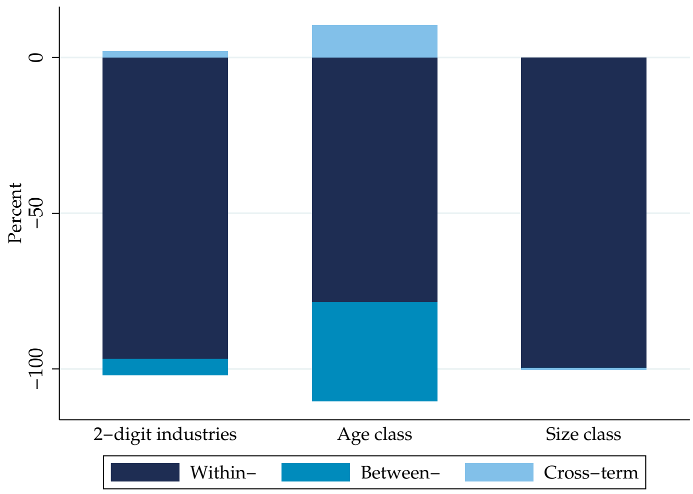
D.1 Further results on job reallocation and responsiveness

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. The light blue dashed line shows the job reallocation rate for the German manufacturing sector from CompNet (firms with at least 20 employees). German microdata and CompNet data with at least 20 employees.

Figure D2. Decomposition of the decline in job reallocation.



Notes: The figure decomposes the decline in job reallocation in the German manufacturing sector (Figure D1) using the decomposition by Foster et al. (2001) as described in Equation (4) of the main text. Industries are 2-digit NACE rev. 1.1 industries. Size classes are defined by small (smaller than 100 employees) and large firms (at least 100 employees). Age classes are defined by mature (older than 5 years) and young firms (not older than 5 years). The age of a firm is approximated with the sample entry using a datatest reporting investment for the population of firms with at least 20 employees that starts in 1995. The industry and size class decompositions refer to the change in job reallocation between 1996 and 2017. The age class decomposition studies the change from 2004 to 2017 to allow for a sufficient accumulation of mature firms in the data (due to our proxy). Each set of stacked bars sums up to -100%, i.e., we decompose the change in job reallocation into the percentage contribution of the within-, between-, and cross-term.

Table D1. Responsiveness: Linear trend and differences between large and small firms.

	Dependent variable: *Employment growth rate* (g_{ijt})	
	(1)	(2)
$tfpr_{it-1}$	0.041***	0.033***
	(0.006)	(0.002)
$tfpr_{it-1} \times T_t$	-0.001***	
	(0.000)	
$tfpr_{it-1} \times$ large		-0.007**
		(0.003)
l_{it-1}	-0.005***	-0.012***
	(0.001)	(0.001)
$l_{it-1} \times T_t$	0.000***	
	0.000	
$l_{it-1} \times$ large		0.010***
		(0.002)
Large		-0.043***
		(0.007)
Industry-Year FE	yes	yes
Observations	180,022	180,022
N of firms	38,721	38,721
R^2	0.053	0.048

Notes: The table shows results estimating Equation (5) (column 1) and form a related specification that omits the linear trend and instead includes a dummy for large firms (more than 100 employees in $t-1$) and an interaction between this dummy variable and i) productivity and ii) employment (column 2). The interaction coefficient between productivity and the size dummy ($tfpr_{it-1} \times$ large) indicates that larger firms have lower responsiveness. The regression includes industry-year fixed effects. Standard errors (in parentheses) are clustered at the firm level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

Table D2. Responsiveness by firm size quintiles.

