Rising Concentration and Wage Inequality*

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Abstract

Wage inequality has risen in many countries over recent decades. At the same time, production has become increasingly concentrated in a small number of firms. In this paper, we show that these two phenomena are linked. Theoretically, we show that a shock that increases consumer price sensitivity will lead to an increase in the sectoral concentration of revenues and employment, as well as an increase in wage dispersion between firms within industries. Empirically, we use industry-level data from 14 European countries over the period 1999–2016 and show robust evidence of a positive and statistically significant correlation between concentration and between-firm wage inequality. We show that this is driven by higher market shares and higher wages in high-productivity firms within more concentrated sectors.

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1 Introduction

In recent years, two important economic phenomena have received a large amount of attention from academics and policymakers. On the one hand, there has been a strong increase in wage inequality since the 1980s (Juhn et al., 1993; Katz and Autor, 1999; Acemoglu and Autor, 2011). A recent literature has shown that a large fraction of this trend is due to increased wage dispersion between firms, rather than within firms (Card et al., 2013; Song et al., 2019; Barth et al., 2016). On the other hand, product markets have become more concentrated, with a smaller number of firms becoming increasingly dominant in many industries (Autor et al., 2017, 2020; Grullon et al., 2019; Bajgar et al., 2019). So far, the rise in inequality and the rise in concentration have largely been studied in isolation. In this paper, we show that the two phenomena are related.

From a theoretical perspective, we show that, in a setting that allows for heterogeneous wages across firms, an increase in consumer price sensitivity – a shock that has been posited as a driver of increased concentration by Autor et al. (2020) – will also lead to increased between-firm wage inequality. Empirically, we use firm-level data aggregated to the 2-digit industry level for 14 European countries over the period 1999–2016 to show that there is a significant positive relationship between inequality and concentration, which is robust to controlling for unobservable factors in a variety of ways. Consistent with the predictions of the model, we find that rising concentration is associated with increasing market shares in the most productive firms within industries, with these firms also disproportionately increasing their average wages.

The paper begins by considering the implications of an increase in consumer price sensitivity – modeled as an increase in the elasticity of substitution between varieties in consumption, as in Autor et al. (2020) – within a setting that allows for wage heterogeneity between firms.[1] Specifically, we consider the heterogeneous firm search and bargaining framework of Helpman et al. (2010). The model predicts that an increase in consumer price sensitivity (which in turn may be driven by factors such as greater economic integration and the availability of new web technologies) will lead to increased concentration of production and employment in the most productive firms within industries, while at the same time increasing wage inequality between firms within industries.

Intuitively, an increase in price sensitivity shifts consumer demand towards more productive firms, which are able to produce goods at a lower price. This leads to an

[1]The conceptual framework considered by Autor et al. (2020) features a competitive labor market, and hence has a unique equilibrium wage and no wage inequality.

endogenous change in the set of firms that choose to remain in operation, generating an (endogenous) increase in the variance of productivity among operating firms. This selection effect is compounded by endogenous within-firm changes which further exacerbate between-firm wage inequality. In particular, more productive firms will increase both the quantity and the quality of the workers that they hire, leading to an increase in the average wages paid to workers in these firms (relative to workers in less productive firms) and hence to more between-firm wage inequality.[2]

We test the predictions of the model using data from the Competitiveness Research Network (CompNet). The dataset provides information on concentration and between-firm wage inequality at the 2-digit industry level for 14 European countries over the period 1999-2016. The dataset also provides information on sales, employment and average wages for firms at different deciles of the productivity distribution within each industry-country-year cell.

Our empirical strategy consists of regressing inequality on concentration as well as various combinations of industry, country, and year fixed effects. This strategy allows us to control for different types of confounding factors, and to exploit different sources of variation for identification in order to determine the robustness of the results. Our key finding is that there is a positive and statistically significant relationship between sectoral concentration and sectoral between-firm wage inequality. This relationship is robust to various ways of restricting identification. This is consistent with the model prediction that the two outcomes are linked to each other.

To further explore the mechanisms highlighted by the model, we explore how employment, sales and wages vary across firms with different productivity levels in industries that become more concentrated. In line with the model, we find that increases in concentration are associated with higher sales in the most productive firms in an industry. These firms also become larger in terms of their total employment, and pay higher average wages to their workers.

Our paper makes an important contribution to the literature by providing evidence of the link between concentration and wage inequality. Our results highlight the importance of considering common driving forces that can account for both of these patterns. Autor et al. (2020) consider the implications of rising concentration for the labor share,

[2]The increased quality of workers at high-productivity firms may arise due to stricter screening of match-specific abilities by high-productivity firms (as we discuss in the baseline model), as well as increased sorting of high-wage (e.g. skilled) workers to high-wage (high-productivity) firms (as we discuss in the model extensions).

with implications in terms of inequality between workers and capital owners. Here, we instead consider the link between concentration and worker-level inequality, focusing on differences between workers employed at different firms. We thereby also contribute to the literature that studies the drivers of increased wage inequality – and in particular the literature that highlights the rising importance of between-firm wage differences (Card et al., 2013; Song et al., 2019; Barth et al., 2016) – by proposing a mechanism which gives a relevant role to firms in the widening of the wage distribution. In spite of the empirical evidence regarding the importance of between-firm wage dispersion, the literature has mostly focused on the role of changing demand for skills and tasks without allowing for heterogeneous firms to play a relevant mediating role (see Acemoglu and Autor, 2011, for a review of this literature). Here, we provide evidence of a plausible shock that allows us to understand why wage differentials between firms have been on the rise.

A burgeoning literature has considered how the rise in concentration in the labor market has led to changes in (average) wage outcomes for workers (e.g. Azar et al., 2020a,b; Benmelech et al., 2020; Arnold, 2020; Schubert et al., 2021). While related to this literature, our focus is on concentration in the *product market* (i.e. within a sector), rather than on concentration in the *labor market*. In the model, firms compete within a sector in the product market, but workers are perfectly mobile across sectors, and therefore firms compete for workers at the national level. This is clearly an extreme assumption, but it highlights the fact that the product market and the labor market need not overlap – either in theory or in practice. An increase in the concentration of revenues or employment within a sector (which we analyze in this paper) does not necessarily translate into an increase in firms' monopsony power or an increase in labor market concentration, but as we show, it is associated with important changes in the sectoral wage distribution, with important implications for aggregate wage inequality. Given our focus on product market concentration, our analysis is closer in nature to that in Prager and Schmitt (2021), who study the implications of hospital mergers (which change the product market concentration for health services) for wages.

A more realistic framework might allow firms' monopsonistic market power to vary according to their size (e.g. as in Berger et al., 2021; Jarosch et al., 2020). Loosely speaking, in such a framework, the increase in concentration arising from the rise in consumer price sensitivity would have two opposing forces on the relative wages of top firms: On the one hand, their increased profitability would put upward pressure on their wages (as in our framework). On the other hand, their increased monopsony power

would put downward pressure on their wages. If the monopsony power channel were the dominant force driving the evolution of wages across firms, we would expect higher levels of concentration to be associated with *lower* levels of sectoral wage inequality (see also Mertens, 2021) – a pattern that is at odds with our empirical evidence. Hence, while we cannot rule out that larger firms mark wages down more (and even more so as they become more dominant), our results imply that, in more concentrated industries, any such effect is offset by their incentive to pay higher wages due to their increased profitability arising from the increase in competitive pressures. In line with this, we find that *average* wages are also positively associated with sectoral concentration – a result that is also found by Qiu and Sojourner (2019) and that is consistent with Bighelli et al. (2021), who show that changes in concentration in Europe are positively associated with changes in productivity. These results therefore speak to the debate about the drivers of concentration (see Covarrubias et al., 2019) by providing supportive evidence for the idea that rising concentration in Europe primarily reflects a more efficient market environment rather than weak competition and rising market power.

Two papers that are closely related to ours are Webber (2015) and Rinz (2020). These papers analyze the link between firm monopsony power at the local labor market level and wage inequality using U.S. data. Although we differ in terms of the dimension of the analysis (industry concentration rather than monopsony power at the local labor market level), as well as geographical context (Europe rather than U.S.), our results are consistent with their findings regarding the positive link between concentration (or market power) and inequality. An important contribution of our paper is to conceptualize and rationalize the link between concentration and wage inequality through our theoretical framework. As discussed, standard arguments related to market power would suggest that wages at dominant firms would be declining as market power rises, and hence wage inequality should be lower in environments with higher market power, rendering the results in Webber (2015) and Rinz (2020) somewhat puzzling. In our setting, we can rationalize the positive link between concentration and wage inequality as being driven by increased competitive pressures, and we provide firm-level evidence that is new relative to Webber (2015) and Rinz (2020), and that is consistent with this hypothesis. Even though the product and the labor market are distinct in our framework, the similarity of our findings relative to Webber (2015) and Rinz (2020) suggests that some of the implications that we derive regarding concentration in the product market may also carry over to the labor market setting.

