New Stylised facts on Firm and Polarization Dynamics

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Abstract

We analyze Swedish census data, which experienced a widespread increase in productivity dispersion (polarization), particularly pronounced in the services sector, and aligning with patterns observed in other developed economies during this period. Our main contribution is to decompose the contribution to polarization from different firm dynamic factors. Contrary to traditional narratives that an increase in polarization is driven by technology developments that make it more difficult to challenge the dominance of top firms, we find that productivity improvements among laggard firms, rather than further advances by industry leaders, drove the increased dispersion. This is particularly evident in the services sector, where the rise in polarization primarily stemmed from within-industry dynamics characterized by lower-productivity firms leapfrogging incumbent leaders, rather than from top firms pulling further ahead. Specifically, firms moving from the bottom to the top of the productivity distribution tended to replace incumbent firms that exhibited lower sales-weighted productivity, suggesting a more dynamic and competitive environment than previously understood.

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1 Introduction

The overwhelming majority of governments and companies around the world do not engage in significant R&D expenditures (see Keller, 2004; Comin and Mestieri, 2014). Hence, technology diffusion, the rate at which companies adopt new frontier technologies, is key for aggregate productivity growth. One important trend that emerged in the last 30 years, which is potentially a symptom of a decline in technology diffusion, is a widening gap between the productivity of top firms and of "laggard" firms. We define this gap as "polarization".

Leading explanations consistent with a negative relation between polarization and technology diffusion include technological developments that make it easier for industry leaders to innovate and maintain their advantage over other firms, or that make it harder for laggards to imitate them (e.g. Akcigit and Ates, 2021 and Olmstead-Rumsey, 2022). These include, for example, network effects that arise with the increasing importance of big data.

However, the relation between polarization and firm dynamics is in general complex, and an increase in polarization is both consistent with increases and decreases in technology diffusion, depending on the type of firms at the top of the productivity distribution. On the one hand, it might be that polarization increases because already top productive firms become even larger or more productive. On the other hand, it might be that polarization increases because of innovations introduced by entrants, or because of larger productivity improvements of laggard firms, if such improvements push these new or laggard firms to the top of the productivity distribution and beyond former leaders.

Therefore, to understand the relation between polarization dynamics and technology diffusion, it is essential to carefully analyze not only polarization increases and decreases across industries, but also to quantify the contribution from different firms (entering, exiting, laggard and top firms) to these changes. This paper provides such novel analysis. Our approach is inspired by the productivity literature, which decomposes the contributions of entering, exiting, and incumbent firms to aggregate productivity changes.[1] Our innovation is to apply this type of decomposition to other moments of the productivity distribution. In particular to the weighed average of the distance from the productivity of the median firm for firms on the right tail of the productivity distribution. With respect to simply analyzing the dynamics of given percentiles of the distribution, our approach has the advantage of being able to identify the mapping from the dynamics of different types of firms, such as entering firms, exiting firms, firms moving up and down the productivity distribution, and "incumbent firms" (defined as those that remain at the top over consecutive years), to the overall changes in polarization.

We consider a dataset that comprises the universe of Swedish firms, and we replicate part of the analysis for a similar sample of Spanish firms. Our main results are as follows:

i) The large majority of services industries experienced an increase in productivity dispersion (polarization) in the 2000-2020 period. The positive trend is also predominant in manufacturing industries, but less so than in services industries. This finding confirms similar evidence shown for other countries for the same time period (e.g. see Andrews et al., 2019).

ii) Industries with greater increases in polarization did not exhibit a corresponding rise in top persistence (the probability that top-productive firms remain in this position in the following year) nor a more pronounced decline in firm entry rates.

iii) When we decompose changes in polarization into its determinants, our analysis indicates that productivity improvements from laggards are the most important determinant of the increase in polarization observed in the 2000-2018 period. In particular, in the service sector, which experienced a significant increase in polarization in the sample period, we find such increase to be mainly driven by large within industry dynamics, with laggards (firms not in the top productive group) becoming more productive than incumbents (firms

[1] In particular, we build on the decomposition suggested by Melitz and Polanec (2015).

already in the top group), rather than by productivity improvements in the latter group. In other words, polarization increased almost exclusively because firms that moved from the bottom to the top of the productivity distribution replaced firms with lower (sales-weighted) productivity that moved from the top to the bottom group.

Overall, this evidence sheds new light on the factors that drive the observed increase in productivity dispersion. In particular, findings (ii) and (iii) are consistent with such increase being related to more competition and creative destruction, rather than the opposite. We consider this as evidence that the relation between technological change, firm dynamics and polarization is complex; that it is not easily explained by frameworks in which a single technological development towards less competition explains productivity trends jointly with concentrations and markup trends; and that it requires further theoretical and empirical analysis.

Related literature

This paper is related to the literature that analyses long-run trends in entry, exit, markups and productivity, and relates them to changes in the type and rate of diffusion of new technologies. In particular, Akcigit and Ates (2021), show that a model with slower technology diffusion is able to jointly explain the increase in polarization, and other trends related to firm dynamics (the decline in entry rates), to markups, and to industry concentration (the higher and more concentrated markups and market shares, the decline in labor share).

Other potential explanations for the rise in polarization include limits to competition of a technological nature, such as an increase in entry costs. For example, the rise of digitally intensive sectors and of big data, which allow larger firms to exploit data-network effects, and hence make it more difficult for new firms to enter and compete (e.g. see Calligaris, Criscuolo and Marcolin (2018)), De Ridder (forthcoming), among others). Relatedly, Olmstead-Rumsey (2022) finds that in recent years younger firms appear to be less able to do high impact innovations to catch up with leaders.

The contribution of our paper is to provide a better understanding on how entry-exit and growth dynamics, and polarization trends, interact with each other. Our main motivation is that it is important to better understand the dynamics of firms at the top of the productivity distribution, because whilst most theoretical models identify as top firms those that are simultaneously larger, older, more productive and with larger markups, this correlation is far from clear in the data. In this respect, our work relates to Gutiérrez and Philippon (2020), who notice that most of the literature on frontier/superstar firms measure these firms with productivity. However, when superstar firms are identified as the largest firms, there is no longer evidence of 'rise of superstars', meaning that the largest dominant firms are no more productive now than they were decades ago.

2 Methodology

In this section, we provide a detailed explanation of our analysis of the determinants of "polarization", which we define as the gap between top productive and laggard firms. Our starting point is the estimation of firm level productivity which we denote by (log) revenue productivity $\varphi_{i,j,t}$ for each firm i operating in industry j in year t. We follow the method proposed by Ackerberg, Caves and Frazer (2015) and its application in De Loecker and Warzynski (2012) to estimate firm level productivity.

De Loecker and Warzynski (2012) provides a methodology to jointly estimate firm-level productivity and markups without requiring assumptions on demand or market structure. The method builds on the production function estimation framework of Ackerberg, Caves and Frazer (2015), but extends it by incorporating markup estimation. Firm-level estimates of the output elasticity cannot be easily obtained but, under the assumption that all firms within an industry share the same technology, it is possible to estimate the following industry-specific Cobb-Douglas production function:

$$q_{it} = \alpha + \beta_\ell \ell_{it} + \beta_m m_{it} + \beta_k k_{it} + \varphi_{it} + \epsilon_{it} \tag{1}$$

where lower cases denote log variables: q_{it} is log output, ℓ_{it} is log labor, m_{it} is log materials, k_{it} is log capital, φ_{it} stands for firm productivity, and ϵ_{it} is measurement error/unanticipated shocks.

The traditional estimation challenge to obtain consistent estimates of the output elasticities is simultaneity bias, due to the possibility that the firm productivity (unobserved to the econometrician but known to the firm) is correlated with the input choice. As in De Loecker and Warzynski (2012), we follow the control function approach literature pioneered by Olley and Pakes (1996) and Levinsohn and Petrin (2003) and updated by Ackerberg, Caves and Frazer (2015). The methodology assumes that productivity follows a first-order Markov process and can be expressed as a function of the firm's flexible inputs and capital:

$$\varphi_{it} = h(\ell_{it}, m_{it}, k_{it})$$

Then the method proceeds in two steps. In the first step, one obtains estimates of the expected output that removes measurement error and unanticipated shocks:[2]

$$q_{it} = \phi_t(\ell_{it}, m_{it}, k_{it}) + \epsilon_{it}$$

In the second step, the method relies on the law of motion for productivity, which is assumed to be:

$$\varphi_{it} = g_t(\varphi_{i,t-1}) + \xi_{it}$$

where ξ_{it} are the innovation shocks to productivity, and the estimates are obtained by projecting productivity on its lagged value. Based on these steps, the following moment

[2]In particular, estimates of expected output are obtained from a second-order polynomial approximation of the production function.

conditions can be formed to obtain the output elasticity estimates:

$$E\left[\xi_{it}(\beta)\begin{pmatrix}\ell_{i,t-1}\\ m_{i,t-1}\\ k_{i,t}\end{pmatrix}\right]=0 \tag{5}$$

Note that the moment condition for the flexible input uses $t-1$ as an instrument and addresses the Ackerberg, Caves and Frazer (2015) critique. This assumes that the firm chooses the flexible input after the capital stock was determined at time $t-1$. The production function is estimated separately by industry (2-digit NACE Rev.2 industry classification), obtaining a different output elasticity by industry.

Our main dataset for the analysis is the universe of Swedish firms from the Swedish Companies Registration Office. We also performed part of the analysis on Spanish firms from SABI (*Sistema de Análisis de Balances Ibéricos*), which includes the quasi-universe of firms with more than 5 employees. Both datasets cover the 2000-2018 period.

2.1 Measuring Polarization

Our benchmark measure of polarization, which is computed for all firms above the median productivity $\varphi^{50}_{j,t}$, is the weighted average of the distance from such median. More precisely, we denote by $\varphi^{p}_{j,t}$ the p-th percentile of the productivity distribution of industry j in year t and consider the following baseline top polarization measure:

$$\Phi^{p}_{j,t}=\sum_{i\in\mathcal{I}^{p}_{j,t}} s_{i,j,t}(\varphi_{i,j,t}-\varphi^{50}_{j,t})=s_{i,j,t}\hat{\varphi}_{i,j,t},\ p\geq 50 \tag{2}$$

where $\mathcal{I}^{p}_{j,t}=\{i:\varphi_{i,j,t}>\varphi^{p}_{j,t}\}$, $s_{i,j,t}=\omega_{i,j,t}/\sum_{n\in\mathcal{I}^{p}_{j,t}}\omega_{n,j,t}$, and $\omega_{i,j,t}$ are the sales of firm i. Therefore, $\Phi^{p}_{j,t}$ is the weighed-average distance from the median productivity $\varphi^{50}_{j,t}$ for all firms with productivity above the p-th percentile. Intuitively, these measures capture the right-skewness of the productivity distribution. A higher value implies that a larger share of total sales is produced by firms that are more distant from the median productivity firm. In our benchmark measure $p = 50$, hence $\mathcal{I}$ includes all firms with above median productivity.[3] We also consider alternative measures setting $p = 75$ and $p = 90$. These alternatives still consider deviations from the median $\varphi^{50}_{j,t}$, but only include firms whose productivity is further to the right of the productivity distribution.

These measures are sales-weighted, therefore, they capture not only productivity dispersion but also the market importance of highly polarized firms. In the literature, polarization is typically measured by looking at the distance between median and a higher percentile of the distribution, such as the 90th or 95th (see, e.g., Andrews et al., 2019; Berlingieri et al., 2020). Both our measure and a simple percentile distance measure capture an increase of right-tail productivity dispersion. However, our proposed measure has the considerable advantage: it allows us to separately identify the contribution of different firm dynamics factors as described in detail in sub-section 2.2.

The polarization measures described by equation (2) captures right skewness. Similarly, we can compute measures of left skewness or bottom polarization measures as:

$$\tilde{\Phi}^p_{j,t} = \sum_{i \in \mathcal{I}^p_{j,t}} s_{i,j,t}(\varphi^{50}_{j,t} - \varphi_{i,j,t}) = s_{i,j,t}\hat{\varphi}_{i,j,t}, \; p \leq 50 \tag{3}$$

where $\mathcal{I}^p_{j,t} = \{i : \varphi_{i,j,t} \leq \varphi^p_{j,t}\}$, $s_{i,j,t} = \omega_{i,j,t}/\sum_{n \in \mathcal{I}^p_{j,t}} \omega_{n,j,t}$, and $\omega_{i,j,t}$ are the sales of firm i. For these, we consider $p \in \{10, 25, 50\}$ and their value should be interpreted as the required growth of the average firm in the bottom p-th percentile of the productivity distribution to reach the productivity level of the median firm.[4]

[3] Since productivity measures are in logs, $\Phi^{50}_{j,t}$ can also be interpreted as the required productivity growth for the median productivity firm to reach the average firm among the top 50% firms in the distribution. Note that $\varphi_i = \log x_i$, where x_i is the productivity level of firm i. Therefore, average firm productivity is computed as the geometric average across firms at the top of the productivity distribution as $\sum_{i \in \mathcal{I}} s_i \varphi_i = \sum_{i \in \mathcal{I}} s_i \log(x_i) = \sum_{i \in \mathcal{I}} \log(x_i^{si}) = \log(\Pi_{i \in \mathcal{I}}\, x_i^{si})$ where x_i is productivity and $\Pi_{i \in \mathcal{I}} x_i^{s_i}$ is a weighted geometric average.

[4] The measures proposed in equations (2) and (3) focus on some group $\mathcal{I}$ of the population. For top (bottom) polarization measures the group is defined to include all firms with productivity above (below) the p-th percentile of the productivity distribution. Alternatively, we also compute sales-rank top (bottom) polarization measures where we first rank firms by their productivity but include firms until their joint sales

2.2 The Melitz-Polanec decomposition applied to polarization.

The most important property of our polarization measure is that it can be decomposed to reflect business dynamics. Specifically, we propose a novel application of the dynamic Olley-Pakes (Olley and Pakes, 1996) or Melitz-Polanec decomposition (Melitz and Polanec, 2015), henceforth MP decomposition, to our polarization measures: at any point in time t and industry j, some firms belong to the group of interest $\mathcal{I}_{j,t}$. These firms may be incumbents/continuing firms C, those are firms that belonged to $\mathcal{I}_{j,t-1}$, they may be entrants E, those are young firms (less than 10 years old) that did not belong to $\mathcal{I}_{j,t-1}$, or top switchers TS, those are, operating firms (older than 10 years old) with low productivity in period $t-1$ which improved in period t and entered $\mathcal{I}_{j,t}$. Therefore, we can write any polarization measure $\Phi_{j,t}$ as the sum of the contribution of continuing firms, entrants, and top switchers:

$$\Phi_{j,t} = \underbrace{S^C_{j,t}\Phi^C_{j,t}}_{\text{Contribution of continuing firms}} + \underbrace{S^E_{j,t}\Phi^E_{j,t}}_{\text{Contribution of entrants}} + \underbrace{S^{TS}_{j,t}\Phi^{TS}_{j,t}}_{\text{Contribution of (top) switchers}} \tag{4}$$

where $S^K_{j,t}$ is the sales share of group K and $\Phi^K_{j,t}$ is the sales weighted average polarization within group $K \in \{C, E, TS\}$. Within group polarization can also be written as the unweighted average of gaps between productivity and median productivity $\overline{\Phi}^K_{j,t}$ and the covariance between weights and gaps $n^K_{j,t}\mathbb{C}ov^K(s_{i,j,t}, \varphi_{i,j,t})$:

$$\Phi^K_{j,t} = \overline{\Phi}^K_{j,t} + n^K_{j,t}\mathbb{C}ov^K(s_{i,j,t}, \varphi_{i,j,t}) \tag{5}$$

where here $s_{i,j,t}$ is the sales share of firm i within group K and $n^K_{j,t}$ is the number of firms in this group.

The group classification considered for the decomposition in equation (4) is based on where the firms were in the previous period. Alternatively, we can decompose polarization based on where the firms will be in the following period. At any point in time t and industry

share in total industry sales equals $(100-p)\%$ ($p\%$). Depending on the industry, year, and measure it might be that more or less firms are included in the sales-rank measure than in the benchmark polarization measure.

j, some firms that belong to $\mathcal{I}_{j,t}$ will also belong to $\mathcal{I}_{j,t+1}$, these are continuing firms CF, other firms, the exiting firms X, will exit the economy in year t, while some, the bottom switchers BS, will remain in the economy, but will not belong to $\mathcal{I}_{j,t+1}$. With this classification, we can decompose polarization as

$$\Phi_{j,t} = \underbrace{S^{CF}_{j,t}\Phi^{CF}_{j,t}}_{\text{Contribution of continuing firms}} + \underbrace{S^{X}_{j,t}\Phi^{X}_{j,t}}_{\text{Contribution of exiting firms}} + \underbrace{S^{BS}_{j,t}\Phi^{BS}_{j,t}}_{\text{Contribution of (bottom) switchers}} \tag{6}$$

$S^K_{j,t}$ and $\Phi^K_{j,t}$ are defined as above with $K \in \{CF, X, BS\}$. These two decompositions can be combined to elucidate on the driving forces behind changes in polarization. Since the share of each group of firms add up to one, it follows that $S^C_{j,t} = 1 - S^E_{j,t} - S^{TS}_{j,t}$ and $S^{CF}_{j,t} = 1 - S^X_{j,t} - S^{BS}_{j,t}$. Therefore, we can write yearly polarization changes as:

$$\begin{aligned}
\Delta\Phi_{j,t} \equiv \Phi_{j,t} - \Phi_{j,t-1} = & \underbrace{\Phi^C_{j,t} - \Phi^{CF}_{j,t-1}}_{\text{Contribution of continuing to changes in polarization}} + \\
& \underbrace{\underbrace{S^E_{j,t}(\Phi^E_{j,t} - \Phi^C_{j,t})}_{\text{Contribution of entry dynamics}} + \underbrace{S^X_{j,t-1}(\Phi^{CF}_{j,t-1} - \Phi^X_{j,t-1})}_{\text{Contribution of exit dynamics}}}_{\text{Contribution of entering and exiting firms to changes in polarization}} + \\
& \underbrace{S^{TS}_{j,t}(\Phi^{TS}_{j,t} - \Phi^C_{j,t}) + S^{BS}_{j,t-1}(\Phi^{CF}_{j,t-1} - \Phi^{BS}_{j,t-1})}_{\text{Contribution of switchers to changes in polarization}}
\end{aligned} \tag{7}$$

Equation (7) is novel in the literature that documents trends in productivity dispersion, and it allows us to disentangle to what extent changes in polarization are brought by the behavior of continuing firms, entry and exit dynamics, or switching dynamics. Regarding continuing firms, first notice that the definitions of groups C and CF imply that firms belonging to group CF in year $t-1$ belong to group C in year t and vice-versa. Thus, a positive contribution of continuing firms, $\Phi^C_{j,t} - \Phi^{CF}_{j,t-1}$, indicates that this group became more polarized from year $t-1$ to year t. By equation (5) this may be due to a higher gap between the (unweighted) average of these firms' productivity and that of the median firm or because more polarized firms gained market share. In other words, either because already top productive firms became even more productive, or because the most productive became larger. In both cases, such a finding would highlight that increases in polarization over time are driven by relative performance improvements by incumbents, and would be consistent with the thesis that polarization is a symptom of lack of competition from entrants or from "laggard" firms.

Regarding entry and exit dynamics, for the second line of the equation to be positive either entrants are more productive than incumbents, or exiting firms are less productive than incumbent, or both. Intuitively, entry and exit dynamics contribute to larger polarization if firms that enter at the top of the distribution replace less productive exiting firms.

A similar interpretation applies to firms transitioning between bottom and top of the distribution, the third row of equation (7). A positive value of this row implies that firms that increase productivity and switch from the bottom to the top part of the distribution more than compensate firms that switch from the top to the bottom. Such a finding would indicate dynamism within the distribution of operating firms.

Summing up, the decomposition in equation (7) reveals whether it is productivity improvements by top or bottom incumbents, or entry and exit dynamics that drive polarization dynamics over time. In Section 4 we will investigate in details these different components, and their relative importance for industries that had different degrees of polarization changes over the sample period.

