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; Barth et al., 2016; Kelly et al., 2017; Song et al., 2019). 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. 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

[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.

changes in concentration and wage inequality through two channels. First, there is an 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. Second, this selection effect is compounded by endogenous within-firm changes. In particular, more productive firms will increase their relative sales (thus increasing concentration), and they will also 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]

While we illustrate the impact of a shock to consumer price sensitivity within the context of the Helpman et al. (2010) model, we show that increases in consumer price sensitivity also lead to a simultaneous increase in concentration and wage inequality in various other settings, such as the fair wage model of Egger and Kreickemeier (2012), as well as models that generate wage heterogeneity through idiosyncratic workplace preferences rather than search frictions, such as Card et al. (2018).

We analyze the empirical relationship between concentration and inequality 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 approach consists of regressing inequality on concentration as well as various combinations of industry, country, and year fixed effects (in order to exploit different sources of variation to determine the correlation of interest). Our key finding is that there is a robust positive and statistically significant relationship between sectoral concentration and sectoral between-firm wage inequality. This is consistent with the model prediction that the two outcomes are linked to each other.

To further explore the two channels highlighted by the model, we explore whether the between-firm dispersion of productivity is higher in more concentrated industries, and we analyze how employment, sales and wages vary across firms with different productivity levels in industries with varying degrees of concentration. In line with the model, we find that higher concentration is associated with higher variances in firm

[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).

productivity, and is also associated with a stronger relationship between firm productivity and firm sales, employment and wages.

While we admittedly do not have direct evidence of a shock to consumer price sensitivity, we show that the relationships between productivity, revenues, employment and wages that we observe in the data are inconsistent with other potential shocks, such as a technological change shock which exogenously increases the dispersion of the firm productivity distribution, or a change in union bargaining power.

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, 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; Barth et al., 2016; Kelly et al., 2017; Song et al., 2019) – 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., 2020, 2022; 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., 2022; 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.[3]

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

[3]It is important to acknowledge that our results are obtained from an analysis at the national sectoral level. Local concentration might not evolve in the same way as national concentration (see e.g. Rossi-Hansberg et al., 2021). While there is evidence showing that a positive correlation between concentration and inequality is also observed at the local level in the case of the U.S. (Rinz, 2020), exploring the patterns at the local level in Europe remains an important open empirical question.

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. We also provide evidence on the employment and wage adjustments that are observed across firms with different productivity levels as concentration rises. This evidence is new relative to Webber (2015) and Rinz (2020), and is consistent with our hypothesized driving force. 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 local labor market setting.

An additional closely related paper is by Akerman (2021). His analysis considers how rising concentration (also driven by a rise in consumer price sensitivity) is associated with changes in the demand for skilled workers, using a framework in which firms differ in their relative employment of skilled and unskilled workers. His model and his analysis focus on changes in inequality that arise solely due to changes in the aggregate skill premium. Here, we instead focus on broader patterns of between-firm inequality. Our richer model and our novel analysis of the heterogeneous patterns observed across firms with different productivity levels are complementary to the findings in 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 their paper considers the implications of this type of shock under the assumption that the labor market is competitive (and hence there is no wage inequality), we extend their analysis in order to consider the implications within a framework that allows for wage heterogeneity between firms.

In Section 2.5 we show that the implications obtained in the Helpman et al. (2010) model with regards to the impact of an increase in consumer price sensitivity are also obtained in other types of heterogeneous firm models with wage inequality. Moreover, while we focus primarily on a rich yet parsimonious baseline model that generates between-firm wage heterogeneity in a setting where workers are ex-ante homogeneous, in Section 2.6 and Appendix B we show that we obtain richer, though qualitatively identical predictions, in a setting that allows for ex-ante worker heterogeneity (by having two types of workers, skilled and unskilled, and allowing for worker sorting across firms). In Section 6 we provide a detailed discussion of other potential shocks that may impact concentration and inequality within various theoretical frameworks.

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

[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.

(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. 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 $c a_c^{\delta}/\delta$, 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.

