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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 (e.g., Criscuolo et al., 2014; Decker et al., 2014; Decker et al., 2016a; Dent et al., 2016; Guzman and Stern, 2020; Akcigit and Ates, 2023; Calvino et al., 2018; Calvino and Criscuolo, 2019; Calvino et al., 2020). 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 Sahin, 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 (Chiavari, 2023; De Ridder, 2024), or rising adjustment costs (Decker et al., 2020) have been recently explored for the US. For Europe, evidence regarding the potential firm-level mechanisms driving the decline in business dynamism remains limited.[1] We attribute this, in part, to the absence of accessible, cross-country comparable European data that enables the measurement and study of business dynamism in a consistent and harmonized manner. In this paper, we address this gap by collecting and *publishing* new micro-aggregated data on key indicators of business dynamism for 19 European countries in collaboration with the Competitiveness Research Network (henceforth, CompNet).[2]

We use these novel data to document key facts on business dynamism and firm responsiveness to shock dynamics for an unprecedented number of European countries over the last two decades. Our data covers the years from 1997 to 2021, although with heterogeneous time coverage across countries.[3] Across all European countries analyzed, we find a significant and

[1] One exception is Andrews et al. (2015) that explores declining knowledge diffusion across a subset of OECD countries.

[2] 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. The data that we collected are accessible to researchers in the Data Appendix of this paper and in the 9^{th} vintage of the CompNet database with a simple request procedure at www.comp-net.org/data/9th-vintage/.

[3] The data module that we designed has been included for the first time in the 9^{th} vintage of the CompNet data and will be updated and released in the future every 1-2 years by the CompNet team.

widespread decline in aggregate job reallocation rates (averaging -21%), a trend comparable to the one observed in the US over the same period. Sales reallocation rates exhibit a similar decline, indicating a wider reduction in the reallocation of economic activity across firms. The decline in job reallocation concerns most economic sectors and is mainly driven by dynamics within sectors and size classes rather than by compositional changes. Job reallocation declined mostly among older firms and not (or to a lesser extent) among young firms. However, the employment share of young firms has declined substantially, which points to a structural aging of the economy in which mature firms drive aggregate trends.

Since aggregate job reallocation is ultimately driven by individual firms' decisions to expand or contract in response to changes in their fundamentals and market conditions, we explore the firm-level mechanisms of this decline building on the stylized framework by Decker et al. (2020) (henceforth DHJM). In standard models of firm dynamics, they show that a slowdown in job reallocation can be attributed to two potential mechanisms. First, firms' employment responsiveness to productivity could weaken; that is, firms may hire or downsize less in response to a given productivity change. Second, the dynamics of productivity shocks themselves could have become more muted, which, for a given responsiveness, lowers job reallocation. We examine these alternative mechanisms within each European country.

Our analysis indicates that firms' employment responses to productivity shocks have weakened in many European countries. In relative terms, the magnitudes of these declines are comparable to those in the US. However, regarding the dynamics of productivity shocks, we find a notable difference between European countries and the US, particularly in the last decade. Specifically, we document a generalized reduction in the dispersion of productivity changes, indicating that both the shocks *and* the responsiveness hypotheses are relevant for explaining declining job reallocation in Europe.

We confirm these results with an additional database on German manufacturing firms, which we can directly access, spans a longer timeframe (starting from 1995), and enables us to derive more accurate productivity estimates. Using these data, we also quantify that 40% of the observed decline in job reallocation can be attributed to the reduction in firms' responsiveness - a substantial share, though notably smaller than in the US, where, according to DHJM, it accounts for nearly the entire decline in job reallocation.

The common assessment in the literature is that a decline in responsiveness signals an increase in labor adjustment costs. Although these costs are likely to be higher in Europe than in the US, there has been a concerted policy effort of European economies to increase labor market flexibility over the last decades (Eichhorst et al., 2017; Gehrke and Weber, 2018). At the same time, there is increasing evidence that firms' markups (De Loecker et al., 2020; Calligaris et al., 2024; European Commission, 2024) and technology (Hubmer and Restrepo, 2021; Mertens and Schoefer, 2024) have changed over time. Motivated by this evidence, we derive an empirical production-side framework with labor market imperfections that connects changes in firms' market power and technology to firms' responsiveness.[4] The main insight is that changes in the pass-through of productivity to markups, markdowns, and technology (rather than the levels of these variables) are key elements for understanding changes in responsiveness.

We apply our framework to rich German firm-product level data, where we can estimate markups, markdowns, and output elasticities 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 data sources in this paper, they contain firm-specific price information.[5] Overall, we find that changes in labor market imperfections, including adjustment costs, are an unlikely explanation for the documented decline in responsiveness. If anything, they counteracted it. Instead, we find that, over time, firms have responded to productivity changes by increasing their markups more significantly. At the same time, labor output elasticities have declined more sharply in response to productivity, indicating that more productive firms tend to produce with less labor-intensive technologies. Both trends, which are particularly pronounced among larger firms, are consistent with the observed decline in responsiveness. Although we cannot quantify the contribution of each component (markups, markdowns, technology) separately, our findings offer new insights into the dynamics of responsiveness, suggesting a distinct set of policy implications compared to traditional explanations based on adjustment costs.

The remainder of this article is structured as follows. Section 2 describes the collection process

[4] Our framework allows for a broad interpretation of labor market imperfections that include monopsony power and adjustment costs.

[5] 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).

and main features of our data. Section 3.1 presents stylized facts on European business dynamism. Section 3.2 shows how firms' responsiveness and productivity shocks have changed over the past two decades. Section 5 presents and applies our firm-level framework to analyze how firms' market power and technology shape firms' responsiveness. Section 6 concludes.

2 Data

2.1 The CompNet data

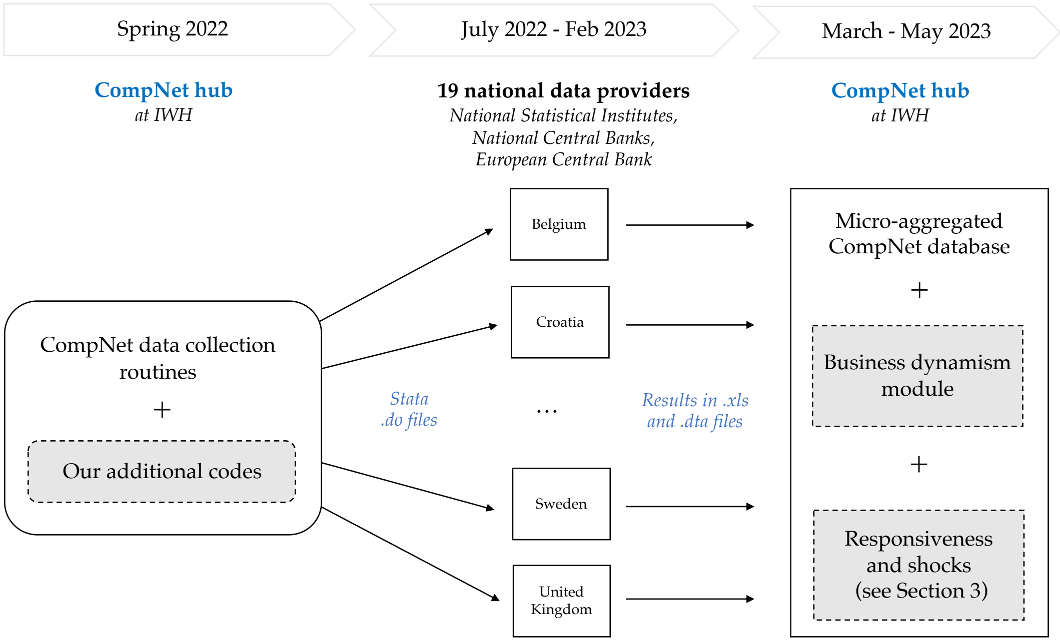
Data collection process. We collect and publish novel data on European business dynamism with the Competitiveness Research Network (henceforth, CompNet). Together with the CompNet team, we designed and distributed harmonized data collection protocols (i.e., Stata codes) across administrative firm-level 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 and are akin to the annual US census surveys. Importantly, we did not access the microdata in person but relied on the cooperation of data providers to harmonize input data across countries (based on our instructions) and to run the identical codes. As illustrated in Figure 1, the outcome of this data collection procedure is a publicly accessible pan-European harmonized micro-aggregated database to which we contribute with a novel module specific to business dynamism. In addition to this, we included a series of firm-level econometric analyses on the productivity shock dynamics and firms' employment responsiveness to productivity 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, which is accessible to researchers via a simple application form.[7]

[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] More information on accessing the database is available at www.comp-net.org/data/.

Figure 1. Data collection process and timeline.



Features and coverage. The data covers firms, defined as independent legal entities, operating in the business sector.[8] 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").[9] Our analyses focus on the sample with at least 20 employees, as this is available for all countries. However, we report key results for the set of countries where the "all sample" is available in online Appendix C.3. Table 1 provides an overview of time and sample coverage across countries. The database covers the last two decades, although the time span differs across countries.[10] As shown in Online Appendix Table A2, the coverage of firms and employees is very high.[11] We refer to CompNet's User

[8]We consider firms with NACE rev.2 codes 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), 69-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities). NACE is the Statistical Classification of Economic Activities in the European Community. We follow the literature and drop the real estate sector from our analysis.

[9]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. To construct the "20e sample", CompNet keeps every firm-year observation in which the number of employees is at least 20.

[10]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.

[11]The "20e sample" covers 75% of total employment and 73% of the number of firms among firms with at least 20 employees 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).

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.

Guide (CompNet, 2023) for further details on the database.[12]

2.1.1 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 sectors and countries. Following Davis et al. (1996) (henceforth, DHS), we define the job reallocation rate as 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 em-

[12]Finally, it is important to note that due to country-specific disclosure rules, a few results in Section 3.1 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.

ployment shares of each firm, $s_{it} = \frac{\overline{L}_{it}}{\sum_{i \in n} \overline{L}_{it}}$.[13] We measure the yearly job reallocation rate at different aggregation levels (country, sector, industry, size, and age classes) denoted by n. 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/contracting firms and excludes entering and exiting firms.

In addition to job reallocation rates, we collect other metrics of business dynamism. In particular, we analyze sales reallocation measures, defined by replacing employment in Eq. (1) with sales, and the employment share of young firms. We define a firm as "young" if its creation does not date back more than five years.[14]

Firm-level productivity. In Section 3.1, we analyze how firms' employment responds to productivity. We estimate it assuming the following Hicks-neutral Cobb-Douglas production function 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 2-digit NACE industries. We deflate gross output and intermediate input expenditures with country-industry-year-specific deflators from EU-KLEMS.[15] To estimate the output elasticities, we rely on the 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.[17] Using our estimates of output elasticities, we compute the log of total factor productivity as

[13] Labor is measured as the headcounts of full- and part-time employees (yearly average), excluding any shareholder/owners. It is defined at a specific point in time for Denmark, Sweden, Germany, the Czech Republic, and Portugal.

[14] We can measure firms' age only for 14 countries where we have data on firms' registration years.

[15] 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.

[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.

[17] We rely on cost-share-based productivity measures as they perform consistently well across all the countries within our micro-distributed data collection process (which prevents us from directly inspecting the firm-level data and intermediate estimation results).

residual from the estimated industry-year-specific production function:

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

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 $TFPR_{it}$.

2.2 German manufacturing sector microdata

In the second part of the paper, we use more detailed firm-level data for the German manufacturing sector. We access these data at the Research Data Centres of the German Statistical Office.[18] In addition to employment, investment, and input expenditures, this dataset contains detailed information on the quantities and prices of the products sold by each firm (approximately 5,000 product categories).[19]

We use these rich firm-product-level data to (i) validate key findings based on the CompNet data, (ii) quantify the importance of productivity shock dynamics and responsiveness in driving job reallocation, and (iii) analyze how production technologies, markups and labor market imperfections affect firms' responsiveness to productivity. The firm-product-specific price information allows us to estimate quantity-based production functions, which is essential to properly estimate firms' markups, wage markdowns, and output elasticities (more details in Section 5.2). Regarding 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.

[18] 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.

[19] Examples of products are "Tin sheets and tapes, thicker than 0.2mm" or "Workwear - long trousers for men, cotton". While employment refers to the September 30$^{\text{th}}$ value, all other variables pertain to the full calendar year.

3 Business Dynamism in Europe

This section leverages our novel data to document key facts on European business dynamism. Section 3.1 confirms and expands on findings previously established for a subset of European countries (e.g., Calvino et al., 2020). Section 3.2 introduces new evidence on the responsiveness of firms to productivity and the dynamics of productivity shocks in Europe. Additional supporting analyses are provided in the online Appendix C.

3.1 Key facts on declining business dynamism

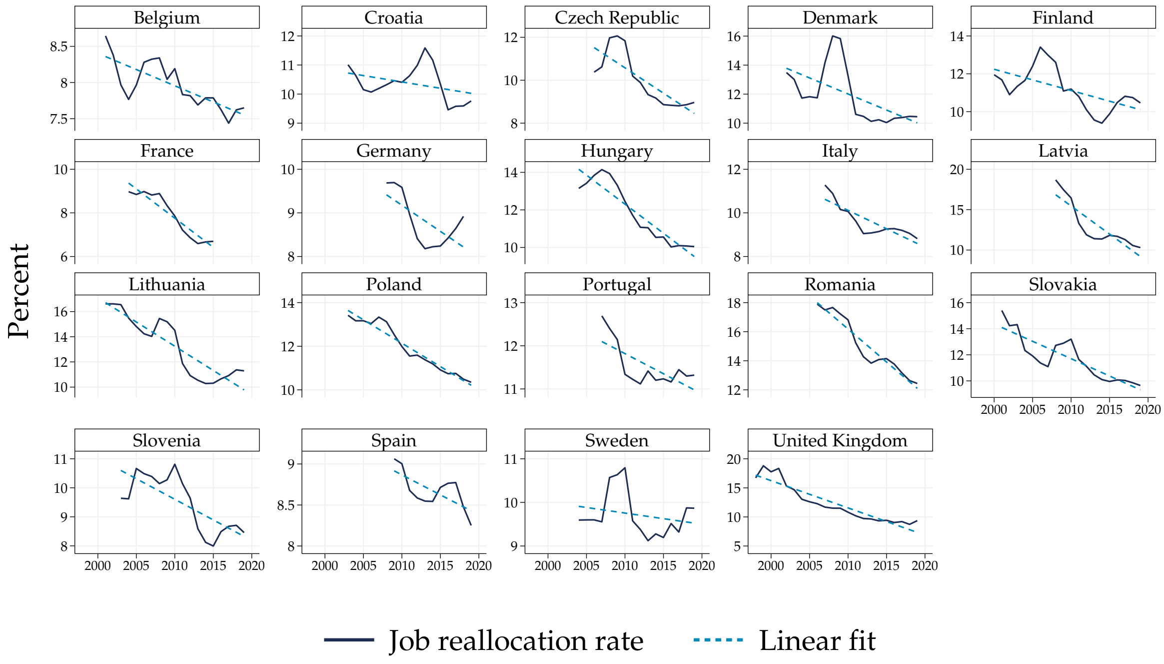
Fact 1. ***There is a pervasive decline in business dynamism in Europe.*** In Figure 2, we document a widespread decline in business dynamism in Europe. Panel (a) reports job reallocation rates for firms with at least 20 employees, showing a stark trend decline (dashed light-blue line) in job reallocation 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 they joined the European Union. In Appendix C.3, 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 C5). 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.[20]

For the 14 countries for which we have data on firms' registration years, Figure 2, Panel (b) shows that the share of employment in young firms also declines. Again, this reduction is more pronounced among Eastern European countries. 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 (Figure C6). High-growth young firms are, by definition, part of the 20-employee sample because most young firms remain below this size threshold in their first years of activity. Therefore, our findings imply that economic activity among high-growth young firms exhibits a particularly strong decline in Europe.[21]

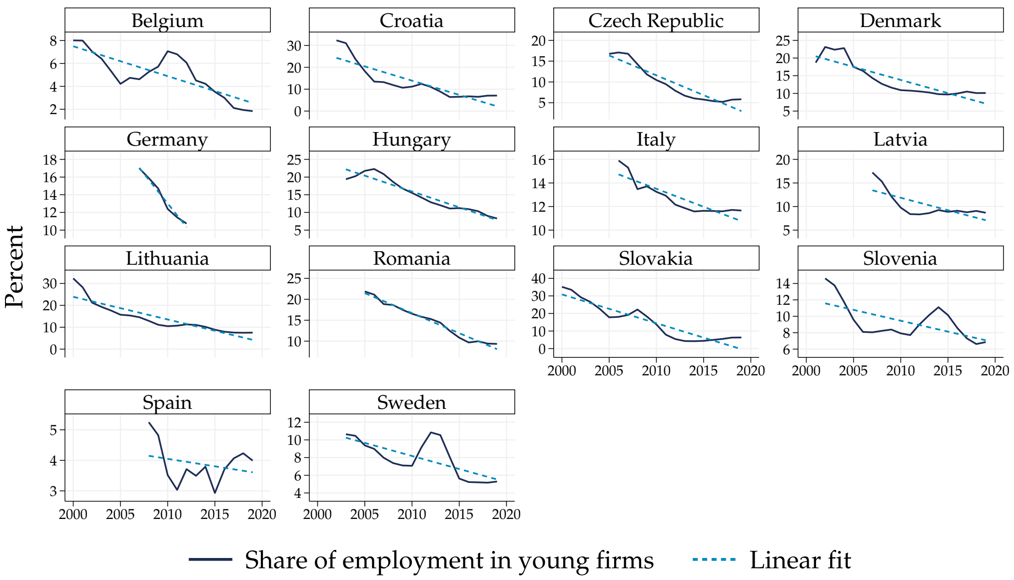
[20] As mentioned in Section 2.1.1, our job reallocation rates abstract from firm entry and exit. Therefore, in online Appendix Figure C1, we use Eurostat data to show that there is no systematic trend in firm entry or exit

Figure 2. Business dynamism in Europe.