2.2.1 Polarization over multiple periods.

In our analysis, we will often consider changes in polarization over multiple periods. In this case equation (7) can be extended as follows:

$$
\begin{aligned}
\sum_{s=0}^{k-1} \Delta\Phi_{j,t-s} = &\sum_{s=0}^{k-1} \left(\Phi^{C}_{j,t-s} - \Phi^{CF}_{j,t-s-1}\right) \\
&+ \sum_{s=0}^{k-1} S^{E}_{j,t-s} \left(\Phi^{E}_{j,t-s} - \Phi^{C}_{j,t-s}\right) \\
&+ \sum_{s=0}^{k-1} S^{X}_{j,t-s-1} \left(\Phi^{CF}_{j,t-s-1} - \Phi^{X}_{j,t-s-1}\right) \\
&+ \sum_{s=0}^{k-1} S^{TS}_{j,t-s} \left(\Phi^{TS}_{j,t-s} - \Phi^{C}_{j,t-s}\right) \\
&+ \sum_{s=0}^{k-1} S^{BS}_{j,t-s-1} \left(\Phi^{CF}_{j,t-s-1} - \Phi^{BS}_{j,t-s-1}\right)
\end{aligned}
\tag{8}
$$

Moreover, each term can be decomposed into an average effect and a covariance effect. For example, similarly to equation (5), the contribution of entry, $\sum_{s=0}^{k-1} S^{E}_{j,t-s} \left(\Phi^{E}_{j,t-s} - \Phi^{C}_{j,t-s}\right)$, can be written as:

$$
\begin{aligned}
\sum_{s=0}^{k-1} S^{E}_{j,t-s} \hat{\Phi}^{E}_{j,t-s} = &\, k\bar{S}^{E}_{j} \bar{\hat{\Phi}}^{E}_{j} \\
&+ \sum_{s=0}^{k-1} \left(S^{E}_{j,t-s} - \bar{S}^{E}_{j}\right) \left(\hat{\Phi}^{E}_{j,t-s} - \bar{\hat{\Phi}}^{E}_{j}\right)
\end{aligned}
\tag{9}
$$

where $\hat{\Phi}^{E}_{j,t-s} \equiv \Phi^{E}_{j,t-s} - \Phi^{C}_{j,t-s}$. The covariance term $\sum_{s=0}^{k-1} \left(S^{E}_{j,t-s} - \bar{S}^{E}_{j}\right) \left(\hat{\Phi}^{E}_{j,t-s} - \bar{\hat{\Phi}}^{E}_{j}\right)$ is potentially interesting because it relates directly to different drivers of firm dynamics usually considered in theoretical models. For example, fluctuations in entry costs should cause a negative covariance (entry costs go up, fewer firms enter, and they are more productive). Finally, in Section A.1 in the appendix, we consider an alternative decomposition that focuses on young versus old firms.

3 Polarization Trends

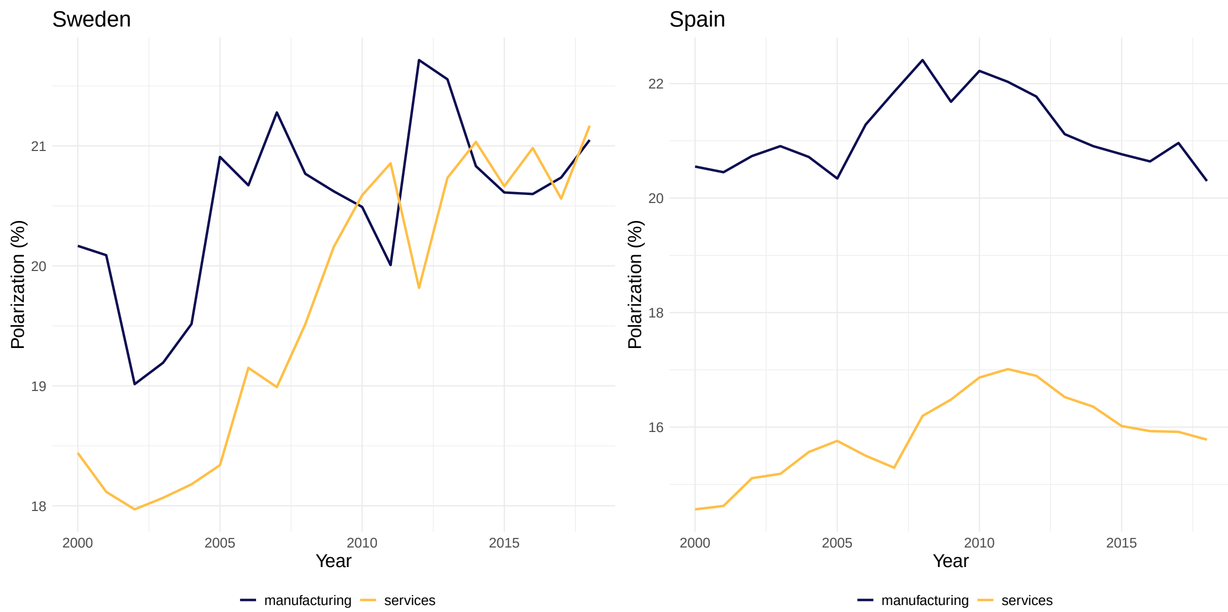
In this section we describe polarization dynamics across the different sectors and industries. Polarization measures are computed at the industry level (2-digit industries within manufacturing and 3-digit industries within services) and subsequently aggregated at the (macro-)sector level (manufacturing and services).[5] The aggregation procedure relies on time-invariant industries weights with weights equal to each industry's 2000-2018 average value-added share such that macro-sector changes in polarization reflect within-industry changes rather than composition shifts.

We focus on $\Phi^{50}_{j,t}$, the (sales) weighted average of the gap between (log) revenue productivity firms in the top half of the productivity distribution and median productivity.[6] We compute this measure for each year between 2000 and 2018 at the industry- and sector-level. As mentioned before, an increase of this measure indicates higher dispersion in productivity on the right tail, and it can be decomposed as in equation (5). That is, it can be driven by either a larger market share of firms whose productivity is further away from the median (the covariance term in equation 5), or by a distancing between the (unweighted) average productivity of top firms and that of the median firm (the first term in equation 5). Figure 1 shows polarization series for Swedish and Spanish manufacturing and services. In both countries, average polarization in services was smaller than in manufacturing at the beginning of the 21st century, nonetheless services saw an increase in polarization from about 18% to 21% in Sweden and from about 15% to 16% in Spain. Meanwhile, manufacturing polarization in Sweden saw large fluctuations, it ranged from 19% to about 22%, staying around 21% at the end of the sample period. Similarly, Spanish manufacturing polarization ranged between 20 and 22% although it was close to 20% at the beginning and at the end of the sample. All in all, Sweden saw an increase of polarization in both manufacturing and services with services catching up to the polarization level of manufacturing while Spain

[5] Appendix A.4 details the considered industries. We exclude Financial Services.

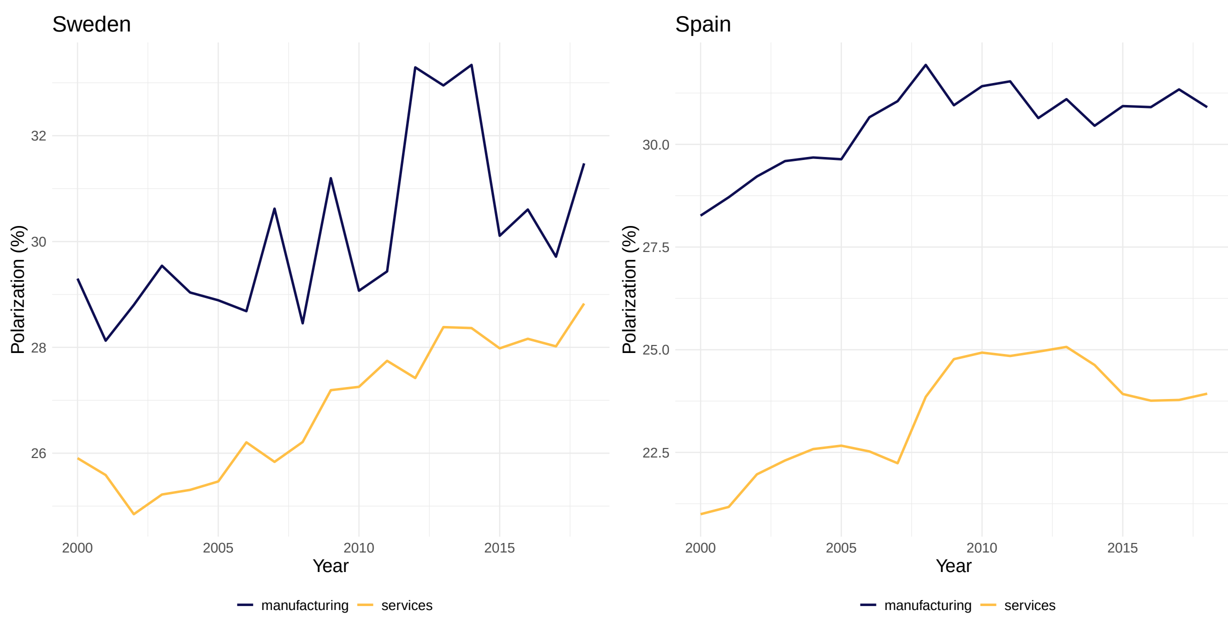
[6] In appendix A.2 we show analogous results where we define polarization based on the top quartile and the bottom half of the TFPR distribution.

saw a less marked increased in services polarization and a relatively flat manufacturing polarization trend. While in this section we focus on top 50% polarization, similar aggregate patterns show for top 25% polarization as depicted in Figure2.



Notes: The panels show the time−series evolution of top 50% polarization for Sweden and Spain for manufacturing and services. Sector results are derived from industry level results using time−invariant weights equal to the industry's average value−added share.

Figure 1: Top 50% polarization



Notes: The panels show the time−series evolution of Polarization top 25% for Sweden and Spain for manufacturing and services. Sector results are derived from industry level results using time−invariant weights equal to the industry's average value−added share.

Figure 2: Top 25% polarization

The sector-level trends reported in Figure 1 reflect industry-level polarization trends, these industry-level series are shown in Figures 3-6 with dark blue lines; Figures 3 and 4 pertain to manufacturing industries in Sweden and Spain, respectively, and Figures 5 and 6 pertain to service industries. For each industry we estimate a linear trend model in equation (10) after trimming the top and bottom 1% of the sector-level polarization change series to avoid contamination by extreme values. The dashed yellow lines show the resulting fitted values.

$$\Phi^{50}_{j,t} = \alpha_j + \beta_j t + \varepsilon_{j,t} \tag{10}$$

For both countries and sectors, industries experienced yearly fluctuations in polarization. Despite them, for the majority of industries, with the exception of the manufacturing industries in Spain, we estimate a positive linear trend coefficient $\hat{\beta}_j$, such that the median polarization trend is positive. Table 1 provides additional details and counts the number of industries with a positive polarization trend. Besides showing that the majority of industries have a positive estimated trend coefficient, it also shows that the increase of polarization phenomenon was more prevalent in service industries than in manufacturing industries.

Table 1: Industry polarization trends

		Industries	$\hat{\beta} > 0$	Share with $\hat{\beta} > 0$ (%)
Sweden	Manufacturing	16	12	75%
	Services	21	17	81%
Spain	Manufacturing	16	8	50%
	Services	21	15	71%

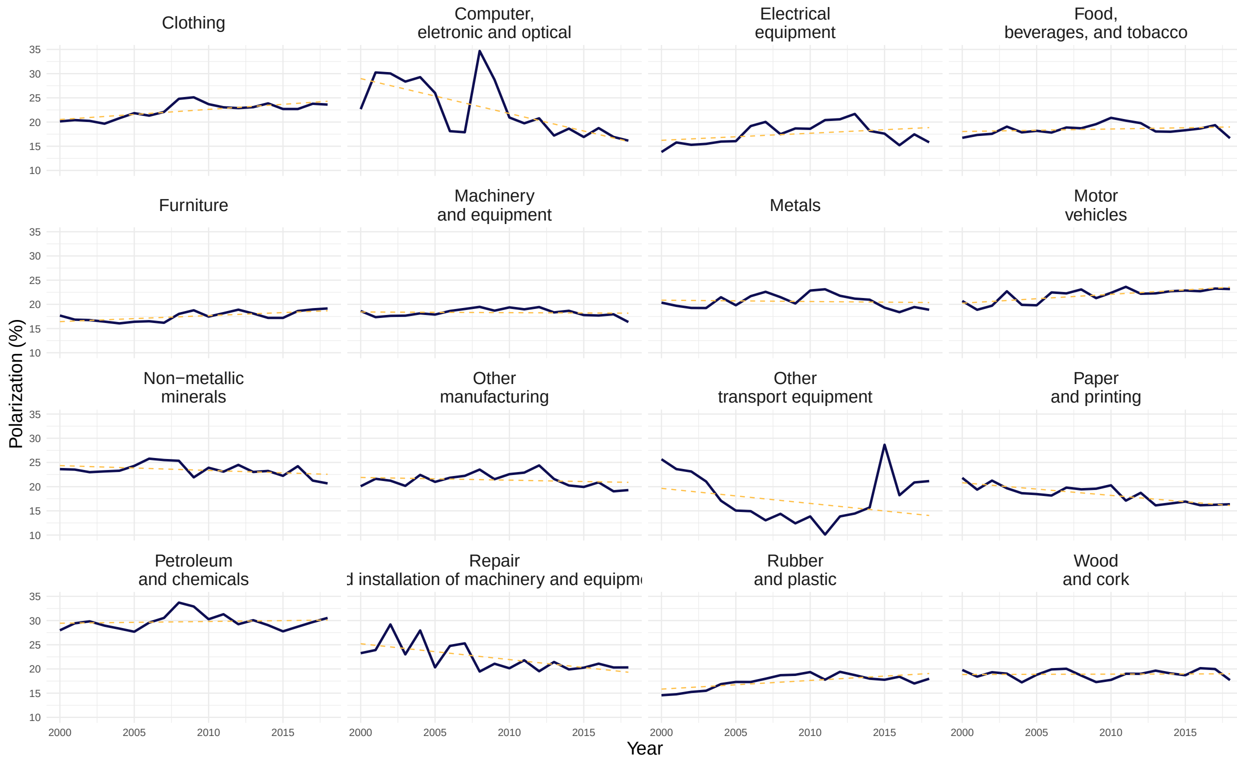
Notes: The table shows the number of sub-sectors with positive polarization trend across the two countries and the two broad sectors. A sub-sector has a positive polarization trend if it has $\hat{\beta}_j > 0$ as estimated from equation (10).

Nevertheless, there is notable industry heterogeneity, with some experiencing substantial increases of polarization, and others seeing only modest changes or even polarization decreases. In the next sections, we explore this industry heterogeneity to uncover mechanisms behind the aggregate polarization rise. Our main finding, that most industries experienced increased productivity dispersion in the right tail of the distribution, aligns with prior findings from studies of U.S. firms. Importantly, the industry trends are very similar across Spain and Sweden, that is, industries with a positive trend in Sweden also have a positive trend in Spain. Ultimately, this analysis uncovers the following fact:

Stylized fact 1: The large majority of services industries, in both Spain and Sweden, experienced an increase in productivity dispersion (polarization) in the 2000-2020 period. The positive trend is also predominant in manufacturing industries, but less so than in services industries.

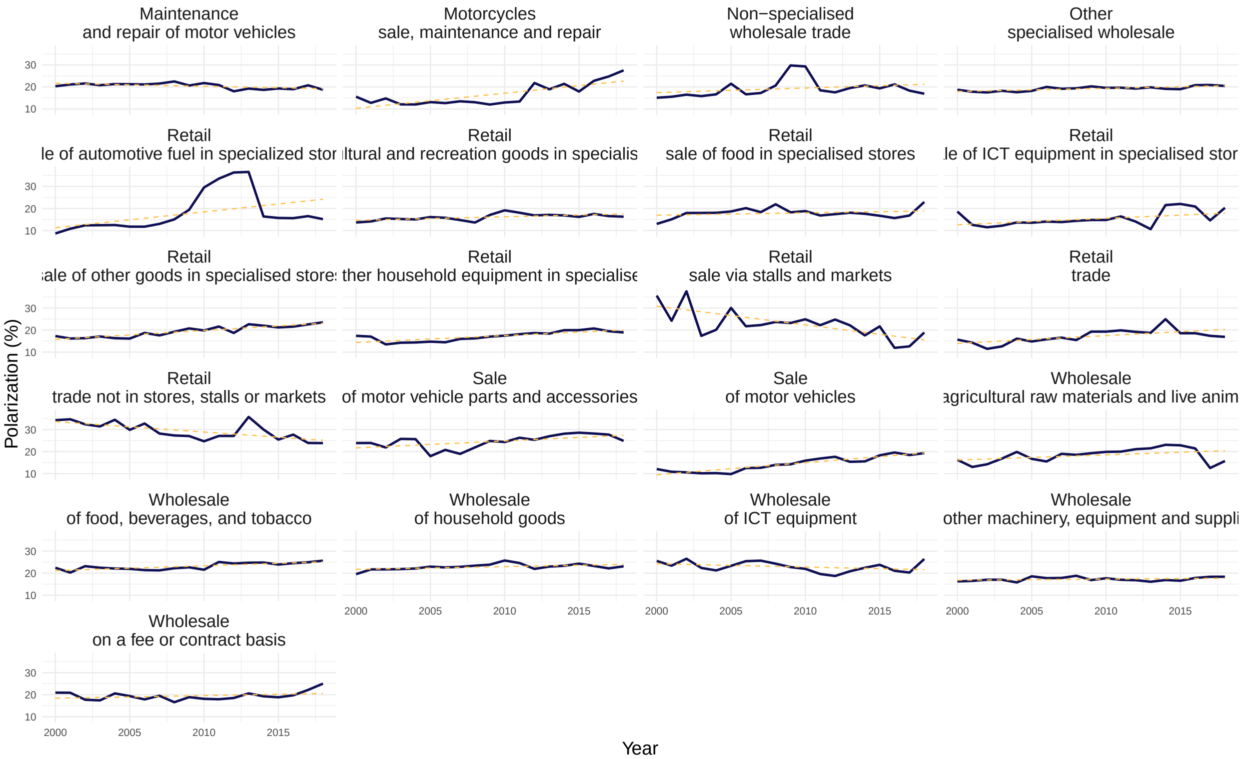
Notes: The figure plots Polarization top 50% in manufacturing industries (dark blue line).
The yellow line shows the fitted linear trend values. The linear trend is estimated after trimming the top and bottom 1% of the sector level yearly polarization changes.

Figure 3: Polarization (Sweden, manufacturing)



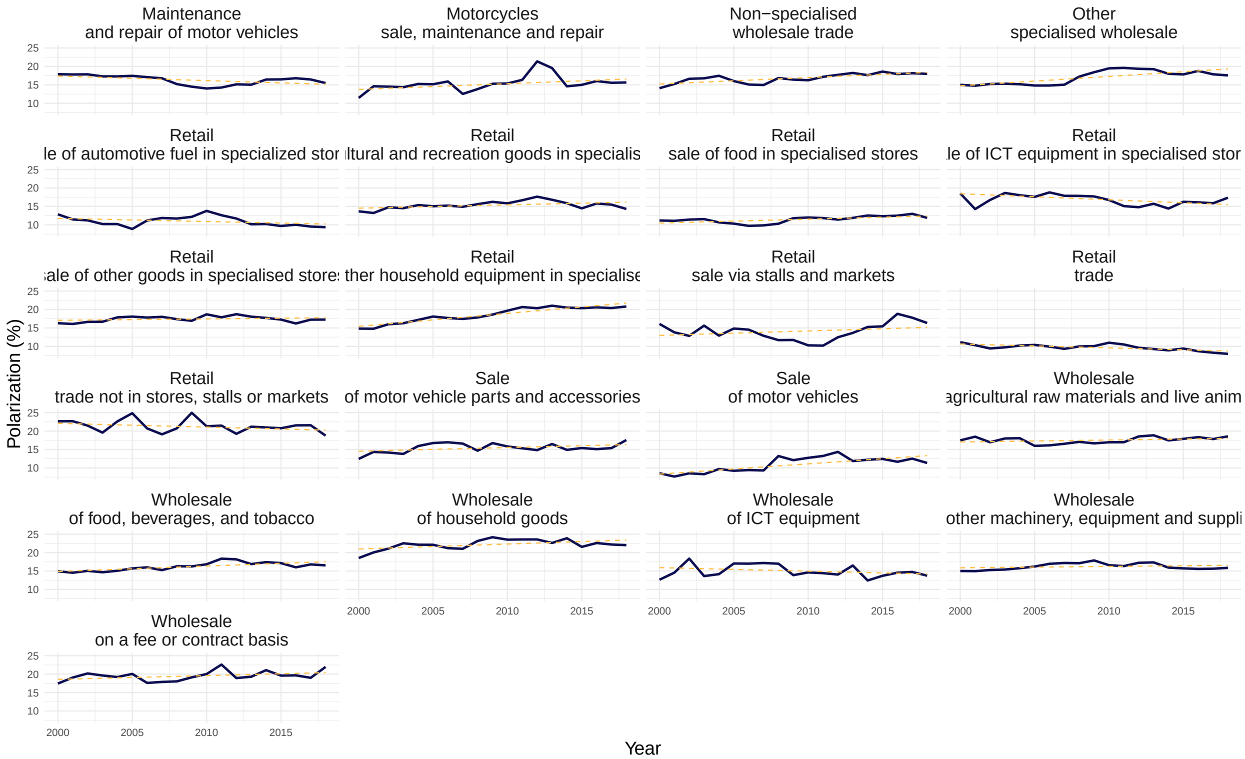
Notes: The figure plots Polarization top 50% in manufacturing industries (dark blue line).
The yellow line shows the fitted linear trend values. The linear trend is estimated after trimming the top and bottom 1% of the sector level yearly polarization changes.