	Dependent variable: Employment growth rate (g_{ijt})				
	1st quintile	**2nd quintile**	**3rd quintile**	**4th quintile**	**5th quintile**
Period	(1)	(2)	(3)	(4)	(5)
1996-1998	0.042***	0.051***	0.080***	0.090***	0.052***
	(0.013)	(0.015)	(0.014)	(0.015)	(0.017)
1999-2002	0.049***	0.037***	0.040***	0.030***	0.043***
	(0.010)	(0.011)	(0.008)	(0.009)	(0.010)
2003-2006	0.041***	0.021***	0.027**	0.022***	0.015*
	(0.008)	(0.008)	(0.010)	(0.006)	(0.009)
2007-2010	0.021***	0.028***	0.037***	0.025***	0.038***
	(0.007)	(0.006)	(0.006)	(0.06)	(0.008)
2011-2014	0.027***	0.027***	0.021***	0.022***	0.015**
	(0.005)	(0.005)	(0.005)	(0.051)	(0.007)
2015-2017	0.040***	0.021***	0.021***	0.014**	0.017**
	(0.007)	(0.007)	(0.005)	(0.059)	(0.007)
Interactions for lagged labor	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes
Observations	36,745	35,633	35,943	35,725	35,961
N of firms	13689	12580	10871	8756	5318
R^2	0.043	0.050	0.052	0.058	0.066

Notes: Results from estimating period-specific responsiveness coefficients by size quintiles of the firm employment distribution. Quintiles are computed within two-digit industries. We interact lagged productivity with a full set of period dummies. We also interact the lagged labor variable with a full set of period dummies (not repoted). All regressions include industry-year fixed effects. Standard errors (in parentheses) are clustered at the firm level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

D.2 Additional results on responsiveness and its determinants

According to our theoretical framework, firms' responsiveness of employment to productivity depends on how sales, markdowns, markups, wages, and output elasticities respond to productivity shocks. Depending on the underlying model, these responses depend also on the initial levels of markups, markdowns, wages, and output elasticities. This section focuses on the role of these levels.

We first use a set of stylized simulations to illustrate how the same firm responds differently to a productivity shock depending on its initial levels of market power, technology, and wages. We then show that these comparative statics predictions find empirical support in the German microdata. Finally, we show how heterogeneity in markups, markdowns, wages, and output elasticities across firms of different sizes provides an intuitive explanation for why larger firms have lower responsiveness.

D.2.1 Simulated scenarios

To understand how firms' employment responds to productivity in different scenarios, we consider a generic firm i that produces output (Q_i) with labor (L_i) and intermediate inputs (M_i) according to a Cobb-Douglas production function, $Q_i = L_i^{\theta^L} M_i^{\theta^M} TFP_i$. In our baseline scenario (1), we set the output elasticities $\theta^L = 0.4$ and $\theta^M = 0.6$, such that returns to scale (RTS) are constant. In each scenario, we consider two firms (1 and 2) of different sizes. To keep the simulation simple, we assume that these firms are isolated monopolists.[53] Their difference in size results from different initial levels of productivity. We hold this difference constant in all simulations.[54] In the baseline scenario, firms are *price-takers* in input markets, and the wage rate and the intermediate input costs are set to $W^{base} = V^{M^{base}} = 0.5$, where the superscript *base* indicates the baseline scenario. We also assume that firms face a constant elasticity of demand $\sigma = 3$ such that they charge a markup of $\mu_i = \dfrac{\sigma}{\sigma - 1} = 1.5$. We compare the baseline scenario to different scenarios, each of which involves relaxing one of these assumptions at a time. Table D3 provides an overview on the considered scenarios.

[53]This is equivalent to considering the same monopolist at two different size.

[54]We set $TFP_1 = 1$ for the small and $TFP_2 = 2$ for the large firm.

Table D3. Details on different scenarios.

Scenario	Description
(1)	Baseline scenario.
(2)	Firms face a lower price elasticity of demand of $\sigma = 2$, which increases their optimal markups. Because of the CES structure, markups are constant irrespective of firm size.
(3)	Firms face a demand with a variable elasticity of demand. As a firm produces more, it faces a lower elasticity and has 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 $\tau = 0.2$. This type of 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)	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 obtained by adding an intercept to the previous inverse supply curve. In particular, we add $W^{base} = 0.5$, such 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, keeping returns to scale constant. In particular, we reduce the output elasticity of labor by 0.01, such 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 the time when* the productivity shock arrives and at different rates for large and small firms. In particular, we set $\Delta\theta_i^L = 0.01$ for the large firm and 0.005 for the small firm. 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 $\theta^L + \theta^M = 1.05$ by increasing proportionally both θ^L and θ^M.
(10)	We increase wages by $W = 0.2$.
(11)	Firms face an isoelastic upward-sloping inverse supply curve defined as $W_i(L_i) = 0.1 * L_i^{(0.5)}$ but do not exercise labor market power.
(12)	Firms face an upward-sloping inverse supply curve where ξ^W increases in L by adding an intercept exactly as in scenario (5). Again, firms do not exercise labor market power.