(a) Job reallocation rates



(b) Young firms' employment shares



Notes: Three-year moving averages of the job reallocation rates defined in Eq. (1) (Panel (a)) and the employment share of firms not older than five years (Panel (b)). The light-blue dashed lines report linear trends. In Panel (b), the 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.

Compared to the US, Europe shows a lower level of job reallocation.[22] Calculations from the

that could offset the decline in job reallocation that we document.

[21]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).

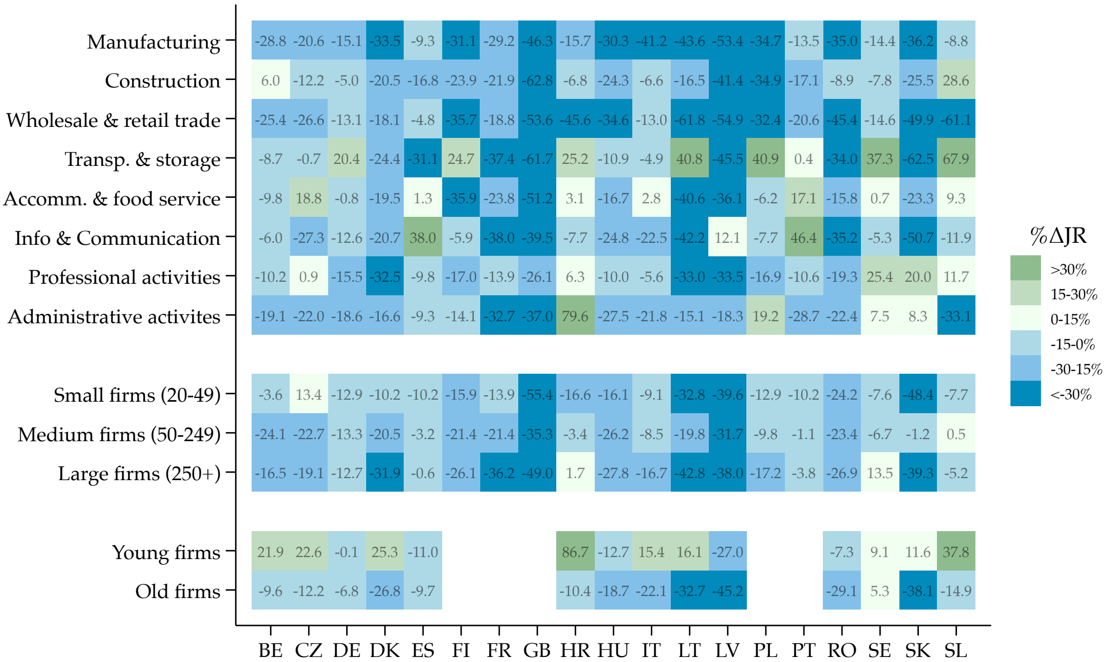
[22]Our results confirm and extend previous findings by Haltiwanger et al. (2014b), who document lower job reallocation rates for a small set of European countries during the 80s and 90s.

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 among firms with at least 20 employees.[23] By contrast, job reallocation rates in Western Europe range from 8% to 12%, with countries like Germany, Spain, and Belgium at the lower end. Eastern European countries display reallocation rates closer to the US. However, an important difference is that job reallocation rates measured by the US Census reflect employment changes at the establishment level, while CompNet measures 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 be broadly more 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 decline in reallocation is evident in most sectors and firm size classes.*** Turning to within-country dynamics, Figure 3 shows percentage changes in job reallocation rates by economic sectors, firm size, and age classes. To compare long-run trends, we plot the percentage change between the average of the first and last two years in each country. In all countries in our sample, we document a reduction in job reallocation rates in most sectors. The relative decline is notably pronounced in manufacturing and in wholesale and retail trade, the two largest sectors in the European economy. Similarly, we find that job reallocation rates declined across the entire firm size distribution, with only a few exceptions. This is confirmed in Figure C7 when we include information on smaller firms (1-9 and 10-19 employees). In terms of age differences, we also find that job reallocation rates decline primarily for old firms, while they increase for younger ones. This final piece of evidence points – yet again – to a structural aging of the economy in which old firms drive aggregate trends.

[23]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 accessed for firm-size classes here.

Figure 3. Relative decline in job reallocation rates by sector, size, and age class.



Notes: Relative changes between the first and last two years for every country-sector, country-size-class, and country-age class combination. The 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.

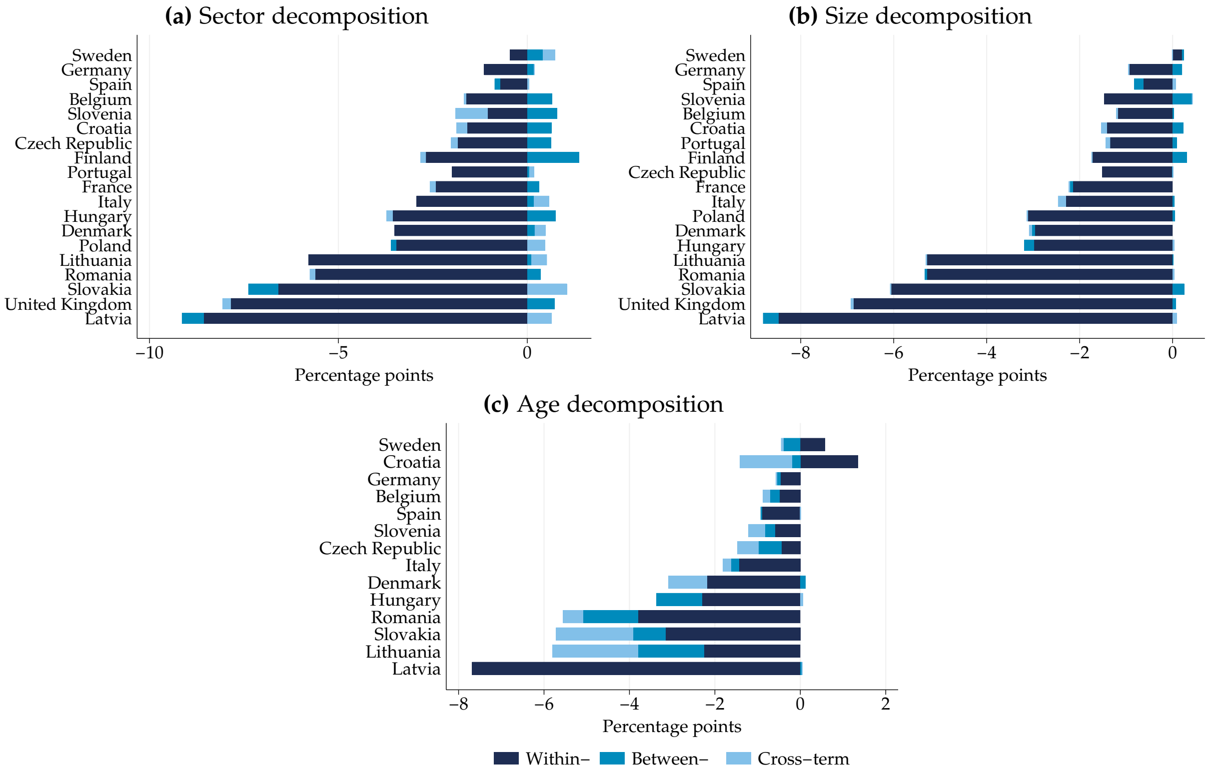
Fact 3. ***The decline in reallocation is mainly driven by within-sector, size-class, and age–class dynamics.*** To inspect whether changes in aggregate job reallocation rates are driven by within-group dynamics or compositional shifts, we use a standard shift-share decomposition (Foster et al., 2001) at the industry, size, and age-class level:

$$\Delta JR_{c(t-t_0)} = \underbrace{\sum_n s_{cnt_0}\,\Delta JR_{cn(t-t_0)}}_{\text{within-term}} + \underbrace{\sum_n \Delta s_{cn(t-t_0)}\,JR_{cnt_0}}_{\text{between-term}} + \underbrace{\sum_n \Delta s_{cn(t-t_0)}\,\Delta JR_{cn(t-t_0)}}_{\text{cross-term}}, \tag{4}$$

where c denotes countries and n denotes the industry, size, or age class. s_{cnt} are a group's employment share. t_0 represents the initial year, which may differ across countries. Figure 4 shows the results of these decompositions for each country.[24] We find that most of the decline in job reallocation is explained by within-group dynamics and not by changes in sectoral, size, or age composition (although age composition somewhat matters in a few countries).

[24]Results for the "all sample" are qualitatively and quantitatively similar (Figure C8).

Figure 4. Decompositions of job reallocation rates.



Notes: Results of the decomposition of job reallocation rates across sectors (Panel (a)), firm size-classes (Panel (b)), and firm age-classes (Panel (c)). Panel (b): The 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 (c): All countries except Romania additionally include the real estate sector as we directly use age-class aggregated data. 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, country-size-class, or country-age-class combination. CompNet data, firms with at least 20 employees.

3.2 Responsiveness *and* shocks hypotheses

To investigate the mechanisms behind the widespread decline in reallocation across Europe, we explore changing patterns of job reallocation following DHJM. In standard models of firm and industry dynamics, job reallocation between firms arises from firms' responses to changes in their productivity (e.g., Hopenhayn, 1992; Hopenhayn and Rogerson, 1993). From this perspective, a decline in 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, which also implies lower reallocation.[25]

[25] This stylized view focuses on 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 examine the influence of market power and technology on shaping responsiveness and job reallocation. By doing so, we implicitly take into account overall trends in technology and market power, which may also be driven by aggregate labor supply-side factors.

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

3.2.1 Responsiveness hypothesis

We estimate the same responsiveness model as in DHJM, with the aim to capture the relationship between a firm's employment growth, g_{it}, and its lagged productivity and employment levels. This ensures a straightforward comparison with their findings for the US.

We provide more details about the derivations and assumptions leading to this specification in online Appendix B. 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 (and its change over time) as follows:

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

l and *tfpr* denote the log values of employment and productivity. β_1 captures the marginal responsiveness of a firm's employment growth to its productivity, conditional on its initial employment, l_{it-1}. Including the linear trend, T_t, allows us to test if this relationship has changed over time. δ_1 will be negative if, on average, the responsiveness to productivity declines over time. 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.[26] To relate our analysis to the decline in the job reallocation rate, which is the employment-weighted average of g_{it}, we weight our regression by firms' employment level using s_{it} (defined in Eq. (1)) as weight. Finally, note that the specification in Eq. (5) closely follows DHJM and also uses lagged productivity on the

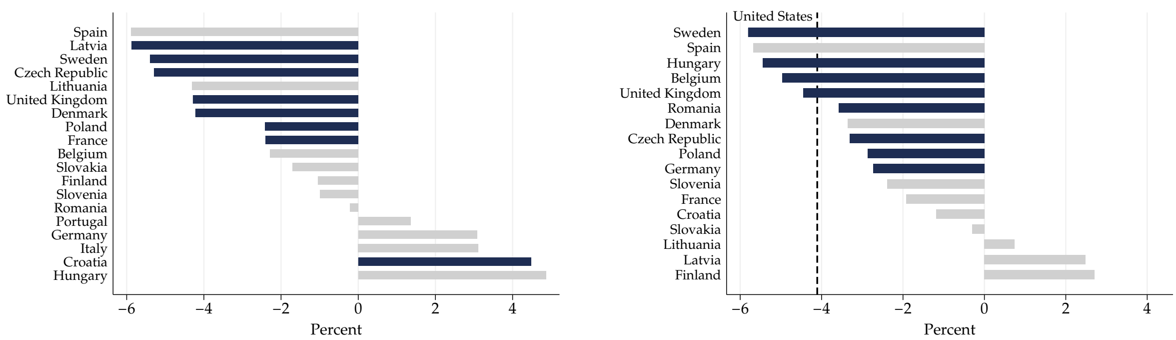
[26] Using German microdata, we also estimate a first-difference version of specification (5) in Section 4. DHJM and online Appendix B show how this specification in levels corresponds to a transformation of a first-difference specification, where employment changes are directly related to productivity changes. With the German manufacturing data in Section 4, we estimate both specifications and find comparable results. As argued in DHJM, however, the specification in levels is less demanding in terms of data.

right-hand side. As discussed in Appendix B and in DHJM, this helps to address differences in the data collection timing between labor and other variables. Furthermore, it allows for potential extra time for employment to adjust.

We report 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 5 separately for the business economy (Panel (a)) and manufacturing (Panel (b)). The separate analysis for manufacturing allows us to compare our results with DHJM, which could estimate total factor productivity for manufacturing only.

Figure 5. Relative changes in responsiveness over time.

(a) Business economy **(b)** Manufacturing only



Notes: Estimated coefficient of the linear trend relative to the initial responsiveness, i.e., δ_1/β_1 in Eq. (5). Underlying estimates for the entire business economy in Panel (a) are reported in Table C1 and for manufacturing only in Panel (b) in Table C4. The overall regression results are available in our data appendix. Countries are ranked in descending order. All results come from our CompNet data collection process within CompNet, except for those from the German manufacturing sector in Panel (b) which we directly estimated using the same method of estimating productivity as in CompNet. Bars are colored if both coefficients, δ_1 and β_1, are statistically significant at least at the 10% level. We excluded Portugal and Italy from the manufacturing results due to unrealistically high, statistically insignificant values (+21% and -39%, respectively), driven by extremely small values in β_1. The dashed line reports the relative change estimated for the United States over 2000-2013 by DHJM. Portuguese data start in 2009 due to missing values in TFPR. CompNet and German microdata (manufacturing sector), firms with at least 20 employees.

We estimate a declining responsiveness coefficient ($\delta_1 < 0$) in most countries. In the "20e sample", the negative δ_1 coefficient is statistically different from zero in around half of them, which are highlighted in blue. These results are confirmed when performing the same analysis for the countries where we observe firms with less than 20 employees (Figure C9). Using the "all sample", we find a statistically significant decline in responsiveness in additional countries, such as Spain or Lithuania.[27] Relative changes in responsiveness range from 2

[27]The fact that the coefficient, δ_1, becomes statistically significant in these countries when using more firms (the number of firms is 8 times larger on average in the "all sample") suggests that statistical power may be an issue in our "20e sample".

to 6 percent per year. This aligns well with US evidence: DHJM report an average annual decline in responsiveness of approximately 4.1 percent over the 2000-2013 period for the US manufacturing sector.[28]

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 Appendix Figure C4, we find evidence of a downward trend in responsiveness in many countries also with this more flexible estimation approach.[29]

3.2.2 Shocks hypothesis

We 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:

$$tfpr_{it} = \rho\, tfpr_{it-1} + X_{jt} + \eta_{it}. \tag{6}$$

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. As highlighted in DHJM, a decline in the dispersion of productivity innovations leads to a decline in the dispersion of firm growth, ultimately reducing job reallocation.