An additional related paper is by Akerman (2021). His analysis considers how rising

concentration (also driven by a rise in consumer price sensitivity) is associated with an increase in the demand for skilled workers. His model and his analysis focus solely on variation in skill shares and skill premia across industries, whereas our paper focuses on broader inequality changes.[3] Our analysis of the heterogeneity across firms with different productivity levels is also an important unique feature relative to Akerman (2021).

2 Theoretical Motivation

In order to motivate our analysis of the relationship between concentration and inequality, we illustrate the theoretical link between these two variables within the closed-economy framework of Helpman et al. (2010). Their model introduces Diamond–Mortensen–Pissarides (Diamond, 1982a,b; Mortensen and Pissarides, 1994) search and matching frictions into a Melitz (2003) model with heterogeneous firms. The model is able to generate wage differences between firms through the combination of: (i) search frictions and wage bargaining, and (ii) heterogeneous match-specific ability and the availability of a screening technology.[4] We refer the reader to the Helpman et al. (2010) paper for full details on their model. Here, we briefly highlight the key features of the model, and we focus on the implications of their equilibrium conditions for concentration and between-firm wage inequality. We then analyze the impact of an increase in consumer price sensitivity, modeled as an increase in the price elasticity of demand, as in Autor et al. (2020). Autor et al. (2020) discuss how consumers may have become more price-sensitive due to greater product market competition (e.g., through globalization) or new technologies (e.g., due to greater availability of price comparisons on the Internet). While Autor et al. (2020) consider the implications of this type of shock within the setting of a competitive labor market (with no wage inequality), we extend their analysis in order to consider the implications within the context of a framework

[3]The theoretical framework in Akerman (2021) features a competitive labor market with equilibrium wages w_s and w_u for skilled and unskilled workers, respectively, and there is therefore no between-firm inequality conditional on worker skill.

[4]Note that match-specific ability and screening are crucial ingredients to generate wage variation across firms in their model; search frictions and wage bargaining alone are not sufficient (see for instance Felbermayr et al., 2011). Intuitively, in a model without match-specific ability and screening, firms face a common search cost; hence, the additional value created by the marginal worker will be identical across firms in equilibrium. This implies that in a standard search and bargaining model with heterogeneous firms, more productive firms would be larger, but wages would be equated across firms with different productivity levels.

that allows for wage heterogeneity between firms.

2.1 Key Features of the Helpman et al. (2010) Model

As in Melitz (2003), each sector features a continuum of horizontally differentiated varieties, with total consumption Q being given by a constant elasticity of substitution (CES) aggregate:

$$Q = \left[\int_{j\in J} q(j)^{\beta} dj\right]^{1/\beta},$$

where j indexes varieties, J is the set of varieties within the sector, $q(j)$ denotes consumption of variety j and $\beta \in (0,1)$ is a function of the elasticity of substitution between varieties, σ, namely $\beta \equiv (\sigma-1)/\sigma$.

The product market is characterized by a continuum of monopolistically competitive firms, each producing a unique variety and facing a fixed cost of production. Firm output is given by:

$$y = \theta h^{\gamma} \overline{a}, \qquad 0 < \gamma < 1$$

where θ is the firm's idiosyncratic productivity draw, h is the measure of workers hired and $\overline{a}$ denotes the average match-specific ability of these workers. The productivity distribution, $G(\theta)$, is assumed to be Pareto with shape parameter z. Note that the assumption of a Pareto distribution is common in the literature on heterogeneous firms. Empirically, Corcos et al. (2012) find empirical support for this assumption, while Axtell (2001) shows that the observed distribution of firm sizes follows a Pareto distribution.

Workers are ex-ante identical but differ in terms of their match-specific ability, which is not transferable across firms.[5] Workers' match-specific ability is drawn from a Pareto distribution, $G_a(a) = 1-(a_{min}/a)^k$. Ability is not directly observable when a firm and a worker meet, but firms have access to a screening technology. In particular, by paying a screening cost of ca_c^{δ}/δ, a firm can identify whether workers are above or below an (endogenously chosen) ability threshold a_c, and will base their decision on whether or not to make a job offer to the worker based on the screening outcome. Neither the firm nor the worker know the match-specific ability of any individual worker, so bargaining occurs under conditions of symmetric information.

[5]In the Appendix, we discuss an extension of Helpman et al. (2010) to two types of workers that allows us to relate increased concentration and wage inequality to changes in worker sorting on observables. We discuss this extension in further detail below.

Equilibrium firm-level revenues, employment and wages are given by:

$$r(\theta) = r_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\Gamma}}, \qquad r_d \equiv \frac{1+\beta\gamma}{\Gamma} f_d$$

$$h(\theta) = h_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\Gamma}(1-k/\delta)}, \qquad h_d \equiv \frac{\beta\gamma}{\Gamma}\frac{f_d}{b}\left[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{c a_{min}^{\delta}}\right]^{-k/\delta}$$

$$w(\theta) = w_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta k}{\delta\Gamma}}, \qquad w_d \equiv b\left[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{c a_{min}^{\delta}}\right]^{k/\delta}$$

where θ_d is the equilibrium productivity threshold below which firms would choose not to operate, b is the search cost, f_d is the fixed cost of production, and $\Gamma \equiv 1 - \beta\gamma - \frac{\beta}{\delta}(1-\gamma k)$. As in Helpman et al. (2010), it is assumed that $\delta > k$ and that $0 < \gamma k < 1$.

These equilibrium conditions (along with the assumptions on δ, γ, and k) imply that, in line with empirical evidence, more productive firms within a sector will have higher revenues, employ more workers, and pay higher wages. Intuitively, more productive firms have an incentive to produce more output. This higher output is achieved both by hiring more workers, and by hiring workers of higher ability (due to the complementarity between workers' abilities and firm productivity). The wage bargaining process leads to an outcome in which firms pay a wage that is equal to the replacement cost of a worker. Since more productive firms screen more intensively (in order to hire workers of higher average ability), their workers are costlier to replace, and hence are paid a higher wage. From the perspective of the worker, the expected wage conditional on being sampled is the same across all firms. Workers are also perfectly mobile across sectors and, in equilibrium, must be indifferent between searching in any sector.

2.2 Concentration and Wage Inequality

In order to measure sectoral concentration, consider the set of firms in the top μ% of the productivity distribution (among operating firms in the sector).[6] The equilibrium relationships described above imply that the share of sectoral revenues accruing to

[6]Derivation details of the concentration measures and wage distribution can be found in Appendix A. Below we also discuss results for other types of concentration measures.

these firms, and the share of sectoral employment concentrated in these firms is given, respectively, by:

$$C_r = \mu^{1-\frac{\beta}{\Gamma z}} \qquad\qquad C_\ell = \mu^{1-\frac{\beta}{\Gamma z}(1-k/\delta)}. \tag{1}$$

The distribution of wages across firms, meanwhile, is given by:

$$G_f(w) = 1 - \left(\frac{w_d}{w}\right)^{\frac{\delta\Gamma z}{\beta k}} \tag{2}$$

This is a Pareto distribution with scale parameter w_d and shape parameter $\frac{\delta\Gamma z}{\beta k}$. Scale-invariant measures of inequality, such as the coefficient of variation, the Gini coefficient, or the Theil index, are decreasing in the shape parameter and are independent of the scale parameter.

2.3 Effects of an Increase in Consumer Price Sensitivity

As mentioned, we consider the impact of an increase in consumer price sensitivity, modeled as an increase in the elasticity of substitution between varieties, σ (as in Autor et al., 2020). Our two key predictions are the following:

Prediction 1: An increase in consumer price sensitivity increases sectoral concentration in terms of revenues and in terms of employment.

Proof: *Given the definitions of β and Γ and since $\gamma k \in (0,1)$, we have that:*

$$\frac{\partial\beta}{\partial\sigma} = \frac{1}{\sigma^2} > 0 \qquad \text{and} \qquad \frac{\partial\Gamma}{\partial\sigma} = -\frac{\partial\beta}{\partial\sigma}\left[\gamma + \frac{1}{\delta}(1-\gamma k)\right] < 0.$$

It is then straightforward to show that:

$$\frac{\partial C_r}{\partial\sigma} > 0 \qquad \text{and} \qquad \frac{\partial C_\ell}{\partial\sigma} > 0.$$

Prediction 2: An increase in consumer price sensitivity increases inequality in firm-level wages within the sector.

Proof: *Recall that the shape parameter of the distribution of firm-level wages is $s \equiv \frac{\delta\Gamma z}{\beta k}$.*

Given the definitions of β and Γ, is is straightforward to show that:

$$\frac{\partial s}{\partial \sigma} < 0.$$

A decrease in the shape parameter will unambiguously increase any scale-invariant measure of inequality.[7]

2.4 Intuition and Mechanisms

A shock that increases consumers' price-sensitivity will shift consumer demand towards the lower cost varieties produced by higher-productivity firms. This leads to an increase in sectoral concentration and inequality due to (i) changes in the composition of operating firms, and (ii) changes in employment and wages within firms. Both of these channels compound each other.