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

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

$$h(\theta) = h_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta}{\Gamma}(1-k/\delta)}, \qquad h_d \equiv \frac{\beta\gamma}{\Gamma}\frac{f_d}{b}\left[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{ca_{min}^{\delta}}\right]^{-k/\delta} \tag{2}$$

$$w(\theta) = w_d \left(\frac{\theta}{\theta_d}\right)^{\frac{\beta k}{\delta\Gamma}}, \qquad w_d \equiv b\left[\frac{\beta(1-\gamma k)}{\Gamma}\frac{f_d}{ca_{min}^{\delta}}\right]^{k/\delta} \tag{3}$$

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).[5] The equilibrium relationships described above imply that the share of sectoral revenues accruing to these firms, and the share of sectoral employment concentrated in these firms is given,

[5] Derivation details of the concentration measures and wage distribution can be found in Appendix A.1. Below we also discuss results for other types of concentration measures.

respectively, by:

$$C_r = \mu^{1-\frac{\beta}{\Gamma z}} \qquad\qquad C_\ell = \mu^{1-\frac{\beta}{\Gamma z}(1-k/\delta)}. \tag{4}$$

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

$$G_f(w) = 1 - \left(\frac{w_d}{w}\right)^{\frac{\delta\Gamma z}{\beta k}} \tag{5}$$

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).[6] 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.

[6] In the model, the elasticity of substitution is an exogenous parameter. One could consider a richer model in which the elasticity of substitution between varieties is a function of the earnings distribution, due to heterogeneous Engel elasticities. In such a setting, an exogenous shock such as a change in the underlying productivity distribution would result in changes in the elasticity of substitution which could amplify or dampen the direct impacts of the shock on concentration and inequality.

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 A.2.1. 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

[7]It is worth noting that the wage distribution in Equation (5) 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.

revenues, employment and wages relative to less productive firms, as shown formally in Appendix A.2.2. 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 $\mu\%$ of firms (as we have derived in Equation 4), 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

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

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 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 other main class of models that have been used in the literature to model firm wage heterogeneity are models in which firms face an upward sloping labor supply curve (Manning, 2011), due to idiosyncratic and unobservable worker valuations of different workplaces (for recent examples, see e.g. Card et al., 2018; Lamadon et al., 2022; Berger et al., 2022). The frameworks in this literature are typically partial equilibrium. This makes it difficult to obtain closed form solutions for equilibrium outcomes and to formally derive the impacts of consumer price sensitivity for concentration and inequality. However, one can intuitively infer that, as in our model, an increase in the elasticity of substitution between varieties (which makes consumers more price sensitive) will shift consumer demand towards the lower cost varieties produced by more productive firms – this mechanism is not affected by the assumptions made about the frictions that exist in the labor market (i.e. search and screening frictions vs heterogeneous worker preferences). This shift in demand towards more productive firms, which are larger to begin with, must lead to an increase in relative output at these firms, thus increasing product market concentration.

Assuming a simple production function in which output is a function of labor only (as in Card et al., 2018) and homogeneous labor, it must be the case that, in order to increase output, firms must increase employment. Therefore, there is also an increase in employment concentration. Given the upward sloping labor supply curve faced by the firm, in order to expand in terms of employment, firms must also increase their wage. As we show in Appendix C.1, as long as workers' marginal utility of labor income is constant or decreasing, the larger (relative) expansion of employment in more productive firms that were already larger at baseline must be met by larger (relative) increases in firm wages, in order to be able to attract the additional workers. This means that wage inequality will also increase in this model.[10]

In short, the intuition that increases in consumer price sensitivity lead to a simulta-

[10]Consistent with the idea that increases in demand for a firm's products are associated with increases in the wages that they pay to their workers, Card et al. (2018) discuss how an empirically-grounded calibration of their model generates a positive (albeit small) elasticity of wages with respect to demand.

neous increase in concentration and wage inequality also goes through in models that generate wage heterogeneity through idiosyncratic workplace preferences rather than search frictions.

2.6 Worker Sorting

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 B we analyze the impact of an increase in consumer price sensitivity within the Helpman et al. (2010) extension that features two types of workers (skilled and unskilled). This framework features endogenous sorting of skilled workers to high productivity firms. 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) stronger sorting of skilled workers to more 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 analyze the empirical relationship 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.[11] 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.