Figure 4: Polarization (Spain, manufacturing)



Notes: The figure plots Polarization top 50% in service industries (dark blue line).
The yellow line shows the fitted linear trend values. The linear trend is estimated after trimming the top and bottom 1% of the sector level yearly polarization changes.

Figure 5: Polarization (Sweden, services)



Notes: The figure plots Polarization top 50% in service industries (dark blue line).
The yellow line shows the fitted linear trend values. The linear trend is estimated after trimming the top and bottom 1% of the sector level yearly polarization changes.

Figure 6: Polarization (Spain, services)

3.1 Decline in Entry, Top persistence, and Polarization

Before decomposing polarization using our new methodology proposed in section 2.2, it is useful to relate the polarization trends analyzed in the previous section to entry and top persistence statistics. These moments are directly related to prevailing theories of polarization, in particular that lack of innovation or imitation from laggard firms increases the technology advantage of dominating (superstar) firms, which then become more entrenched and more difficult to out-compete. We can verify this in our sample by analyzing, across industries, the relation between polarization trends, the persistence of firms at the top, and firm entry.

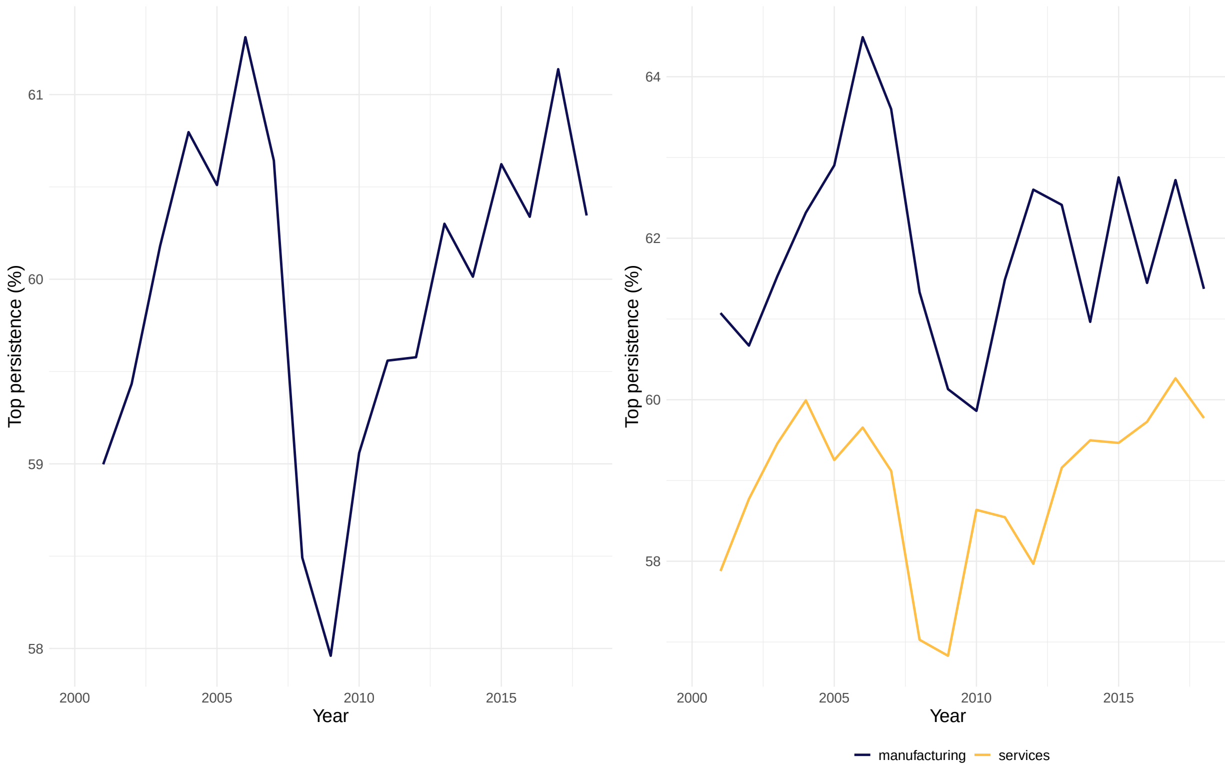
For this and the following sections, we focus our analysis on the dataset of Swedish firms. Our focus on Sweden is motivated by two primary considerations. First, our sample period is centered on the Great Financial Crisis and European sovereign crisis of 2007-2013.

This period was particularly turbulent in Spain and the volatility generated might make it more difficult to identify long run trends. Second and more importantly, the decomposition we propose in this paper requires good coverage of younger firms, that in practice are predominantly smaller firms. The Spanish SABI sample has a problem in this respect as it has limited coverage for firms smaller than 5 employees. Furthermore, as we show in Appendix A.5, The Swedish dataset has better coverage of new firms, while the Spanish sample fails to properly cover entry towards the end of the sample period.

Polarization and persistence of firms at the top

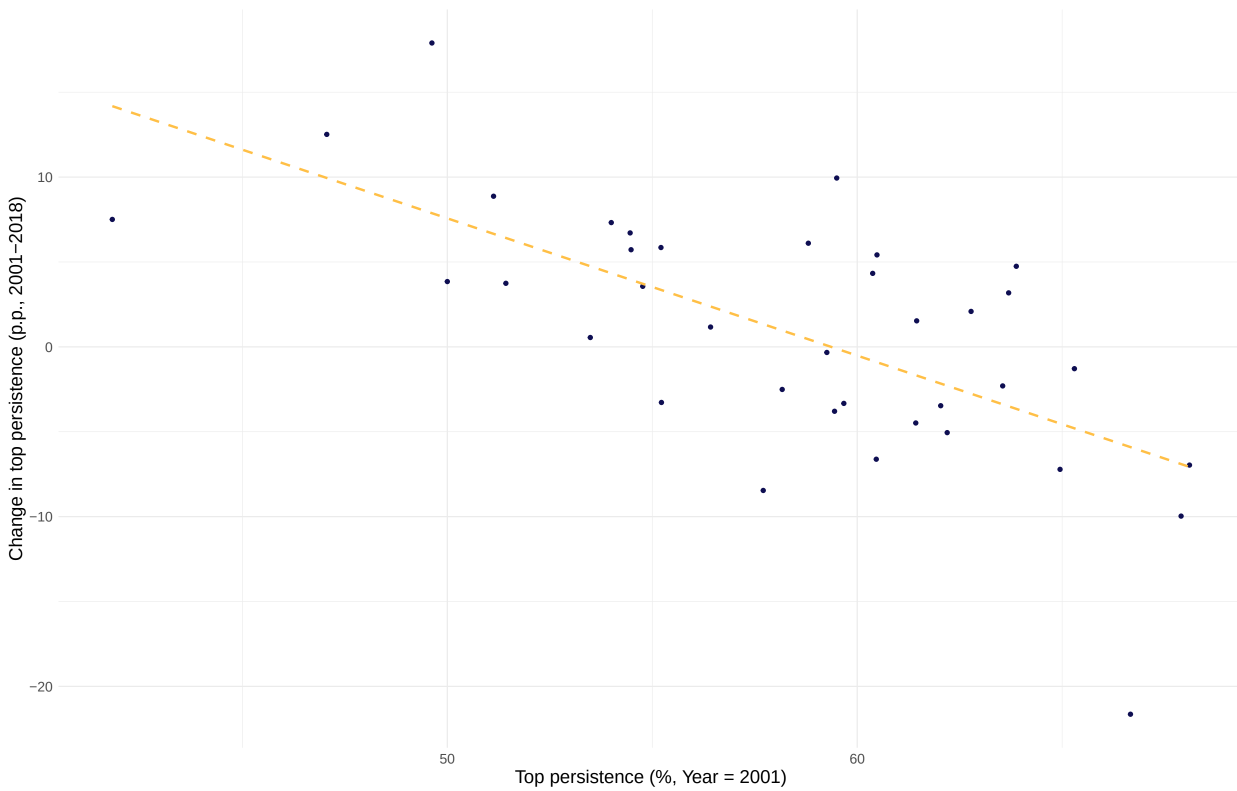
We define top persistence as the share of firms in the top revenue productivity quartile in year $t-1$ that remain at the top in year t. As in the previous section, the distributions are first evaluated at the industry-level, i.e. we measure whether firm i from industry j is at the top quartile of sector j's revenue productivity distribution in both $t-1$ and t.

The left panel of Figure 7 plots our top persistence measure for Sweden between 2001 and 2018 pooling together manufacturing and service industries. The right panel shows the metric separately for manufacturing and services. Throughout the sample period, top persistence exceeds 50% hovering around 60% in both manufacturing and services. In other words, every year more than half of the top productive firms remain at the top. Aggregate results suggest a small increase of top persistence from around 59% in 2001 to 60.5% in 2018 made possible by a considerable increase in the early 2000s, followed by a substantial drop during the financial crisis and subsequent recovery. Overall, the increase is smaller for manufacturing (top persistence is around 61% at the beginning and end of the sample period), slightly larger for services (from 58% to 60%), and relatively much smaller than the increase in polarization. That is, for services polarization increased by around 16% (see section 3) in the sample period, while top persistence increased only by around 3%.



Notes: Top persistence is the ratio of firms in the top quantile of the productivity distribution in both year t and year t−1 to the number of firms in the top quantile in t−1.

Figure 7: Evolution of persistence at the top



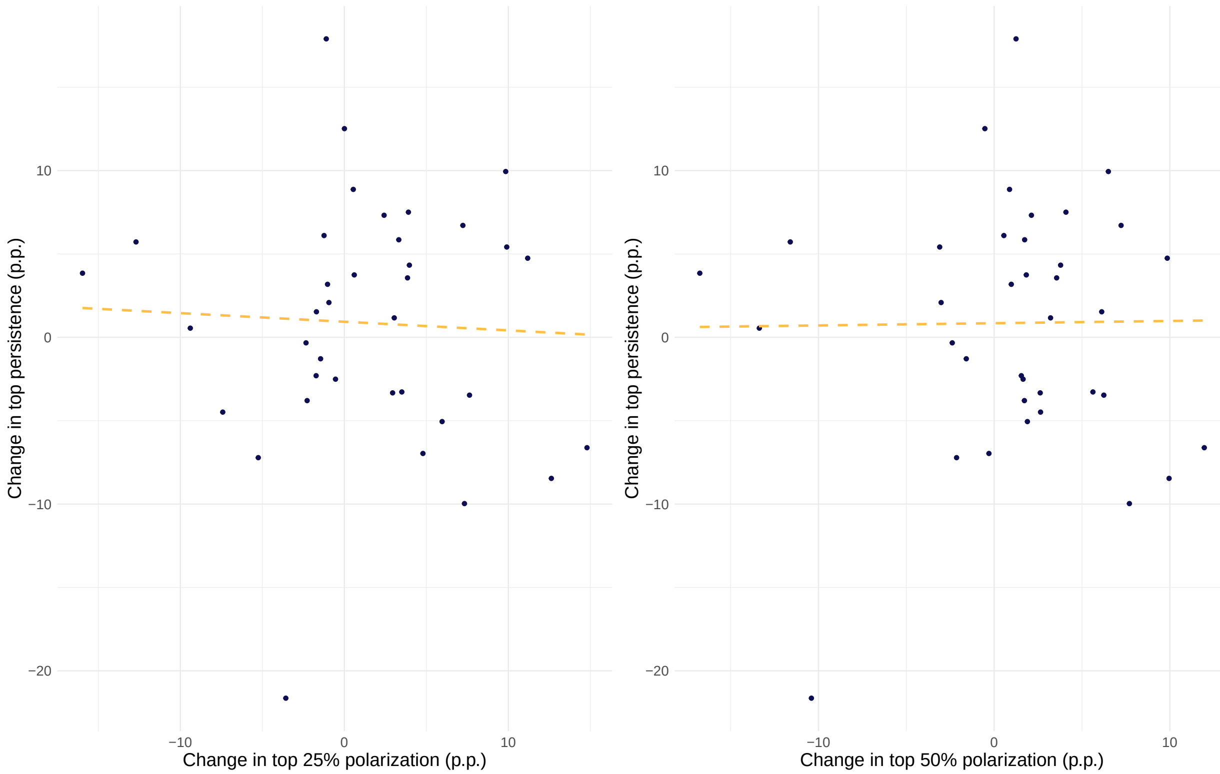
Notes: The figure plots industry level top persistence in 2001 against the percentage point change in top persistence between 2001 and 2018. The dashed yellow line shows the fitted regression line.

Figure 8: Industries experienced heterogeneous top persistence paths

Figure 8 plots the industry level change in top persistence against its initial level. The dashed yellow line shows the estimated relation between the two variables; the estimated slope is negative and statistically significant at 1% suggesting a negative correlation between the initial top persistence level and its subsequent change. Nevertheless, there is no systematic industry-level relation between changes in polarization and changes in top persistence as shown in Figure 9. Therefore, it is not the case that industries that experienced a considerable rise in polarization also experienced an above average rise in persistence at the top despite the rise of both metrics at the sector level. This result goes against the "superstar firms" view that polarization in productivity is driven by the increasing productivity advantage of top firms, and is summarized in stylized fact 2.

Stylized fact 2: Industries that experienced a larger increases in polarization did not also experience a larger increase in top-persistence than the other

industries.



Notes: The left (right) panel plots changes in top 25(50)% polarization against changes in top persistence.
The dashed yellow line shows the fitted regression line.

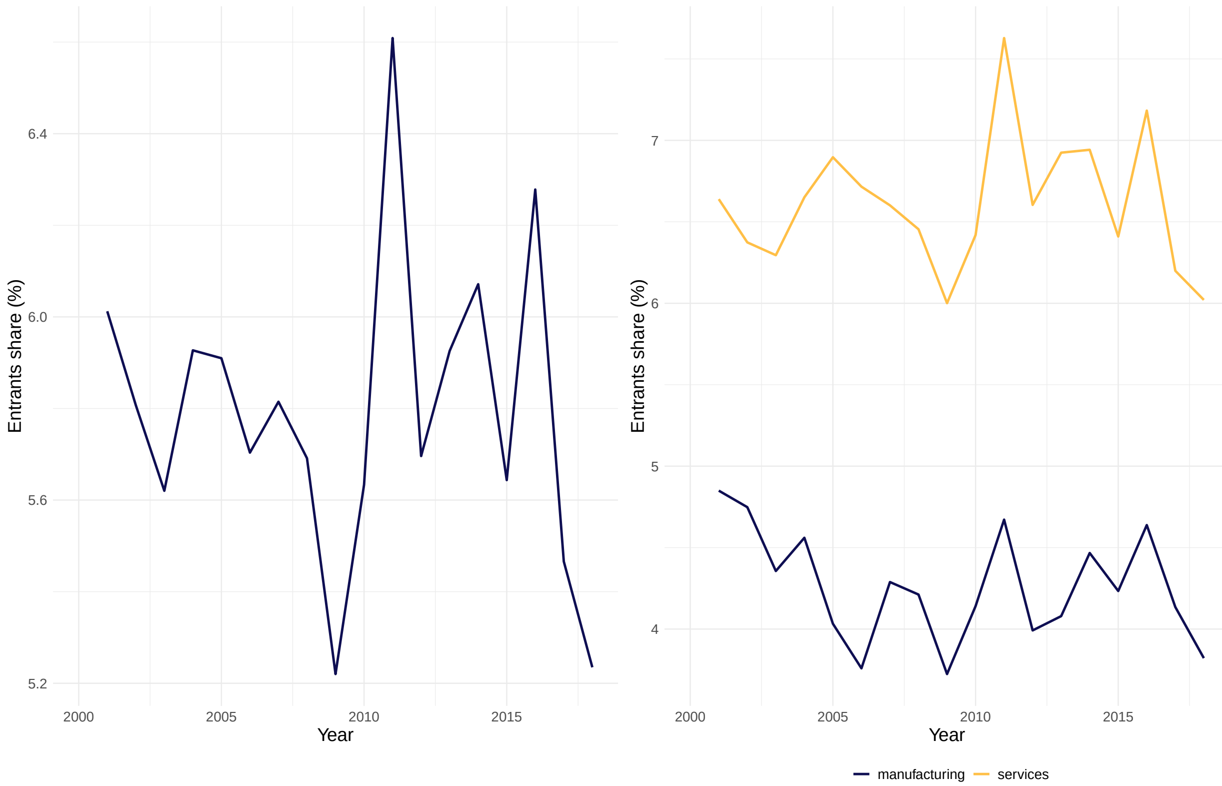
Figure 9: No systematic relation between changes in top persistence and in polarization

Polarization and Entrants

Persistence at the top, explored in the previous sub-section, is an indicator of competition, another is entry dynamics. Did industries become more polarized due to entry barriers? If so then we expect to see a declining importance of new entrants, a fact that has been documented for the overall of the US economy, specially in industries that experienced large polarization increases. In this section, we explore this hypothesis by comparing the evolution of entry rates across industries and juxtaposing them with changes in top polarization. For the purposes of this analysis, a firm is considered an entrant at t if the firm makes its first sample appearance in year t, the firm is at most 5 years old (based on incorporation date) and it employs at most 100 employees.

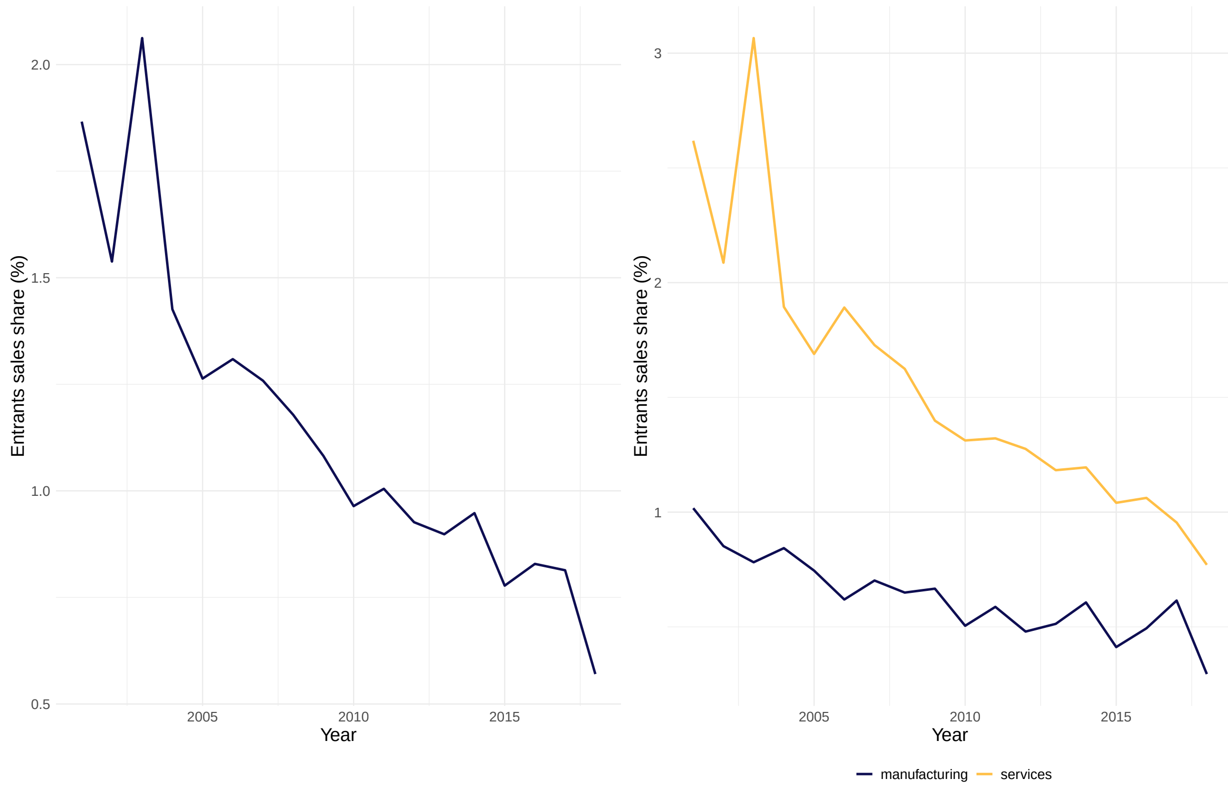
Figure 10 shows the evolution of the share of entrants between 2001 and 2018. The left panel pools together manufacturing and services and the right panel plots the series for the two sectors separately. On the whole, the entry share of entrants dropped from around 6% in 2000 to close to 5.2% in 2018. The financial crisis provoked a substantial drop in this series in 2009 followed by a quick recovery in 2011, and after milder fluctuations the entry share dropped markedly in 2017 and further in 2018. Comparing manufacturing and services, the entrant shares in manufacturing are lower than in services and both fell during our sample period: in manufacturing the entry share dropped from close to 5% to close to 4% and in services it dropped from 6.5% to 6%.

Figure 11 shows the evolution of the market share of entrants, measured as the ratio of total sales of entrants to total sales of incumbents. This is a better measure of the competition from entrants than the simple share of entrants shown in Figure 10. Figure 11 reveals a steady decline in the sales share of entrants, especially in services since 2001. In services, the market share of entrants dropped from around 2.5% to less than 1%, while in manufacturing it dropped from 1% to about 0.5%. This overall significant decline is consistent with evidence from the US and other countries.