The change in firm composition arises due to the fact that, as demand for the higher cost varieties produced by low productivity firms falls, they are no longer able to operate profitably and must exit. This leads to an increase in the productivity threshold θ_d, as shown formally in Appendix B.1. Although the increase in the threshold reduces the range of firm types that operate, under the assumption that productivity is Pareto-distributed, this will actually *increase* the variance of productivity among operating firms.[8] Since employment and wages are proportional to productivity, the endogenous increase in the variance of productivity among operating firms induced by the shock will lead to an increase in concentration and inequality, even absent any changes in employment and wage choices conditional on firm type.

This compositional change is compounded by within-firm changes among the firms that remain in operation. In particular, to meet the increased demand generated by the change in consumer price sensitivity, high-productivity firms increase their output by hiring more workers and screening more intensively, which leads to an increase in their revenues, employment and wages relative to less productive firms, as shown formally in

[7]It is worth noting that the wage distribution in Equation (2) is obtained when assigning equal weight to all firms, regardless of their size. This is in line with the variable used in our empirical analysis below. The fact that employment becomes more concentrated in high-productivity/high-wage firms implies that employment-weighted measures of between-firm wage inequality would increase even more strongly in response to an increase in consumer price sensitivity.

[8]Intuitively, this occurs because the increase in the threshold is associated with the exit of a mass of firms that are relatively homogenous (at the bottom end of the distribution, where the mass is large given the Pareto assumption), and a relative increase in the mass of firms towards the tail.

Appendix B.2. As a result, sectoral concentration and wage inequality increase further.

While the first channel (compositional change) is sensitive to the Pareto assumption about the productivity distribution, the second channel is not: revenues, employment and wages will increase at more productive firms relative to less productive firms regardless of the shape of the productivity distribution. If firm productivity is not Pareto-distributed, then the compositional change due to the exit of low-productivity firms may potentially counteract some of the increase in concentration and inequality induced by the changes in relative revenues, employment and wages among continuing firms. It would then become an empirical question in terms of which channel dominates.[9] Note also that the relative growth of revenues and employment at more productive firms implies that their market share – which was already higher than that of less productive firms before the shock – will increase further, while the market share of less productive firms will shrink. Thus, sectoral concentration would increase not only if measured as the share of revenues or employment in the top μ% of firms (as we have derived in Equation 1), but also if measured through other indices such as the Herfindahl-Hirschman Index (HHI).

2.5 Extensions to Other Frameworks

The implications of an increase in consumer price sensitivity for concentration and wage inequality carry over to other heterogeneous firm settings that feature a mechanism that links worker wages to firm rents. For example, in the fair-wage framework of Egger and Kreickemeier (2012), workers adjust their effort according to whether they perceive the wage that they receive to be fair. The "fair-wage" is anchored by a firm-external point of reference (workers should consider their wage to be fair relative to the wage of employees at other firms), as well as a firm-internal point of reference (workers should consider their wage to be fair given their own firm's performance). In equilibrium, it is in the firms' best interest to pay workers the fair wage in order to elicit the optimal amount of effort. In this framework, an increase in consumer price sensitivity also leads to a relative increase in the demand for the varieties produced by the most productive firms. As in the Helpman et al. (2010) model, this will lead to an increase in the relative size of the most productive firms in terms of employment and sales (increased concentration). The increased profitability of the most productive firms translates into

[9] As mentioned above, however, there is empirical support for the assumption of a Pareto distribution (e.g. Corcos et al., 2012; Axtell, 2001).

higher relative wages for workers in these firms, due to the fair-wage considerations. Hence, in this model, increases in concentration and increases in (between-firm) wage inequality are also linked.

The empirical literature has shown that there is an important role for changes in worker sorting in accounting for the increase in between-firm wage inequality in several countries (Card et al., 2013; Song et al., 2019). There is also evidence that increased outsourcing opportunities have led to increased establishment specialization and worker segregation (Cortes and Salvatori, 2019). The model discussed in Section 2.1 only predicts increases in wage dispersion among ex-ante homogeneous workers, without allowing for these empirically-relevant changes in sorting patterns. In Appendix C, we consider the Helpman et al. (2010) extension that features two types of workers (skilled and unskilled).

We show that, in this setting, an increase in consumer price sensitivity also leads to increases in both concentration and between-firm wage inequality. The increase in between-firm wage inequality in this case is driven both by: (i) increased sorting of skilled workers to the most productive firms, and (ii) increases in between-firm wage inequality conditional on (observable) worker skill type. These predictions are consistent with the observed increases in between-firm wage inequality documented in the empirical literature. In our empirical analysis below, we only observe overall average firm-level wages, and cannot disentangle the importance of changes in sorting from changes in wages conditional on observable skills. However, regardless of the relative importance of these two channels, the key conclusion from the theoretical framework is that a common shock (increased consumer price sensitivity) would lead to simultaneous increases in both concentration and between-firm wage inequality at the industry level.

3 Data

In order to test the prediction of the model about the link between sectoral concentration and inequality, we use data from the Competitiveness Research Network (CompNet). This dataset draws on various administrative and public sources, and compiles information for non-financial corporations with at least one employee in various European countries. We work with the 6th vintage of the data, which provides information for 18 countries over the period 1999–2016, though not all years are available for all countries. We focus on the 14 countries which have representative data for the full

universe of firms.[10] The data is made available at various levels of aggregation. We work with the finest level of aggregation available in the data, which is the industry-country-year level, where industries are coded at the 2-digit NACE Revision 2 level.

For roughly 40% of the overall sample, the CompNet dataset also provides information on various outcomes for firms at different deciles of the productivity distribution within each industry-country-year cell. Productivity is measured by a firm's total factor productivity (TFP), computed from the estimation of a production function using a weighted two-step instrumental variable regression.[11] This information allows us to directly analyze how various outcomes evolve for firms with different productivity levels. In what follows, we refer to firms in the top decile of the productivity distribution within an industry-country-year as "superstar" firms. Appendix Figure A.1 confirms that, as implied by the model, more productive firms within an industry-country-year cell are larger in terms of both sales and employment, and pay higher average wages.

The CompNet dataset provides two concentration measures: the share of sales (turnover) in the top 10 firms in each industry-country-year cell, and the Herfindahl-Hirschman index of market concentration. Our measures of sectoral wage inequality are also constructed from the CompNet data. Information is available on the distribution of labor costs per employee across firms. This allows us to measure dispersion in average firm-level wages by computing the log 90-10 ratio of labor costs per worker. It is worth noting that this measure of between-firm wage dispersion is not employment weighted, in line with the distribution of firm-level wages obtained from the theoretical framework (see also the discussion in footnote 7). It is therefore not mechanically affected by changes in the distribution of firm size within industries. Note also that the wage differentials that we compute from the data do not account for heterogeneity in worker characteristics and therefore capture both pure firm wage premia (i.e. wage

[10]These are Belgium, Croatia, Denmark, Finland, France, Hungary, Italy, Lithuania, Netherlands, Portugal, Romania, Slovenia, Spain and Sweden. Due to missing data on some variables, Denmark, Netherlands and Romania are not included in all specifications. Representativeness is achieved through a reweighting procedure as detailed in the CompNet User Guide available at `https://www.comp-net.org/fileadmin/_compnet/user_upload/Documents/User_Guide_6th_Vintage.pdf`. Although data for the Czech Republic is available, its use is not recommended due to the very low coverage rate of small firms.

[11]Specifically, TFP is estimated by pooling all firms operating in a given sector and assuming a Cobb Doublas production function expressed in logs. Firm output is measured as real gross output (real revenues), and is regressed on the firm real book value of net capital and firm total employment. The estimation is performed using a control function approach, following the methodology developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). More details on the estimation of the TFP measure can be found in the user guide for the 6th vintage of the CompNet dataset.

differences for otherwise identical workers), as well as sorting of workers to firms based on observable or unobservable characteristics (see also the discussion in Section 2.5).

Panel A of Table 1 presents summary statistics for our measures of concentration and between-firm wage inequality. We show summary statistics separately for our full sample, and for the restricted sample where information across deciles of the productivity distribution is available. All summary statistics are weighted using each industry's time-averaged share of total value added in each country.[12] Both in the full and in the restricted sample, the average log 90-10 ratio of firm-level wages is around 1.5 (implying nearly a fivefold gap in average firm wages), with quite a bit of heterogeneity across industry-country-year cells. The concentration measures are somewhat lower in the restricted sample, but even for this sample, more than 15% of overall sales in each cell are on average concentrated in just 10 firms.

At the bottom of Panel A we present two alternative measures of concentration which, instead of ranking firms according to their total sales (as would be done for the computation of the top 10 and HHI concentration measures), focus on the share of sales or employment in the *most productive* firms in an industry (namely firms in the top productivity decile). Consistent with the fact that more productive firms are larger, we find that firms in the top decile of productivity account for more than 40% of sales and more than 20% of employment.