It is worth noting that the underlying definition of a firm is not necessarily the same across all countries in the dataset. As discussed in CompNet (2018), most countries gather firm data at the level of the legal unit, whereas a selected number of countries use the enterprise level (which is a higher level of aggregation).[12] Below we discuss how our analysis will include country (or country-year) fixed effects, in order to ensure that our results are not driven by cross-country differences in the level of aggregation at which the data is reported. We also perform a number of robustness checks in Section 4 where we restrict the sample to subsets of countries where issues of comparability are less severe, and where we estimate our relationship of interest country by country.

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.[13] 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

[11]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.

[12]According to Eurostat (`http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Enterprise`), an enterprise is defined as "an organisational unit producing goods or services which has a certain degree of autonomy in decision-making. An enterprise can carry out more than one economic activity and it can be situated at more than one location. An enterprise may consist out of one or more legal units."

[13]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.

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 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 2.6).

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.[14] 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

[14]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.

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. Our equation of interest is:

$$INEQ_{ict} = \alpha CONC_{ict} + \gamma_i + \delta_c + \tau_t + u_{ict} \tag{6}$$

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 to identify our coefficient of interest α, we experiment with different combinations of industry, country and time fixed effects, as discussed below.[15]

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 specoification which includes industry, country and year fixed effects. We find that there is a positive and statistically

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

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 variations for the identification of the correlation coefficient of interest. 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 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. Put differently, our estimate of 0.503 implies that differential concentration (HHI) between the most and the least concentrated industries (*Manufacture of coke and refined petroleum products* vs *Wholesale trade*) accounts for roughly 38% of the observed differential unweighted wage inequality. Comparing the coke and petroleum industry to the median industry (*Travel agency, tour operator reservation service and related activities*), concentration (HHI) makes up for 34% of the differential wage inequality. When concentration is measured with Top 10 (and hence using an estimate of 0.176), the corresponding shares are 22% and 13%. These estimates suggest that increased concentration can account for a sizeable share of the variation in between-firm wage inequality.

As discussed in Section 3, the underlying definition of a firm is not necessarily the same across all countries in the dataset. CompNet (2018) provides information on the reporting unit for each country in the data, which allows us to perform some robustness checks of our correlations. Specifically, CompNet (2018) reports that a cross-country comparability problem related to the unit of observation may appear when including France, the Netherlands and Italy. Hence, in Panel A of Appendix Table A.1 we repeat the analysis from the top panel of Table 2, but dropping these three countries from the sample. CompNet (2018) also discusses the related issue of consolidation, which refers to the cancelling out of intra-firm flows in consolidated income statements. We evaluate this issue in Panel B of Appendix Table A.1, where we drop Finland, Croatia, Lithuania and Romania, which are the countries that provide unconsolidated enterprise data. Focusing on our preferred specification (Column 4), the correlations between concentration and wage inequality are similar to the baseline results and precisely estimated in both panels, which suggests that the reporting unit and consolidation issues do not play a significant role in our estimations.

Figure 1 provides more details about the link between concentration and inequality, by considering the correlations along the entire distribution of firm-level wages, based on the sample from the bottom panels of Table 2. 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.[16] Overall, we conclude that the positive association between concentration and inequality is also widespread across different sectors of the economy.

5 Mechanisms

The results in the previous section show a positive correlation between concentration and inequality, which is consistent with the theoretical predictions of Section 2 regarding the impact of an increase in consumer price sensitivity. In order to explore whether the empirical patterns are consistent with the reallocation effects predicted by the model, in this section we analyze the link between firm productivity, concentration and inequality. In the model, the shock generates an increase in concentration that is driven by the increased dominance of the most productive firms within an industry. Empirically, however, higher concentration might be associated with relatively less productive firms being entrenched and exploiting their market power.

The left-hand panels of Figure 2 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 log 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 (log) 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 log 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, higher concentration is associated with highly productive

[16] 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.

firms being larger in terms of their sales *and* paying higher average wages. This is the key mechanism generating greater wage inequality. While we cannot determine the relationship between concentration and firm-level wage markdowns, these results imply that any potential negative effect of concentration on wage markdowns in high-productivity firms is more than offset by the effect of concentration on the incentive to pay higher wages, on average, in these firms, due to their increased profitability. Note that these results also imply that at least some workers benefit from an increase in market concentration.[17]

Finally, the panels on the right of Figure 2 show the results when considering log 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.