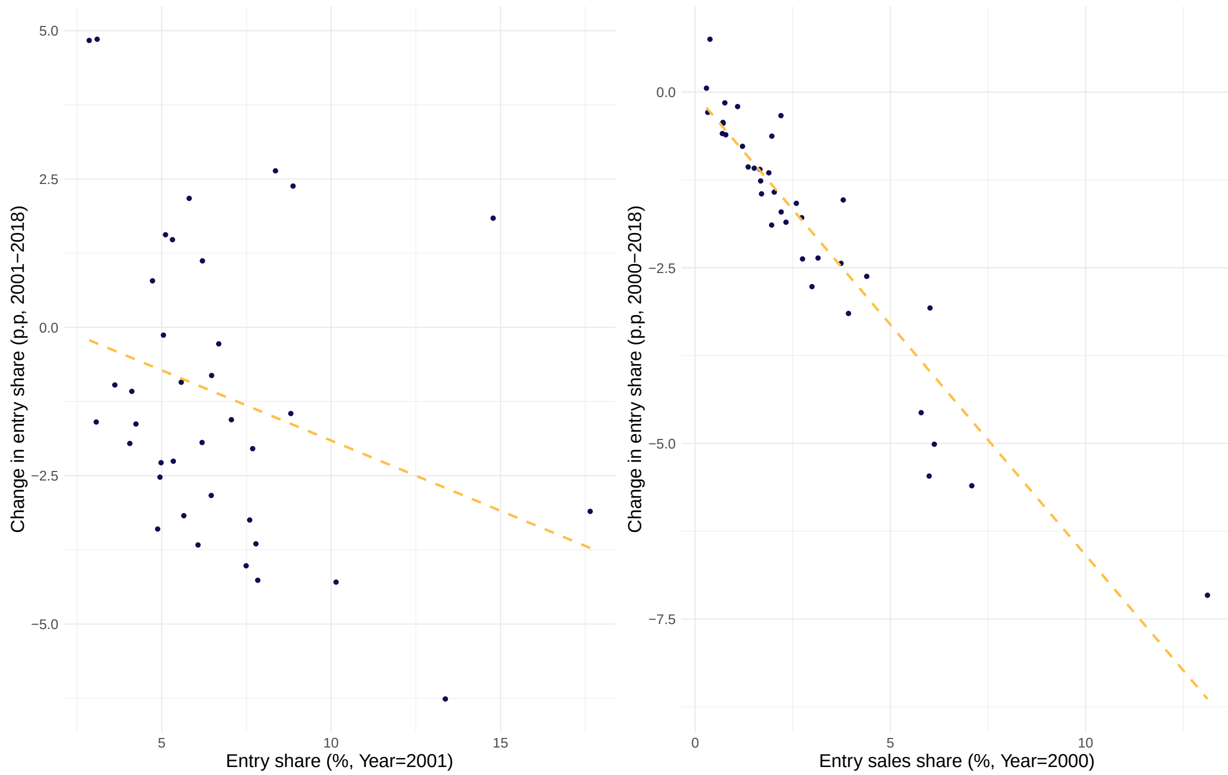
Notes: Entrants share is the entrants to the number of active firms in the previous period.

Figure 10: Evolution of entrants share



Notes: Entrants sales share is the ratio of entrants sales to incumbents sales.

Figure 11: Evolution of entrants share



Notes: The figure plots industry level initial entry shares against the percentage point change in entry shares.
The dashed yellow line shows the fitted regression line.

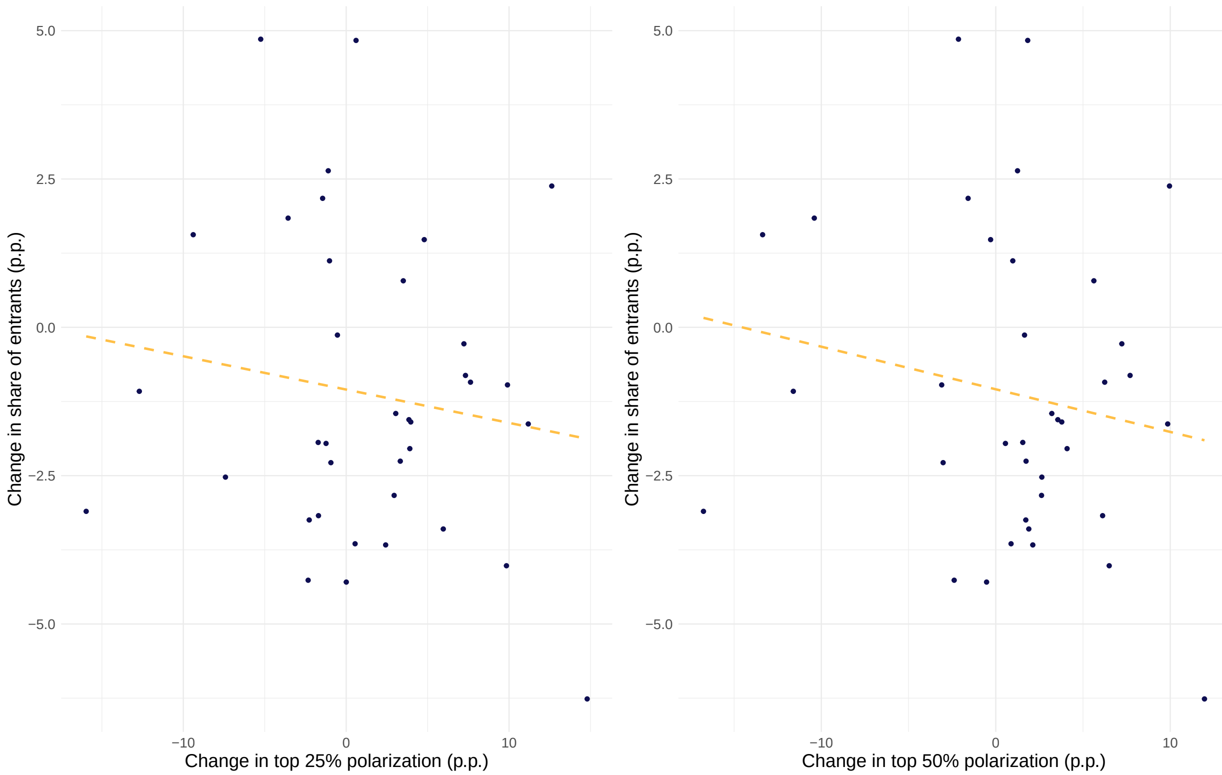
Figure 12: Industries experienced heterogeneous entry share changes

The aggregate series mask industry heterogeneity as shown in Figure 12: for the majority of industries there was a decline in entry shares, especially entry sales shares, but there is heterogeneity in the extent of these changes. Moreover, as with top persistence, the initial level of entry rates is negatively correlated with its initial level, once again suggesting some sort of convergence phenomenon. However, Figure 13 reveals that there is no systematic relation between changes in polarization and changes in entry shares.

Importantly, Figure 14 analyzes the relation between the change in polarization and the change in the sales shares of entrants, across industries. The latter, as seen before, has been strongly declining on average, but if anything, the relation with polarization is positive, meaning that polarization has increased the most in sectors that had the smallest decline in the importance of new firms for overall sales:

Stylized fact 3: Industries that experienced larger increases in polarization

do not seem to have also experienced a larger reduction in entry (either raw or sales-weighted) than the other industries.



Notes: The left (right) panel plots changes in top 25(50)% polarization against changes in the share of entrants.
The dashed yellow line shows the fitted regression line.

Figure 13: No systematic relation between changes in entry shares and in polarization

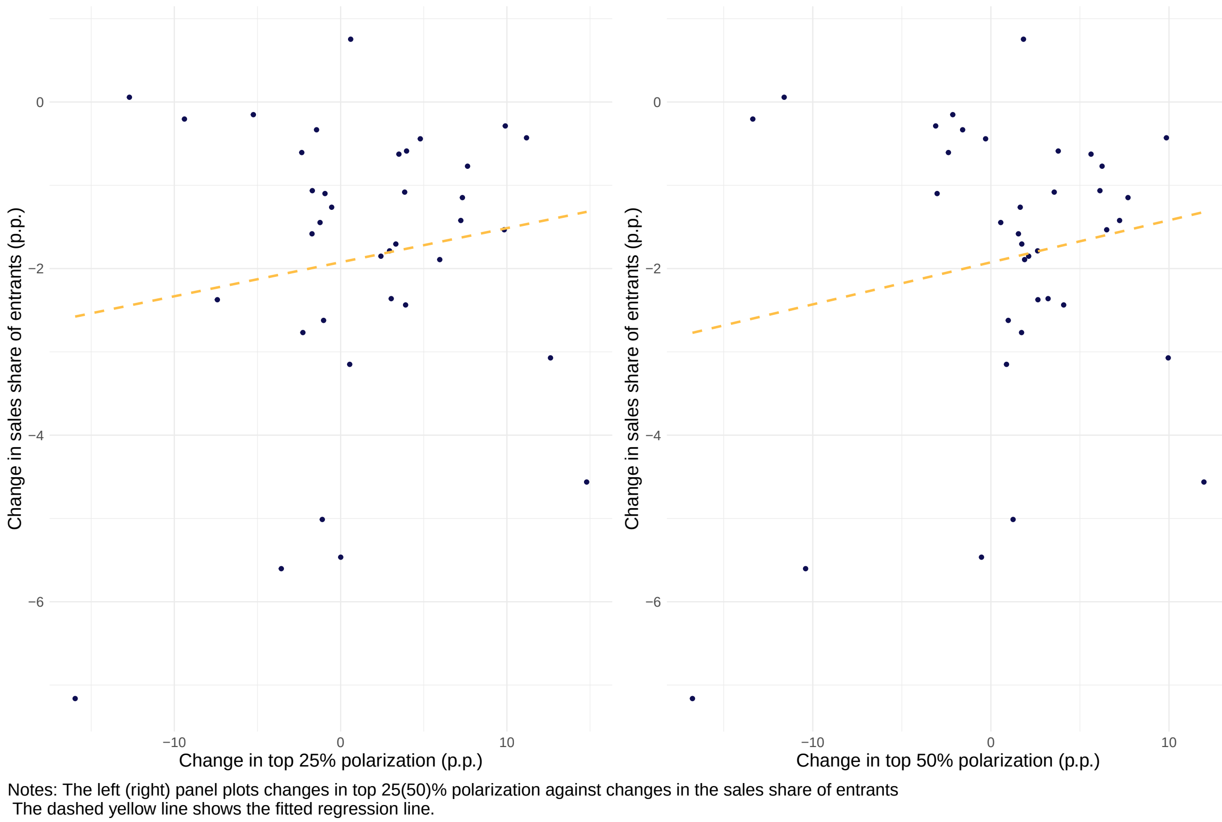
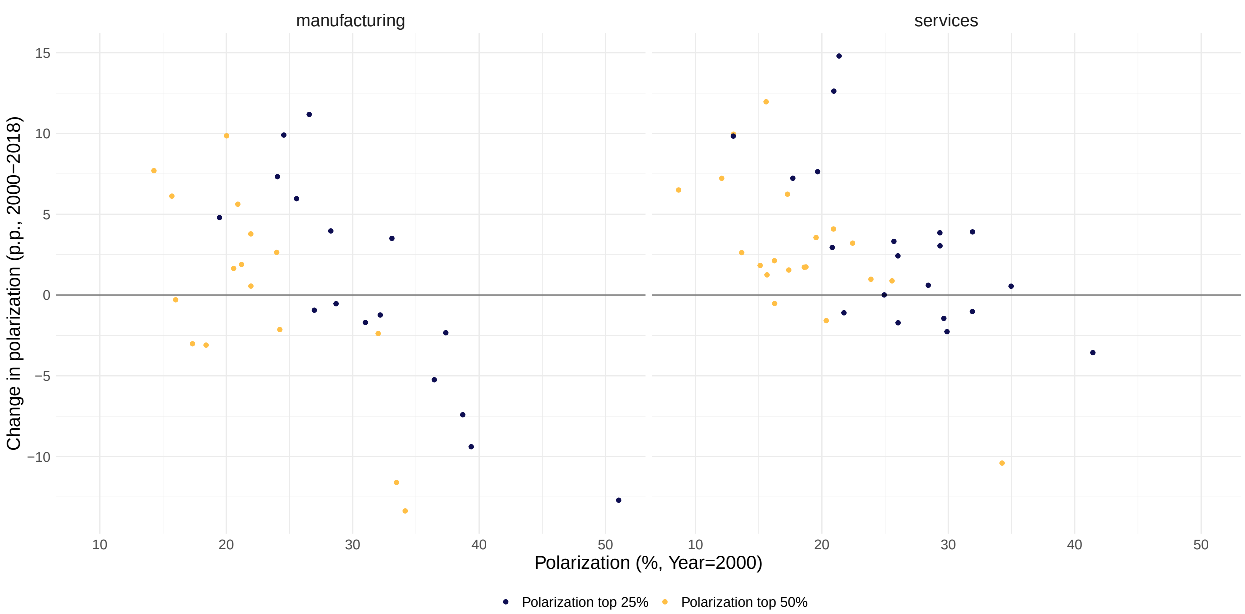


Figure 14: No systematic relation between changes in market share of entrants and in polarization

4 The factors determining polarization changes

The previous section highlights two main results. First, we observe an overall increase in polarization, especially in the service industries. Second, across industries such increase is unrelated to commonly used indicators of lack of competition, such as the persistence of firms at the top, and the share of new entrants. This evidence emphasizes the importance of detailing the factors that determined the increase in polarization in Sweden described before (see figures 1 and 2), which is the objective of this section.

Figure 15 looks at industry-level results and plots industry changes in top polarization measures against the initial polarization level pooling together top 25% and top 50% measures. While the majority of service industries experienced an increase of polarization over the sample period the results for manufacturing industries are more mixed. Furthermore, within sectors (manufacturing and services) there is a considerable amount of cross-sectional dispersion of polarization changes with some industries experiencing increases above 10 percentage points and others decreases of about the same magnitude. The results depicted also show a negative correlation between the initial level of polarization and the subsequent change possibly suggesting convergence, i.e. that the increase in polarization is concentrated among industries in which polarization was relatively low in year 2000.[7] This is in line with the convergence results shown for top persistence and entry shares.



Notes: Industry−level top polarization measures reveal productivity growth required of the median firm reach the productivity of the average firm (sales−weighted) i productivity distribution.

Figure 15: Industries experienced heterogeneous polarization paths

We now turn to our main objective, to decompose the top 50% and top 25% polarization metrics into the contribution of incumbents, entrants and switching firms (laggards). To this end we rely on the MP decomposition described in equation (7) and write changes in polarization as the sum of the contribution of continuing firms, the contribution of entry and exit dynamics, and the contribution of switching firms. In this section we consider the entire 2000-2018 period, therefore the contribution of any category K to the total change

[7]This finding is robust to considering alternative starting periods.

in polarization is equal to the sum of its yearly contributions to changes in polarization. Figures 16 - 19 show the average contribution of continuing, entering, exiting and switching firms to changes in top 50% and top 25% polarization, respectively.

Figure 16 considers the decomposition of the changes in top 50% polarization, with manufacturing on the left panel, and services on the right panel. Several considerations emerge. First, switching firms are by far the most important determinant of positive changes in polarization. Their contribution is positive and large for both sectors. It implies that firms that move from the bottom to the top of the distribution substitute firms with lower (sales-weighted) productivity that move from the top to the bottom. Importantly, for services, comprised of industries that experienced the largest increases in polarization, this component is the only positive one, since continuing firms have a contribution close to zero, and the other categories have a negative contribution. In other words, for services, we find evidence strongly consistent with polarization being related to more competition and creative destruction, rather than the opposite. For manufacturing the contribution of continuing firms is slightly larger, but still smaller than that of switching firms.

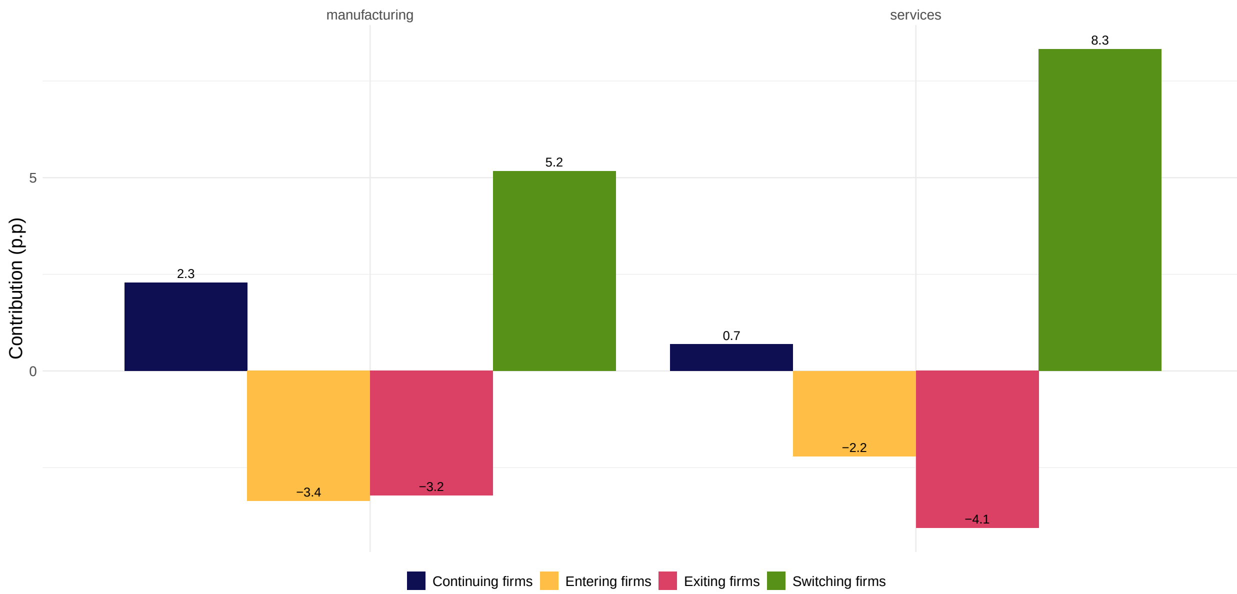
Regarding entry and exit, both components are negative. For entrants, this reflects the fact that these firms are less productive than the average incumbent. Moreover, it might also be driven by lower entry share, as documented before. For exiting firm, a negative value indicates that on average these have been more productive than incumbent firms. This finding is quite surprising, and further analysis, to verify whether some of these firms classified as exiting are actually changing denomination because of mergers and acquisitions, is currently in progress.

Figure 17 further separates manufacturing and services in two groups of industries with positive and negative polarization changes. For services, it is still the case that switching firms is the only positive determinant. So for the few industries with negative changes in polarization, the latter declines because of the worse performance of entrants and continuing firms. This is again evidence against the view that polarization in productivity has increased because incumbent firms have become more entrenched. For manufacturing, the evidence is more mixed. For the industries with positive changes in polarization, continuing firms had an important contribution, but still smaller than the one of switching firms.

Figures 18 and 19 repeat the analysis for the more extreme polarization measure which focuses on the firms at the top quartile of productivity, and confirms the previous results. In particular, in services we again find a preponderance of switching firms in terms of contributions to top 25% polarization. This finding is particularly striking considering that, as seen before, continuing firms are the majority, since top persistence is larger than 50% (see Figure 7).

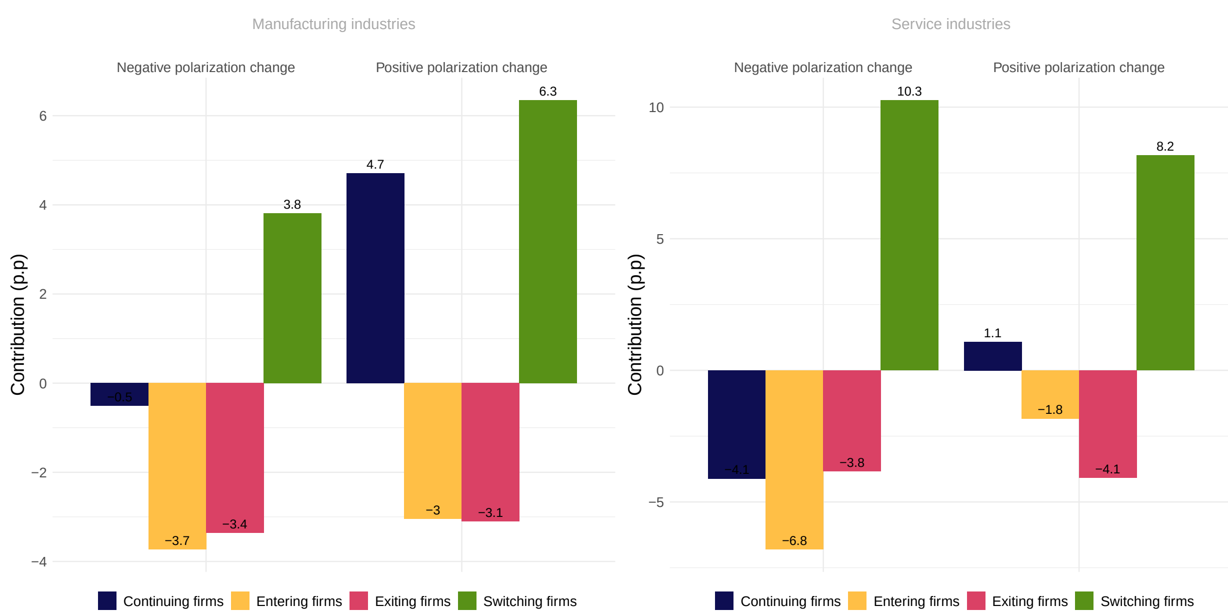
Summing up, our analysis indicates that productivity improvements from laggards are the most important determinant of the increase in polarization observed in the 2000-2018 period.