Panel B analyzes the correlation between these alternative measures of concentration based on productivity rankings and the more traditional measures based on the top 10 firms or the HHI. We find that all correlations are positive and statistically significant. This means that in industry-country-year cells where concentration is higher based on the share of sales in the top 10 firms or the HHI index, we also observe a larger concentration of both employment and sales in the most productive firms in the industry.

4 Findings: Concentration and Inequality

In order to explore the empirical link between concentration and between-firm wage inequality, we exploit variation across industry-country-year cells in the CompNet data.

[12]We use the same weighting procedure in the empirical analysis below. Using time-averaged industry shares allows us to rule out any effects driven by changes in the industry structure within countries, while giving equal total weight to each country-year cell. Our use of value added to weight industries is similar to Autor et al. (2020); using time-averaged shares of total employment rather than value added yields similar results.

Our equation of interest is:

$$INEQ_{ict} = \alpha CONC_{ict} + \gamma_i + \delta_c + \tau_t + u_{ict} \tag{3}$$

The dependent variable is a measure of inequality in firm-level wages in industry i in country c at time t. The key independent variable is a measure of concentration in industry i in country c at time t. In order to exploit different sources of variation for identification, and to control for different sources of shocks, we experiment with different combinations of industry, country and time fixed effects, as discussed below.[13]

Table 2 presents our main set of results. Different panels use different measures of concentration, and each column considers a specification with a different set of fixed effects, as detailed at the bottom of the table. All regressions are weighted using each industry's time-averaged share of total value added in each country, which allows us to rule out any effects driven by changes in the industry structure within countries, while giving equal total weight to each country-year cell.

The top panels of Table 2 show results for each of the two standard concentration measures using our full sample. Column (1) presents a specification which includes industry, country and year fixed effects. We find that there is a positive and statistically significant correlation between concentration and between-firm wage inequality. The remaining columns of Table 2 consider different combinations of fixed effects in order to exploit different sources of identification. Column (2) includes country-year and industry fixed effects. This would control for any country-specific policy changes that affect outcomes across industries. Identification is achieved from differential variation across industries within country-year cells. Column (3) includes industry-year and country fixed effects. This would account for any industry-specific variation in outcomes over time. Here, identification is achieved from differential changes over time within industries across countries. Column (4) is our most restrictive specification, which includes both industry-year and country-year fixed effects. Regardless of the source of variation used for identification, the correlation between concentration and inequality remains positive and strongly statistically significant.

The remaining panels of Table 2 show results for our restricted sample, where we also consider the concentration measures based on the share of sales or employment in the most productive firms in an industry. In all specifications, the estimated coefficient

[13]The inclusion of these different sets of fixed effects also alleviates potential concerns about the cross-country comparability of the data sources underlying CompNet.

is positive, and statistically significant at the 1% level, confirming the positive empirical correlation between concentration and inequality.

To get a sense of the magnitude of the correlation, consider the estimates for the full sample in Column (4). Conditioning on country-year and industry-year fixed effects, a one standard deviation increase in concentration (which as shown in Table 1 is around 0.1 if measured through the HHI and around 0.3 if measured through the share of sales in the top 10 firms) would be associated with an increase in inequality of around 0.05. This is slightly less than 10% of one standard deviation in the sample.

Figure 1 provides more details about the link between concentration and inequality, by considering the correlations along the entire distribution of firm-level wages in the restricted sample. In particular, we regress firm-level wages at percentile p in an industry-country-year cell on concentration in that cell (based on the HHI in the top panel and based on the share of sales in the top 10 firms in the bottom panel), as well as industry-year and country-year fixed effects. The figure plots the estimated coefficients and 95% confidence intervals obtained from these regressions at different percentile levels p, ranging from the fifth to the 99th percentile. Consistent with our finding regarding the positive correlation between concentration and inequality, we find that concentration is associated with a widening of the distribution of average firm-level wages. Depending on the measure of concentration used, we find that wages at the bottom of the distribution in more concentrated industries are either similar or somewhat lower than in less concentrated industries, whereas wages at the top of the distribution are much higher in more concentrated industries.

Appendix Figure A.2 explores the extent to which the correlation between concentration and inequality is observed within each of the countries and each of the industries in our sample. The correlation, conditional on industry and time fixed effects, is positive for the majority of the countries in our sample, with the only exceptions being Finland, France and Lithuania. The pattern that we have identified is therefore widespread across European countries and does not seem to be particularly related to country-specific institutions. The correlation between concentration and inequality (conditional on country and time fixed effects) is also positive and statistically significant in most sectors. The main exception is wholesale and retail trade – which is excluded from the graph for visual clarity – where the estimated coefficient is substantially negative.[14]

[14]Negative point estimates are also obtained for the administrative sector when measuring concentration based on the HHI and for the real estate sector when measuring concentration based on the top 10 firms; however, neither of these negative point estimates are statistically significant.

Overall, we conclude that the positive association between concentration and inequality is also widespread across different sectors of the economy.

5 Changes along the Productivity Distribution

The theoretical framework presented in Section 2 features an increase in concentration that is driven by the increased dominance of the most productive firms within an industry. In practice, higher concentration may be associated with relatively less productive firms being entrenched and exploiting their market power. Figure 2 analyzes the link between firm productivity, concentration and inequality. The left-hand panels consider how sales for firms at different deciles of the TFP distribution within an industry-country-year cell vary according to the level of concentration in that cell. We do this by regressing average sales at each productivity decile on concentration (using the HHI in the top panel and the share of sales in the top 10 firms in the bottom panel), as well as a full set of country-year and industry-year fixed effects. The results show that higher concentration is associated with nearly monotonic differences in sales along the TFP distribution, with low productivity firms having lower average volumes of sales, and higher productivity firms having higher average sales in more concentrated industries. Hence, in line with the theoretical framework, we find that, in Europe, higher concentration is associated with the increased dominance of the *most productive* firms within industries.

The middle panels show the associated wage changes, by running an analogous set of regressions, but with average firm-level wages at each productivity decile as the outcome of interest. Higher concentration is associated with lower wages in the less productive firms in an industry, and higher wages for more productive firms. In line with the prediction of the model, when highly productive firms are larger in terms of their sales, they also pay higher average wages, and this is the key mechanism generating greater wage inequality. Note that this is contrary to the notion of top firms exploiting their market power to reduce wages. These results also imply that certain groups of workers do benefit from an increase in market concentration.

Finally, the panels on the right of Figure 2 show the results when considering employment as an outcome. Once again we see a (nearly) monotonic pattern: higher concentration is associated with higher employment at more productive firms. When high productivity firms are more dominant in terms of sales, they also tend to be more

dominant in terms of employment. This has an additional important implication for wage inequality. Although our measures of inequality give equal weight to all firms, the fact that more productive, high wage firms in more concentrated industries not only pay higher wages but are also larger in terms of employment implies that if we were to construct *employment-weighted* measures of between-firm inequality, they would be even higher in more concentrated industries, given this reallocation of employment.

6 Alternative Explanations and Discussion

The patterns documented in the previous sections show a clear empirical link between concentration and inequality within sectors. Are there other shocks that, from the perspective of the model discussed in Section 2, would generate this type of co-movement? One such shock would be an exogenous increase in the dispersion of the productivity distribution across firms, i.e. a decrease in z. This, however, is somewhat trivial, as it would directly assume that firms become more heterogeneous and would mechanically generate the result. A change in consumer price sensitivity, on the other hand, generates an endogenous change in the distribution of productivity among operating firms. Moreover, it generates endogenous changes in the employment and wage outcomes of different firms, conditional on productivity – a pattern that would not arise as a result of a change in z.

The other potentially relevant parameters, given Equations (1) and (2), are γ, the curvature of the production function, δ, the curvature of the screening cost function, and k, the shape of the match-specific ability distribution. Changes in these parameters, however, cannot unambiguously generate a positive co-movement of concentration and inequality.[15]

Although we do not have a direct measure of changes in competitive pressure or consumer price sensitivity, the evidence that we have shown is in line with the mechanisms highlighted by the model, thus supporting the plausibility of this type of shock as an underlying driving force behind the increase in both sectoral concentration and within-sector wage inequality in Europe.[16] The results show that higher concentration is associated with the best firms in a sector being more dominant and, in spite of their

[15]Changes in γ and δ induce oppositely signed changes in concentration and inequality, whereas the impact of a change in k on inequality is ambiguous.

[16]Further plausibility for this type of shock as a driver of the increase in concentration and the decline in the labor share in the U.S. and other countries is provided by Autor et al. (2020).

higher dominance, paying higher average wages.

An alternative, and more concerning reason for the increase in concentration would be the entrenchment of incumbent firms due to barriers to entry. De Loecker et al. (2020), for example, document an increase in firm-level markups and profits among U.S. firms, which may be interpreted as evidence of entrenchment. If concentration in Europe were driven by the entrenchment of unproductive incumbent firms, however, we would not expect to see the pattern that we have documented in Figure 2, with higher levels of revenues, employment and wages being observed in the most productive firms within industries with higher concentration levels.