Our discussion in Section 2.4 highlights the fact that an increase in consumer price sensitivity is predicted to lead to higher concentration and between-firm wage inequality through two channels: (i) an endogenous change in the industry's productivity distribution (due to the exit of unproductive firms), and (ii) differential increases in revenues, employment and wages among firms that remain in operation, *conditional on productivity*. By comparing outcomes within productivity deciles across industries with different levels of concentration, our analysis in Figure 2 captures the simultaneous effect of both of these channels. We can also directly test for each of the two channels.

First, in Table 3 we determine whether concentration is associated with higher levels of productivity dispersion across firms. Here, we run a set of regressions analogous to those in Table 2, but where the dependent variable is the variance of TFP across firms within an industry-country-year cell (divided by one million). The results show that higher levels of concentration are associated with significantly higher levels of TFP

[17] Given the aggregated nature of the CompNet data, we have no information on how the distribution of wages within firms changes, and hence we cannot rule out that the increases in mean wages at high productivity firms are disproportionately accruing to specific workers within the firm (e.g. executives). Exploring these heterogeneous effects within firms would be an interesting direction for future research.

dispersion between firms, in line with the first channel highlighted by our theoretical model.

In order to explore the evidence for the second channel in the model, we analyze whether the relationship between firm-level outcomes and firm productivity is stronger in more concentrated industries. Specifically, from Equations (1)-(3) one can see that log sales, log wages and log employment are an increasing function of log productivity, where the coefficient on log productivity is increasing in consumer price sensitivity.[18]

We take this prediction to the data in Table 4, where we regress mean log firm-level outcomes within an industry, country, year, and productivity decile cell on mean log firm productivity in that cell, and an interaction of productivity with concentration at the industry-country-year level. In order to solely exploit differences across firms operating in the same industry, country and year, we include a set of fully interacted industry-country-year fixed effects.[19] The inclusion of this set of fixed effects implies that we cannot estimate the direct effect of concentration on firm-level outcomes; however, our interest is not on the direct effect of concentration, but rather on the coefficient on the interaction term, as it indicates whether the relationship between firm productivity and firm sales, wages and employment is stronger *within* more concentrated industry-country-year cells (as predicted by the model).

The first column in Panel A of Table 4 shows that firm sales are increasing in firm productivity but, as indicated by the coefficient on the interaction term, the relationship between sales and productivity is much stronger in industry-country-year cells in which concentration – as measured by the HHI – is higher. Column (2) shows that there is also a much stronger relationship between productivity and wages in more concentrated industries, while Column (3) shows that the same is true in the case of employment. Panel B shows that similar conclusions are obtained when measuring concentration through the share of sales concentrated in the top 10 firms, rather than the HHI.

Overall, the results across all three columns and across both panels of Table 4 are strongly in line with the model prediction regarding the disproportionate increases in sales, wages and employment in more productive firms within more concentrated

[18]Recall that an increase in consumer price sensitivity leads to an increase in β and a decrease in Γ.

[19]This set of fixed effects is also justified by Equations (1)-(3). The industry-country-year fixed effects would control for changes in the industry-country-year-specific intercepts r_d, h_d and w_d, as well as the industry-country-year-specific productivity threshold θ_d (and its industry-country-year-specific coefficient). Naturally, we cannot include this set of fixed effects in our main specifications, where variation occurs at this level of aggregation. Here, however, since we exploit variation across productivity deciles within cells, we are able to include these fixed effects.

industries (conditional on productivity) induced by an increase in consumer price sensitivity. These results, in combination with the results in Table 3, are consistent with an increase in consumer price sensitivity leading to changes in both the composition of operating firms, as well as firm outcomes conditional on productivity – the two channels highlighted by the model.

It is worth noting that a long-standing literature in labor economics has documented the relationship between firm size and wages (e.g. Oi and Idson, 1999; Bayard and Troske, 1999; Helpman et al., 2017; Berlingieri et al., 2018; Barth et al., 2018). The fact that larger firms tend to pay higher wages creates a natural link between (employment) concentration and wage inequality: If rising concentration is associated with more heterogeneity in firm sizes, it will also be associated with more heterogeneity in firm wages. The results above indeed show that, in more concentrated industries, more productive firms are larger and pay higher wages.