We report our estimates for the dispersion in productivity innovations, η_{it}, for the periods 2009-2013 and post-2013 in Figure 6, Panel (a), showing that it declined in most countries. Unfortunately, our data collection codes did not yield results before 2009. Therefore, we use complementary results on the standard deviations of industry-demeaned yearly productivity changes in Figure 6, Panel (b). We observe that, for most countries, the dispersion of productivity changes post-2013 is also below its pre-2009 level. Figure C10 reports similar results based on the "all sample" countries. This decline in the dispersion of productivity shocks is a key difference between Europe and the US, where DHJM document a substantial *increase* in

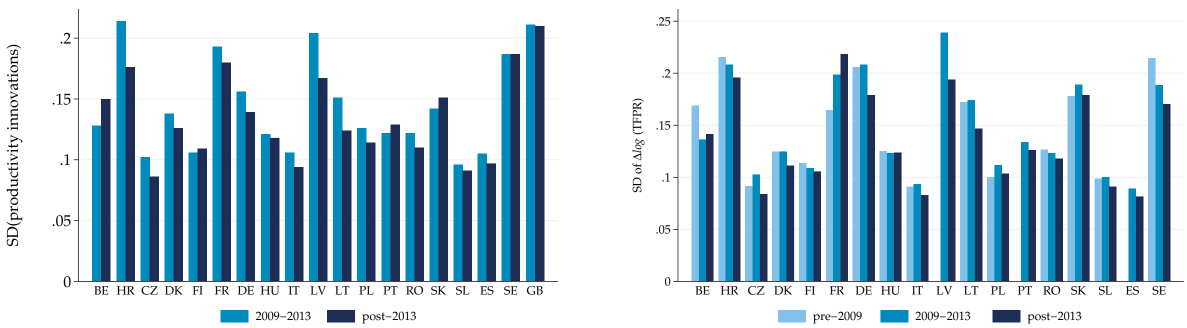
[28] We calculate the relative changes for the United States based on coefficient estimates reported by DHJM in Table 1 - Panel B. The relative decline in responsiveness for their entire period is 2.25%.

[29] 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.

the dispersion of productivity innovations.[30] In contrast to US evidence, our result suggests that the decline in job reallocation in Europe is, in part, also the result of muted productivity dynamics.[31]

Figure 6. Evolution in the dispersion of productivity innovations.

(a) AR(1) process **(b)** Productivity changes



Notes: Standard deviation of the residuals of the AR(1) process in Eq. (6) estimated over two consecutive periods. Overall regressions results are reported in our data appendix. Data on (b) was not supplied for the United Kingdom. CompNet data, firms with at least 20 employees.

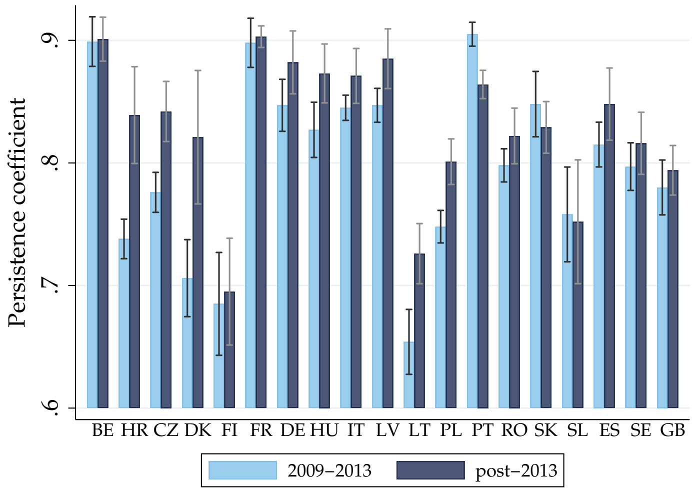
Productivity persistence. The estimation of the AR(1) process also provides us with information about the persistence of productivity, i.e., the coefficient ρ in Eq. (6). This is informative on potential mechanisms behind the declining responsiveness, as a declining shock persistence may reduce firms' incentives to adjust to a given productivity shock if firms anticipate the lower permanence of productivity realizations. Put differently, if firms expect that a productivity shock is not persistent, they might not adjust their labor inputs in response to it. As a result, lower productivity persistence could already provide one explanation for declining responsiveness. However, Figure 7 illustrates that, if anything, persistence increased in most countries. In Section 4, we replicate these results, including earlier years, with our German microdata and find similar results. This suggests that we need to think about alternative

[30] Unfortunately, we cannot compare our results with productivity shock dispersion in the US after 2009, given their analysis was until the 2000s. 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.

[31] 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 and follower firms declined.

mechanisms to rationalize declining responsiveness, which is the focus of Section 5.

Figure 7. Evolution of productivity persistence.



Notes: Point estimates of the persistence coefficient ρ in the AR(1) in Eq. (6) estimated over two consecutive periods. Complete regression results are available in our data appendix. CompNet data, firms with at least 20 employees.

4 Evidence from German Manufacturing

While CompNet stands out for its extensive coverage and cross-country comparability, we are unable to directly access the underlying firm-level data, which limits our capacity to refine and expand our analyses. Moreover, our regression analyses using CompNet data are based on relatively basic estimates of firm-level productivity. To overcome these restrictions, we access a richer firm-product-level dataset on German manufacturing, one of the most important economic sectors in Europe. As the data contain firm-specific price information, we can estimate firm productivity with a more refined approach. Moreover, as the data range from 1995 to 2017, we can analyze trends over a longer period. We use these richer data to confirm our results on the responsiveness and shock hypotheses, shed light on differences by firm size, and quantify their relative importance in explaining declining aggregate job reallocation - something that we could not do with the CompNet data.

4.1 Estimating refined measures of productivity

Using the German data, we derive productivity from estimating a *translog* production function that allows for firm- and time-specific output elasticities. This more flexible production function is defined as follows:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \\ \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + tfp_{it} + \epsilon_{it}, \tag{7}$$

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 productivity term and ϵ_{it} is an i.i.d. error term. We estimate Eq. (7) 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 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. (7). p_{it} is the log of a firm-level output price index as defined in Eslava et al. (2004) and described in Appendix E.[32]

4.2 Responsiveness and shocks hypotheses in German microdata

With these refined productivity estimates, we confirm that both the shock and responsiveness hypotheses are relevant for the decline in job reallocation.[33]

Responsiveness. In Table 2, we report the results on the responsiveness regression (Eq. (5)) using the German microdata. As reported in Column (1), we find a significant declining linear trend in responsiveness. To allow for more flexibility, we estimate the same regression with a period interaction (as in Figure C4), yielding consistent results (Column (2)).

[32] To ensure that outliers do not drive our results, we drop the top and bottom one percent in industry-demeaned TFPR.

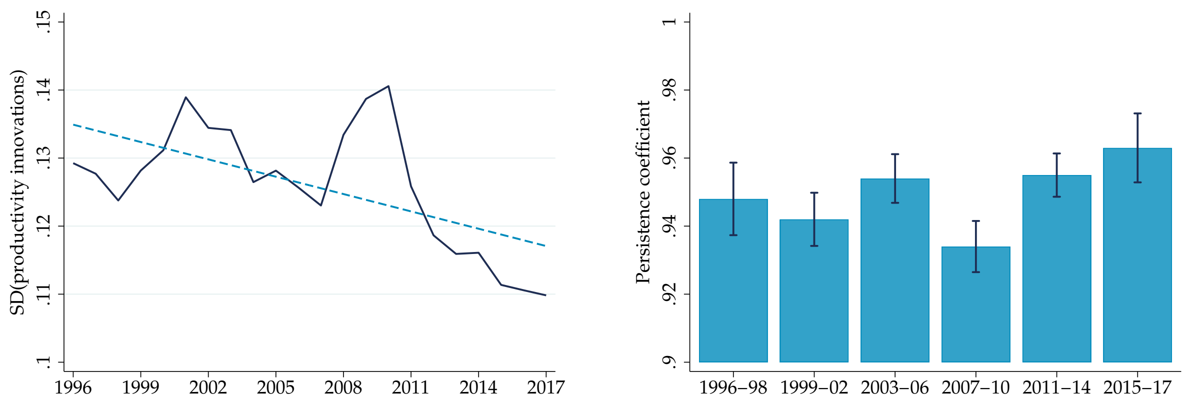
[33] The job reallocation rate decreased by one-third, from 8.3% in 1996 to less than 5.6% in 2017. Appendix Figure D1 compares the dynamics in job reallocation rates estimated with CompNet data and the German firm-level data, highlighting that both datasets lead to comparable results, both in levels 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 results across Europe.

In Appendix Table D1, we report similar results also for alternative specifications in first-differences. Columns (3)-(7) estimate the period specification by size (number of employees) quintiles. The 3^{rd} and 4^{th} quintiles show the most pronounced declines in responsiveness, and overall, larger firms tend to display stronger declines than smaller firms.

Productivity shock dynamics. Regarding productivity dynamics, Figure 8 shows the results on the dispersion of productivity shocks derived from estimating the AR(1) process (Eq. (6)) of our TFPR measure over six different time windows while controlling for industry-year fixed effects. 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. Table 3 replicates this analysis by size quintiles and reports the first and last years of the time series of the standard deviation of productivity innovations from an AR(1) for productivity that is estimated separately for six periods and by five firm size quintiles. We find that the dispersion of productivity shocks declines similarly in all parts of the firm size distribution.

Figure 8. Productivity dynamics in the German manufacturing sector.

(a) Dispersion in productivity shocks **(b)** Persistence over time



Notes: Estimates based on an AR(1) process for log $TFPR_{it}$ 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) and for five size quintiles (number of employees) defined by industry. 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.

Table 2. Responsiveness regressions in the German manufacturing sector.

	Employment growth rate (g_{ijt})						
	All firms		**1st quintile**	**2nd quintile**	**3rd quintile**	**4th quintile**	**5th quintile**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$tfpr_{it-1}$	0.0409***						
	(0.0063)						
$tfpr_{it-1} \times T_t$	-0.0013***						
	(0.0004)						
Period 1996-98		0.0482***	0.042***	0.051***	0.080***	0.090***	0.052***
		(0.0110)	(0.013)	(0.015)	(0.014)	(0.015)	(0.017)
Period 1999-02		0.0343***	0.049***	0.037***	0.040***	0.030***	0.043***
		(0.0066)	(0.010)	(0.011)	(0.008)	(0.009)	(0.010)
Period 2003-06		0.0165***	0.041***	0.021***	0.027**	0.022***	0.015*
		(0.0059)	(0.008)	(0.008)	(0.010)	(0.006)	(0.009)
Period 2007-10		0.0334***	0.021***	0.028***	0.037***	0.025***	0.038***
		(0.0052)	(0.007)	(0.006)	(0.006)	(0.06)	(0.008)
Period 2011-14		0.0161***	0.027***	0.027***	0.021***	0.022***	0.015**
		(0.0044)	(0.005)	(0.005)	(0.005)	(0.051)	(0.007)
Period 2015-17		0.0156***	0.040***	0.021***	0.021***	0.014**	0.017**
		(0.0045)	(0.007)	(0.007)	(0.005)	(0.059)	(0.007)
Labor controls in $t-1$	yes	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes	yes
Observations	180,022	180,022	36,745	35,633	35,943	35,725	35,961
N of firms	38,721	38,721	13689	12580	10871	8756	5318
R^2	0.053	0.053	0.043	0.050	0.052	0.058	0.066

Notes: Results from estimating responsiveness coefficients in various specifications. Column (1) reports the estimates of the responsiveness regression with a linear trend as in Eq. (5), while Column (2) with a period interaction instead of a linear trend. Columns (3)-(7) replicate the specification in Column (2) by size (number of employees) quintiles that are computed within each industry. 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.

Table 3. Productivity shock dispersion in the German manufacturing sector, by size quintiles.

	SD(Productivity innovations)				
	1st quintile	**2nd quintile**	**3rd quintile**	**4th quintile**	**5th quintile**
	(1)	(2)	(3)	(4)	(5)
1996	0.15	0.14	0.14	0.12	0.12
2017	0.13	0.12	0.12	0.10	0.09

Notes: Columns (1)-(5) report the standard deviation of log productivity shocks for five size (number of employees) quintiles. We estimate the standard deviation of productivity shocks based on an AR(1) process for log $TFPR_{it}$ 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) and by five size (number of employees) quintiles. German microdata.

4.3 Quantification of the responsiveness and shock hypotheses

Based on these results, we can quantify the importance of the responsiveness and shock hypotheses for the decline in job reallocation following the quantification approach in DHJM. The idea behind this approach is that JR_t equals the weighted sum of the (absolute value of the) firm-level employment growth rate (g_{it}), which is the dependent variable of our responsiveness regressions above. In particular, we use our estimates of these regressions to compute the implied aggregate reallocation with and without the measured declining responsiveness trends. To allow for more flexibility, we rely on our regressions by size quintiles for this analysis.

For each firm, these regressions provide a predicted employment growth rate in any given period. We denote by $\widehat{g}_{it}^{DR}$ the predicted growth rate based on the estimated period-specific coefficients, where the "*DR*" superscripts refer to the *declining responsiveness* scenario. Imposing the responsiveness coefficients to remain constant at the initial period, we predict the growth rates of each firm ($\widehat{g}_{it}^{CR}$) in a counterfactual scenario where responsiveness is kept constant at its initial level. We denote this scenario of *constant responsiveness* with the superscript "*CR*". Using these predicted employment growth rates and firms' initial employment, we calculate firms' predicted employment shares in each following period under the scenarios of decreasing and constant responsiveness ($\widehat{s}_{it}^{DR}$ and $\widehat{s}_{it}^{CR}$).[34] Based on these predicted employment growth rates and employment shares, we recover the implied job reallocation rate, $\widehat{JR}_t^{DR} = \sum_i \widehat{s}_{it}^{DR}|\widehat{g}_{it}^{DR}|$, considering the specification with varying responsiveness coefficients. Similarly, we construct a counterfactual job reallocation rate, $\widehat{JR}_t^{CR} = \sum_i \widehat{s}_{it}^{CR}|\widehat{g}_{it}^{CR}|$, under the assumption that responsiveness has remained at its initial level.

Comparing the evolution of $\widehat{JR}_t^{DR}$ and $\widehat{JR}_t^{CR}$ throughout our sample (1995-2017) yields an estimate of the importance of the decline in responsiveness in explaining the overall decline in job reallocation. Table 4 reports the results from this quantification exercise. The first row reports the decline in responsiveness in the data (33%). The second row reports the predicted decline in aggregate job reallocation with declining responsiveness, which is close to what we observe in the data (36%). Under the scenario of constant responsiveness (third row), aggregate job reallocation would have declined "only" by 21%. Using these estimates, we infer that $(1 - \frac{21}{36})100$ = 42% of the decline in job reallocation within the German manufacturing sector can be explained by the reduction in responsiveness. Through the lens of this framework, the remaining 58% can be attributed to changing productivity shock dynamics.[35] While declining responsiveness accounts for a significant share of the decline in job reallocation, our results differ from findings for the US manufacturing sector, where DHJM estimate that it accounts for almost the entire decline in job reallocation.

[34]Note that we can use the equation for the growth rate, $g_{it} = \frac{L_{it} - L_{it-1}}{0.5 \times (L_{it} + L_{it-1})}$, to derive L_{it} from the predicted growth rates and initial employment (L_{it-1}). This allow us to recover the weights $s_{it} = \frac{\overline{L}_{it}}{\sum_i \overline{L}_{it}}$, where $\overline{L}_{it} = 0.5 \times (L_{it} + L_{it-1})$. This approach follows DHJM.

[35]In as much as we might have omitted observable in the regression, the 58% constitutes an upper bound.

Table 4. Predicted ΔJR with declining *vs.* constant responsiveness.

Data	$\%\Delta JR_t = -33\%$
Declining responsiveness	$\%\Delta \widehat{JR}_t^{DR} = -36\%$
Constant responsiveness	$\%\Delta \widehat{JR}_t^{CR} = -21\%$

Notes: Counterfactual changes in job reallocation rates using predicted employment growth rates from firm-level responsiveness regressions that estimate period-specific responsiveness coefficients reported in Table 2. German microdata.

The remainder of our study will concentrate on examining the potential drivers of changes in firm responsiveness. While understanding changing patterns in productivity dynamics is of key importance for Europe, a deeper exploration of these dynamics lies beyond the scope of this paper.

5 Understanding the decline in responsiveness

The common assessment in the literature is that a declining responsiveness signals an increase in labor adjustment costs. Although these costs are likely to be higher in Europe than in the US, there has been a concerted policy effort of European economies to increase labor market flexibility over the last decades (Eichhorst et al., 2017; Gehrke and Weber, 2018). Appendix Figure F1 provides evidence for this notion and reports declines in OECD employment protection indices, a widely used indicator for hiring and firing costs, across most European countries. On the other hand, there is increasing evidence that firm market power and the relative importance of labor in production have changed in Europe (De Loecker et al., 2020; Mertens and Schoefer, 2024; De Ridder, 2024; European Commission, 2024). Motivated by this evidence, we derive a stylized framework with adjustment costs to examine whether changes in firms' technology and market power played a role in the observed decline in responsiveness.