Consistent with the idea that a more competitive market environment is likely to be the main driving force behind the rise in concentration in Europe (rather than increased market power), Bighelli et al. (2021) show that changes in concentration are positively associated with changes in productivity and allocative efficiency.[17] The top panel of Table 3 provides further evidence along these lines. It shows results from a set of regressions analogous to those in Table 2, but where we use the log of the (unweighted) average wage across firms in an industry-country-year cell as the dependent variable. The results consistently show evidence of a positive correlation between concentration and average firm-level wages in our sample.

The bottom panel of Table 3 considers the relationship between concentration and overall sectoral employment. The results using the HHI as a measure of concentration are somewhat mixed; however, the stricter specification in Column (4) points towards a negative relationship between concentration and total sectoral employment. The results that use the share of sales in the top 10 firms in the sector consistently indicate a statistically significant and negative relationship between concentration and sectoral employment. Appendix Table A.1 shows that this is due to a decline in both job creation and job destruction rates in more concentrated industries, with the decline in job creation rates being quantitatively larger.

Overall, our results show that in more concentrated sectors in Europe, highly productive firms are more dominant and pay higher wages. Average wages are higher in these sectors. However, not everyone benefits, given that there tends to be a smaller number of jobs in these sectors, and wages are more unequally distributed. Moreover, we cannot rule out that larger firms are marking their wages down more as they become

[17] See also the evidence in Gutiérrez and Philippon (2018) regarding the role of supra-national institutions in the European Union in driving the increased enforcement of competition policies within the region.

more dominant – though our results imply that any such effect is more than offset by the incentive to pay higher wages due to the increased profitability of these firms. On net, our results support the notion that rising concentration in Europe primarily reflects a more efficient market environment rather than weak competition and rising market power.

7 Conclusions

We document a theoretical and an empirical link between concentration and between-firm wage inequality. Conceptually, in a setting where worker wages are linked to firm outcomes, such as the search and bargaining framework of Helpman et al. (2010) or the fair wage framework of Egger and Kreickemeier (2012), a shock that favors the most productive firms in an industry, such as the increase in consumer price sensitivity posited by Autor et al. (2020), leads to an increase in employment and revenue concentration in high-productivity firms, as well as an increase in the relative wages of workers in those firms. The shock therefore simultaneously increases sectoral concentration and sectoral between-firm wage inequality.

We confirm the empirical relevance of this conceptual link using data on concentration and between-firm wage inequality at the industry level for 14 European countries over the period 1999-2016. We find evidence of a statistically significant positive relationship between concentration and inequality, which is robust to allowing for a variety of different combinations of industry, country and year fixed effects. These changes are associated with increased sales, employment, and average wages in the most productive firms in the industry, suggesting that increased competitive pressures are a plausible mechanism underlying changes in both concentration and inequality in Europe.

Further understanding how and why competitive pressures have changed, as well as the underlying adjustments occurring at the firm level using detailed micro-data would be promising avenues for future research.

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Table 1: Summary statistics and correlations of concentration measures

Panel A: Descriptive statistics

	Mean	Std. Dev.	P10	P90	N
Full Sample					
Log 90-10 ratio of wage bill per worker	1.617	0.653	0.914	2.479	8820
Concentration (HHI)	0.034	0.098	0.0003	0.087	9809
Concentration (top 10)	0.226	0.271	0.015	0.714	9118
Restricted Sample					
Log 90-10 ratio of wage bill per worker	1.502	0.559	0.894	2.236	3660
Concentration (HHI)	0.012	0.031	0.0002	0.025	4185
Concentration (top 10)	0.156	0.199	0.010	0.433	4025
Share of sales in superstar firms	0.416	0.175	0.179	0.628	3262
Share of employment in superstar firms	0.223	0.142	0.072	0.397	3154

Panel B: Correlations

	HHI	Top 10	Share of sales
Top 10	0.843***		
	4025		
Share of sales in superstar firms	0.265***	0.288***	
	3262	*3162*	
Share of employment in superstar firms	0.343***	0.417***	0.778***
	3154	*3067*	*3026*

Note: The restricted sample refers to industry-country-year cells for which information for firms at all deciles of the TFP distribution is available. Superstar firms are those in the top decile of the TFP distribution in their industry-country-year cell. Summary statistics (panel A) and correlations (panel B) are weighted using each industry's time-averaged share of total value added in each country. The number of observations for each correlation in Panel B is shown in italics. ***p<0.01,**p<0.05, *p<0.1.

Table 2: Concentration and wage inequality

	Dep var: log 90-10 ratio of wage bill per worker			
	(1)	(2)	(3)	(4)
Full sample:				
Concentration (HHI)	0.183	0.231	0.452	0.503
	(0.072)**	(0.059)***	(0.081)***	(0.065)***
Obs.	8820	8813	8806	8798
R^2	0.683	0.798	0.726	0.833
Concentration (top 10)	0.237	0.197	0.225	0.176
	(0.036)***	(0.029)***	(0.039)***	(0.03)***
Obs.	8175	8168	8166	8158
R^2	0.689	0.814	0.727	0.842
Restricted sample:				
Concentration (HHI)	0.653	0.588	0.668	0.520
	(0.163)***	(0.144)***	(0.192)***	(0.169)***
Obs.	3660	3657	3577	3574
R^2	0.881	0.912	0.895	0.922
Concentration (top 10)	0.155	0.143	0.118	0.101
	(0.038)***	(0.034)***	(0.043)***	(0.038)***
Obs.	3506	3503	3402	3399
R^2	0.883	0.913	0.897	0.923
Share of sales in superstar firms	0.124	0.134	0.134	0.122
	(0.031)***	(0.027)***	(0.035)***	(0.031)***
Obs.	2819	2812	2680	2672
R^2	0.895	0.926	0.907	0.934
Share of employment in superstar firms	0.212	0.219	0.229	0.208
	(0.038)***	(0.034)***	(0.043)***	(0.038)***
Obs.	2743	2738	2595	2589
R^2	0.9	0.928	0.911	0.935
Industry FE	Yes	Yes		
Country FE	Yes		Yes	
Year FE	Yes			
Country x Year FE		Yes		Yes
Industry x Year FE			Yes	Yes

Note: Observations are at the country-industry-year level. All regressions are weighted using each industry's time-averaged share of total value added in each country. The restricted sample refers to industry-country-year cells for which information for firms at all deciles of the TFP distribution is available. Superstar firms are those in the top decile of the TFP distribution in their industry-country-year cell. ***p<0.01,**p<0.05, *p<0.1.