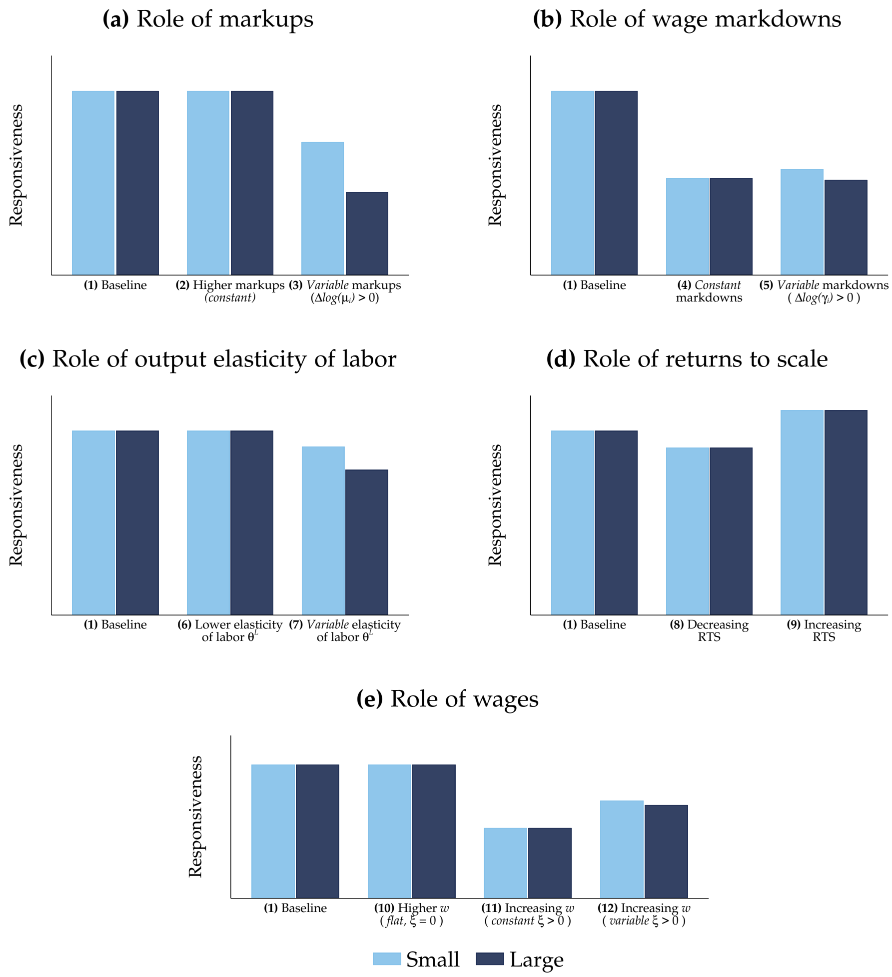
D.2.2 Comparative statics predictions

We now present the results of our numerical simulations. We also connect this analysis to the documented size gradient in firm responsiveness and discuss how differences in the levels of market power, wages, and/or technology that are correlated with firm size can rationalize why larger firms are less responsive than smaller firms.

Figure D3 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) and large monopolist (dark blue). The baseline scenario (1) considers a setting where markups, markdowns, labor output elasticities, returns to scale, and wages are constant and identical, irrespective of a firm's size. In this case, firms respond identically to a productivity shock. Scenario (2) shows that the responsiveness of labor to productivity is smaller when firms set a higher markup.

Scenario (3) illustrates how differences in responsiveness across size classes arise when larger firms set higher markups. As shown in Biondi (2022), larger firms have a lower responsiveness

Figure D3. Simulated responsiveness to productivity shocks by size class.