Stylized fact 4: In the service sector, which experienced a significant increase in polarization in the sample period, we find such increase to be mainly driven by large within industry dynamics, with laggards (firms not in the top productive group) becoming more productive than incumbents (firms already in the top group), rather than by productivity improvements in the latter group.



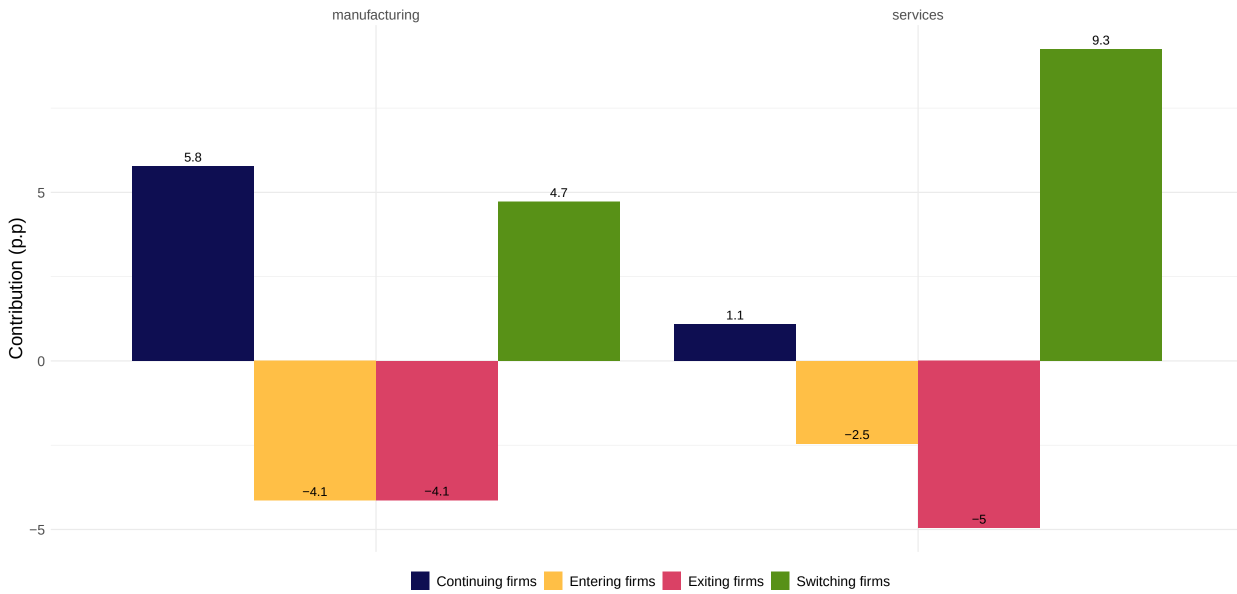
Notes: This plots shows the contribution of several categories to changes in top 50% polarization.
Sector level results are obtain from industry results as a weighted average. We use the time−series average value−added shares as industry weights.

Figure 16: An MP decomposition of top 50% polarization



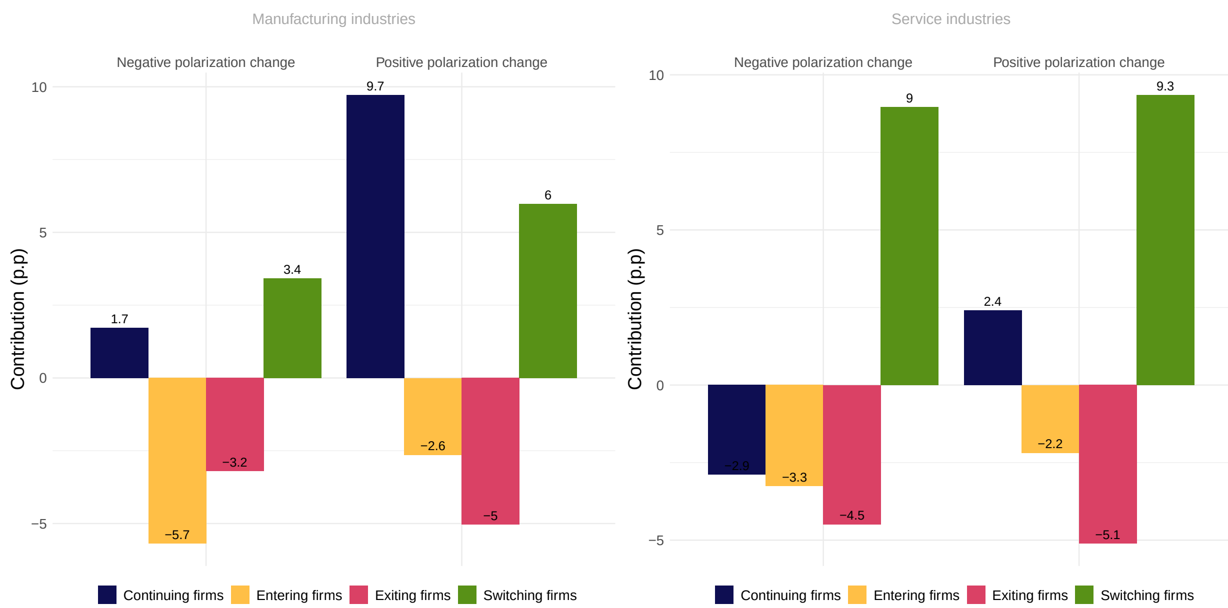
Notes: This plots shows the contribution of several categories to changes in top 50% polarization.
Aggregate results are obtain from industry results as a weighted average. We use the time−series average value−added shares as industry weights.

Figure 17: An MP decomposition of top 50% polarization



Notes: This plots shows the contribution of several categories to changes in top 25% polarization.
Sector level results are obtain from industry results as a weighted average. We use the time−series average value−added shares as industry weights.

Figure 18: An MP decomposition of top 25% polarization



Notes: This plots shows the contribution of several categories to changes in top 25% polarization.
Aggregate results are obtain from industry results as a weighted average. We use the time−series average value−added shares as industry weights.

Figure 19: An MP decomposition of top 25% polarization

4.1 Beyond top productivity polarization

We also performed several additional tests, which are reported in the Appendix. First, appendix A.2 shows the evolution of all top and bottom polarization measures described in section 2.1. Besides our proposed measures, the analysis includes other tail dispersion measures used in the literature, for example the distance between the 75th and the 50th percentile of the productivity distribution. Second, appendix A.3 looks at sales polarization, i.e. the average gap between sales of firms in the top half of the sales distribution and the media firm. In particular, it finds a positive correlation the growth of sales polarization that of top 50% polarization.

5 Analysis of February 2025

Comments on the new results available in the folder `/Technology diffusion/Technology diffusion - Data and Estimation/Technology diffusion /04_Reports/044_February_2025/`.

The pdf files include 3 versions of the results depending on the minimum thresholds of observations per sector per year: 50, 100, 200. Using 50 seems to include some outliers, using 100 yields more stable results, and going from 100 to 200 does not change much. So the comments below are based on the "100" version.

Results are usually consistent across countries, so unless a specific country is mentioned, comments below apply more or less similarly to all three countries.

5.1 Polarization Decomposition

Polarization increases in the sample period for both services (S) and manufacturing (M). More so for services.

Regarding the categories of switching firms, entrants, exiters, it is useful to keep in mind that if an industry is in the steady state, and so there is no change in polarization, the sum of these three components is exactly zero, but the individual components can be positive or negative (see equation 7). In the data we find entrants and exiters components to be generally negative (so entrants are less productive than incumbents and exiters are more productive than incumbents), while we find that Switching firms' component is always positive (top switchers substitute less productive bottom switchers).

As mentioned above, polarization increases across both M and S, and the first striking fact is that there is no significant positive contribution of continuing top firms. Contribution is approximately zero for both M and S for all three countries for the benchmark top50 decomposition. Instead the increase in polarization is driven by a large positive contribution of switching firms (which is largest for services, which also experience the largest overall increase in polarization) which is not offset by the negative contribution of entrants and exiters.

The fact that the switchers component is so large seems to indicate that switchers dynamics are asymmetric. Top switchers on average replace less productive bottom switchers, implying that the productivity improvements of firms coming from the bottom are larger than the productivity losses of firms that switch from top to bottom. (This is consistent with a model in which innovation allows less productive firms to experience large discrete jumps in productivity, so more like radical than incremental improvements).

The importance of switchers as drivers of polarization, and the non-importance of continuers, is confirmed both when looking at the top25 polarization and at the top50.

Note: for entrants, a more negative contribution can have different interpretations, since it is a result of the positive share multiplied by the negative productivity gap. Therefore, a more negative contribution could indicate actually lower barriers to entry and more dynamism (more low productivity firms enter, so both the share and the gap increase). More barriers to entry would imply entrants should be more productive, and therefore the entrants contribution could actually become less negative.

Within M and S sub-sectors, it is still the case that switchers have the largest positive contribution, but in general results are less consistent across M, S and countries. One potential problem is that some firms might be switching sectors over the sample period. One interesting robustness check would be to replicate the analysis after assigning all firms permanently to a given sector.

We always see beta convergence in polarization. That is, sectors that are less polarised at the beginning of the sample are more likely to experience an increase in polarization. This is most likely spurious convergence due to observational errors at the beginning of the sample. If so, it is another reason to take with caution these sub-sectors results.

5.2 Entry Shares

For the entry shares, the most reliable data are from Sweden. In terms of unweighted entry shares, they decline slightly for M but they increase for S. However, weighted for sales they decline more strongly, for both M and S. So it means entrants are still numerous, but get relatively smaller. Again this is not consistent with more barriers to entry, which would imply less entrants but larger. It is consistent with lower barriers to entry and higher innovation prospects for laggards. Low productivity new firms might be encouraged to enter even if they are small because of the chances to innovate and become top firms (related to the positive contribution of top switchers). This interpretation is basically opposite to the "decline in technology diffusion story".

Looking within sub-sectors for Sweden, the change in the entry share is slightly negatively correlated to the change in polarization. But again these results should be taken with caution. Also for the entry shares we observe strong beta convergence, which can be interpreted as measurement error at the beginning of the sample.

5.3 Top Persistence

Looking at M and S sectors, top persistence fluctuates but there is no clear upward or downward trend, consistently with the finding that top firms do not contribute to the increase in polarization.

Consistently with the previous comment, we find no correlation between change in top persistence and change in polarization across sub-sectors in S and M.

Beta convergence is less pronounced for Top persistence than for entry. Measurement error at the beginning of the sample is presumably less of a problem for top incumbent firms.

5.4 Future Work

5.4.1 Data Analysis Tasks

- Do the analysis also for ICT sectors. Probably we have enough observations for Italy, Spain, and later for France.

- Our decomposition in equation 7 follows Melitz-Polanec. But intuitively one alternative decomposition is continuers vs [(entry+top switchers)-(exiters+bottom switchers)]. Basically is a creative destruction interpretation. The component in the square brackets [ ] is positive if entry+top switchers substitutes less productive exiters+bottom switchers.

- Redo the analysis by assigning all firms to a given sector for the whole sample period.

- For entry, decompose into the contribution of the share and the contribution of the difference in productivity of the incumbents (like we did at some point in the past). It helps to identify the theoretical entry conditions.

5.4.2 Theoretical Framework

- We should start thinking of a model of firm dynamics that can rationalize these findings. That is, a model with various forces (radical innovation, tech adoption, incremental innovation. . .) that affect firm dynamics, and that can be calibrated to replicate the polarization decomposition dynamics in the data. The added value of the model would be to identify the likely forces behind the increase in polarization.

- The tricky questions on the model are first what type of broad structure (in the literature there are either duopoly models (one leader versus one laggard or versus the rest) or models with many atomistic firms, while we might need a combination of the two.

- And also how to identify/map all the moments we compute with the forces in the model.

6 Model

In this section, we propose a firm dynamics model in the style of Melitz (2003) with endogenous innovations. Time is discrete and indexed by t. There is a continuum of monopolistically competitive firms indexed by $\omega \in \Omega$ who face CES demands. These firms produce differentiated products. They are heterogeneous in their productivity z, and can invest in R&D to improve it. R&D investments can be applied to two types of innovation: incremental innovation or radical innovation.

Demand: A representative consumer has CES preferences over a continuum of goods indexed by ω:

$$U = \int_{\omega \in \Omega} [q(\omega)^{\rho} \mathrm{d}\omega]^{\frac{1}{\rho}}, \ \ \rho \in (0,1) \tag{11}$$

The elasticity of substitution between the goods is governed by ρ and given by $1/(1-\rho) > 1$. The CES aggregate price index P_t is equal to:

$$P_t = \left[\int_{\omega \in \Omega} p_t(\omega)^{\frac{\rho}{\rho-1}} \mathrm{d}\omega \right]^{\frac{\rho-1}{\rho}} \tag{12}$$

From consumer optimization, the demand for variety ω is given by:

$$q_t(\omega) = Q_t \left[\frac{P_t}{p_t(\omega)} \right]^{\frac{1}{1-\rho}} \tag{13}$$

where Q_t is given by:

$$Q_t = \left[\int_{\omega \in \Omega} q_t(\omega)^{\rho} \mathrm{d}\omega \right]^{\frac{1}{\rho}} \tag{14}$$

Production: Each firm in the continuum of firms produces a differentiated variety ω. There is a single input, labor, with inelastic supply at the aggregate level L. We normalize the wage to 1. At any point in time t, the producer of variety ω produces with a constant marginal product of labor equal to $z_t(\omega)$. The ex-ante productivity distribution is bounded between $\underline{z}$ and $\bar{z}$. $\bar{z}$ defines the technological frontier. Production requires the payment of an overhead cost F_t. Since the problem is identical for all varieties, we omit the ω indicator. Static profits are given by:

$$\pi_t(z_t, \varepsilon_t) = p_t q_t - \frac{q_t}{z_t} - F_t \tag{15}$$

where F_t is given by

$$F_t = (1 + \varepsilon_t) F(z_t), \;\; F'(z_t) > 0 \tag{16}$$

and ε_t is a shock drawn from an i.i.d. zero-mean distribution across time and varieties. Following Caggese (2019) use the following functional form for $F(z_t)$:

$$F(z_t) = \left(\frac{z_{it}}{\hat{z}_0}\right)^{\kappa}, \;\; \kappa > 0 \tag{17}$$

Firms choose p_t to maximize static profits:

$$\max_{\{p_t\}} \pi_t(z_t, \varepsilon_t) = p_t \cdot q_t(p_t) - \frac{q_t(p_t)}{z_t} - F_t \tag{18}$$

subject to the demand function in equation (13). The first-order condition yields the standard pricing function:

$$p_t = \frac{1}{\rho} \cdot \frac{1}{z_t} \tag{19}$$

with

$$q_t = Q_t P_t^{\frac{1}{1-\rho}} (\rho z_t)^{\frac{1}{1-\rho}} \tag{20}$$

It follows that static profits are given by:

$$\pi(z_t, \varepsilon_t) = Q_t P_t^{\frac{1}{1-\rho}} z_t^{\frac{\rho}{1-\rho}} \rho^{\frac{1}{1-\rho}} (1-\rho) - F_t \tag{21}$$

Incumbents: The timing of the model for a firm that was already in operation in period $t-1$, an incumbent, is as follows: at the beginning of time t, the firm's technology may become forever useless with probability d and the firm ceases activity. With probability $1-d$ the firm is able to continue. In this latter case, it observes the realizations of z_t and ε_t. It decides whether to continue operation or to exit the market. We assume the outside option for the firm is zero. If it continues, it receives the maximized static profits in equation (21) and it chooses between innovation types. There are two innovation types: incremental and experimentation.

Incremental innovation: successful incremental innovations increase firm-level productivity from z_t to z_{t+1}. The growth depends on the distance to the frontier $z_t/\bar{z}$:

$$z_{t+1}(z_t) = \bar{z}\left(\frac{z_t}{\bar{z}}\right)^{\gamma}, \ \gamma \in (0,1) \tag{22}$$

The function in equation (22) has the following nice properties. First, if a firm has technology at the frontier, i.e. $z_t = \bar{z}$, even if the incremental innovation is successful $z_{t+1} = z_t = \bar{z}$. Second, z_{t+1} is strictly increasing in z_t. Third, the productivity growth rate is decreasing in z_t such that the productivity growth is increasing in the distance to the frontier (see equation (23)) .

$$\frac{z_{t+1}}{z_t} - 1 = \bar{z}^{1-\gamma} z_t^{\gamma-1} - 1 \tag{23}$$

Firms can influence the probability of successful incremental innovation by choosing how much to invest M_t. The probability of a successful incremental innovation $\mathbb{P}$ relates to the amount invested M_t in the following way:

$$\mathbb{P}(M_t) = \left(\frac{M_t}{M_t + 1}\right)^{\frac{1}{\sigma}}, \ \sigma > 0, \ M_t \geq 0 \tag{24}$$

Equation (24) has the following nice properties. First, if a firm does not invest the probability of success is zero, $\mathbb{P}(0) = 0$. Second, the probability of success is strictly increasing in M_t but has an asymptote at 1. The firms must choose $M_t \geq 0$.

Experimentation: in each period, each firm draws its current experimentation cost E_t from some distribution b in the interval $[0, \bar{E}]$.[8] Experimentation has a constant probability of success $\mathbb{S}$. If experimentation is successful, the firm draws its new productivity from a distribution concentrated near the technological frontier.[9] If the experimentation is unsuccessful:

$$z_{t+1} = z_t(1 - g), \ g > 0 \tag{25}$$

Value functions: the previously described incumbent problem can be summarized by value-functions. First, an incumbent decides whether to continue and receive $V^c(z_t, \varepsilon_t)$ or exit and get zero (outside option), such that $V(z_t, \varepsilon_t)$ is given by:

$$V(z_t, \varepsilon_t) = \max\{V^c(z_t, \varepsilon_t), 0\} \tag{26}$$

[8] September 9th: In the current version, there is a unique experimentation cost.

[9] September 10th: In the current version, after a successful experiment, the firm draws its new productivity from a uniform distribution.

If the firm decides to continue, it receives current profits $\pi(z_t, \varepsilon_t)$ and decides whether to invest in incremental innovation or experiments:

$$V^c(z_t, \varepsilon_t) = \pi(z_t, \varepsilon_t) + \max\{V^i(z_t, \varepsilon_t), V^r(z_t, \varepsilon_t)\} \tag{27}$$

The value of incremental innovation is given by:

$$V^i(z_t, \varepsilon_t) = \max_{M_t} -M_t + \frac{1}{R} \cdot (1-d) \left[\mathbb{P}(M_t)\mathbb{E}\left[V(z_{t+1}, \varepsilon_{t+1})\right] + (1 - \mathbb{P}(M_t))\mathbb{E}\left[V(z_t, \varepsilon_{t+1})\right]\right] \tag{28}$$

and the value of experimenting is given by:

$$V^r(z_t, \varepsilon_t) = -E_t + \frac{1}{R} \cdot (1-d) \left[\mathbb{S}\mathbb{E}\left[\int_{\tilde{z}}^{\bar{z}} V\left(z_{t+1}, \varepsilon_{t+1}\right) h'(z_{t+1}) \mathrm{d}z_{t+1}\right] + (1 - \mathbb{S})\mathbb{E}\left[V(z_t(1-g), \varepsilon_{t+1})\right]\right] \tag{29}$$

where $\tilde{z}$ is the lower support of the productivity distribution conditional on a successful experiment and h' is the probability density function.[10].

Entrants: In each period t there is a large number of potential entrants. These potential entrants pay the entry cost F^e to draw their productivity from a right-skewed distribution g with support $[\underline{z}, \bar{z}]$. For example, z may be drawn from a truncated normal distribution with mean μ and standard deviation σ. For example,

$$\mu = \nu\underline{z} + (1 - \nu)\bar{z}, \ \nu \in (0.5, 1) \tag{30}$$

and some small standard deviation. After learning their type, they decide whether they

[10] September 10th: In the current version, if $z_t(1 - g) < \underline{z}$, and the experiment fails, the firm is forced to exit

want to enter the market. The free entry condition requires ex-ante, the expected value of paying F^e conditional on the expectation of the initial values.

$$V^e = \int_{\underline{z}}^{\bar{z}} \max\{\mathbb{E}^{\varepsilon_0}\left[V(z_0, \varepsilon_0)\right], 0\} g(z_0) \mathrm{d}z_0 - F^e = 0 \tag{31}$$

6.1 Mapping the model with empirical evidence

In the context of equilibrium industry models, the key aspect of the Melitz Polanec decomposition is that it is by construction analyzing a "transition" outside the steady state.