Table 3: Concentration, average wages and sectoral employment

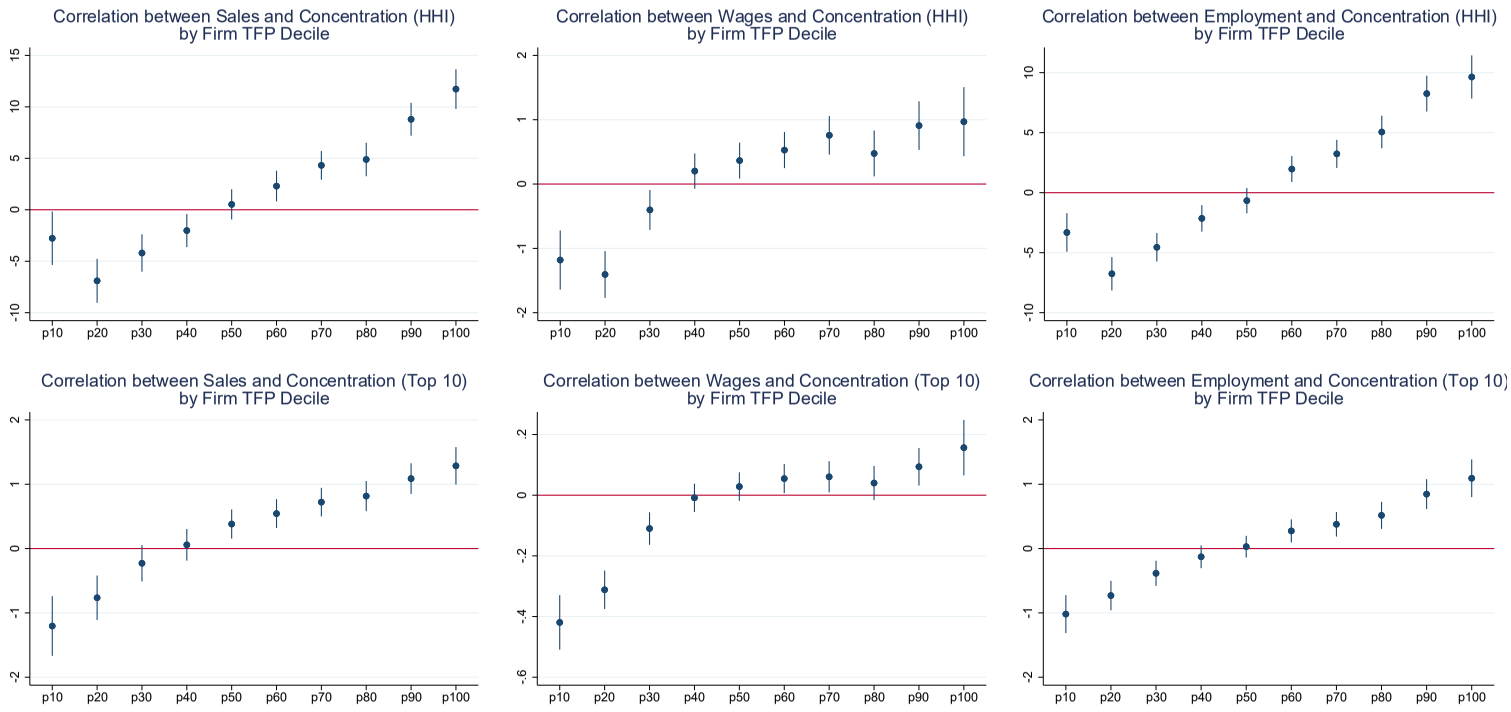
	Dep var: log average firm wages			
	(1)	(2)	(3)	(4)
Concentration (HHI)	0.353	0.303	0.259	0.286
	(0.115)***	(0.105)***	(0.132)**	(0.122)**
Obs.	4178	4178	4123	4123
R^2	0.960	0.969	0.965	0.971
Concentration (top 10)	0.112	0.122	0.103	0.113
	(0.027)***	(0.025)***	(0.029)***	(0.027)***
Obs.	4024	4024	3950	3950
R^2	0.953	0.962	0.957	0.965
	Dep var: log total employment			
	(1)	(2)	(3)	(4)
Concentration (HHI)	0.086	0.11	-.145	-.102
	(0.347)	(0.349)	(0.401)	(0.401)
Obs.	4166	4166	4109	4109
R^2	0.938	0.941	0.945	0.947
Concentration (top 10)	-.376	-.342	-.320	-.282
	(0.08)***	(0.08)***	(0.088)***	(0.087)***
Obs.	4006	4006	3930	3930
R^2	0.940	0.943	0.947	0.949
Industry FE	Yes	Yes		
Country FE	Yes		Yes	
Year FE	Yes			
Country x Year FE		Yes		Yes
Industry x Year FE			Yes	Yes

Note: Regressions are based on the restricted sample (industry-country-year cells for which information for firms at all deciles of the TFP distribution is available). Observations are at the country-industry-year level. All regressions are weighted using each industry's time-averaged share of total value added in each country. ***p<0.01,**p<0.05, *p<0.1.

Figure 1: Results across the distribution of firm-level wages

Note: The figure plots the estimated coefficients and 95% confidence intervals obtained from regressions of wages at different percentiles of the firm wage distribution within an industry-country-year cell on concentration in that cell, controlling for industry-year and country-year fixed effects, based on the restricted sample (industry-country-year cells for which information for firms at all deciles of the TFP distribution is available). Regressions are weighted using each industry's time-averaged share of total value added in each country.

Figure 2: Differential changes in sales, wages and employment along the productivity distribution



Notes: The figure shows the estimated coefficients and 95% confidence intervals obtained from regressions of industry-country-year mean firm sales (wages, employment) at each decile of the TFP distribution on industry-country-year concentration. Each regression includes country-year and industry-year fixed effects, and is weighted using each industry's time-averaged share of total value added in each country.

Online Appendix for:

Rising Concentration and Wage Inequality

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Appendix A Deriving Concentration Measures and the Wage Distribution

Concentration Measures Let $\overline{\theta}$ denote the productivity level corresponding to the $(100-\mu)$th percentile of the productivity distribution. The share of sectoral revenues accruing to firms in the top μ% of the productivity distribution is given by:

$$\begin{aligned} C_r &= 1 - \frac{\int_{\theta_d}^{\overline{\theta}} r(\theta) dG_\theta(\theta)}{\int_{\theta_d}^{\infty} r(\theta) dG_\theta(\theta)} \\ &= 1 - \frac{\int_{\theta_d}^{\overline{\theta}} \theta^{\frac{\beta}{\Gamma}} dG_\theta(\theta)}{\int_{\theta_d}^{\infty} \theta^{\frac{\beta}{\Gamma}} dG_\theta(\theta)} \\ &= \left(\frac{\overline{\theta}}{\theta_d}\right)^{\frac{\beta}{\Gamma}-z}. \end{aligned} \tag{A.1}$$

where the second equality is obtained using the equation of equilibrium firm-level revenues $r(\theta) = r_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\Gamma}}$, and the last equality uses the fact that with a Pareto distribution $g(\theta) = z\theta^{-(z+1)}$ and $1 - G_\theta(\theta_d) = \theta_d^{-z}$.

Finally, to express C_r as a function of μ, it is useful to relate $\frac{\overline{\theta}}{\theta_d}$ to the share of firms with $\theta \geq \overline{\theta}$:

$$\begin{aligned} \mu &= 1 - \int_{\theta_d}^{\overline{\theta}} g(\theta \mid \theta \geq \theta_d) d\theta \\ &= 1 - \frac{1}{\theta_d^{-z}} \int_{\theta_d}^{\overline{\theta}} z\theta^{-(z+1)} d\theta \\ &= \left(\frac{\overline{\theta}}{\theta_d}\right)^{-z}. \end{aligned}$$

It follows that $\frac{\bar{\theta}}{\theta_d} = \mu^{-\frac{1}{z}}$. Replacing the latter equation in (A.1) we obtain an expression for the share of revenues accruing to firms in the top $\mu\%$ of the productivity distribution:

$$C_r = \mu^{1-\frac{\beta}{\Gamma z}}. \tag{A.2}$$

The concentration measure of employment is obtained in a similar way by computing the share of sectoral employment concentrated in the firms in the top $\mu\%$ of the productivity distribution.

Wage Distribution Let θ_w denote the productivity level associated with $w(\theta_w) = w$. The wage distribution is given by:

$$\begin{aligned} G_f(w) &= Pr\left[w(\theta) \leq w\right] \\ &= Pr\left[\theta \leq \theta_w \mid \theta \geq \theta_d\right] \\ &= 1 - \left(\frac{\theta_d}{\theta_w}\right)^z, \end{aligned} \tag{A.3}$$

where the last equality uses the fact that productivity follows a Pareto distribution with shape parameter z. Finally, using the fact that $w(\theta_w) = w_d \left(\frac{\theta_w}{\theta_d}\right)^{\frac{\beta k}{\delta\Gamma}}$, we have that $\frac{\theta_d}{\theta_w} = \left(\frac{w_d}{w}\right)^{\frac{\delta\Gamma}{\beta k}}$ and we can rewrite (A.3) as follows:

$$G_f(w) = 1 - \left(\frac{w_d}{w}\right)^{\frac{\delta\Gamma z}{\beta k}}. \tag{A.4}$$

Hence, firm-level wages are Pareto distributed with scale parameter w_d and shape parameter $\frac{\delta\Gamma z}{\beta k}$.

Appendix B Impacts of an Increase in Consumer Price Sensitivity

Appendix B.1 Changes in the Productivity Threshold for Production

In the closed economy version of the Helpman et al. (2010) model, the equilibrium productivity cutoff for production is given by:

$$\theta_d = \left(\frac{\beta}{z\Gamma - \beta}\right)^{1/z} \left(\frac{f_d}{f_e}\right)^{1/z} \theta_{min}. \tag{A.5}$$

From (A.5) it is straightforward to see that

$$\frac{\partial \theta_d}{\partial \beta} = \left(\frac{f_d}{f_e}\right)^{1/z} \left(\frac{\beta}{z\Gamma - \beta}\right)^{1/z-1} \frac{\theta_{min}}{(z\Gamma - \beta)^2} > 0. \tag{A.6}$$

Hence, an increase in the elasticity of substitution increases the productivity threshold for production and leads to a reduction in the range of firm types.

This, however, does not imply that the variance of productivity among operating firms is reduced. The productivity distribution among operating firms is a truncated version of the Pareto distribution $G(\theta)$, with the same shape parameter z, but with scale parameter θ_d. The variance of productivity among operating firms is given by

$$\frac{z\theta_d^2}{(z-1)^2(z-2)},$$

which is increasing in θ_d. Intuitively, this is due to the fact that an increase in θ_d implies that firms with relatively homogeneous firm types at the bottom of the productivity distribution exit, and hence there is a relative increase in the mass of firms towards the tail. The increase in the productivity threshold induced by an increase in consumer price sensitivity will therefore lead to an increase in the variance of productivity among operating firms, further compounding the increase in inequality due to changes in employment and wages within continuing firm types. Scale-invariant measures of the dispersion of productivity among operating firms would not be affected by the change in θ_d.