Notes: Different scenarios for the responsiveness of labor to productivity changes $\frac{\Delta l_{it}}{\Delta tfp_{it}}$.

whenever the price elasticity of demand decreases along the demand curve.[55] Intuitively, consumers become less willing to pay for each additional unit as output levels increase. As a result, a highly productive firm finds it unprofitable to continue expanding its output at the same rate as this results in a rapid decline in its marginal revenue. Instead, the profit-maximizing strategy is to expand output - and thus employment - at a decreasing rate after a productivity shock.

A similar logic applies to wage markdowns. In scenario (4), a firm is less responsive to productivity if it exerts 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 was a *wage-taker*, its marginal factor costs become upward-sloping if it exerts monopsony power. Mirroring the case of markups, a more productive firm refrains

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

from expanding output and, thus, labor demand. If markdowns increase with firm size, larger firms' responsiveness to productivity becomes relatively weaker (scenario (5)).

We analyze the role of technology in Figure D3c and Figure D3d. In scenario (6), we reduce the labor output elasticity compared to the baseline (1), making technology less labor-intensive. Although employment is undoubtedly lower in this scenario because labor is less relevant in the production process, firms' responsiveness to productivity is the same as in the baseline. Changes in output elasticities of labor that do not affect the returns to scale affect firms' responsiveness only if these changes occur jointly with the productivity shock (see main text Eq. (12)). We illustrate this in scenario (7), where changes in output elasticities occur as a firm expands after a productivity shock. As shown, responsiveness declines for all firms. Additionally, there is a gradient of responsiveness across firms of different sizes if the labor output elasticity declines at higher rates for larger firms. We highlight the role of returns to scale in scenarios (8) and (9). Under 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, Figure D3e illustrate the role of wages. In scenario (10), we consider a higher wage under a perfectly elastic labor supply curve. As shown, firms' responsiveness remains unchanged. This is because wages influence responsiveness only if the inverse supply elasticity (i.e., ξ) differs from zero.[56] 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, reflected by ξ, is constant in scenario (11), while it increases with size in scenario (12).

In summary, our general framework provides a clear connection between differences in responsiveness and differences in market power, wages, and technology across firms. If larger firms exert greater market power, employ increasingly less labor-intensive technologies as they grow, or pay higher wages while facing an increasing wage schedule, our framework can rationalize the size gradient of firm responsiveness observed in most European countries.

[56] To see that, note that the term related to wages in Equation (13), $\frac{\Delta w_{it}}{\Delta tfpr_{it}}$, 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.

D.2.3 Empirical evidence

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 using the German microdata. Specifically, we estimate an extension of our responsiveness regressions that allows firms' responsiveness to differ by the *levels* of firms' market power, technology, and wages. This extended responsiveness regression is defined as:

$$g_{it} = \beta_0 + \beta_{tfpr} tfpr_{it-1} + \beta_l l_{it-1} + (\boldsymbol{\beta}'_{tfpr\times\Lambda}\boldsymbol{\Lambda}_{it-1}) \times tfpr_{it-1} + \boldsymbol{\beta}'_{\Lambda}\boldsymbol{\Lambda}_{it-1} + X_{jt} + \epsilon_{it}. \quad \text{(D1)}$$

The vector $\boldsymbol{\Lambda}'_{it-1} = [log(\mu_{it-1}), log(\gamma_{it-1}), log(\theta_{it-1}), log(RTS_{it-1}), w_{it-1}, f(.)_{it-1}]$ captures the components of our firm growth decomposition (Eq. (11)). As the labor output elasticity captures relative factor intensities and returns to scale, we also include firms' returns to scale into the regression (RTS_{it-1}). We write the model as a level specification. Still, we also estimate a first difference version that substitutes $tfpr_{it-1}$ with $\Delta tfpr_{it-1}$ and omits the lagged labor control (other variables remain in lagged levels). Consistent with our previous regressions, we control for industry-year fixed effects (X_{jt}). The coefficients of interest are $\boldsymbol{\beta}'_{tfpr\times\Lambda}$, which capture the interaction effect of productivity with the components of our firm growth decomposition. These coefficients indicate how firms' employment growth response to productivity changes with the levels of firms' markups, markdowns, returns to scale, labor output elasticities, wages, and output net of productivity.