Consider the equilibrium of the model described in the previous section. In equilibrium, polarization Φ_t is constant by construction, and $\Delta\Phi_t = 0$. So an increase in polarization ($\Delta\Phi_t > 0$) implies the industry is not at the steady state.

We can of course simulate different equilibria that imply different values of Φ_t in the steady state, but again Φ_t is constant over time in each of these equilibria, it only varies in the transition. The MP decomposition cannot be used to compare steady states.

In terms of theory, this is not a problem, we can shock the industry so to generate a transition towards more polarization and then apply the decomposition to see what factors determine it. As a first approximation we can use a "myopic transition", that is, we compute a steady state, then we compute transition after shocks holding fixed equilibrium prices. Later we can do the proper transition model.

In terms of interpreting the data with the model, I think that the contribution of incumbent, switchers, entry, exit to changes in polarization can only be evaluated relative to a given steady state.

More precisely consider the decomposition in equation 7. If the industry is in the steady state, then $\Delta\Phi_t = 0$. This means that the sum of all the terms on the right hand side is equal to zero, but it does not mean that each term is equal to zero. So for example in the steady state typically the contribution of continuing firms $\Phi_t^C - \Phi_{t-1}^{CF}$ should be positive if on average continuing firms become more productive relative to the median. As we have seen in the data, the contribution of entry $(\Phi_t^E - \Phi_t^C)$ is typically negative, etc...

So we should ideally first calibrate the steady state of the model. One simple approach would be:

1) assume that certain sub-periods (or certain industries) are in the steady state because $\Delta\Phi_t = 0$ on average in the subperiod.

2) calibrate the model so that in the steady state it matches the contributions of each component of the RHS of equation 7.

3) Then compute again the decomposition 7 in the data for the periods in which polarization increases, and compares these RHS components of equation 7 with those computed in the steady state.

4) Finally, simulate transitions of the model after given shocks. Which type of shocks generate a decomposition in the transition that looks like the one in the data.

For example, consider the following shocks:

i) A change in technology favours incumbents. This could be modeled as a shock that increases the efficiency of prod. improvement (by spending the same, more prob. success), but lowers the importance of the distance from the frontier. So it is more difficult for firms far from the frontier to imitate. This shock will likely make incumbents more productive relative to the steady state. Polarization increases because of a stronger contribution of continuers, while contribution of switchers might become worse.

ii) A shock that increases in the importance of distance from the frontier (so better imitation): This should increase polarization by increasing the net contribution of TS, but might also increase the contribution of continuers (some continuers are far from the frontier). So it might cause more polarization both because continuers become more polarised and because the contribution of switchers increase (relative to SS).

iii) An increase in efficiency of experimentation. This increases the contribution of TS but at the same time it should reduce the contribution of continuers (they invest less in innovation because they might be more easily targeted). So polarization increases because Switchers' contribution increases while continuers contribution decreases (again, relative to SS).

7 Conclusions

This paper examines the drivers of productivity dispersion, referred to as "polarization" between 2000 and 2018 in Sweden. In the sample period a notable increase in polarization was observed especially for the services sector, aligning with trends witnessed in other developed economies during this period.

We developed a novel application of the Melitz-Polanec decomposition to analyze the contributions of various firm dynamics to changes in polarization. The analysis reveals that the rise in polarization is primarily attributed to within-industry dynamics, characterized by "laggard" firms improving their productivity and substituting less productive firms at the top of the productivity distribution.

The findings are difficult to reconcile with theories attributing productivity polarization to factors like slower technology diffusion, increased entry costs, or the dominance of "superstar" firms. Relatedly, we find no systematic relation between polarization increases and indicators of diminished competition, such as increased persistence of top firms or reduced entry rates. Overall, the evidence presented suggests that the relationship between technological change, firm dynamics, and polarization is complex and multifaceted. Further theoretical and empirical investigation is necessary to fully understand the interplay of these factors in driving productivity dispersion.

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A Appendix

A.1 An alternative decomposition

The decompositions in equations (4), (6), and (7) reflect business dynamics. Alternatively, we might be interested in whether polarization dynamics are driven by young or old firms. A firm is considered young Y if it is younger than 10 years old, and it is considered old O otherwise. We can write polarization as:

$$\Phi_{j,t} = \Phi^{Y}_{j,t} + S^{O}_{j,t}(\Phi^{O}_{j,t} - \Phi^{Y}_{j,t}) \tag{32}$$

Where $S^{O}_{j,t}$ is the sales share of old firms and $\Phi^{K}_{j,t}$ is defined as above. Changes in polarization can then be written as:

$$\Delta\Phi_{j,t} = \underbrace{\Delta\Phi^{Y}_{j,t}}_{\text{Evolution of polarization of young firms}} + \underbrace{S^{O}_{j,t}(\Phi^{O}_{j,t} - \Phi^{Y}_{j,t}) - S^{O}_{j,t-1}(\Phi^{O}_{j,t-1} - \Phi^{Y}_{j,t-1})}_{\text{Evolution of polarization gap}} \tag{33}$$

A positive value for the term $\Delta\Phi^{Y}_{j,t}$ in equation (33) captures that young firms at t are more polarized than young firms at $t-1$. This might be caused by several factors including a higher market share of highly polarized young firms or new young firms being more polarized than those who leave the group. Meanwhile the term $S^{O}_{j,t}(\Phi^{O}_{j,t} - \Phi^{Y}_{j,t}) - S^{O}_{j,t-1}(\Phi^{O}_{j,t-1} - \Phi^{Y}_{j,t-1})$ reveals whether young and old firms are polarizing at the same pace: if the market share of old firms remains relatively constant from one period to the next, a positive evolution of the polarization gap reveals that old firms are becoming relatively more polarized than young firms.

A.2 Additional polarization metrics

In this project we propose new measures of polarization and we focus particularly on top polarization. In this section, we show the evolution of several other polarization metrics including standard distance measures. We show results both at the industry level and at the sector level. Figures 20–23 show the evolution of several top polarization measures between 2000 and 2018 at the sector-level. Figures 24-27 show bottom polarization measures at the sector-level. The same measures at the industry level are shown in Figures 28–35.

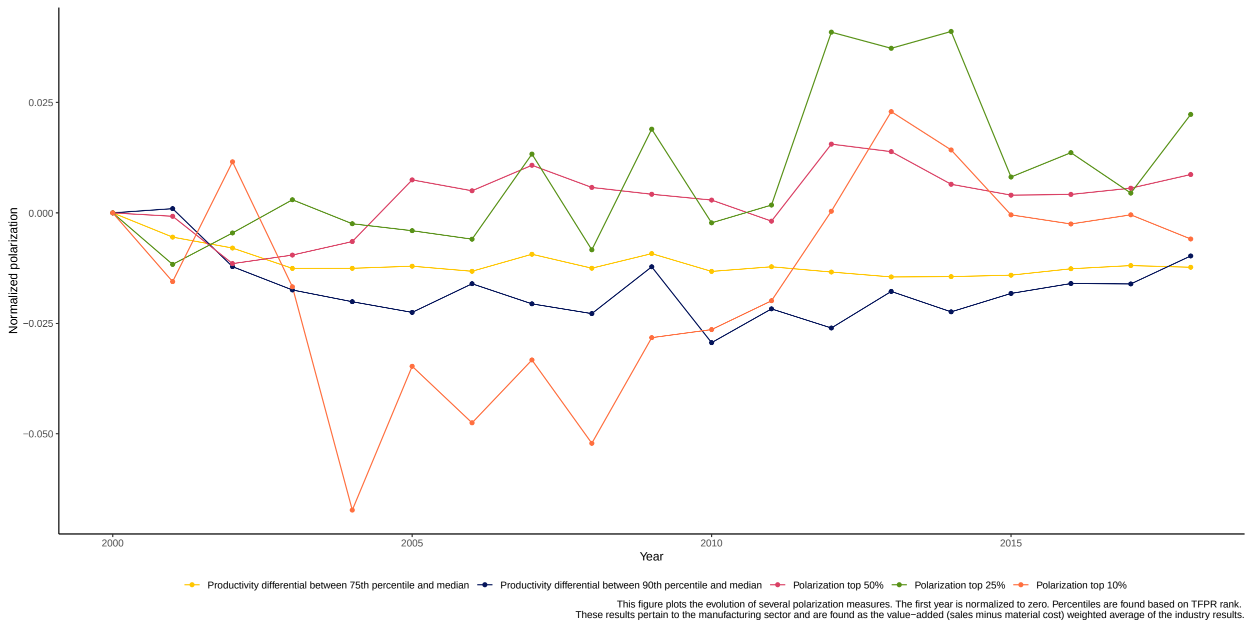

Figure 20: Top polarization measures (Sweden, manufacturing)

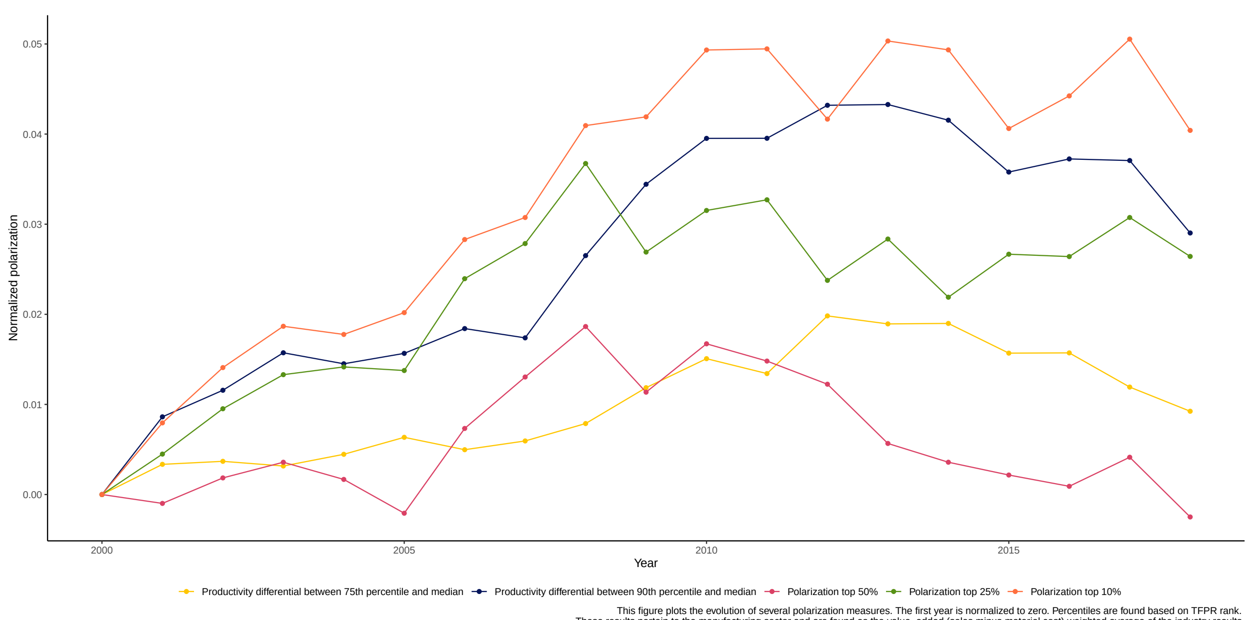

Figure 21: Top polarization measures (Spain, manufacturing)

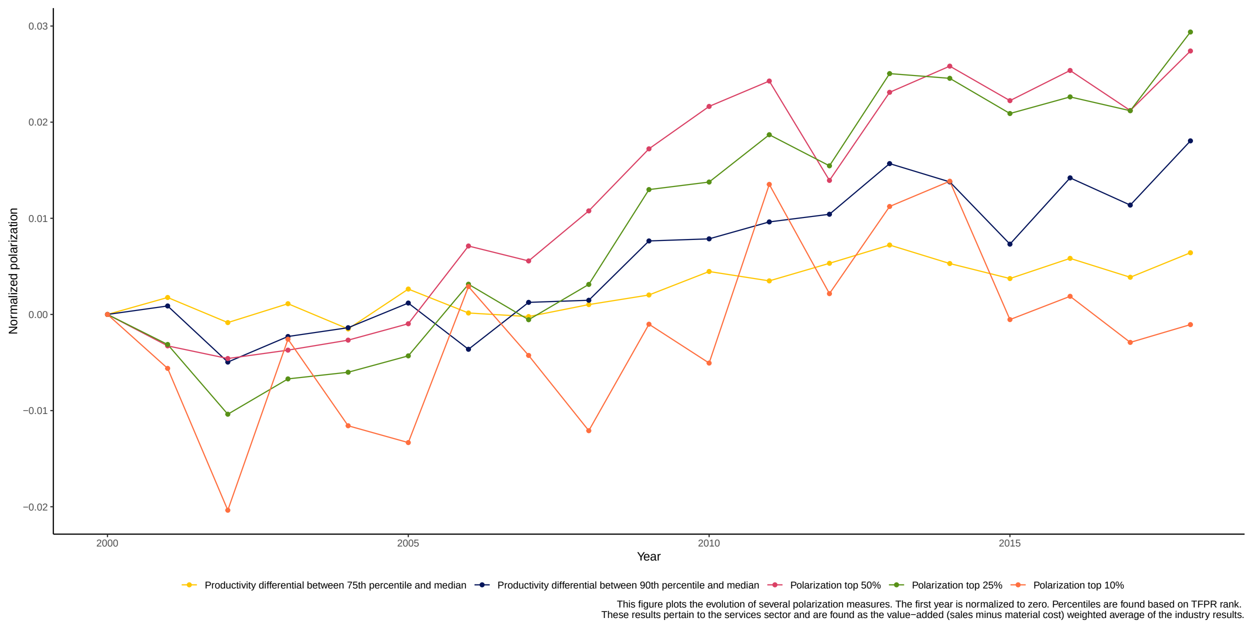

Figure 22: Top polarization measures (Sweden, services)

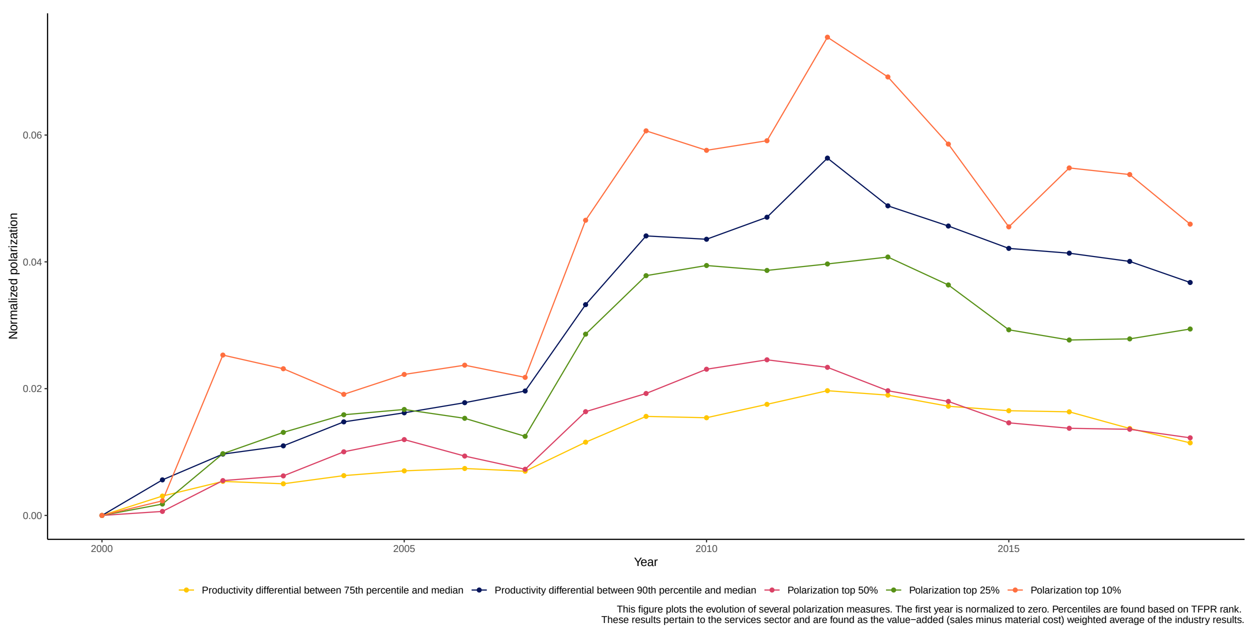

Figure 23: Top polarization measures (Spain, services)

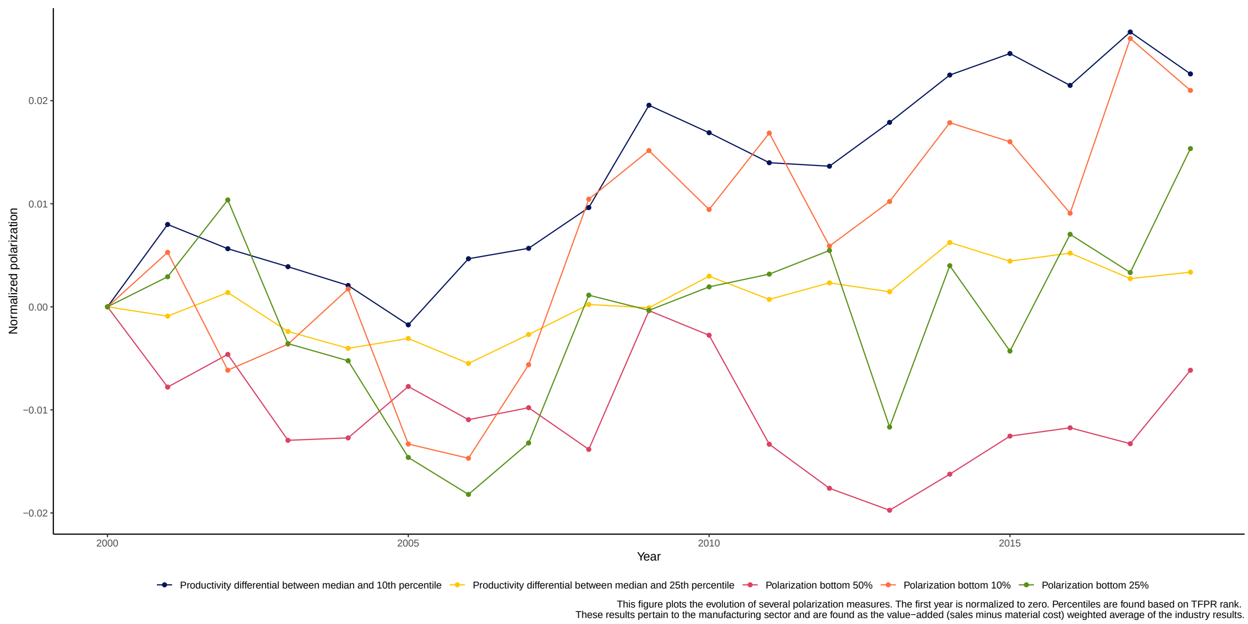

Figure 24: Bottom polarization measures (Sweden, manufacturing)

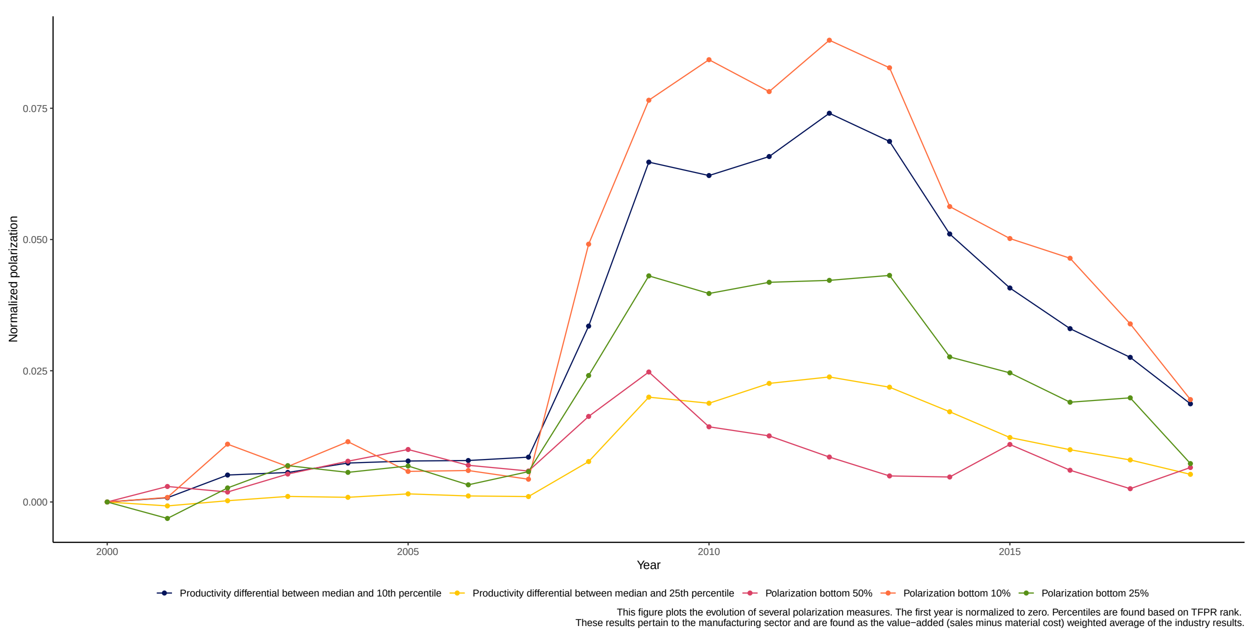

Figure 25: Bottom polarization measures (Spain, manufacturing)