Appendix B.2 Changes in Relative Revenues, Employment and Wages

Consider two firms, firm 1 and firm 2, with productivities θ_1 and θ_2 respectively, and suppose that $\theta_1 > \theta_2$.

Using the equilibrium firm-level revenues equation, the ratio of revenues between these two firms is given by:

$$\frac{r(\theta_1)}{r(\theta_2)} = \left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta}{\Gamma}}. \tag{A.7}$$

Taking the derivative of this ratio with respect to σ we obtain:

$$\frac{\partial}{\partial \sigma}\left[\frac{r(\theta_1)}{r(\theta_2)}\right] = \ln\left(\frac{\theta_1}{\theta_2}\right)\left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta}{\Gamma}-1}\frac{1}{\Gamma^2}\left(\Gamma\frac{\partial \beta}{\partial \sigma} - \beta\frac{\partial \Gamma}{\partial \sigma}\right) \quad > \quad 0, \tag{A.8}$$

given that $\theta_1 > \theta_2$, $\frac{\partial \beta}{\partial \sigma} > 0$ and $\frac{\partial \Gamma}{\partial \sigma} < 0$. Therefore, the revenue gap between a relatively more productive firm and a relatively less productive firm increases in response to a rise in the elasticity of substitution. Given that more productive firms have larger revenues to begin with, their share of revenues increases, thereby increasing measures of concentration such as the fraction of revenues in the top $\mu\%$ of firms in the sector, or the Herfindahl-Hirschman Index.[1] Note that this result holds regardless of the assumptions that one makes about the distribution of θ.

The ratio of employment between firm 1 and firm 2 is given by:[2]

$$\frac{h(\theta_1)}{h(\theta_2)} = \left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta}{\Gamma}\left(1-\frac{k}{\delta}\right)}. \tag{A.9}$$

[1] Since

$$\frac{\partial r(\theta)}{\partial \theta} = \frac{\beta}{\Gamma} r(\theta)\theta^{-1} > 0,$$

more productive firms have higher revenues.

[2] Note that more productive firms are larger and employ more workers as

$$\frac{\partial h(\theta)}{\partial \theta} = \frac{\beta}{\Gamma}\left(1 - k/\delta\right) h(\theta)\theta^{-1} > 0.$$

Taking the derivative of this ratio with respect to σ we obtain:

$$\frac{\partial}{\partial\sigma}\left[\frac{h(\theta_1)}{h(\theta_2)}\right] = \ln\left(\frac{\theta_1}{\theta_2}\right)\left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta}{\Gamma}\left(1-\frac{k}{\delta}\right)}\left(1-\frac{k}{\delta}\right)\frac{1}{\Gamma^2}\left(\Gamma\frac{\partial\beta}{\partial\sigma}-\beta\frac{\partial\Gamma}{\partial\sigma}\right) \quad > \quad 0, \quad \text{(A.10)}$$

given that $\theta_1 > \theta_2$, $\frac{\partial\beta}{\partial\sigma} > 0$, $\frac{\partial\Gamma}{\partial\sigma} < 0$ and $\delta > k$. Thus, the employment gap between firm 1 and firm 2 grows when the elasticity of substitution increases, leading to an increase in concentration and employment-weighted between-firm wage inequality (regardless of the assumptions that one makes about the distribution of θ).

Finally, consider the wage gap between these two firms:[3]

$$\frac{w(\theta_1)}{w(\theta_2)} = \left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta k}{\delta\Gamma}} \quad \text{(A.11)}$$

The derivative of the wage gap with respect to σ is positive:

$$\frac{\partial}{\partial\sigma}\left[\frac{w(\theta_1)}{w(\theta_2)}\right] = \ln\left(\frac{\theta_1}{\theta_2}\right)\left(\frac{\theta_1}{\theta_2}\right)^{\frac{\beta k}{\delta\Gamma}}\frac{k}{\delta}\frac{1}{\Gamma^2}\left(\Gamma\frac{\partial\beta}{\partial\sigma}-\beta\frac{\partial\Gamma}{\partial\sigma}\right) \quad > \quad 0. \quad \text{(A.12)}$$

given that $\theta_1 > \theta_2$, $\frac{\partial\beta}{\partial\sigma} > 0$ and $\frac{\partial\Gamma}{\partial\sigma} < 0$. This leads to an increase in between-firm wage inequality across firms with different productivity levels, once again regardless of the assumptions that one makes about the distribution of θ.

Appendix C Concentration, Wage Inequality and Worker Sorting

Helpman et al. (2010, Section 5.1) present an extension to their model that allows for worker heterogeneity in observable characteristics. This makes it possible to also think about the impacts operating through the increased sorting of good workers to good firms in terms of observables. Here we illustrate the key features of this extension

[3]Note that more productive firms pay higher wages because

$$\frac{\partial w(\theta)}{\partial\theta} = \frac{\beta k}{\delta\Gamma}w(\theta)\theta^{-1} > 0.$$

to the model, and derive the key predictions of interest for our purposes regarding concentration and between-firm wage inequality.

Consider an economy with two types of workers, $\ell = H, L$, with H denoting skilled workers and L unskilled workers. The production function is given by:

$$y = \theta \left(\overline{a}_H h_H^{\gamma_H}\right)^{\lambda_H} \left(\overline{a}_L h_L^{\gamma_L}\right)^{\lambda_L}, \qquad \lambda_H + \lambda_L = 1 \tag{A.13}$$

The match-specific ability of each group has a Pareto distribution with shape parameter k_ℓ and lower bound $a_{min,\ell}$. Search and matching for skilled and unskilled workers occur in separate markets, so search costs b_ℓ are allowed to differ by type.

Helpman et al. (2010) show that firm-level employment and wages for workers of type ℓ are given by:

$$h_\ell(\theta) = h_{d,\ell} \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\Gamma}(1-k_\ell/\delta)}, \qquad h_{d,\ell} \equiv \frac{\lambda_\ell \beta \gamma_\ell}{\Gamma} \frac{f_d}{b_\ell} \left[\frac{\lambda_\ell \beta (1-\gamma_\ell k_\ell)}{\Gamma} \frac{f_d}{c a_{min,\ell}^{\delta}}\right]^{-k_\ell/\delta}$$

$$w_\ell(\theta) = w_{d,\ell} \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta k_\ell}{\delta \Gamma}}, \qquad w_{d,\ell} \equiv b_\ell \left[\frac{\lambda_\ell \beta (1-\gamma_\ell k_\ell)}{\Gamma} \frac{f_d}{c a_{min,\ell}^{\delta}}\right]^{k_\ell/\delta}$$

where now:

$$\Gamma = 1 - \beta(\lambda_H \gamma_H + \lambda_L \gamma_L) - \frac{\beta}{\delta}[1 - (\lambda_H \gamma_H k_H + \lambda_L \gamma_L k_L)]$$

The relative employment of skilled workers within a firm with productivity θ is given by:

$$\frac{h_H(\theta)}{h_L(\theta)} = \frac{h_{d,H}}{h_{d,L}} \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\delta\Gamma}(k_L - k_H)}$$

And the relative wage of skilled workers is given by:

$$\frac{w_H(\theta)}{w_L(\theta)} = \frac{w_{d,H}}{w_{d,L}} \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\delta\Gamma}(k_H - k_L)}$$

For sufficiently high values of $\frac{w_{d,H}}{w_{d,L}}$, we have that in all firms, skilled workers are paid more than unskilled workers, i.e. $\frac{w_H(\theta)}{w_L(\theta)} > 1 \ \forall \theta$.

Assuming that $k_H < k_L$, i.e. that the match-specific ability distribution is more

dispersed among skilled workers than among unskilled workers, we have that the relative employment of skilled workers is increasing in firm productivity.

Average firm wages will be higher in more productive firms because they: (i) employ a larger proportion of skilled workers, and (ii) pay higher wages to both worker types. Hence, wages differ across firms both because of the composition/sorting of workers, and because of firm premia conditional on worker type.

The concentration of type ℓ workers in the top $\mu\%$ of firms is given by:

$$C_{h,\ell} = \mu^{1-\frac{\beta}{\Gamma z}(1-k_\ell/\delta)} \tag{A.14}$$

Given that $k_H < k_L$, we have that $C_{H,h} > C_{L,h}$.

We have the following prediction:

Prediction: An increase in the elasticity of substitution, σ, increases concentration of employment in the most productive firms, particularly so for skilled workers:

$$\frac{\partial C_{h,H}}{\partial \sigma} > \frac{\partial C_{h,L}}{\partial \sigma} > 0$$

Corollary: The disproportionate increase in employment concentration for skilled workers implies stronger sorting of skilled workers to high productivity firms. This increased sorting and the implied changes in the composition of workers across firm types will increase between-firm inequality in average firm-level wages.