5.1 A firm-level framework to study responsiveness

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

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

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. Denoting by primes the value of next-period variables, the dynamic optimization problem of the firm consists of choosing inputs to maximize the present discounted value of its profits:

$$V(L_{-1}; \mathbf{S}) = \max_{\{L,M,K\}} \left\{ P(Q)Q - W(L)L - P^M M - P^K K - \chi(L_{-1}, L) + \delta\, \mathbb{E}[V(L; \mathbf{S'})] \right\}$$

where V is the value function, which depends on lagged employment stock (L_{-1}) and a vector of state variables, $\mathbf{S}$, such as productivity. P denotes the output price. W, P^M, and P^K are input prices for labor, intermediates, and capital. This formulation is similar to canonical models in the literature (Bloom et al., 2018; Cooper et al., 2007; 2015) but includes adjustment costs and labor market power. While firms are assumed to be price-takers in the material and capital markets, wages are expressed as a function of labor demand to account for firm monopsonistic power. The function $\chi(L, L_{-1}) \geq 0$ captures any cost that a firm incurs to adjust its labor force, which is assumed to be zero if $L = L_{-1}$. We do not impose a functional form for $\chi(\cdot)$, but we require it to be differentiable. $\delta \in (0, 1)$ is a discount factor.

The first-order condition for labor implies that, in each period, the firm's marginal revenue product of labor ($MRPL$) is equated to the marginal cost of hiring an additional worker (MCL):

$$\overbrace{\frac{\partial R}{\partial Q}\frac{\partial Q}{\partial L}}^{MRPL} = \overbrace{W\left(\underbrace{1 + \xi(L)}_{\text{Monopsony power}} + \underbrace{\frac{1}{W}\frac{\partial \chi(L_{-1}, L)}{\partial L} - \frac{\delta}{W}\mathbb{E}\left[\frac{\partial V(L; \mathbf{S'})}{\partial L}\right]}_{\text{Adjustment costs}} \right)}^{MCL}. \tag{8}$$

The marginal cost of labor (MCL_{it}) may reflect both monopsonistic power and adjustment costs. The degree of monopsonistic power depends on the *inverse* labor supply elasticity perceived by the firm, $\xi(L_{it}) \equiv \dfrac{\partial W_{it}}{\partial L_{it}}\dfrac{L_{it}}{W_{it}} \geq 0$. The higher this elasticity, the higher the firm's wage-setting power and the lower workers' wages relative to their marginal revenue product. The influence of adjustment costs on MCL_{it} is reflected in two terms: the first one represents the costs incurred to search, hire, and fire new employees, while the second reflects the expected long-run effects on the discounted value of profits from marginal changes in employment.

Because of monopsonistic power and/or adjustment costs, there may be a wedge between the wage paid by the firm and the marginal revenue product of labor. We refer to this wedge as markdown and denote it by $\gamma_{it} \equiv \frac{MRPL_{it}}{W_{it}}$. On the output market side, profit maximization ensures that the marginal revenue $MR_{it} = \frac{\partial R_{it}}{\partial Q_{it}}$ can be expressed as the ratio of price to the markup ($\mu_{it} \equiv \frac{P_{it}}{MC_{it}}$). Using these reformulations and multiplying Eq. (8) with $\frac{L_{it}}{Q_{it}}$ yields the derived labor demand equation:

$$L_{it} = \frac{P_{it}Q_{it}}{\gamma_{it}\mu_{it}}\frac{\theta^L_{it}}{W_{it}} \quad \Rightarrow \quad L_{it} = \frac{P_{it}Q_{it}}{\gamma_{it}\mu_{it}W_{it}}\frac{\theta^L_{it}}{RTS_{it}}RTS_{it}, \tag{9}$$

where $\theta^L_{it} = \frac{\partial Q_{it}}{\partial L_{it}}\frac{L_{it}}{Q_{it}}$ is the output elasticity of labor. The latter can be further decomposed into returns to scale ($RTS_{it} = \theta^L_{it} + \theta^M_{it} + \theta^K_{it}$) and the relative technological importance of labor vis-à-vis other production factors, $\frac{\theta^L_{it}}{RTS_{it}}$.[36] By taking logs and first differences of Eq. (9), we decompose relative changes in employment as:

$$\begin{aligned}
g_{it} \approx \Delta l_{it} &= l_{it} - l_{it-1} \\
\Delta l_{it} &= r_{it} + \log\left(\frac{\theta^L_{it}}{RTS_{it}}\right) + \log(RTS_{it}) - \log(\gamma_{it}) - \log(\mu_{it}) - w_{it} - l_{it-1} \\
\Delta l_{it} &= \Delta r_{it} + \Delta\log\left(\frac{\theta^L_{it}}{RTS_{it}}\right) + \Delta\log(RTS_{it}) - \Delta\log(\gamma_{it}) - \Delta\log(\mu_{it}) - \Delta w_{it},
\end{aligned} \tag{10}$$

where Δ denotes changes between t and $t-1$ and lowercase letters denote logged variables. Eq. (10) provides a decomposition of employment growth at the firm level which highlights the role of changes in firms' sales, technology (relative output elasticity and returns to scale), markups, markdowns, and wages. Finally, dividing Eq. (10) by the relative change in productivity, $\Delta tfpr_{it}$, leads to the following decomposition for a firm's responsiveness:

$$\frac{\Delta l_{it}}{\Delta tfpr_{it}} = \frac{\Delta r_{it}}{\Delta tfpr_{it}} + \frac{\Delta\log\left(\frac{\theta^L_{it}}{RTS_{it}}\right)}{\Delta tfpr_{it}} + \frac{\Delta\log(RTS_{it})}{\Delta tfpr_{it}} - \frac{\Delta\log(\gamma_{it})}{\Delta tfpr_{it}} - \frac{\Delta\log(\mu_{it})}{\Delta tfpr_{it}} - \frac{\Delta w_{it}}{\Delta tfpr_{it}}. \tag{11}$$

The key insight of this decomposition is that changes in firms' technology, markdowns, and markups matter for the responsiveness of labor demand to productivity. If output elasticities of labor increase after a positive productivity shock and output expansion, responsiveness increases because firms now rely on more labor-intensive technologies. If returns to scale increase when a firm becomes more productive and expands output, any productivity shock

[36]If we further decompose revenue, we can express labor demand in terms of $L_{it} = F_{it}(\cdot)\frac{TFPR_{it}}{\gamma_{it}\mu_{it}}\frac{\theta^L_{it}}{W_{it}}$, where $TFPR_{it}$ 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. 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. (9) becomes $L_{it} = \left(K_{it}^{\theta^K_{it}}M_{it}^{\theta^M_{it}}\frac{TFPR_{it}}{\gamma_{it}\mu_{it}}\frac{\theta^L_{it}}{W_{it}}\right)^{\frac{1}{1-\theta^L_{it}}}$.

will lead to larger output and, thus, labor increases. On the other hand, if markups or markdowns increase in response to productivity, firms will demand relatively less labor for a given productivity shock and responsiveness declines. In this regard, Eq. (11) establishes the *pass-through* of productivity changes into markups, labor market imperfection, and technology changes (rather than the levels of these variables) as key elements for studying changes in responsiveness.[37]

It is crucial to recognize that any of these changes are endogenous and likely coincide with simultaneous changes in other components as well, particularly for the wage and sales terms. After all, all these pass-through rates ultimately depend on firms' fundamentals and market conditions. The advantage of our firm-level framework is that it nests different demand, production functions, and market structures in both output and input markets. While taking a stance on them within a full structural model would allow running counterfactuals to estimate the quantitative relevance of each component of responsiveness, our contribution is to estimate Eq. (11) as flexibly as possible and let the data speak first. In particular, we study the time trends in these pass-through terms to *qualitatively* (rather than quantitatively) infer if changes in markups, markdowns and technology are consistent with the observed change in aggregate firm responsiveness documented before.[38]

5.2 Estimation of markups, markdowns, and output elasticities

To estimate the components of responsiveness, we rely on our production function estimation from Section 4 and recover firm-year-specific estimates of output elasticities, markups, and markdowns. The output elasticity of labor is the derivative of the logged production function: $\theta_{it}^{L} = \dfrac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$. We estimate markups using the firm's first-order condition for intermediates following De Loecker and Warzynski (2012):

$$V_{it} = MRPM_{it} \;\Rightarrow\; \mu_{it} = \frac{P_{it}}{MC_{it}} = \theta_{it}^{M} \frac{P_{it} Q_{it}}{V_{it}^{M} M_{it}}, \tag{12}$$

[37]Notably, the level of responsiveness depends *indirectly* on the initial levels of firms' markups, markdowns, and technology. As shown in Biondi (2022) and summarized in a series of simulations in the online Appendix D.2, a firm that *ceteris paribus* has a higher markup, or higher markdown, or lower returns to scale is expected to be less responsive to productivity because these variables indirectly influence how much a firm is expanding its sales in response to productivity. However, what is relevant for studying *changes in responsiveness* is whether and how the components of Eq. (11) change in response to productivity.

[38]We focus our interpretation explicitly on markups, markdowns, and technology rather than on sales and wages, as these encompass multiple factors and are consequently more challenging to interpret. Studying markups, markdowns, and output elasticities also allows us to speak to the qualitative importance of labor adjustment costs (included in markdowns) versus markups and technology (output elasticities).

where $MRPM_{it}$ is the marginal revenue product of intermediate inputs and $\theta_{it}^M = \dfrac{\partial q_{it}}{\partial m_{it}}$ is the output elasticity of intermediates.[39] Combining the first-order condition of labor from our framework (Eq. (8)) with Eq. (12) yields an expression for markdowns:

$$\gamma_{it} = \frac{MRPL_{it}}{W_{it}} = \frac{\theta_{it}^L}{\theta_{it}^M} \frac{V_{it}^M M_{it}}{W_{it} L_{it}}, \tag{13}$$

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). Empirically, it is challenging to separate adjustment costs from firms' monopsonistic power. Therefore, we interpret γ_{it} as reflecting labor market imperfections in general, without explicitly defining its sources.

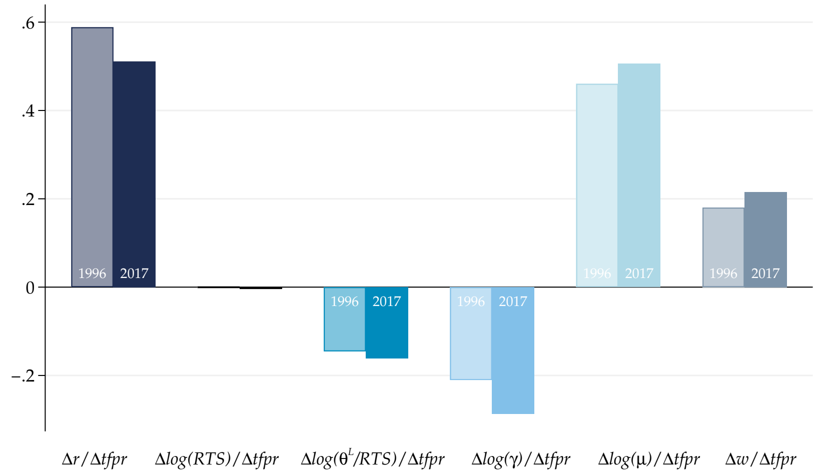
We present summary statistics on estimated markups, markdowns, and output elasticities in online Appendix Table A5. The estimates are meaningful and in line with previous work. The average markup, markdown, and labor output elasticity equal 1.07, 1.08, and 0.3, respectively. These results indicate that 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. As is common in the literature, underlying these averages, we find substantial heterogeneity across firms.

5.3 Results of the responsiveness decomposition

Based on these estimates, we empirically decompose responsiveness into its different pass-through terms. In Figure 9, we report the employment-weighted average of each term, at the beginning (lighter bars) and the end (darker bars) of our sample. The first takeaway is that firms do change their output elasticity of labor, markdowns, and markups, in response to a productivity shock. With the exception of returns to scale that remained approximately constant, all the other pass-through terms are different from zero. This confirms our initial hypothesis that changes in market power and technology matter for responsiveness.

[39] As in De Loecker and Warzynski (2012), we assume that intermediate inputs are flexible and that intermediate input prices are exogenous to firms in order to recover markups using Eq. (12).

Figure 9. Components of aggregate responsiveness and their evolution over time.



Notes: Employment-weighted averages of the components of responsiveness, i.e., the right-hand side terms of Eq. (11) among firms with a productivity change (positive or negative) of at least 0.5%, i.e., with $|\Delta tfpr_{it}| \geq 0.005$. Averages of the first and last two years in the sample. The complete time series is reported in Figure D3. German microdata.

In terms of signs, our results indicate that, on average, 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 their wages ($\frac{\Delta w_{it}}{\Delta tfpr_{it}} > 0$). Concurrently, they experience declines in markdowns ($\frac{\Delta log(\gamma_{it})}{\Delta tfpr_{it}} < 0$) and output elasticities of labor ($\frac{\Delta log(\theta^L_{it})}{\Delta tfpr_{it}} < 0$).[40] By comparing darker bars with lighter ones, we can examine whether each pass-through rate changed over time.

While the direction of these responses has remained the same over the past two decades, their magnitudes have changed. The average pass-through of productivity shocks to markups increased, which lowers responsiveness and implies that, for a given productivity increase, firms extract higher rents from their customers. Consistent with 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. Labor output elasticities declined relatively more in response to productivity increases. This indicates that firms tend to operate with less labor-intensive production technologies as output and productivity rise, lowering firms' responsiveness to productivity.

The reduction in the pass-through term for markdowns suggests that firms experiencing an increase in productivity reduced their markdowns relatively more. This may reflect a reduction in labor market power, consistent with the observed increase in the pass-through of pro-

[40] In this section, we describe all the results in terms of productivity increases, but results of Figure 9 are based on both positive and negative productivity changes. In case of a negative productivity change, the economic interpretation in the text would be reversed.

ductivity to wages. Alternatively, the reduction in the pass-through term for markdowns may also reflect a reduction in the wedge between realized and optimal labor expenditures due to the presence of adjustment costs. Since $\frac{\Delta log(\gamma_{it})}{\Delta tfpr_{it}}$ enters negatively in Eq. (11), the changes in markdowns actually *increased* responsiveness, which is in line with the documented increase in Europe's labor market flexibility as well as with empirical evidence by Diez et al. (2022) that markdowns declined among European manufacturing firms. Although we cannot distinguish whether these changes are caused by a reduction in adjustment costs or labor market power, we argue that changes in markdowns are an unlikely explanation for the documented decline in responsiveness in our German data. Instead, observed changes in the pass-through of productivity to markups and technology (labor output elasticities) align with the observed decline in responsiveness.

Although we cannot quantify the contribution of each component separately, our results provide important insights for qualitatively understanding the dynamics of responsiveness as they imply a different set of policy implications relative to explanations rooted in labor market imperfections/adjustment costs. Specifically, the increase in pass-through of productivity to markups suggests that increasing product market competition can foster reallocation processes, whereas the decline in the labor output elasticity suggests that declining responsiveness and business dynamism are by-products of technological change. Quantifying the role of markups vs. labor-replacing technologies goes beyond the scope of our empirical framework but is an important task for future work.

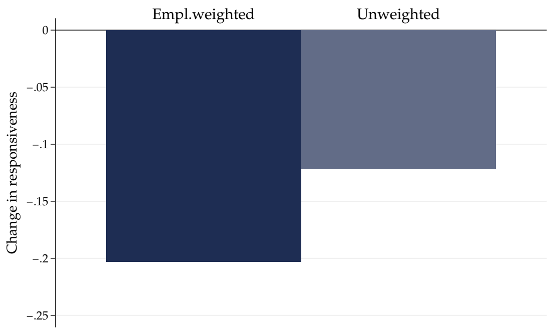
5.4 Change in responsiveness across the size distribution

A final noteworthy result is that the decline in average responsiveness has been smaller than the decline in aggregate (i.e., employment-weighted) responsiveness. We illustrate both declines in Figure 10a based on measuring responsiveness in the data (and consistent with our framework) as the ratio between the change in log labor and the change in log productivity. As in previous analyses, we focus on long-term changes in responsiveness, comparing the beginning with the end of our sample.

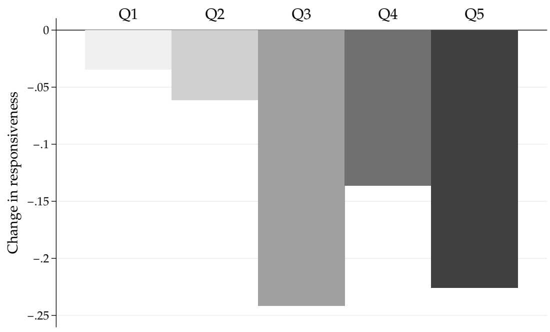
The source of the difference between the aggregate and average decrease in responsiveness is the fact that larger firms experienced stronger declines in responsiveness (consistent with our previous results in Table 2). The bars in Figure 10b illustrate the changes in responsiveness by employment quintiles (within industries). Firms in higher quintiles (darker gray bars) decreased their responsiveness more than those in lower quintiles (lighter bars). As larger firms command higher employment shares, this gradient of responsiveness declines leads to a more prominent decline in aggregate responsiveness.