Table D4 presents results on the interaction coefficients from estimating Eq. (D1). The results are in line with our theoretical discussion and simulations. On average, higher markups, higher markdowns, and higher returns to scale are strongly associated with a lower responsiveness of employment to productivity. The evidence for a negative association between wages and responsiveness is weaker and only statistically significant in the first difference model. This aligns with our simulation, which shows that the impact of wages on responsiveness depends on the shape of the labor supply curve. Concerning labor output elasticities, we do not find a notable impact on firms' responsiveness; the coefficient is small and statistically significant at the 10% level only in the levels specification, while almost zero and statistically insignificant in the first difference model. This confirms our simulation results in which the output elasticity levels do not affect responsiveness when holding fixed returns to scale.

Table D4. Extended responsiveness regressions.

	Dep. variable *Employment growth rate* (g_{it})	
	Levels	FD
Lagged variables (in logs)	(1)	(2)
$TFPR$	0.162	0.466**
	(0.102)	(0.185)
$TFPR \times Markup$	-0.131***	-0.209***
	(0.019)	(0.044)
$TFPR \times Markdown$	-0.033***	-0.054***
	(0.007)	(0.016)
$TFPR \times$ $Labor\ output\ elasticity$	-0.014*	0.001
	(0.007)	(0.015)
$TFPR \times Wage$	-0.004	-0.042**
	(0.010)	(0.018)
$TFPR\times$ $Prod.\ fun.\ net\ of\ productivity$	-0.000	-0.000
	(0.001)	(0.001)
$TFPR \times$ $Returns\ to\ scale$	0.138***	0.137*
	(0.031)	(0.078)
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	0.069	0.071

Notes: This table presents results from estimating Equation (D1) in levels (column 1) and in first differences (column 2). All regressions control for lagged markups, markdowns, labor output elasticities, returns to scale, wages, and production function terms net of productivity (i.e., "main effects"). All regressions include industry-year fixed effects. The level specifications control for lagged levels of labor. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

In sum, our empirical results suggest that the *levels* of markup, wage markdown, and returns to scale have an influence on firms' responsiveness. We now study how these and other variables have changed over time and how they differ between small and large firms.

Size differences an evolution over time. Table D5 documents how the levels of market power, technology, and wages have changed over time and how they differ between small and large firms. Panel (a) shows that markups are low in the German manufacturing sector but have increased by approximately 5%. Wage markdowns are, on average, much larger but have not changed over time. Together, these results imply that firms' overall market power (i.e., the "combined" term) predominantly results from imperfect labor markets.[57]

Small and large firms have similar markups.[58] However, large firms have much more labor market power than small firms, which gives them higher overall market power. This differ-

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

[58] If anything, small firms tend to have higher (employment-weighted) markups. This is consistent with recent evidence in Mertens and Mottironi (2023).

ence in wage markdowns can rationalize the lower responsiveness of large firms. Over time, market power rises for large firms only, and our results suggest that this is due to rising product market power. Panel (b) shows the results for technology and wages. Across all firms, we find a substantial decline in the labor output elasticity. Concurrently, the intermediate input output elasticity increased, indicating that intermediates became a more important input factor relative to capital and labor. To the extent that these changes are correlated with productivity changes, this substitution towards intermediates reduces firms' employment responsiveness as highlighted in Section 5.4. Returns to scale are higher for large firms and only slightly changed. Also changes in output elasticities are similar across small and large firms. Regarding wages, large firms pay higher wages and experience a stronger wage growth.

Table D5. Levels and 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€

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, markdowns, and the combination of markups and markdowns as measure for firms total market power 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. German microdata.

Taking the results from Appendix D.2 together, the key takeaway is that cross-sectional differences in large and small firms' markdowns can rationalize cross-sectional differences in responsiveness between large and small firms. Additionally, increasing markup levels can contribute to a lower responsiveness of firms, for instance, by limiting the extent to which firms expand sales after a productivity shock (as discussed in the main text). The effect of changing output elasticities depends on the firm level correlation of those changes with firms' productivity shocks. Similarly, the effect of wages depends on the form of labor supply curve and the correlation of firms' wage changes with productivity shocks.