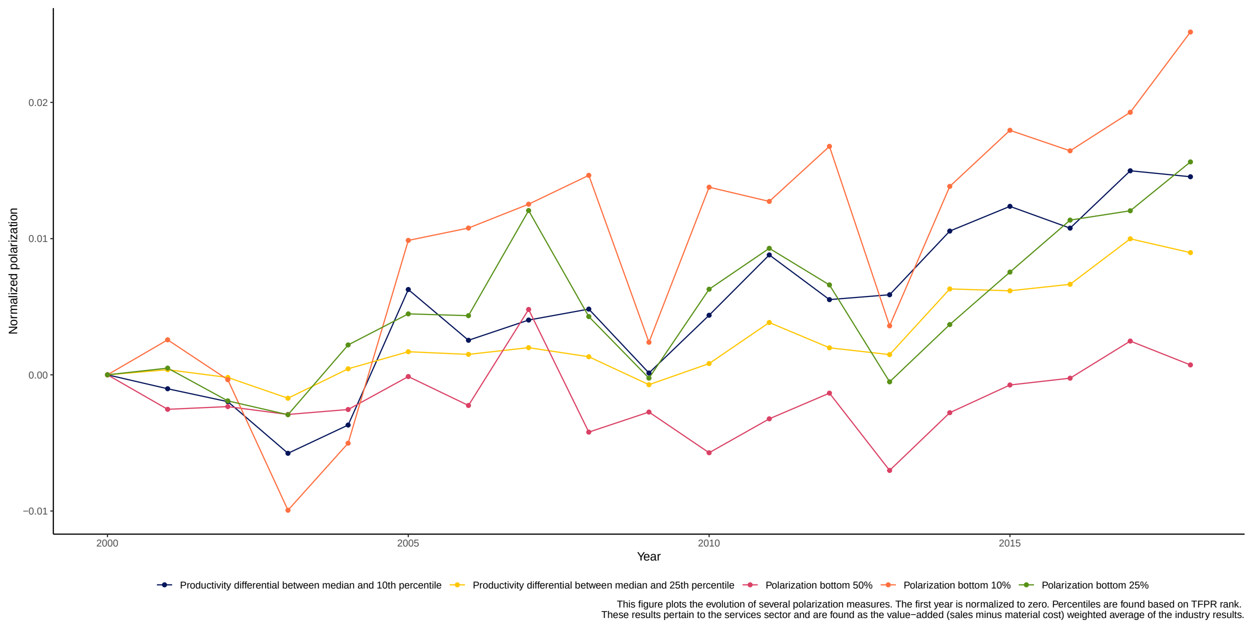

Figure 26: Bottom polarization measures (Sweden, services)

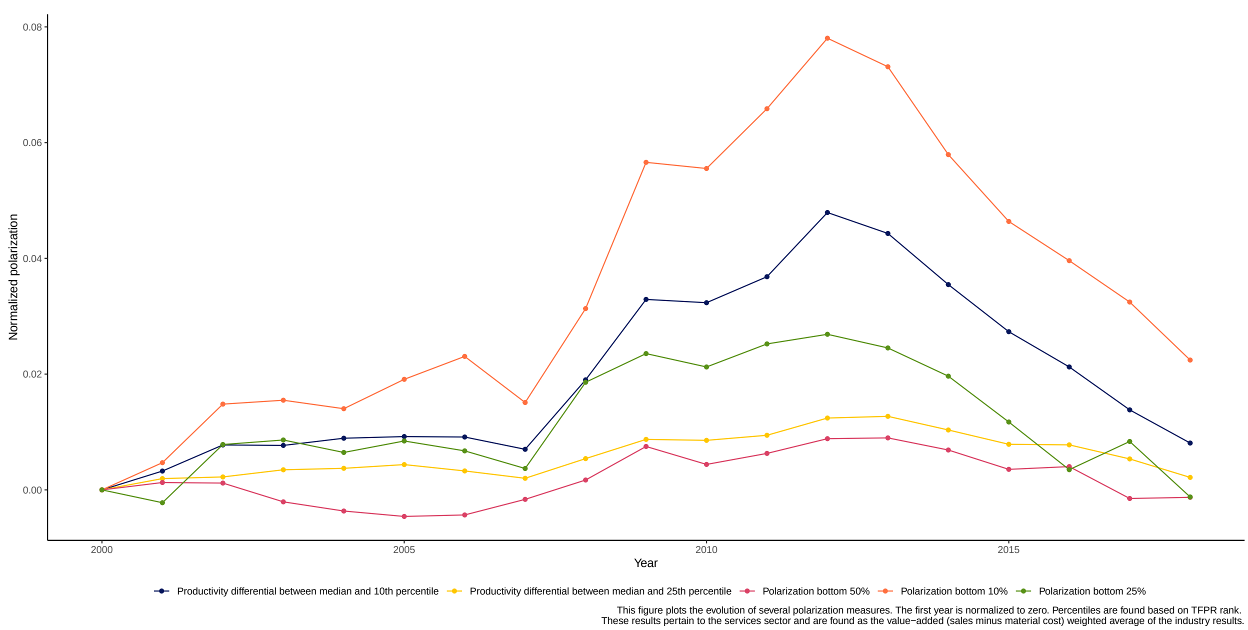

Figure 27: Bottom polarization measures (Spain, services)

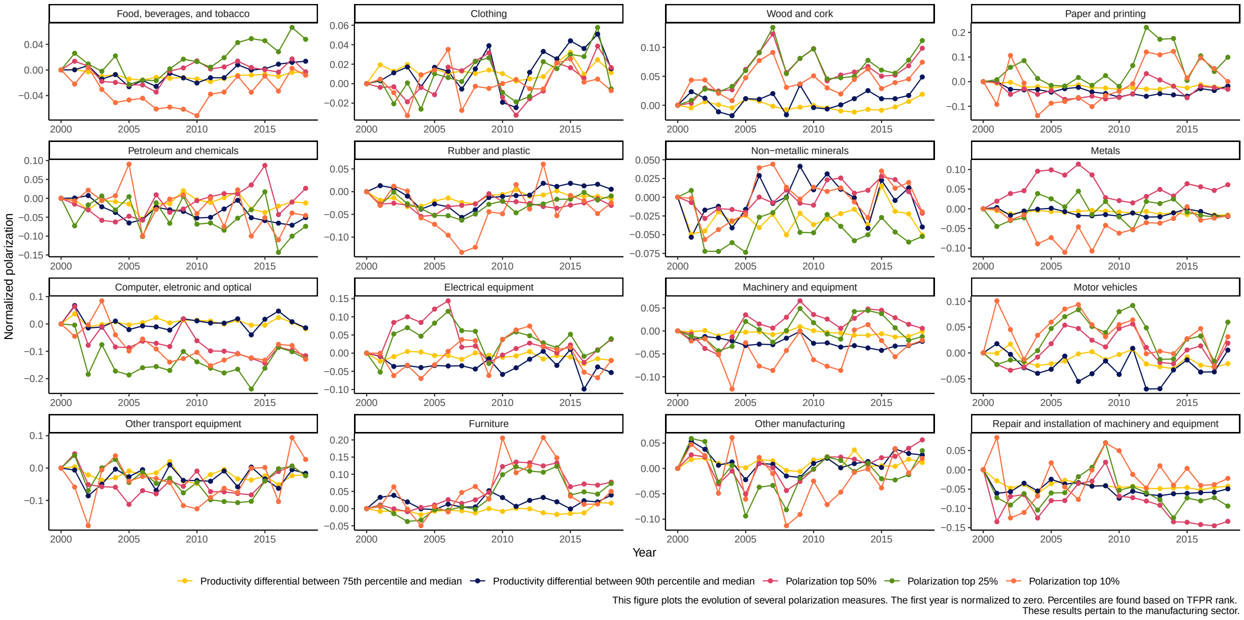

Figure 28: Top polarization measures (Sweden, manufacturing)

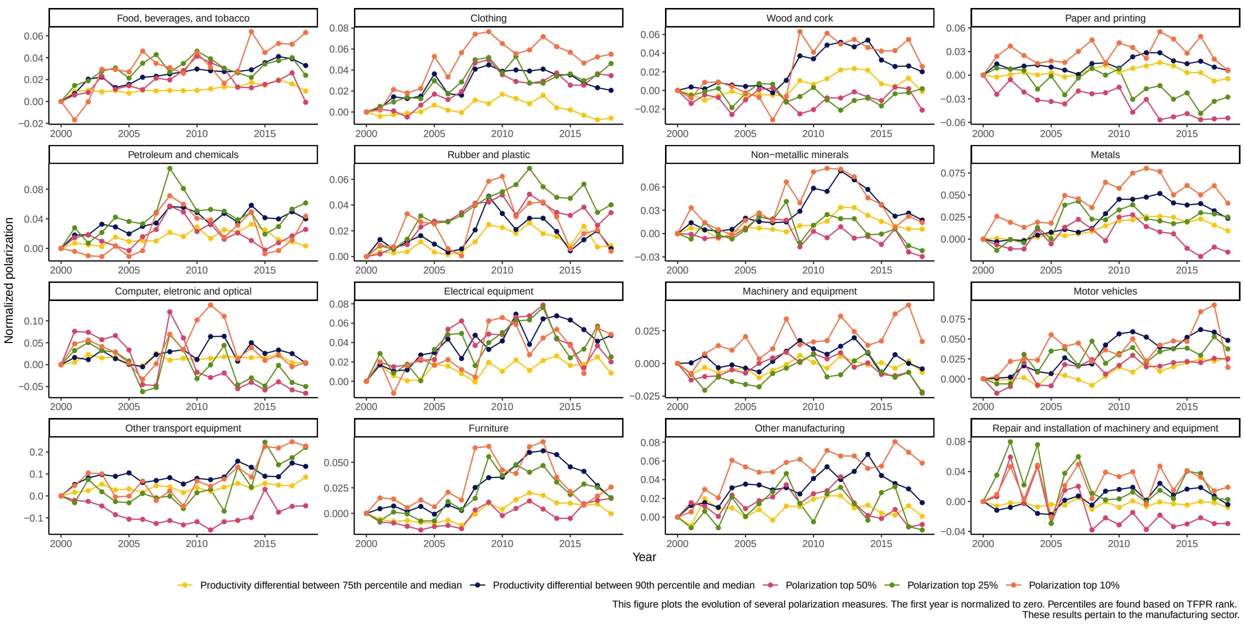

Figure 29: Top polarization measures (Spain, manufacturing)

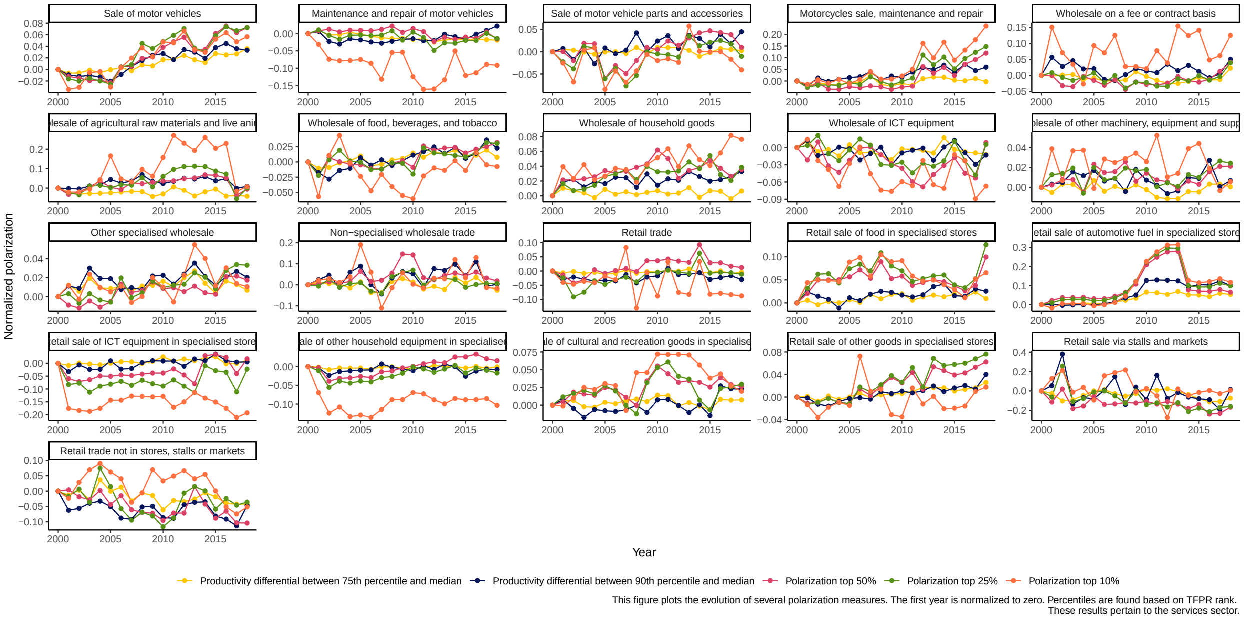

Figure 30: Top polarization measures (Sweden, services)

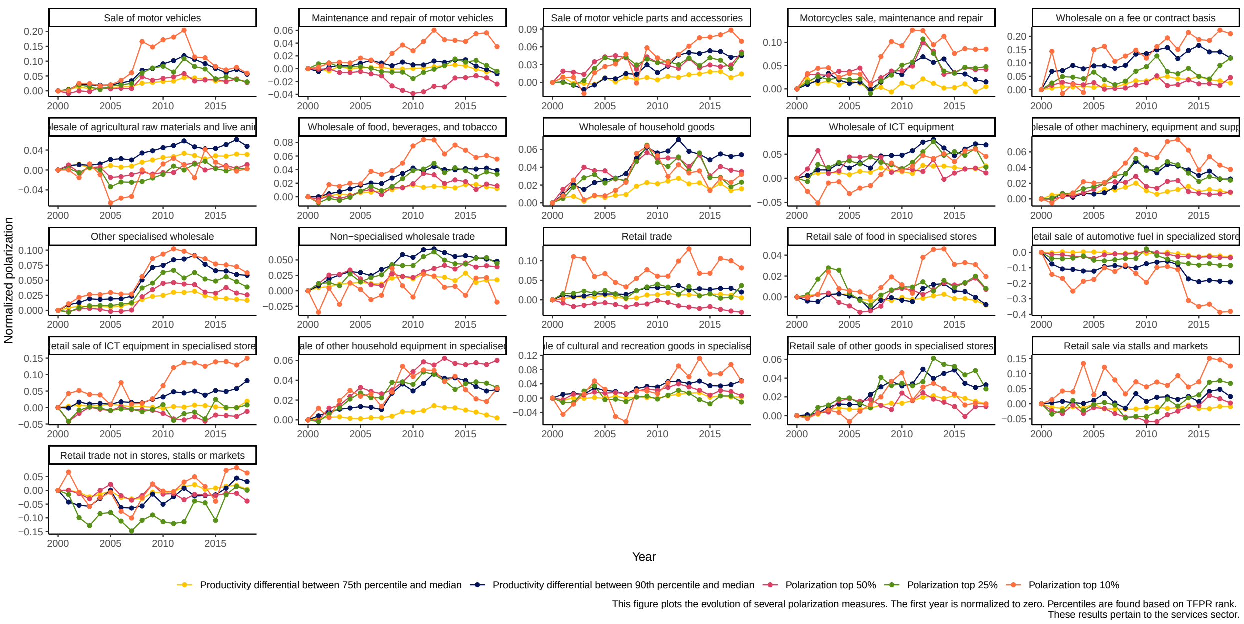

Figure 31: Top polarization measures (Spain, services)

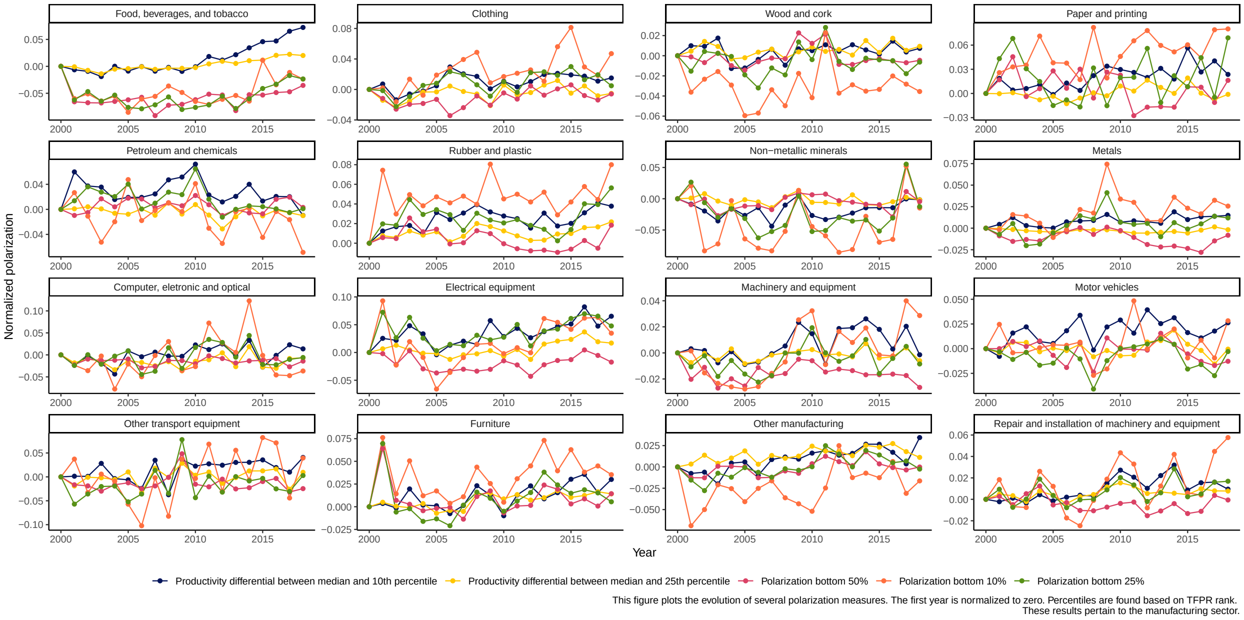

Figure 32: Bottom polarization measures (Sweden, manufacturing)

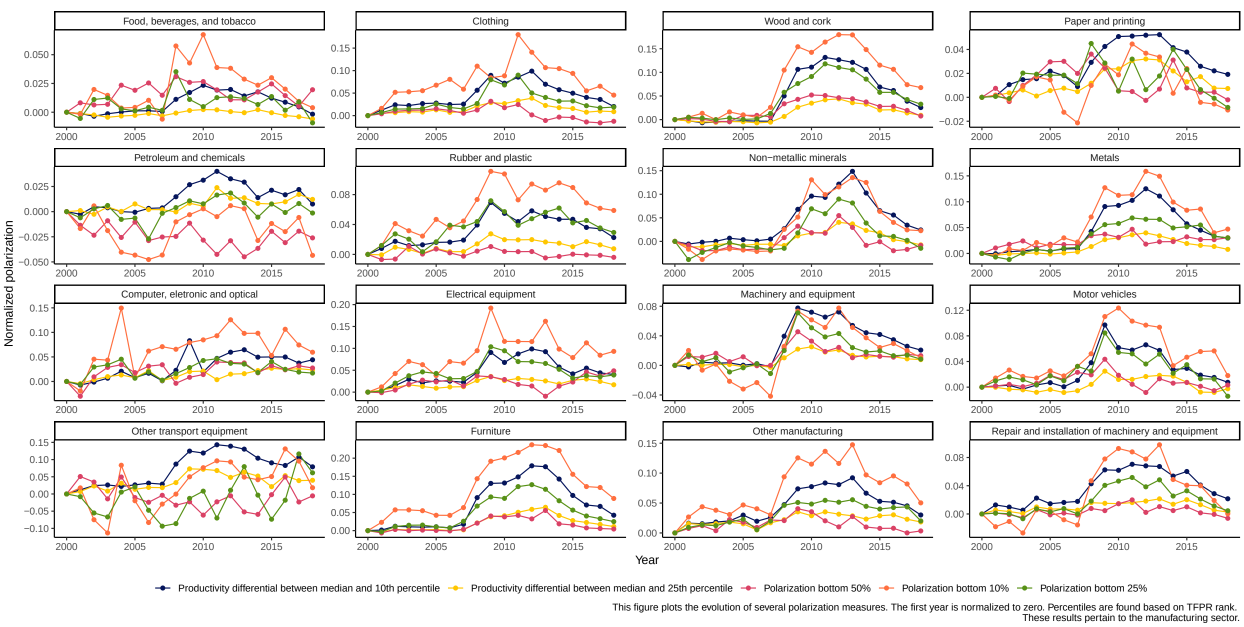

Figure 33: Bottom polarization measures (Spain, manufacturing)