Figure 10. Decline in responsiveness, overall and by firm size

(a) Aggregate *vs.* average responsiveness



(b) By quintile of employment

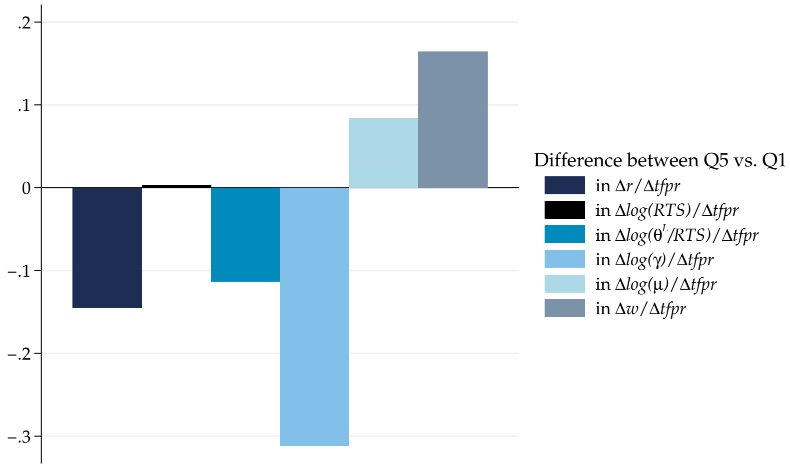


Notes: Changes in the employment-weighted and unweighted averages of $\frac{\Delta l_{it}}{\Delta tfpr_{it}}$. Grey bars show changes in averages by quintile of employment. QJ with $J = 1, .., 5$ denotes the quintile of firm employment, measured separately by industry. Changes are measured between the first and last two years in the sample.

To understand why larger firms have experienced a stronger decline, we apply the decomposition of responsiveness from Figure 9 by firm size quintiles and examine how the different components have changed over time. Overall, we find that changes in the different pass-through terms discussed before have the same directions but are amplified for larger firms. To illustrate these findings, Figure 11 plots the differences in the evolution of each pass-through term between the largest (5$^{\text{th}}$ quintile) and smallest (1$^{\text{st}}$ quintile) firms.[41] Overall, the pass-through of productivity to sales, markdowns, and output elasticities decreased more significantly among the largest firms, while the pass-through of productivity to markups and wages increased relatively more over time. These differences in markup and technology (and also sales and wage) adjustments between large and small firms can rationalize the sharper decline in large firms' responsiveness.

[41]Specifically, the first bar indicates the differences between the largest (Q5) and smallest (Q1) firms in changes over time in the pass-through of productivity to sales, which is calculated as $\left[\Delta_{('17-'96)}\left(\frac{\overline{\Delta r_{iQ5}}}{\Delta tfpr_{iQ5}}\right) - \Delta_{('17-'96)}\left(\frac{\overline{\Delta r_{iQ1}}}{\Delta tfpr_{iQ1}}\right)\right]$. Similarly, for all the other pass-through terms that compose responsiveness.

Figure 11. Differences in the responsiveness decline by components (large *vs.* small firms)



Notes: Differences in the changes of each responsiveness component between the largest (Q5) and smallest (Q1) firms. Changes are measured between the first and last two years in the sample. German microdata.

Although our analysis primarily focuses on the German manufacturing sector, where we have direct access to detailed firm-product-level data, we believe our findings contribute to broader evidence on shifts in market power and technology by linking these trends to declining responsiveness and reallocation. Specifically, recent research documented considerable changes in concentration (Autor et al., 2020; Bighelli et al., 2023; Bajgar et al., 2023), market power (De Loecker and Eeckhout, 2018; European Commission, 2024), and production technologies (Hubmer and Restrepo, 2021; Mertens and Schoefer, 2024). To the extent that these developments are correlated with (or an outcome of) changes in productivity increases, our framework predicts that these changes contribute to a lower responsiveness of firms and, therefore, lower job reallocation rate. The contribution of our framework is thus to highlight that, besides changes in adjustment costs, there is a direct link between these aggregate trends 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 for future research to extend this analysis to other countries and datasets.

6 Conclusions

This article documents new facts on European business dynamism using novel data that we collected across multiple administrative firm-level databases within CompNet. Using this data, we document a widespread decline in job reallocation across 19 European countries.

Our findings suggest that overall declines in job reallocation are not unique to the US but rather span geographies with very different labor market institutions.

We show that declining job reallocation in Europe results from a lower responsiveness of firms to productivity shocks *and* from declines in productivity shock dynamics that induce less reallocation for a given level of responsiveness. 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 is an important task for future research, given its implications for productivity growth and reallocation. Finally, we develop a framework that highlights how changes in firms' responsiveness can be explained by changes in the pass-through of productivity shocks to markups, markdowns, and technology.

Compared to existing work that focuses on the role of adjustment costs in explaining declining responsiveness and job reallocation, our paper offers a more structural interpretation based on changes in market power and technology. Applying our framework to German manufacturing firm-level data indicates that, rather than changes in adjustment costs, changes in market power and technology seem more important in explaining declining responsiveness. This is also in line with the increase in labor market flexibility in Europe as well as increases in market power and declines in the importance of labor in firms' production processes that have been documented in the literature. Our findings also suggest that if productivity gains become increasingly tied to labor-replacing technologies (be it through robotization, AI, or offshoring), technological change and growth are likely to result in a sustained decline in firms' responsiveness of labor to productivity and, ultimately, job reallocation.

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References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., & Kerr, W. (2018). Innovation, Reallocation, and Growth. *American Economic Review*, *108*(11), 3450–91.

Akcigit, U., & Ates, S. T. (2021). Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory. *American Economic Journal: Macroeconomics*, *13*(1), 257–98.

Akcigit, U., & Ates, S. T. (2023). What Happened to U.S. Business Dynamism? *Journal of Political Economy*, *131*(8), 2059–2124.

Akcigit, U., Baslandze, S., & Lotti, F. (2023). Connecting to Power: Political Connections, Innovation, and Firm Dynamics. *Econometrica*, *91*(2), 529–564.

Alon, T., Berger, D., Dent, R., & Pugsley, B. (2018). Older and Slower: the Startup Deficits Lasting Effects on Aggregate Productivity Growth. *Journal of Monetary Economics*, *93*, 68–85.

Andrews, D., Criscuolo, C., & Gal, P. N. (2015). *Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries* (OECD Productivity Working Papers No. 2). OECD Publishing.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics*, *135*(2), 645–709.

Bajgar, M., Berlingieri, G., Calligaris, S., Criscuolo, C., & Timmis, J. (2023). Industry concentration in Europe and North America. *Industrial and Corporate Change*, dtac059.

Bighelli, T., Di Mauro, F., Melitz, M. J., & Mertens, M. (2023). European Firm Concentration and Aggregate Productivity. *Journal of the European Economic Association*, *21*(2), 455–483.

Biondi, F. (2022). *Firm Productivity and Derived Factor Demand under Variable Markups*.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. (2018). Really Uncertain Business Cycles. *Econometrica*, *86*(3), 1031–1065.

Bloom, N., Jones, C. I., Van Reenen, J., & Webb, M. (2020). Are Ideas Getting Harder to Find? *American Economic Review*, *110*(4), 1104–1144.

Bond, S., Hashemi, A., Kaplan, G., & Zoch, P. (2021). Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data. *Journal of Monetary Economics*, *121*, 1–14.

Calligaris, S., Chaves, M., Criscuolo, C., De Lyon, J., Greppi, A., & Pallanch, O. (2024). Exploring the Evolution and the State of Competition in the EU.

Calvino, F., & Criscuolo, C. (2019). *Business Dynamics and Digitalisation* (OECD Science, Technology and Industry Policy Papers No. 62). OECD Publishing.

Calvino, F., Criscuolo, C., & Menon, C. (2018). A cross-country Analysis of Start-up Employment Dynamics. *Industrial and Corporate Change*, *27*(4), 677–698.

Calvino, F., Criscuolo, C., & Verlhac, R. (2020). *Declining Business Dynamism: Structural and Policy Determinants* (OECD Science, Technology and Industry Policy Papers No. 94). OECD Publishing.

Caselli, M., Nesta, L., & Schiavo, S. (2021). Imports and Labour Market Imperfections: Firm-level Evidence from France. *European Economic Review*, *131*, 103632.

Chiavari, A. (2023). *Customer Accumulation, Returns to Scale, and Secular Trends*.

CompNet. (2023). *User Guide for the 9th Vintage of the CompNet Dataset* (tech. rep.). Competitiveness Research Network.

Cooper, R., Haltiwanger, J., & Willis, J. L. (2007). Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics*, *54*, 56–78.

Cooper, R., Haltiwanger, J., & Willis, J. L. (2015). Dynamics of labor demand: Evidence from plant-level observations and aggregate implications. *Research in Economics*, *69*(1), 37–50.

Criscuolo, C., Gal, P. N., & Menon, C. (2014). *The dynamics of employment growth: New evidence from 18 countries* (OECD Science, Technology and Industry Policy Papers No. 14). OECD Publishing.

Davis, S., Haltiwanger, J., & Schuh, S. (1996). *Job Creation and Destruction*. Cambridge, MA: MIT Press.

De Loecker, J., & Eeckhout, J. (2018). Global Market Power. *NBER Working Paper 24768*.

De Loecker, J., Eeckhout, J., & Mongey, S. (2021). Quantifying Market Power and Business Dynamism in the Macroeconomy. *NBER Working Paper 28761*.

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, *135*(2), 561–644.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, Markups, and Trade Reform. *Econometrica*, *84*(2), 445–510.

De Loecker, J., & Syverson, C. (2021). An Industrial Organization Perspective on Productivity. In *Handbook of Industrial Organization* (4th ed., pp. 141–223). Elsevier.

De Loecker, J., & Warzynski, F. (2012). Markups and Firm-level Export Status. *American Economic Review*, *102*(6), 2437–71.

De Ridder, M. (2024). Market Power and Innovation in the Intangible Economy. *American Economic Review*, *114*(1), 199–251.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives*, *28*(3), 3–24.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2016a). Declining Business Dynamism: What We Know and the Way Forward. *American Economic Review*, *106*(5), 203–07.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2016b). Where Has All the Skewness Gone? The Decline in High-growth (Young) Firms in the US. *European Economic Review*, *86*, 4–23.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2017). Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown. *American Economic Review*, *107*(5), 322–26.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2020). Changing Business Dynamism and Productivity: Shocks Versus Responsiveness. *American Economic Review*, *110*(12), 3952–90.

Dent, R. C., Karahan, F., Pugsley, B., & Sahin, A. (2016). The Role of Startups in Structural Transformation. *American Economic Review*, *106*(5), 219–23.

Diez, F. J., Malacrino, D., & Shibata, I. (2022). *The Divergent Dynamics of Labor Market Power in Europe.* (Working paper No. 2022/247). International Monetary Fund.

Dobbelaere, S., & Mairesse, J. (2013). Panel Data Estimates of the Production Function and Product and Labor Market Imperfections. *Journal of Applied Econometrics*, *28*(1), 1–46.

Eichhorst, W., Marx, P., & Wehner, C. (2017). Labor Market Reforms in Europe: Towards More Flexicure Labor Markets? *Journal for Labour Market Research*, *51*, 1–17.

Eslava, M., Haltiwanger, J., Kugler, A., & Kugler, M. (2004). The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia. *Journal of Development Economics*, *75*(2), 333–371.

European Commission. (2024). *Protecting competition in a changing world. Evidence on the evolution of competition in the EU during the past 25 years* (tech. rep.). European Commission, DG Competition.

Foster, L., Haltiwanger, J., & Krizan, C. J. (2001). Aggregate Productivity Growth: Lessons from Microeconomic Evidence. In *New Developments in Productivity Analysis* (pp. 303–372). University of Chicago Press.

Foster, L., Haltiwanger, J., & Syverson, C. (2008). Reallocation, Firm turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review*, *98*(1), 394–425.

Gehrke, B., & Weber, E. (2018). Identifying Asymmetric Effects of Labor Market Reforms. *European Economic Review*, *110*, 18–40.

Guzman, J., & Stern, S. (2020). The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 32 US States, 1988-2014. *American Economic Journal: Economic Policy*, *12*(4), 212–43.

Haltiwanger, J., Hathaway, I., & Miranda, J. (2014a). *Declining Business Dynamism in the US High-technology Sector* (tech. rep.). Ewing Marion Kaufman Foundation.

Haltiwanger, J., Scarpetta, S., & Schweiger, H. (2014b). Cross Country Differences in Job Reallocation: The Role of Industry, Firm Size and Regulations. *Labour Economics*, *26*, 11–25.

Hopenhayn, H. (1992). Entry, Exit, and Firm Dynamics in Long Run Equilibrium. *Econometrica*, 1127–1150.

Hopenhayn, H., Neira, J., & Singhania, R. (2022). From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. *Econometrica*, *90*(4), 1879–1914.

Hopenhayn, H., & Rogerson, R. (1993). Job turnover and Policy Evaluation: a General Equilibrium Analysis. *Journal of Political Economy*, *101*(5), 915–938.

Hubmer, J., & Restrepo, P. (2021). Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital–Labor Substitution. *NBER Working Paper 28579*.

Klette, T. J., & Griliches, Z. (1996). The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous. *Journal of Applied Econometrics*, *11*(4), 343–361.

Mertens, M. (2022). Micro-mechanisms Behind Declining Labor Shares: Rising Market Power and Changing Modes of Production. *International Journal of Industrial Organization*, *81*, 102808.

Mertens, M., & Schoefer, B. (2024). From Labor to Intermediates: Firm Growth, Input Substitution, and Monopsony. *NBER Working Paper 33172*.

Pugsley, B., & Sahin, A. (2019). Grown-up Business Cycles. *The Review of Financial Studies*, *32*(3), 1102–1147.

Pugsley, B., Sahin, A., Karahan, F., et al. (2015). Understanding the 30-year Decline in Business dynamism: a General Equilibrium Approach. *Society for Economic Dynamics Meeting Papers No. 1333*.

Sterk, V., Sedláek, P., & Pugsley, B. (2021). The Nature of Firm Growth. *American Economic Review*, *111*(2), 547–579.

Wooldridge, J. M. (2009). On Estimating Firm-level Production Functions using Proxy Variables to Control for Unobservables. *Economics letters*, *104*(3), 112–114.

Yeh, C., Macaluso, C., & Hershbein, B. (2022). Monopsony in the US Labor Market. *American Economic Review*, *112*(7), 2099–2138.