E Estimating production functions with the German data

Production function estimation. As discussed in the main text, we assume a translog production function:

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

where ϕ'_{it} captures the production inputs capital (K_{it}), labor (L_{it}), and intermediates (M_{it}) and its interactions. There are three identification issues preventing us from estimating the production function using OLS. First, 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. Second, 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. Third, as firms' flexible input decisions depend on unobserved productivity shocks, we face another endogeneity problem. We now discuss how we solve these three identification problems.

Solving (1) by deriving a firm-specific output price index. As one cannot aggregate output quantities (measured in different units) across a firm's product portfolio, we follow Eslava et al. (2004) and construct a firm-specific price index from observed output prices. We use this price index to deflate observed firm revenue.[59] We construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products in the following way:

$$PI_{it} = \prod_{o=1}^{n} \frac{p_{iot}}{p_{iot-1}}^{1/2(share_{iot}+share_{iot-1})} PI_{it-1}\,. \tag{E2}$$

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 in t and $t-1$. The first year available in the data is the base year ($PI_{i1995} = 100$). 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

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

in other cases with an average of product price changes within the same industry.[60] 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}.[61]

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)):

$$q_{it} = \tilde{\phi}'_{it}\boldsymbol{\beta} + B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\phi}^c_{it}) + tfp_{it} + \epsilon_{it}\,. \tag{E3}$$

$B(.) = B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\phi}^c_{it})$ 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}). $\tilde{\phi}^c_{it} = [1; \tilde{\phi}_{it}]$, where $\tilde{\phi}_{it}$ includes the production function input terms. 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 $\tilde{\phi}^c_{it}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\tilde{\phi}_{it}$ (a consequence of the translog specification). 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. In particular, 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 absorb the remaining differences in local and four-digit industry-specific input prices. Conditional on elements in

[60] 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.

[61] 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. Alternative approaches that deal with multi-product firms require 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.

$B(.)$, 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, which implicitly assume that firms face identical input and output prices within industries.

A difference between the original approach of De Loecker et al. (2016) and our version is that they estimate product-level production functions. We transfer their framework to the firm level using firm-product-specific sales shares in firms' total product sales to aggregate firm-product-level information to the firm level. This implicitly assumes that (i) firm aggregates of product quality increase in firm aggregates of product prices and input quality, (ii) firms' input costs for inputs entering as deflated expenditures increase in firms' input quality, and (iii) product price elasticities are equal across the firms' products. 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 the best practice. This is because the price control function can nevertheless absorb some of the unobserved price variation and does not require that input prices vary between firms with respect to all elements of $B(.)$. 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.

Solving (3) by controlling for unobserved productivity. To address the dependence of firms' intermediate input decision on unobserved productivity, we employ a control function approach (Olley and Pakes, 1996). We base our control function on firms' energy consumption and raw materials (e_{it}), which are part of intermediate inputs. Inverting the demand function for e_{it} defines an expression for productivity:

$$tfp_{it} \equiv g(.) = g(e_{it}, k_{it}, l_{it}, \mathbf{\Gamma}_{it}). \tag{E4}$$

$\mathbf{\Gamma}_{it}$ 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 a firm's number of products ($NumP_{it}$), and the log of its average wage (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 De Loecker (2013): $tfp_{it} = h(tfp_{it-1}, \mathbf{Z}_{it-1}) + \xi_{it}^{tfp} = k(.) + \xi_{it}^{tfp}$, where ξ_{it}^{tfp} 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.[62] Plugging Eq. (E4) and the law of motion for productivity into Eq. (E3) yields:

$$q_{it} = \tilde{\phi}_{it}' \boldsymbol{\beta} + B(.) + k(.) + \epsilon_{it} + \xi_{it}^{tfp} . \tag{E5}$$