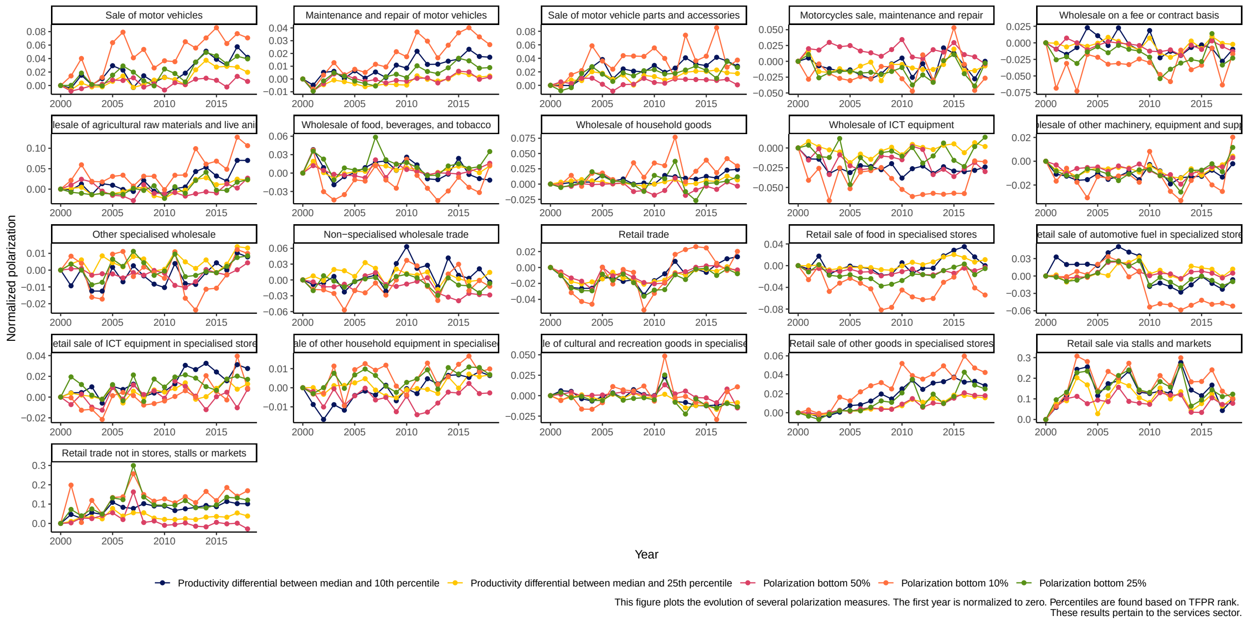

Figure 34: Bottom polarization measures (Sweden, services)

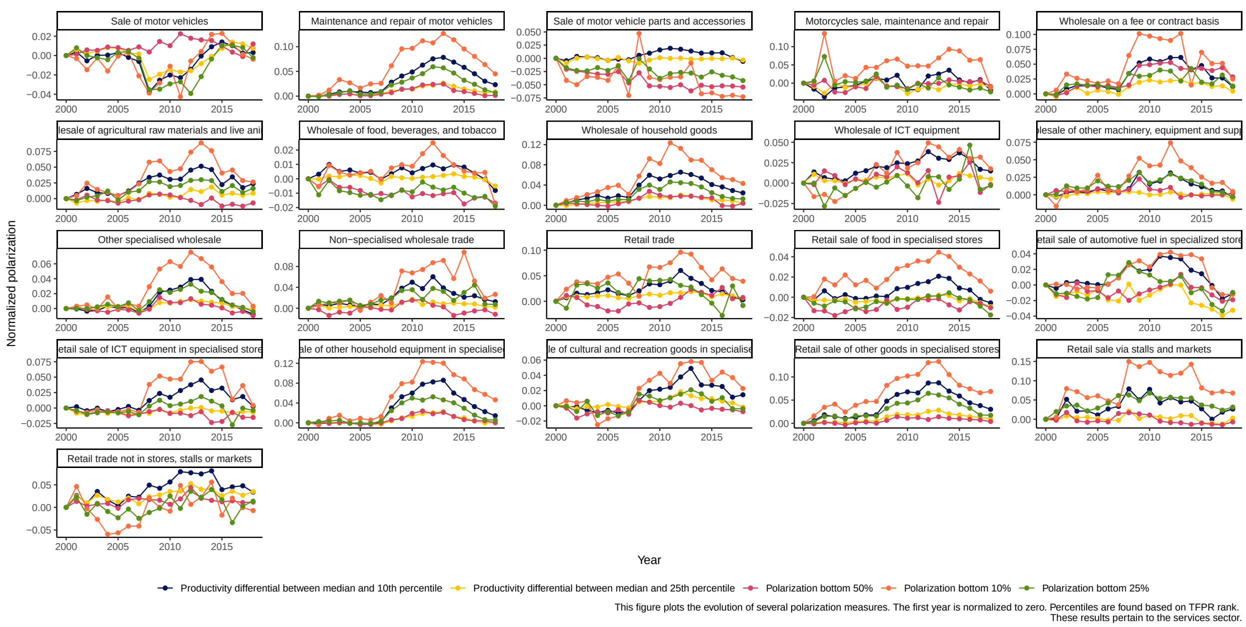

Figure 35: Bottom polarization measures (Spain, services)

A.3 Productivity and sales polarization

In this section, we compare the revenue productivity polarization series with a sales polarization series. To construct the sales polarization series, for each sub-sector/year pair we select firms in the top half of the (deflated) sales distribution. The sales polarization series is the average gap between sales and median sales for firms in the top half of the distribution. We are interested in whether sub-sectors that experienced large productivity polarization increases also experienced large sales polarization increases. Figures 36 and 37 plot the sales polarization growth rate against the productivity polarization growth rates where growth rates were computed as the difference between polarization in the last and in the first period over initial polarization. The Swedish sales polarization growth is much more pronounced than the Spanish. This pattern is not as clear in the productivity polarization. With the exception of Sweden in the manufacturing sector, there seems to be a positive correlation between the two series suggesting that the sub-sectors with the largest sales polarization growth also have the largest productivity polarization growth.

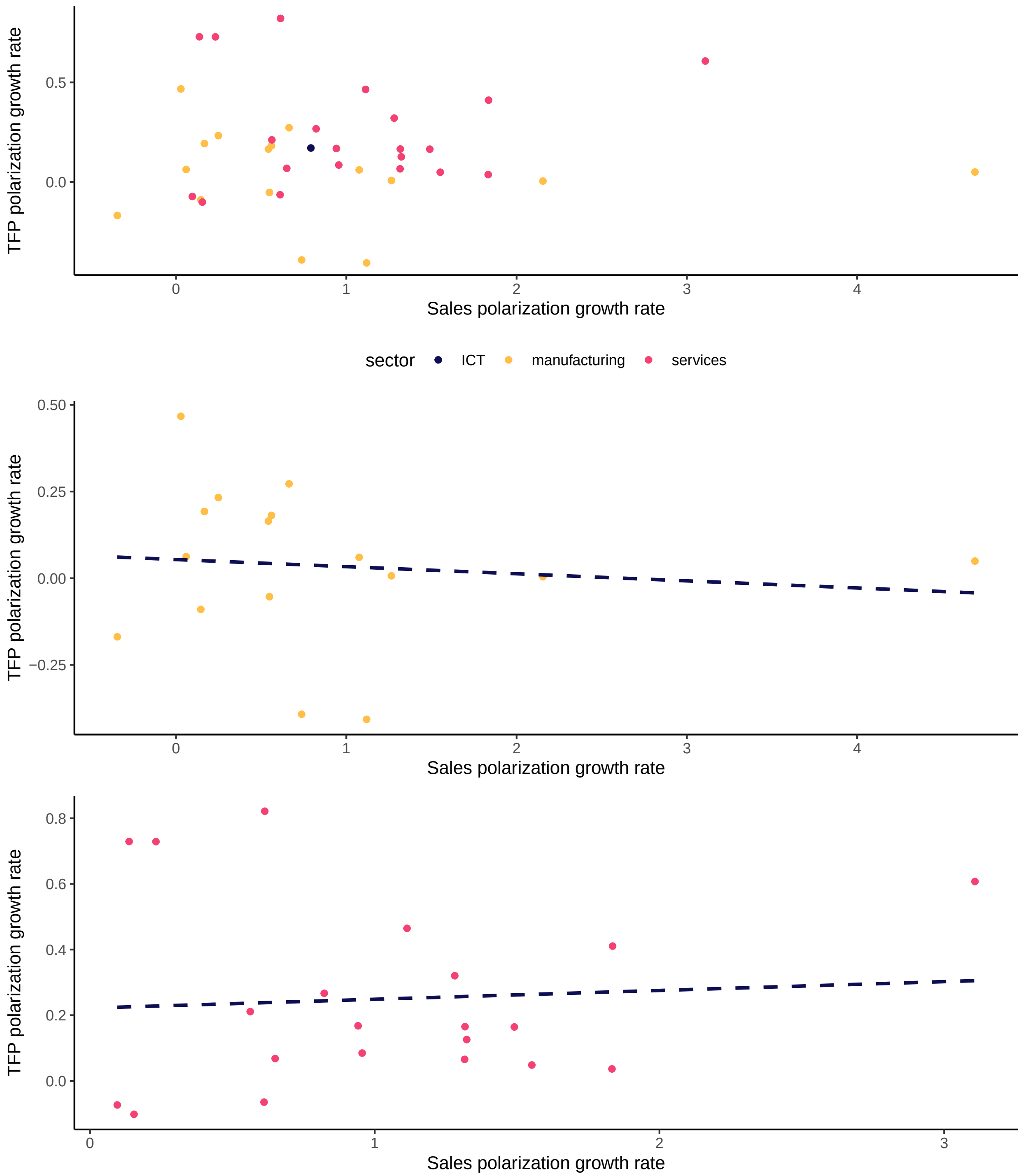

Figure 36: TFP and sales polarization growth (Sweden)

Notes: To construct the sales polarization series we use deflated sales. The ploted polarization growth rates were computed as the difference between polarization in the last and in the first period over initial polarization.

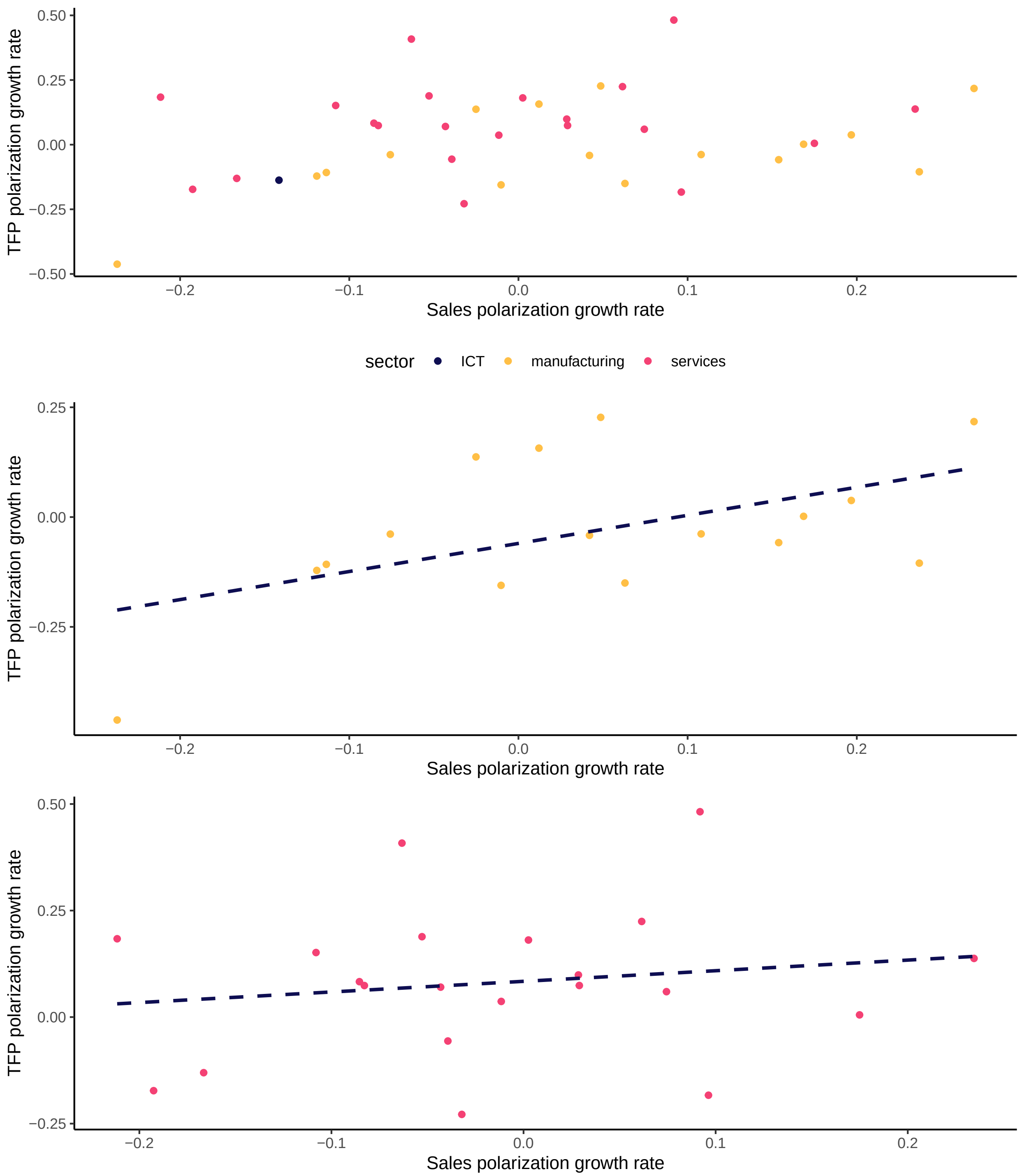

Figure 37: TFP and sales polarization growth (Spain)

Notes: To construct the sales polarization series we use deflated sales. The ploted polarization growth rates were computed as the difference between polarization in the last and in the first period over initial polarization.

A.4 Nomenclature of Economic Activities Rev. 2

Manufacturing

Division	Description	Aggregation
10	Manufacture of food products	Food, beverages, and tobacco
11	Manufacture of beverages	Food, beverages, and tobacco
12	Manufacture of tobacco products	Food, beverages, and tobacco
13	Manufacture of textiles	Clothing
14	Manufacture of wearing apparel	Clothing
15	Manufacture of leather and related products	Clothing
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	None
17	Manufacture of paper and paper products	Paper and printing
18	Printing and reproduction of recorded media	Paper and printing
19	Manufacture of coke and refined petroleum products	Petroleum and chemicals
20	Manufacture of chemicals and chemical products	Petroleum and chemicals

Division	Description	Aggregation
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Petroleum and chemicals
22	Manufacture of rubber and plastic products	None
23	Manufacture of other non-metallic mineral products	None
24	Manufacture of basic metals	Metals
25	Manufacture of fabricated metal products, except machinery and equipment	Metals
26	Manufacture of computer, electronic and optical products	None
27	Manufacture of electrical equipment	None
28	Manufacture of machinery and equipment n.e.c.	None
29	Manufacture of motor vehicles, trailers and semi-trailers	None
30	Manufacture of other transport equipment	None
31	Manufacture of furniture	None

Division	Description	Aggregation
32	Other manufacturing	None
33	Repair and installation of machinery and equipment	None

Services

Division	Description	Aggregation
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	None
46	Wholesale trade, except motor vehicles and motorcycles	None
47	Retail trade, except of motor vehicles and motorcycles	None
64	Financial service activities, except insurance and pension funding	Financial activities
65	Insurance, reinsurance and pension function, except compulsory social security	Financial activities
66	Activities auxiliary to financial services and insurance activities	Financial activities

ICT

Division	Description	Aggregation
58	Publishing activities	ICT
59	Motion picture, video and television programme production, sound recording and music publishing activities	ICT
60	Programming and broadcasting activities	ICT
61	Telecommunications	ICT
62	Computer programming, consultancy and related activities	ICT
63	Information service activities	ICT

For the services sector, the following 3-digit NACE Rev. 2 industry classifications were also employed.

Division	Description
45.1	Sale of motor vehicles
45.2	Maintenance and repair of motor vehicles
45.3	Sale of motor vehicle parts and accessories
45.4	Sale, maintenance and repair of motorcycles and related parts and accessories
46.1	Wholesale on a fee or contract basis
46.2	Wholesale of agricultural raw materials and live animals

Division	Description
46.3	Wholesale of food, beverages and tobacco
46.4	Wholesale of household goods
46.5	Wholesale of information and communication equipment
46.6	Wholesale of other machinery, equipment and supplies
46.7	Other specialised wholesale
46.9	Non-specialised wholesale trade
47.1	Retail sale in non-specialised stores
47.2	Retail sale of food, beverages and tobacco in specialised stores
47.3	Retail sale of automotive fuel in specialised stores
47.4	Retail sale of information and communication equipment in specialised stores
47.5	Retail sale of other household equipment in specialised stores
47.6	Retail sale of cultural and recreation goods in specialised stores
47.7	Retail sale of other goods in specialised stores
47.8	Retail sale via stalls and markets
47.9	Retail trade not in stores, stalls or markets

A.5 Coverage of young firms

We analyze the age of firms when they are first observed in our sample to understand the coverage of young firms. For each year of our sample (and separately for the two sectors and countries) we compute the percentage of first observed young firms among all first observed firms. We report these statistics for three definitions of young firms; two years old or younger, five years old or younger, nine years old or younger. We also report the median age of first observed firms.

Spain -Manufacturing				
year	Median age	% firms aged ≤ 2	% firms aged ≤ 5	% firms aged ≤ 9
2001	5	35	55	80
2002	2	52	68	85
2003	1	65	78	89
2004	1	71	82	90
2005	1	71	83	90
2006	1	70	83	90
2007	1	73	84	90
2008	2	62	79	87
2009	1	62	78	86
2010	1	68	82	90
2011	1	68	82	90
2012	1	69	83	91
2013	1	74	87	92
2014	1	76	87	92
2015	1	76	87	94
2016	1	78	90	94
2017	2	51	78	88
2018	4	23	64	81

Table 6: Statistics about the age of firms when we first observe them in our sample for Manufacturing in Spain, computed separately for each sample year. Median age refers to median age of first observed firms only. % firms aged $\leq$ N is the percentage of firms that were at most N years old when we first observe them among all first observed firms.

Spain - Services

year	Median age	% firms aged ≤ 2	% firms aged ≤ 5	% firms aged ≤ 9
2001	4	35	57	80
2002	2	50	67	83
2003	1	61	75	86
2004	1	66	79	88
2005	1	68	80	89
2006	1	66	80	88
2007	1	68	82	89
2008	2	55	75	85
2009	2	57	75	84
2010	1	63	80	88
2011	1	65	81	89
2012	1	67	81	90
2013	1	70	84	91
2014	1	72	84	92
2015	1	68	83	90
2016	1	71	85	92
2017	3	44	71	84
2018	5	16	56	78

Table 7: Statistics about the age of firms when we first observe them in our sample for Services in Spain, computed separately for each sample year. Median age refers to median age of first observed firms only. % firms aged $\leq$ N is the percentage of firms that were at most N years old when we first observe them among all first observed firms.

Sweden - Manufacturing

year	Median age	% firms aged ≤ 2	% firms aged ≤ 5	% firms aged ≤ 9
2001	7	39	48	62
2002	3	47	55	66
2003	2	51	61	69
2004	2	59	69	75
2005	2	58	68	74
2006	2	59	68	75
2007	2	61	72	78
2008	1	64	74	79
2009	2	61	72	79
2010	1	66	77	82
2011	1	71	81	86
2012	1	70	79	86
2013	1	65	76	83
2014	2	60	76	82
2015	2	64	83	88
2016	2	62	81	88
2017	2	63	79	88
2018	2	58	76	85

Table 8: Statistics about the age of firms when we first observe them in our sample for Manufacturing in Sweden, computed separately for each sample year. Median age refers to median age of first observed firms only. % firms aged $\leq$ N is the percentage of firms that were at most N years old when we first observe them among all first observed firms.

Sweden - Manufacturing

year	Median age	% firms aged ≤ 2	% firms aged ≤ 5	% firms aged ≤ 9
2001	5	42	50	65
2002	2	53	63	73
2003	2	57	68	76
2004	1	62	72	77
2005	1	65	75	80
2006	1	66	75	80
2007	1	65	76	82
2008	1	69	80	85
2009	1	66	80	85
2010	1	68	82	87
2011	1	74	85	90
2012	1	73	84	89
2013	1	69	84	90
2014	2	63	78	85
2015	2	64	84	91
2016	2	64	83	91
2017	2	60	79	90
2018	2	59	80	91

Table 9: Statistics about the age of firms when we first observe them in our sample for Services in Sweden, computed separately for each sample year. Median age refers to median age of first observed firms only. % firms aged $\leq$ N is the percentage of firms that were at most N years old when we first observe them among all first observed firms.