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 (Preparation of annual business statistics, Unified Business Statistics System, All Employees Database.)	Statistics France (INSEE)	Statistics France (INSEE)
Germany	Official firm data in Germany (AFiD), cost structure survey in the construction sector, annual survey of accommodation and food services industries, annual survey in the wholesale and retail trade sector, investment survey in the manufacturing industry, mining, and quarrying.	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).
Notes: 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 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 4 (c)	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 (c)	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 4 (b)	17/451 country-sector-size-class combinations for the countries Belgium, Germany, Latvia, Romania, Slovakia, Slovenia, and the United Kingdom
Figure C6	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 C8 (b)	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 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 $(t1)$ to t, A_{it} is the productivity realization at time t, and L_{it1} 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.[42] In this setting, the firms 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-

[42]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:

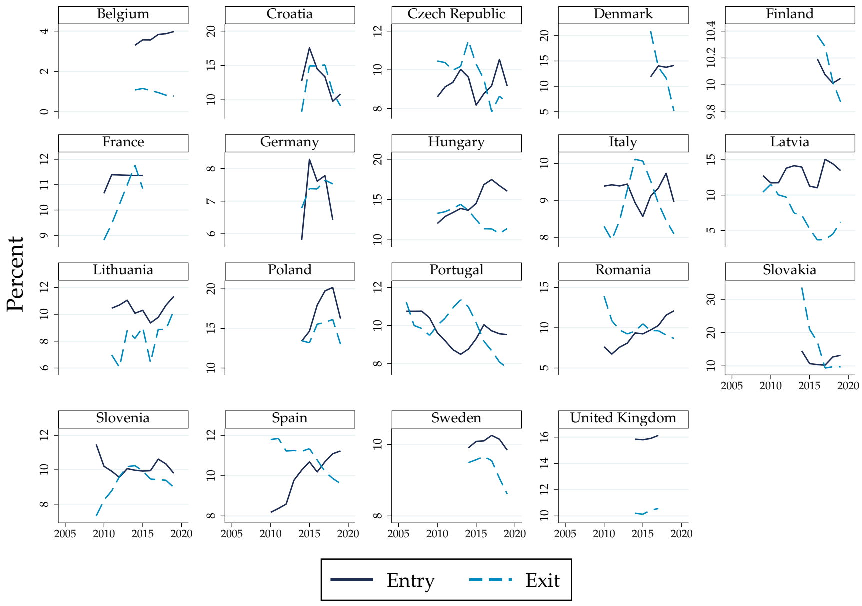
$$g_{it} = \beta_0 + \beta_{1t} a_{it-1} + \beta_{2t} l_{it-1} + \epsilon_{it}\,. \tag{B5}$$

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

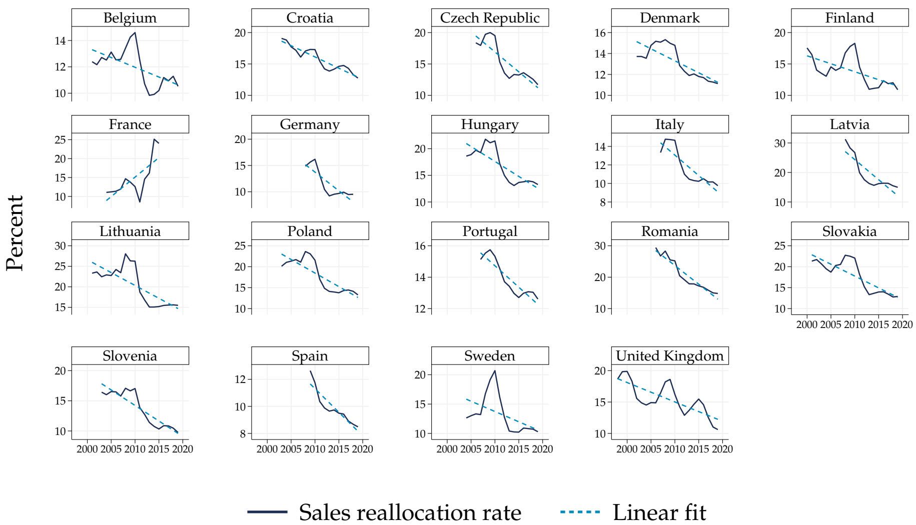
C.1 Further evidence on reallocation dynamics

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*).

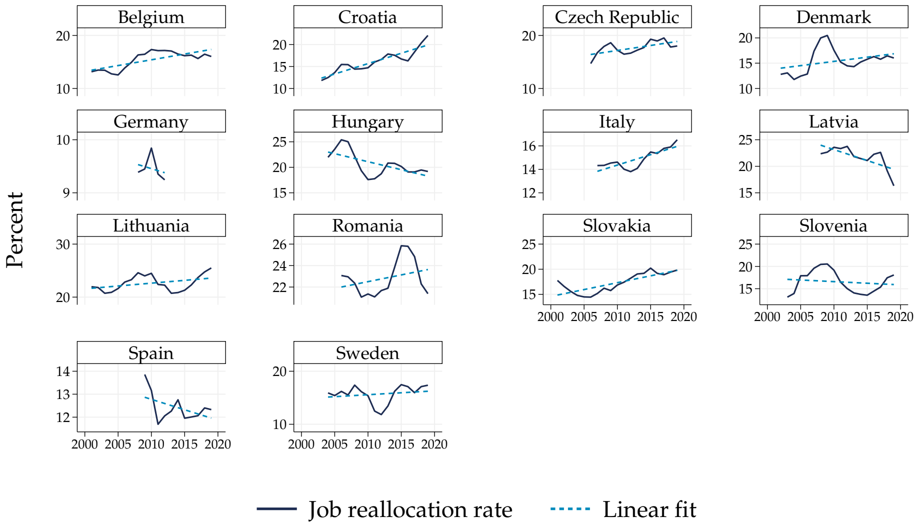
Figure C2. Sales reallocation rates in European countries.



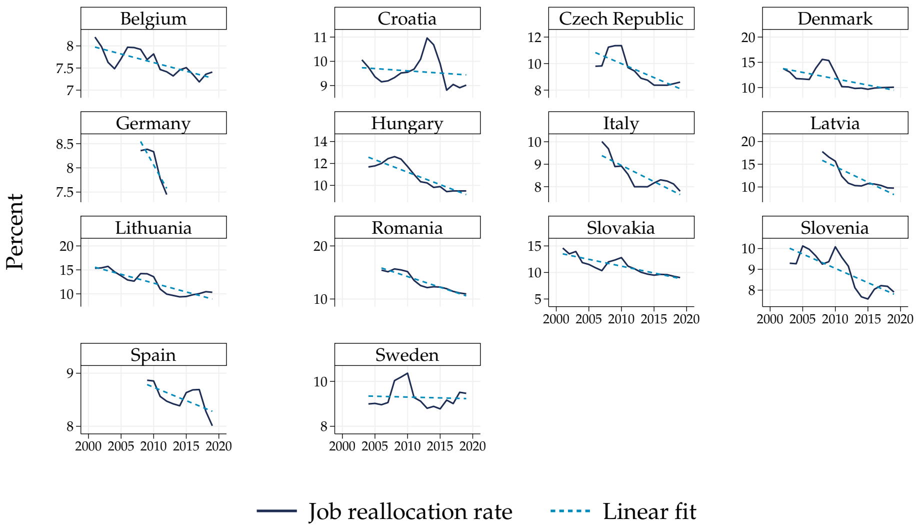
Notes: Three-year moving averages of sales reallocation rates, which we define as job reallocation rates in Equation (1) but using sales instead of employment. The light blue dashed lines report linear trends. CompNet data, firms with at least 20 employees.

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.

C.2 Responsiveness and shocks hypotheses

Table C1. Responsiveness of employment to productivity across countries (20e sample).

Country	β_1	(S.E.)	δ_1	(S.E.)	N	R^2
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.

As an alternative to Equation (5), we estimate a more flexible period-specific model to allow for nonlinearities in the responsiveness decline. More specifically, we estimate:

$$g_{it} = \beta_0 + \sum_{z=1}^{3} \mathbb{I}_{zit-1} \left(\beta_{1z} tfpr_{it-1} + \beta_{2z} l_{it-1}\right) + X_{jt} + \epsilon_{it} \tag{C1}$$

$$\text{for } \; z = \begin{cases} 1, & t < 2009 \\ 2, & t \in [2009, 2013] \\ 3, & t > 2013 \end{cases}$$

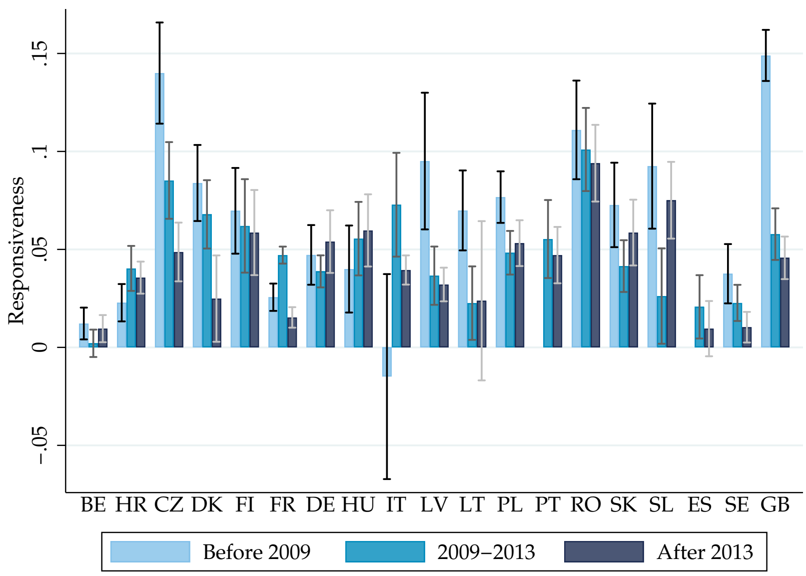
to compare responsiveness in different periods of time. We are interested in $\beta_{1z} \,\forall z$, which measure the level of responsiveness in each time period. We plot all the relevant coefficients and associated 90% confidence interval in Figure C4.

Table C2. Responsiveness of employment to productivity (20e sample - manufacturing).

Country	β_1	(S.E.)	δ_1	(S.E.)	N	R^2
Belgium	0.032**	(0.0131)	–0.002*	(0.0009)	31,017	0.13
Croatia	0.059***	(0.0146)	–0.001	(0.0012)	27,382	0.10
Czech Republic	0.170***	(0.0175)	–0.006***	(0.0019)	53,515	0.14
Denmark	0.155***	(0.0406)	–0.005	(0.0034)	35,197	0.15
Finland	0.063**	(0.0286)	0.002	(0.0021)	41,732	0.11
France	0.035***	(0.0100)	–0.001	(0.0008)	257,453	0.08
Germany	0.156***	(0.012)	–0.004***	(0.0009)	177,219	0.064
Hungary	0.072***	(0.0174)	–0.004***	(0.0015)	62,340	0.09
Italy	–0.033	(0.0797)	0.013	(0.0079)	290,236	0.12
Latvia	0.077	(0.0580)	0.002	(0.0062)	8,402	0.22
Lithuania	0.079***	(0.0275)	0.001	(0.0023)	24,528	0.19
Poland	0.122***	(0.0137)	–0.003***	(0.0012)	180,051	0.06
Portugal	0.020	(0.0235)	0.004**	(0.0019)	55,354	0.06
Romania	0.152***	(0.0203)	–0.005***	(0.0021)	68,960	0.12
Slovakia	0.090**	(0.0369)	0.000	(0.0029)	29,582	0.14
Slovenia	0.108***	(0.0368)	–0.003	(0.0028)	19,184	0.16
Spain	0.057***	(0.0158)	–0.003	(0.0020)	54,930	0.12
Sweden	0.079***	(0.0226)	–0.005**	(0.0019)	49,252	0.14
United Kingdom	0.310***	(0.0437)	–0.014***	(0.0028)	85,585	0.12

Notes: the table reports the results of our estimation with OLS of Equation (5). 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' employment levels.
Source: own calculations based on CompNet data and German manufacturing microdata, firms with at least 20 employees in the manufacturing sector.

Figure C4. Responsiveness to productivity over different time windows.

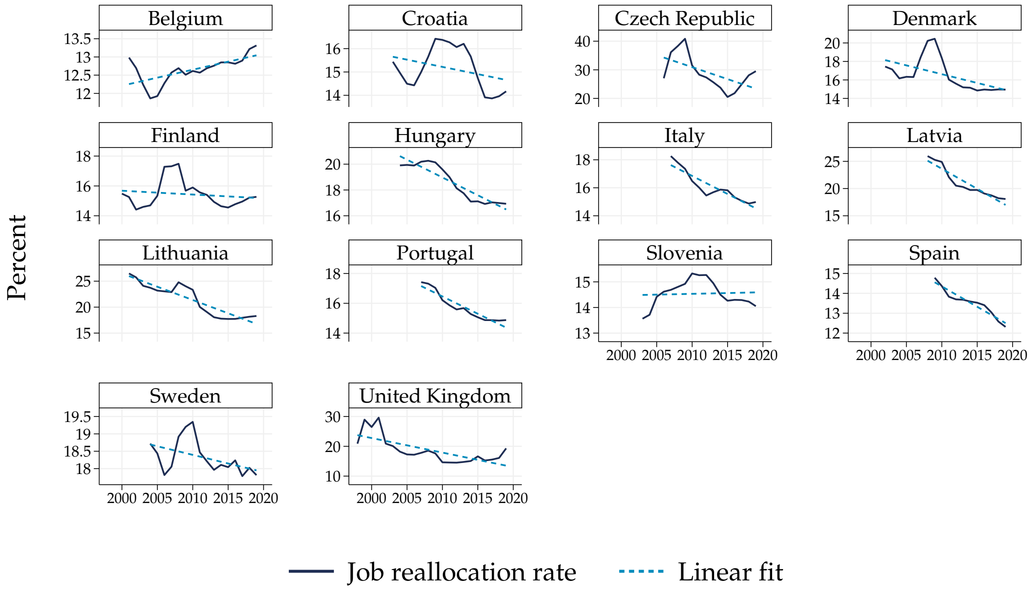


Notes: Estimated coefficients of period-specific responsiveness regressions where we included interactions with three time-period dummies instead of the linear trend. 90% confidence intervals are reported for each coefficient estimate. CompNet data, firms with at least 20 employees.

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

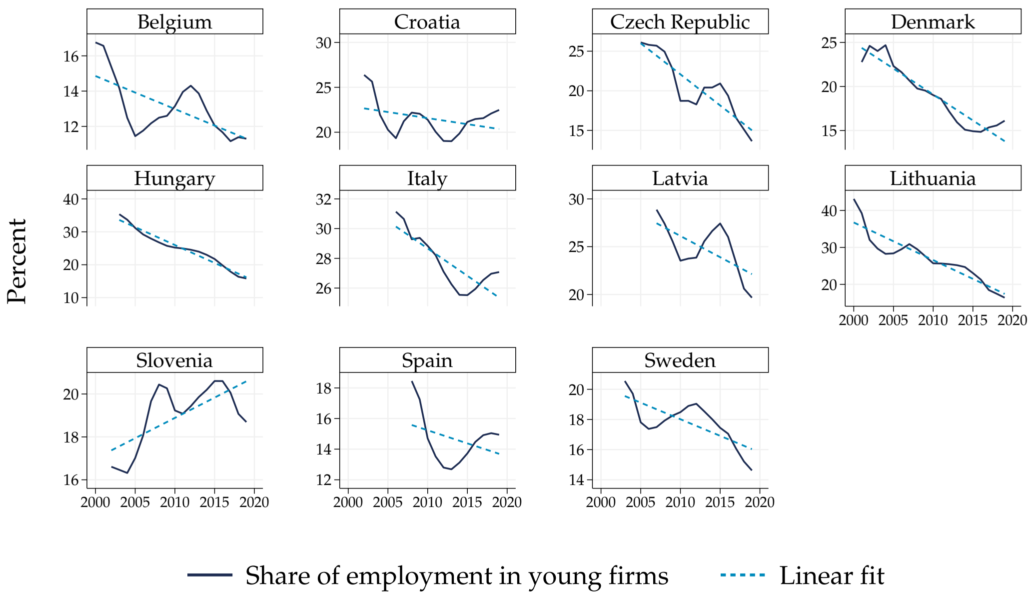
C.3.1 Stylized facts

Figure C5. Job reallocation rate in the "all sample".



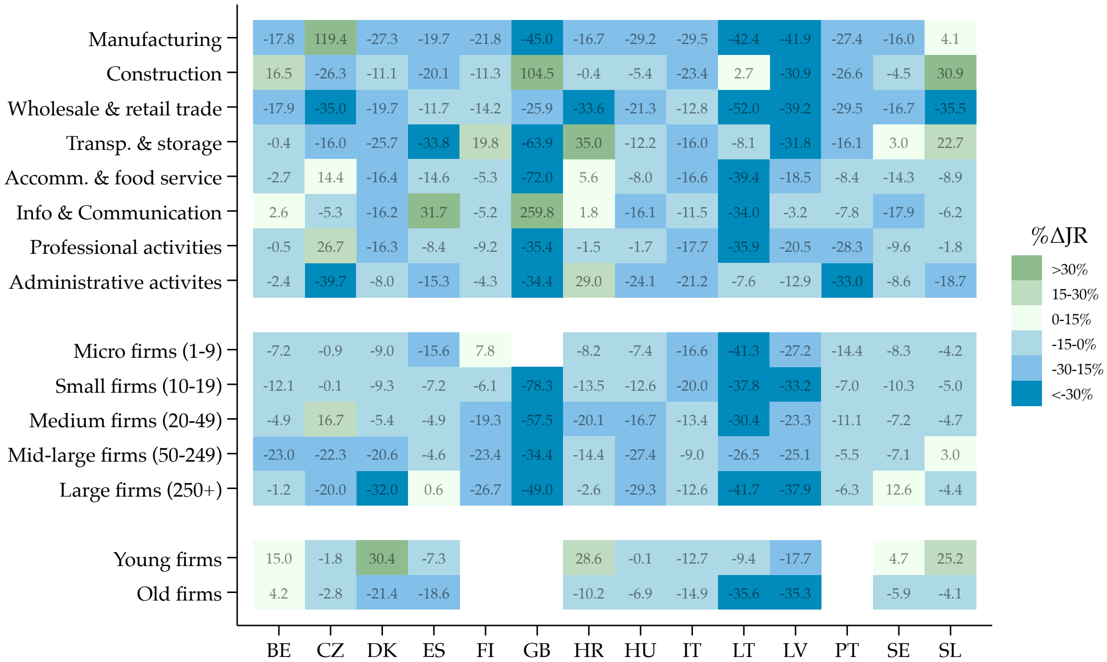
Notes: Three-year moving averages of job reallocation rates defined in Equation (1). The light blue dashed lines report linear trends. CompNet data. Firms with at least one employee.