Identifying moments and results We estimate Eq. (E5) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[63] 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_{it}^{tfp}. Similarly, we use lagged values of terms including firms' market share and output price index as instruments for their contemporary values.[64] Our identifying moments are:

$$E[(\epsilon_{it} + \xi_{it}^{tfp})\mathbf{O}_{it}] = 0, \tag{E6}$$

where $\mathbf{O}_{it}$ 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:

$$\mathbf{O}_{it}' = (\boldsymbol{J}(.), \boldsymbol{A}(.), \boldsymbol{\Theta}(.), \boldsymbol{\Psi}(.),) , \tag{E7}$$

where for convenience, we defined:

$$\boldsymbol{J}(.) = (Exp_{it-1},\ NumP_{it-1},\ w_{it-1}, l_{it},\ k_{it},\ l_{it}^2,\ k_{it}^2,\ l_{it}k_{it},\ G_{it},\ D_{it}) ,$$

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

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

[62] Doraszelski and Jaumandreu (2013) also highlight the role of R&D investment in shifting firms' productivity process. Unfortunately, we do not observe R&D expenditures for the early years in our data.

[63] We approximate $k(.)$ 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).

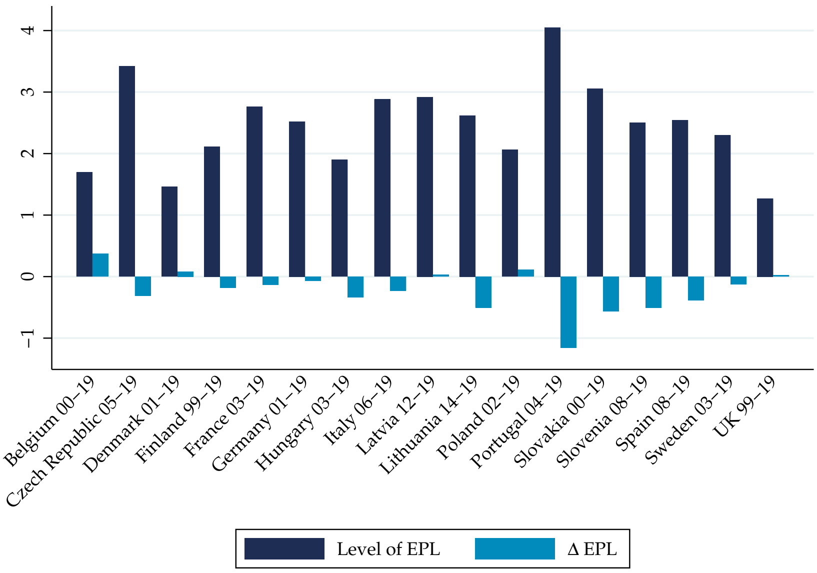
[64] This also addresses simultaneity concerns with respect to the price variables entering our estimation.

$\Psi(.) = \sum_{n=0}^{3} \sum_{w=0}^{3-b} \sum_{h=0}^{3-n-b} l_{it-1}^{n} \, k_{it-1}^{b} \, e_{it-1}^{h}$.

Table A5 reports summary statistics for output elasticities, markups, and wage markdowns based on our production function estimation. We drop observations with negative output elasticities from the data (2%) as these are inconsistent with our production model.

F Proxies of labor adjustment costs in Europe

Figure F1. Employment protection legislation index (EPL), vintage 1.



Notes: This figure plots the weighted Employment Protection Legislation index created by the OECD. For each country, we plot in the first bar the weighted average between the index for temporary and regular contracts for the first year in the data, using the share of temporary contracts in a country as weights. In the second bar, we plot the difference between the first and last year in the data. Data on Croatia and Romania was not available. OECD data.

Figure F1 reports employment protection legislation indicators by countries based on OECD data. To enhance cross-country comparability, the OECD has collected and ranked legislation-induced costs across countries OECD (2020). The index ranges from 0 to 6 and assigns a score for each of the identified criteria based on the legislation as of January 1st of each year. In a nutshell, this metric measures the ease with which employers hire or fire employees. The index is created separately for regular and temporary workers. Figure F1 displays a weighted version of this metric using the share of temporary workers in each country-year reported by the OECD as weights (dark-blue bars). As shown by the light-blue bars, the measure of legislation-induced labor adjustment costs has decreased in most countries.

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