The distribution of wages across firms for workers of type ℓ is given by:

$$G_f(w_\ell) = 1 - \left(\frac{w_{d,\ell}}{w_\ell}\right)^{\frac{\delta\Gamma z}{\beta k_\ell}}$$

This is a Pareto distribution with scale parameter $w_{d,\ell}$ and shape parameter $\frac{\delta\Gamma z}{\beta k_\ell}$. Inequality, as measured by any scale-invariant measure, will be a function of the shape parameter only.

Prediction: An increase in the elasticity of substitution, σ, increases within-group, between-firm wage inequality for both worker types.

Corollary: An increase in the elasticity of substitution, σ, increases inequality in average firm wages both because of (i) increased worker sorting and (ii) increased dispersion

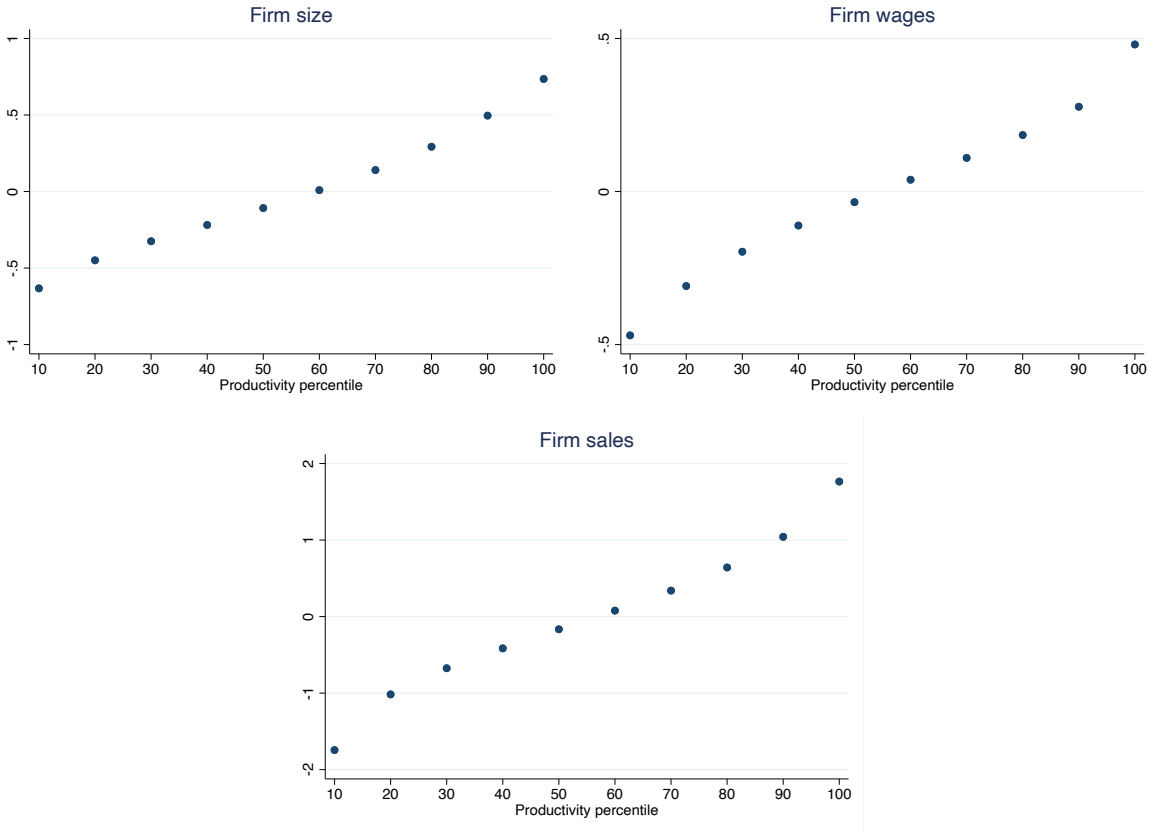
in firm premia conditional on worker types.

Table A.1: Concentration and average job creation and job destruction rates

	Dep var: average firm job creation rate			
	(1)	(2)	(3)	(4)
Concentration (HHI)	-.076	-.060	-.081	-.078
	(0.022)***	(0.019)***	(0.023)***	(0.019)***
Obs.	3988	3988	3916	3916
R^2	0.602	0.709	0.707	0.796
Concentration (top 10)	-.026	-.028	-.028	-.030
	(0.005)***	(0.004)***	(0.005)***	(0.004)***
Obs.	3856	3856	3771	3771
R^2	0.587	0.694	0.697	0.785
	Dep var: average firm job destruction rate			
	(1)	(2)	(3)	(4)
Concentration (HHI)	0.051	0.036	0.013	-.001
	(0.026)*	(0.023)	(0.026)	(0.021)
Obs.	4009	4009	3938	3938
R^2	0.475	0.632	0.648	0.781
Concentration (top 10)	-.016	-.019	-.014	-.018
	(0.006)***	(0.005)***	(0.006)**	(0.005)***
Obs.	3871	3871	3788	3788
R^2	0.434	0.606	0.611	0.759
Industry FE	Yes	Yes		
Country FE	Yes		Yes	
Year FE	Yes			
Country x Year FE		Yes		Yes
Industry x Year FE			Yes	Yes

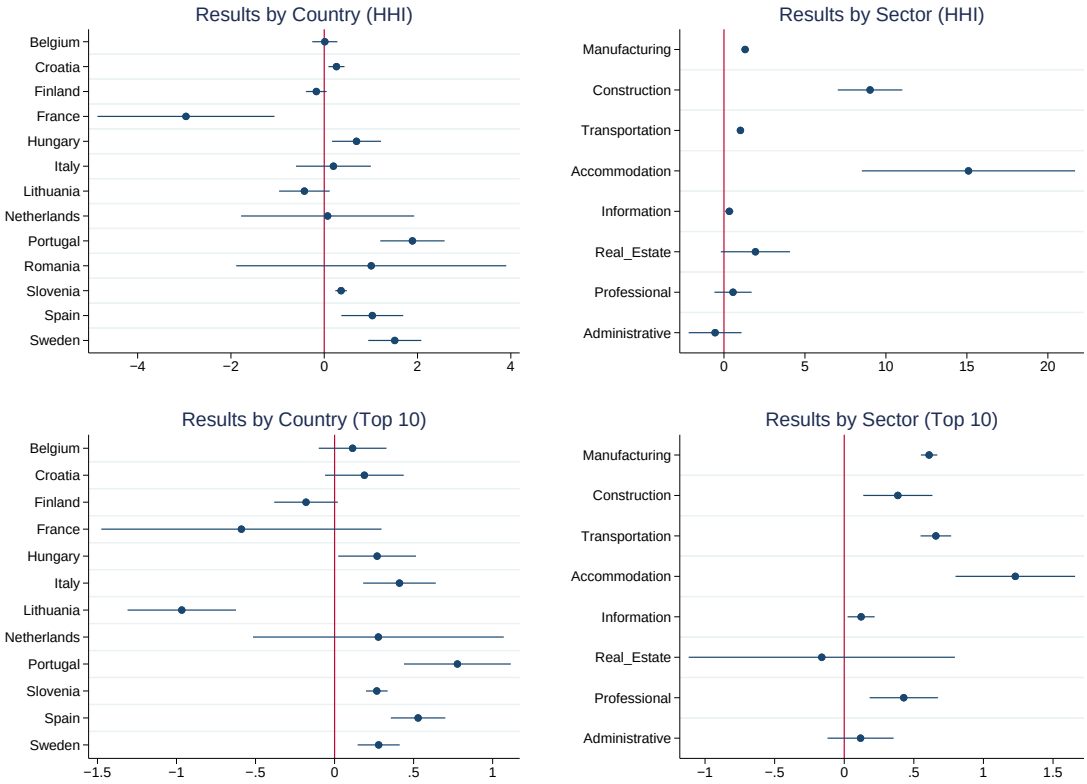
Note: Regressions are based on the restricted sample (industry-country-year cells for which information for firms at all deciles of the TFP distribution is available). Observations are at the country-industry-year level. All regressions are weighted using each industry's time-averaged share of total value added in each country. ***p<0.01,**p<0.05, *p<0.1.

Figure A.1: Firm size, wages and sales (turnover) along the productivity distribution



Note: The left (right, bottom) panel shows the relationship between firm size (wages, sales) and firm productivity across percentiles of the TFP distribution. Firm size (wages, sales) is the average of residuals from an unweighted regression of log firm size (log wages, log sales) on a full set of industry-country-year fixed effects, averaged across firms in a given TFP percentile bin.

Figure A.2: Results by Country and by Broad Sector



Note: The figure plots the estimated coefficients and 95% confidence intervals obtained from regressions of inequality on concentration. The top panels use the HHI index as the concentration measure, while the bottom panels use the share of sales in the top 10 firms. In the left panels, regressions are run separately for each country, controlling for industry and time fixed effects. Note that we drop Denmark as we only have 18 observations (industry-year cells). In the right panels, regressions are run separately for each broad sector, controlling for country and time fixed effects. Wholesale and retail trade is excluded from the figure for visual clarity, but it is included in the baseline regressions.