Figure C6. 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.

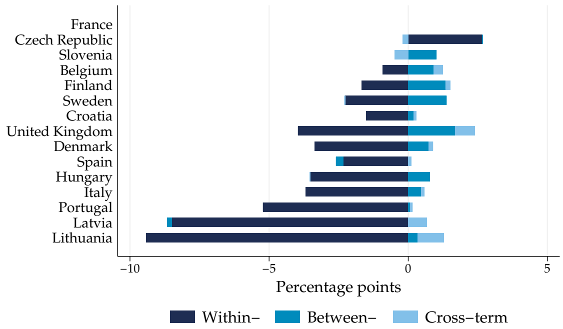
Figure C7. Relative decline in job reallocation rates by sector, size, and age class (all sample(.



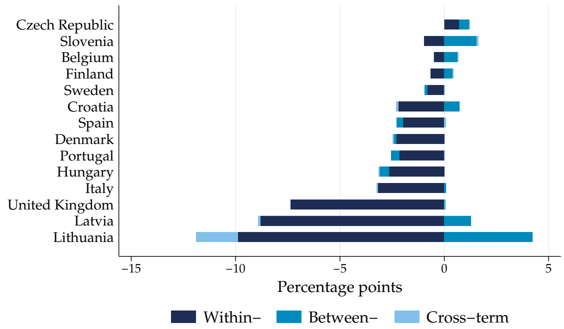
Notes: Changes between the first and last two years for every country-sector, country-size-class, and country-age class combination. The data are aggregated from sector-size-class data, resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Table A3). CompNet data, firms with at least one employee.

Figure C8. Decompositions of job reallocation rates (all sample).

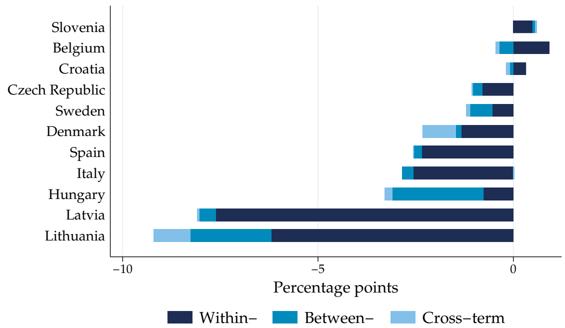
(a) Sector decomposition



(b) Size decomposition



(c) Age decomposition

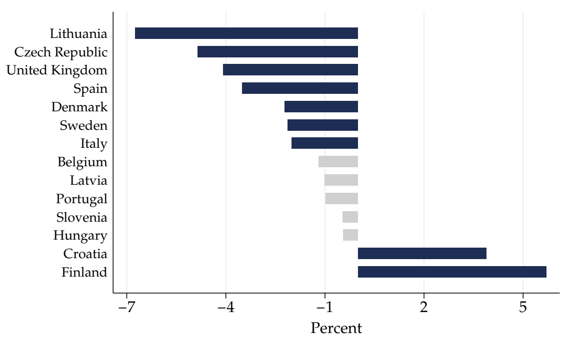


Notes: Results of the decomposition of job reallocation rates across sectors (Panel (a)), firm size-classes (Panel (b)), and firm age-classes (Panel (c)). Panel (b): The data are aggregated from sector-size-class data, resulting in a drop of a few sector-size-class cells due to country-specific disclosure rules (see online Table A3). Panel (c): All countries except Romania additionally include the real estate sector as we directly use age-class aggregated data. 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, country-size-class, or country-age-class combination. CompNet data, firms with at least one employee.

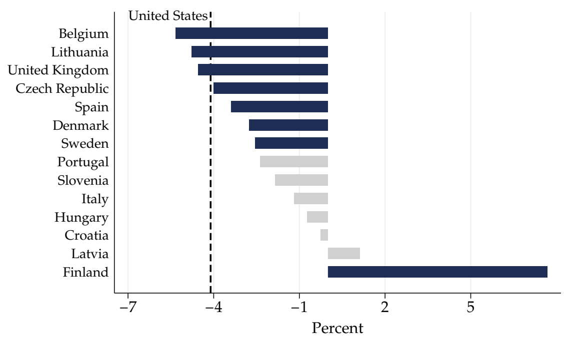
C.3.2 Responsiveness hypothesis

Figure C9. Relative changes in responsiveness over time.

(a) Business economy



(b) Manufacturing only



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 2000-2013 by DHJM (own calculations based on Table 1, Panel B). CompNet data, firms with at least one employee.

Table C3. Responsiveness of employment to productivity (full sample).

Country	β_1	(S.E.)	δ_1	(S.E.)	N	R^2
Belgium	0.0181***	(0.0057)	–0.0002	(0.0004)	292,083	0.06
Croatia	0.0299***	(0.0047)	0.0012***	(0.0004)	786,443	0.04
Czech Republic	0.2250***	(0.0321)	–0.0109***	(0.0030)	155,587	0.12
Denmark	0.1900***	(0.0113)	–0.0042***	(0.0010)	802,407	0.08
Finland	0.0660***	(0.0104)	0.0038***	(0.0008)	1,297,264	0.06
Hungary	0.0960***	(0.0118)	–0.0004	(0.0013)	2,198,831	0.03
Italy	0.1430***	(0.0044)	–0.0029***	(0.0005)	4,454,703	0.04
Latvia	0.0567***	(0.0053)	–0.0006	(0.0006)	311,924	0.08
Lithuania	0.0763***	(0.0149)	–0.0051***	(0.0012)	410,731	0.06
Portugal	0.0919***	(0.0104)	–0.0009	(0.0009)	1,808,029	0.04
Slovenia	0.1270***	(0.0117)	–0.0006	(0.0009)	430,276	0.06
Spain	0.1350***	(0.0075)	–0.0047***	(0.0010)	2,294,839	0.08
Sweden	0.1110***	(0.0051)	–0.0024***	(0.0004)	1,217,233	0.05
United Kingdom	0.1790***	(0.0111)	–0.0073***	(0.0007)	267,115	0.08

Notes: the table reports the results of our estimation with OLS of Equation (5). 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' employment levels.
Source: own calculations based on CompNet data, firms with at least one employee.

Table C4. Responsiveness of employment to productivity (full sample - manufacturing).

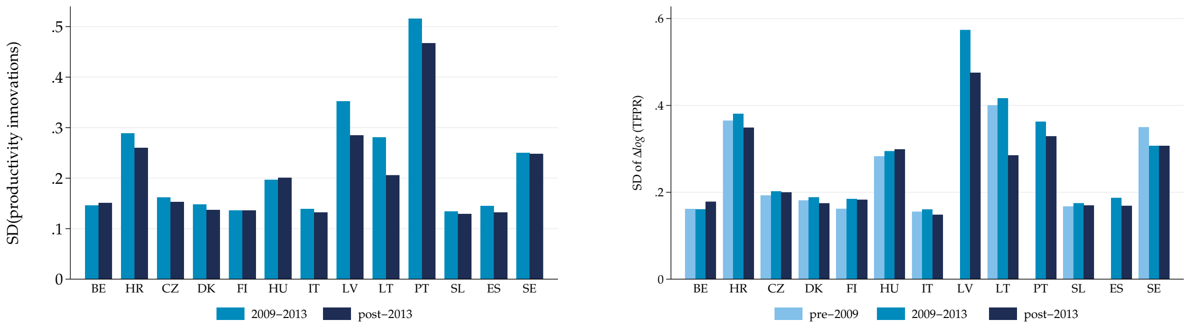
Country	β_1	(S.E.)	δ_1	(S.E.)	N	R^2
Belgium	0.042***	(0.0124)	–0.002***	(0.0008)	54,072	0.09
Croatia	0.054***	(0.0104)	0.000	(0.0008)	129,964	0.05
Czech Republic	0.201***	(0.0382)	–0.008**	(0.0038)	61,621	0.15
Denmark	0.203***	(0.0253)	–0.006**	(0.0023)	108,118	0.10
Finland	0.054**	(0.0237)	0.004**	(0.0017)	194,804	0.07
Hungary	0.068***	(0.0209)	0.000	(0.0015)	333,014	0.04
Italy	0.144***	(0.0125)	–0.002	(0.0012)	1,170,705	0.05
Latvia	0.100***	(0.0288)	0.001	(0.0032)	41,362	0.12
Lithuania	0.159***	(0.0243)	–0.008***	(0.0020)	62,763	0.09
Portugal	0.146***	(0.0275)	–0.003	(0.0027)	281,643	0.04
Slovenia	0.169***	(0.0281)	–0.003	(0.0021)	83,770	0.08
Spain	0.162***	(0.0114)	–0.005***	(0.0014)	386,972	0.07
Sweden	0.093***	(0.0139)	–0.002**	(0.0012)	215,226	0.07
United Kingdom	0.306***	(0.0421)	–0.014***	(0.0027)	96,070	0.12

Notes: the table reports the results of our estimation with OLS of Equation (5). 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' employment levels.
Source: own calculations based on CompNet data, firms with at least one employee.

C.3.3 Shocks hypothesis

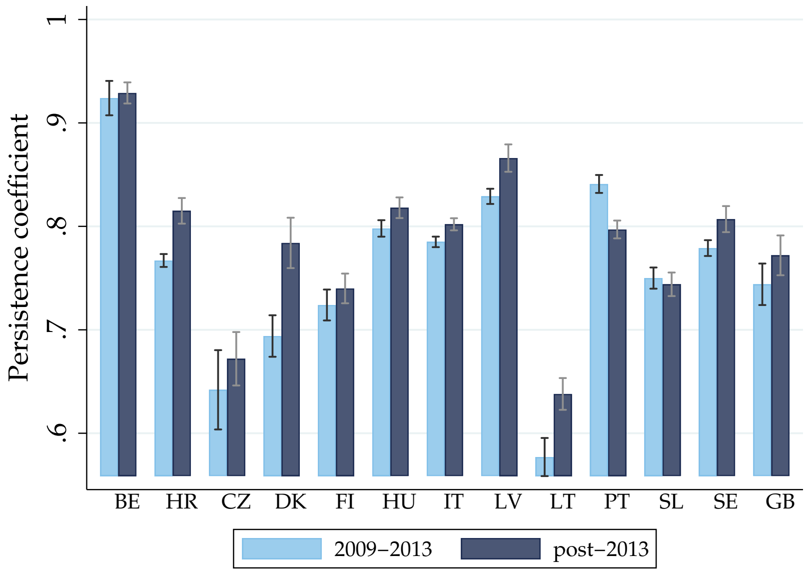
Figure C10. Non-increasing dispersion of productivity innovations ("all sample").

(a) AR(1) process **(b)** Non-parametric differences



Notes: Standard deviation of the residuals of the AR(1) process in Eq. (6) estimated over two consecutive periods. Overall regressions results are reported in our data appendix. Data on (b) was not supplied for the United Kingdom and Czech Republic. CompNet data, firms with at least one employee.

Figure C11. Increasing persistence in productivity dynamics ("all sample").

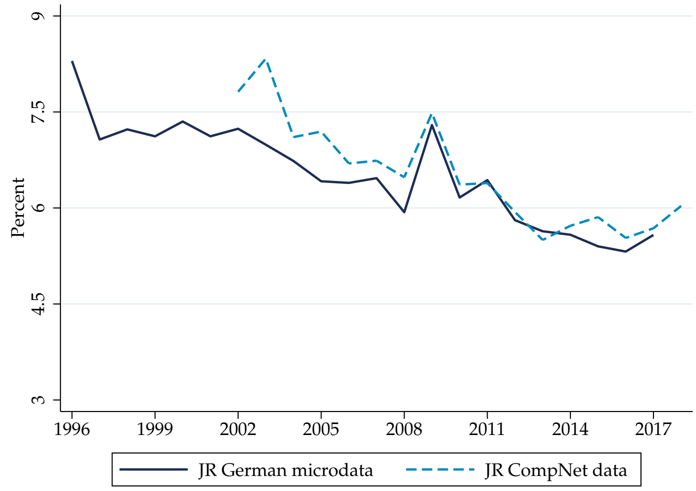


Notes: Point estimates of the persistence coefficient, ρ_t, in the AR(1) in Equation (6) estimated over two consecutive periods. Complete results of the regressions are available in our data appendix. CompNet data, firms with at least one employee.

D Additional results on the German manufacturing sector

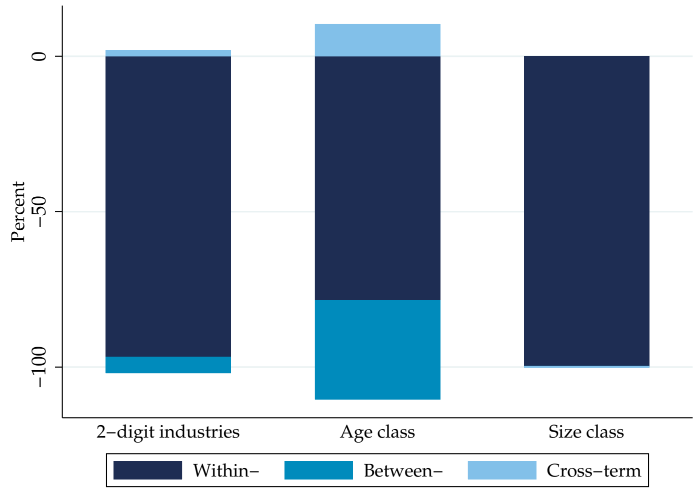
D.1 Further results on job reallocation and responsiveness

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 dataset 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 regressions, first difference specification.

	Employment growth rate (g_{ijt})	
	(1)	(2)
$\Delta tfpr_{it-1}$	0.0609***	
	(0.0121)	
$\Delta tfpr_{it-1} \times T_t$	-0.00143	
	(0.0010)	
Period 1996-98		0.0637***
		(0.0207)
Period 1999-02		0.0344***
		(0.0131)
Period 2003-06		0.0515***
		(0.0114)
Period 2007-10		0.0775***
		(0.0137)
Period 2011-14		0.0182*
		(0.0103)
Period 2015-17		0.0292
		(0.0197)
Industry-Year FE	yes	yes
Observations	122,659	122,659
N of firms	27,480	27,480
R^2	0.053	0.048

Notes: Results from estimating responsiveness coefficients in various first difference specifications. Column (1) reports the estimates of the responsiveness regression where we project employment growth on the lagged first difference in log productivity and a linear trend interaction with the lagged first difference in log productivity. Column (2) estimates a similar first difference specification but includes interactions between period dummies and the lagged first difference in productivity. 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.

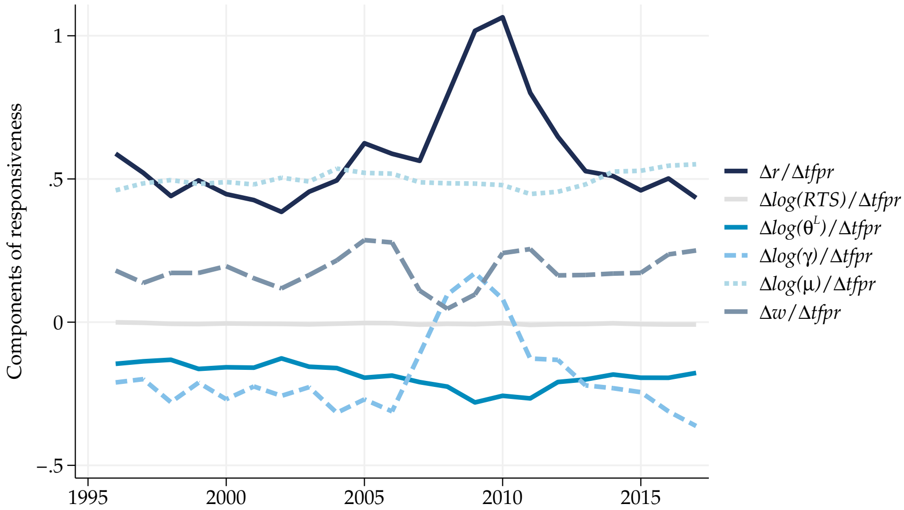
For each size quintile s, we estimate the following model to allow for a greater level of flexibility when conducting our counterfactual exercise.

$$g_{it} = \beta_0^s + \sum_{z=1}^{3} \mathbb{I}_{zit-1}^s \left(\beta_{1z}^s tfpr_{it-1}^s + \beta_{2z}^s l_{it-1}^s \right) + X_{jt} + \epsilon_{it}^s \tag{D1}$$

$$\text{for } z = \begin{cases} 1, & t \in [1996, 1998] \\ 2, & t \in [1999, 2002] \\ 3, & t \in [2003, 2006] \\ 4, & t \in [2007, 2010] \\ 5, & t \in [2011, 2014] \\ 6, & t \in [2015, 2017] \end{cases}$$

where we are interested in the responsiveness coefficient β_{1z}^s for each time period z and each size quintile s. The responsiveness coefficient for each group is reported in Table 2, column (2).

Figure D3. Components of aggregate responsiveness and their evolution over time.



Notes: Evolution of employment-weighted averages of the components of responsiveness, i.e., the right-hand side terms of Eq. (11) among firms with a productivity change (positive or negative) of at least 0.5%, i.e., with $|\Delta tfpr_{it}| \geq 0.005$. Three-years moving averages. German microdata.

D.2 Changes vs. *levels* in market power and technology.

In the main text, we highlight how changes in markups, markdowns, and output elasticities that are correlated with productivity shocks are relevant for studying changes in the responsiveness of labor demand to productivity. A subtle point that we clarify in this section is that also the *initial levels* of markups, markdowns, and output elasticities have an *indirect* influence on the *level* of responsiveness. In a set of numerical simulations, we show that higher initial levels of markup and markdown are associated with lower responsiveness. The opposite holds for returns to scale, while the levels of the output elasticity of labor *per se* does not influence the level of responsiveness. However, we show that only if markup and/or markdown and/or technology are allowed to vary in response to productivity, responsiveness may vary over time. In addition, a larger firm may decrease its responsiveness relatively more.

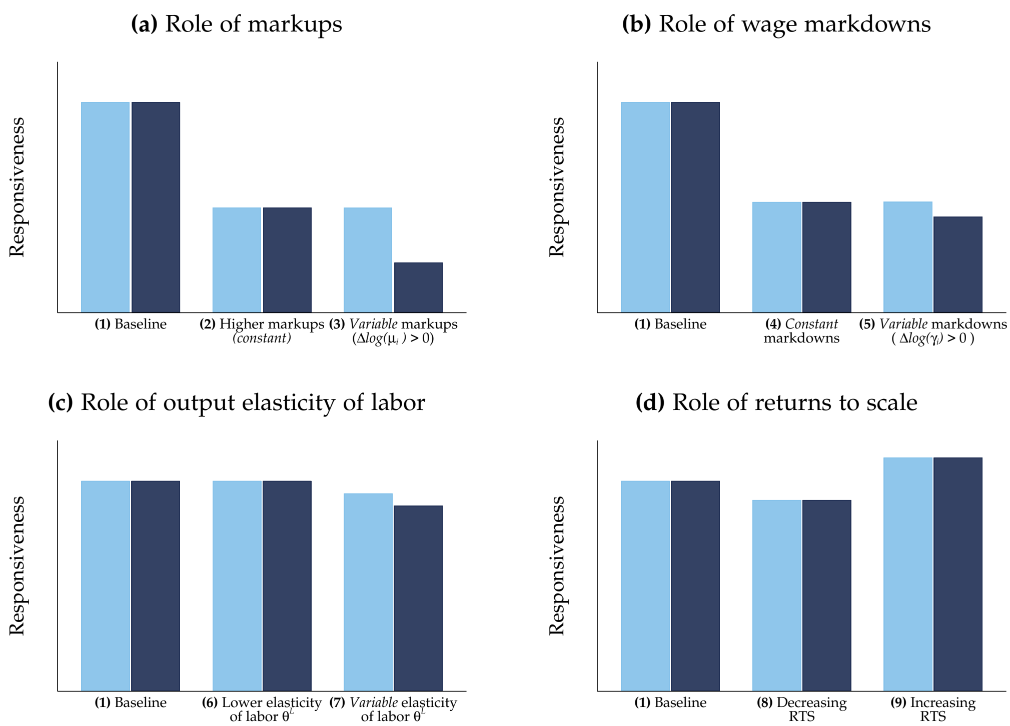
Simulated scenarios. To understand how firms' employment responds to productivity in different scenarios, we consider a generic firm i that produces output (Q_i) with labor (L_i) and intermediate inputs (M_i) according to a Cobb-Douglas production function, $Q_i = L_i^{\theta^L} M_i^{\theta^M} TFP_i$. In our baseline scenario (1), we set the output elasticities $\theta^L = 0.4$ and $\theta^M = 0.6$, such that returns to scale are constant ($RTS = \theta^L + \theta^M = 1$). In each scenario, we follow this firm over three following periods (t_0, t_1 and t_2) and investigate how it responds to a +100% increase in productivity. To keep our simulation as simple as possible, we assume that this firm is a monopolist in its market.[43] In the baseline scenario, this firm is a *price-taker* in the input markets, and the wage rate and the intermediate input costs are both set to 0.5. We also assume that the firm faces a constant elasticity of demand $\sigma = 3$ such that it charges a markup of $\mu_i = \dfrac{\sigma}{\sigma - 1} = 1.5$. We compare the baseline scenario to different scenarios, in which we relax these assumptions one at a time. Table D2 provides an overview of the considered scenarios.

[43] However, since any firm with market power acts as a monopolist on its residual demand curve, this can be easily extended to other imperfectly competitive settings. For detailed discussion on responsiveness to productivity in monopolistic and oligopolistic settings, we refer to Biondi (2022).

Table D2. Details on different scenarios.

Scenario	Description
(1)	Baseline scenario.
(2)	The firm faces a lower price elasticity of demand of $\sigma = 2$, which increases its optimal markups. Because of the CES structure, markups are constant irrespective of firm productivity and size.
(3)	The firm faces a demand with a variable elasticity of demand. When the firm becomes more productive and expands production, it moves to a region of demand with a lower elasticity where it has an incentive to increase its 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 $\chi = 0.7$, $b = 3$, 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 markups increasing in firm size. In this scenario, we have $\Delta log(\mu_i) > 0$.
(4)	The firm exerts some market power also in the labor market. However, we assume that the inverse supply curve is isoelastic, such that the firm faces the same elasticity ξ^W and thus set the same markdowns $\gamma = (1 + \xi^W) > 0$, irrespective of its 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 variable 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 assume that $W_i(L_i) = 1 + 0.1 * L_i^{(0.5)}$. This implies that when the firm becomes more productive and expands, it sets a higher markdown so that $\Delta log(\gamma_i) > 0$.
(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 0.1, such that $\theta^L = 0.3$ and increase θ^M likewise to 0.7.
(7)	We shift the relevance of labor in the production process towards materials *at the time when* the firms experience the productivity increase. In particular, we set $\Delta\theta_i^L = 0.05$ between t_0 and t_1 and $\Delta\theta_i^L = 0.1$ between t_1 and t_2. This is a very stylized way to illustrate what a more flexible (e.g., translog) production function may imply in terms of variable output elasticities of labor which is decreasing in firm size (as we found in our data). Importantly, we hold 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.

Figure D4. Simulated responsiveness to productivity over time.



Notes: Different scenarios for the responsiveness of labor to a 100% productivity increase between t_0 and t_1 (lighter blue bars) and between t_1 and t_2 (darker blue bars).

Comparative statics predictions. Figure D4 illustrates the predicted responsiveness of the firm's employment to a 100% productivity increase between t_0 and t_1 (lighter blue bars) and between t_1 and t_2 (darker blue bars) under different scenarios. The baseline scenario (1) considers a setting where markups, markdowns, labor output elasticities, returns to scale are constant and identical, irrespective of the firm's productivity and, thus, size. In this case, the responsiveness remains stable over time. Scenario (2) shows that the responsiveness of labor to productivity is lower when firms set a higher markup. Scenario (3) illustrates how a decline in responsiveness arises when a firm increases its markups in response to productivity. As shown in Biondi (2022), a firm has a lower responsiveness whenever the price elasticity of demand decreases along the demand curve.[44] Intuitively, consumers become less willing to pay for each additional unit as output levels increase. As a result, a highly productive (i.e., large) 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 the 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 (larger) firm refrains from expanding output and, thus, labor demand. If markdowns increase with firm size, which is what we consider in scenario (5), responsiveness to productivity becomes relatively weaker as a firm becomes more productive and larger over time. This occurs whenever the elasticity of inverse supply varies with employment.

We illustrate the role of technology in Figure D4c and Figure D4d. 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, responsiveness to productivity remains the same as in the baseline. Changes in output elasticities of labor that do not change the returns to scale affect responsiveness only if these changes occur jointly with the productivity shock (see main text Eq. (10)). We illustrate this in scenario (7), where changes in output elasticities occur at higher rates as a firm expands after a productivity shock. As shown, responsiveness declines over time. Finally, we highlight the role of returns to scale in scenarios (8) and (9). Under decreas-

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

ing 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.

Empirical evidence These comparative statics predictions are based on simulations. The extent to which they hold in the data depends on the functional forms of firms' demand, labor supply, and production functions. Using information on firms' initial markups, markdowns, and technology that we flexibly estimated with the German microdata, we find supportive evidence for all these comparative statics predictions. In particular, we regress responsiveness at the firm-year level on the initial levels of markups, markdowns, and technology. Since we are pooling observations of firms operating in different industries and years, we also include industry-year dummies. The results of this simple analysis are reported in Table D3. In Column (1), we include the output elasticity of labor as a regressor, while in Column (2) we separate the labor output elasticity term into the relative importance of labor in overall production ($\frac{\theta^L_{it-1}}{RTS_{it-1}}$) and the returns to scale level. In line with theoretical predictions, we find that higher initial levels of markups and markdowns are, on average, associated with lower responsiveness, while the relationship is not statistically significant with respect to the initial level of the output elasticity of labor. Once we split the output elasticity into i) the relative importance of the labor output elasticity vis-à-vis other production inputs and ii) returns to scale, we find that higher returns to scale are associated with higher responsiveness. (the negative coefficient on $\frac{\theta^L_{it-1}}{RTS_{it-1}}$ in Column (2) is only statistically significant at the 10% level and might capture other factors that our simple simulation framework ignores).

E Estimating production functions with the German data

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

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

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

Table D3. Responsiveness and initial values.

	Dependent variable Responsiveness ($\frac{\Delta l_{it}}{\Delta tfpr_{it}}$)	
Initial values of	(1)	(2)
Markups $log(\mu_{it-1})$	-0.112*	-0.167**
	(0.0662)	(0.0675)
Markdown $log(\gamma_{it-1})$	-0.0422*	-0.0996***
	(0.0254)	(0.0300)
Labor output elasticity $log(\theta^L_{it-1})$	-0.0271	
	(0.0263)	
Rel. labor elasticity $log(\frac{\theta^L_{it-1}}{RTS_{it-1}})$		-0.0525*
		(0.0277)
Returns to scale $log(RTS_{it-1})$		0.417***
		(0.121)
Industry-Year FE	yes	yes
Observations	162,233	162,233
Number of firms	37,767	37,767
R^2	0.05	0.05

Notes: The table reports regression results from projecting firm responsiveness as measured by changes in employment relative to changes in productivity on markups, wage markdowns, labor output elasticities, labor output elasticities divided by returns to scale, and returns to scale. All regressions include industry-year fixed effects. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. German microdata.

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.[45] We construct firm-specific Törnqvist price indices for each firms composite revenue from its various products in the following way:

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

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

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 in other cases with an average of product price changes within the same industry.[46] 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}.[47]

Solving (2) by accounting for unobserved input price variation. To control for input price variation across firms, we use a firm-level adaptation of the approach in De Loecker et al. (2016) and define a price-control function from firm-product-level output price information that we add to the production function (Eq. (E1)):

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

$B(.) = B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\phi}_{it}^c)$ is the price control function consisting of our logged firm-specific output price index (pi_{it}), a logged sales-weighted average of firms product market sales shares (ms_{it}), a headquarter location dummy (G_{it}), and a four-digit industry dummy (D_{it}). $\tilde{\phi}_{it}^c = [1; \tilde{\phi}_{it}]$, where $\tilde{\phi}_{it}$ includes the production function input terms. The tilde indicates that some of these inputs enter in monetary terms and are deflated by an industry-level deflator (capital and intermediates), while other inputs enter in quantities (labor). The constant entering $\tilde{\phi}_{it}^c$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\tilde{\phi}_{it}$ (a consequence of the translog 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

[46] 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.

[47] 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.

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 $B(.)$, 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:

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

$\boldsymbol{\Gamma}_{it}$ captures state variables of the firm that, in addition to k_{it} and l_{it}, affect firms' demand for e_{it}. Ideally, $\boldsymbol{\Gamma}_{it}$ should include a wide set of variables affecting productivity and demand for e_{it}. We include a dumm variable 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 $\boldsymbol{\Gamma}_{it}$. 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.[48] 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 We estimate Eq. (E5) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[49] 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.[50] 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:

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

[48] 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.

[49] 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).

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

where for convenience, we defined:

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

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

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

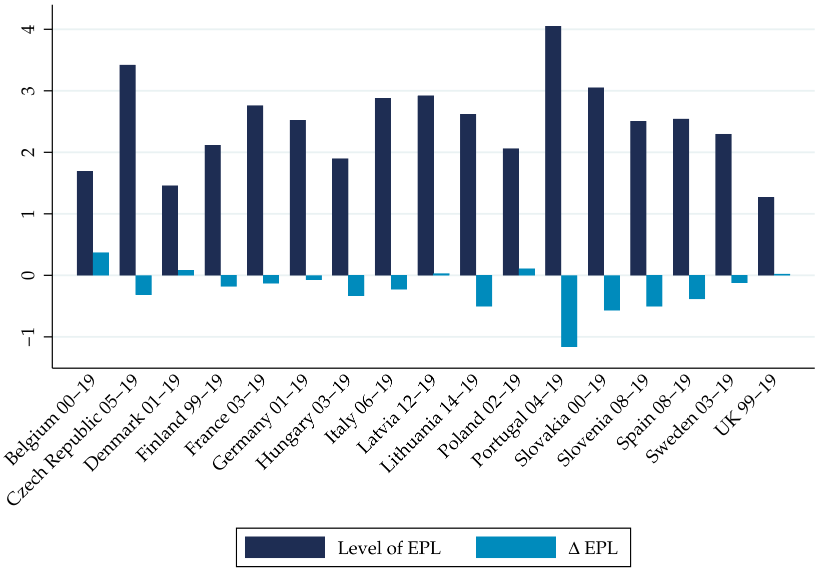
$$\boldsymbol{\Psi}(.) = \textstyle\sum_{n=0}^{3} \sum_{w=0}^{3-b} \sum_{h=0}^{3-n-b}\ l_{it-1}^n\, k_{it-1}^b\, e_{it-1}^h\ .$$

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 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.

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.

References

Biondi, F. (2022). *Firm Productivity and Derived Factor Demand under Variable Markups*.

Bond, S., Hashemi, A., Kaplan, G., & Zoch, P. (2021). Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data. *Journal of Monetary Economics*, *121*, 1–14.

Bräuer, R., Mertens, M., & Slavtchev, V. (2023). Import Competition and Firm Productivity: Evidence From Eerman Manufacturing. *The World Economy*.

Carlsson, M., Messina, J., & Nordström Skans, O. (2021). Firm-Level Shocks and Labour Flows. *The Economic Journal*, *131*(634), 598–623.

CompNet. (2023). *User Guide for the 9th Vintage of the CompNet Dataset* (tech. rep.). Competitiveness Research Network.

De Loecker, J. (2013). Detecting Learning by Exporting. *American Economic Journal: Microeconomics*, *5*(3), 1–21.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, Markups, and Trade Reform. *Econometrica*, *84*(2), 445–510.

Doraszelski, U., & Jaumandreu, J. (2013). R&D and Productivity: Estimating Endogenous Productivity. *Review of Economic Studies*, *80*(4), 1338–1383.

Eslava, M., Haltiwanger, J., Kugler, A., & Kugler, M. (2004). The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia. *Journal of Development Economics*, *75*(2), 333–371.

Foster, L., Haltiwanger, J., & Krizan, C. J. (2001). Aggregate Productivity Growth: Lessons from Microeconomic Evidence. In *New Developments in Productivity Analysis* (pp. 303–372). University of Chicago Press.

OECD. (2020). *OECD Employment Outlook 2020 Worker Security and the COVID-19 Crisis*, OECD.

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment. *Econometrica*, *64*(6), 1263–1297.

Smeets, V., & Warzynski, F. (2013). Estimating Productivity with Multi-product Firms, Pricing Heterogeneity and the Role of International Trade. *Journal of International Economics*, *90*(2), 237–244.

Wooldridge, J. M. (2009). On Estimating Firm-level Production Functions using Proxy Variables to Control for Unobservables. *Economics letters*, *104*(3), 112–114.