In Appendix Table A.2 we analyze whether the magnitude of the large firm wage premium varies with concentration. We do this by running a set of regressions analogous to those in Table 4, but where we regress (log) wages on (log) employment and its interaction with concentration. Interestingly, we find that the relationship between firm employment and firm wages is much smaller – though still positive – within more concentrated industry-country-year cells.[20] This implies that in more concentrated industries, large firms do not pay wages that are as high as would be expected based on their size. However, it is not necessarily clear that this is because they exploit their market power, given that, as Table 4 shows, they do pay higher wages than what would be expected given their *productivity* level. What seems to drive the lower large firm wage premium in more concentrated industries is the fact that more productive firms in these industries are *much* larger in terms of employment, relative to what would be expected given their productivity level (note the difference in the magnitudes of the coefficients on the interaction terms in Column (3) vs Column (2) of Table 4, as well as the difference in the scale of the y-axis in the right-hand panels vs the middle panels of Figure 2). Another interesting implication of the result in Table A.2 is that the decline in the large firm wage premium documented by Bloom et al. (2018) could potentially be linked to the rise in concentration in the U.S.

[20]Note from the summary statistics in Table 1 that the 90th percentile of HHI is 0.087, and the 90th percentile of the Top 10 measure is 0.714. Thus, in spite of the large negative coefficient on the interaction terms in Table A.2, the marginal effect of log employment on log wages remains positive even for highly concentrated industries.

6 Alternative Explanations and Discussion

The patterns documented in the previous sections show a clear empirical link between concentration and inequality within sectors, which is associated with higher sales, employment and wage levels in high-productivity firms. We now consider whether there are other shocks that could generate this type of co-movement.

Within the context of the model discussed in Section 2.1, a natural candidate could be a shock to z, the dispersion of the productivity distribution across firms. A decrease in z (which would exogenously increase the dispersion of the underlying productivity distribution) could be interpreted as a form of technological change due to automation and digitalization. It is straightforward to see from Equations (4) and (5) that a decrease in z would increase both concentration and wage inequality (note that Γ, β and w_d are independent of z).

While this shock and our proposed shock (i.e. an increase in consumer price sensitivity) both lead to a rise in concentration and wage inequality, they generate different predictions regarding the relationship between productivity and other firm-level outcomes. Specifically, as discussed above, a shock to consumer price sensitivity leads to a stronger relationship between firm productivity and firm revenues, employment and wages. A shock to z does not generate such a prediction, as it induces changes in concentration and wage inequality that are solely driven by the change in the composition of operating firms, but not by changes in firm-level outcomes conditional on productivity. The results in Section 5, however, show evidence for both of the channels predicted by a shock to consumer price sensitivity. The evidence presented in Table 4 in particular is consistent with a shock to consumer price sensitivity, but not with a technological change shock in the form of a change in z, as the underlying driver of concentration and inequality.

Given Equations (4) and (5), the other potentially relevant parameters that, from the perspective of the model, could drive changes in concentration and inequality 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.[21]

A potentially relevant shock which is outside of the scope of the model would be

[21] 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.

a change in unions' bargaining power. In order to consider the implications of such a shock, we make use of the vintage capital model of Moene and Wallerstein (1997), in which firm productivity is directly linked to age, and wages are determined through bargaining. Under centralized bargaining, there is no wage dispersion across firms as there is a unique economy-wide bargained wage, and hence we focus on the case of decentralized bargaining which does allow for between-firm inequality.

In Moene and Wallerstein (1997), technical progress evolves at an exogenous rate and is embodied in new firms and equipment, implying that firm productivity decays with age. With decentralized bargaining, wages are proportional to value added for younger, more productive firms. Firms beyond a certain (endogenously determined) age threshold instead pay a constant (and lower) market clearing wage. Employment at each firm is fixed at one worker, and hence the only decision a firm faces is whether to enter or exit the market. The total number of firms is also fixed, and therefore aggregate employment is fixed as well. The key endogenous object is the age up to which firms operate (i.e. the age of the oldest firm). This age threshold is analogous to the productivity threshold above which firms operate in the Helpman et al. (2010) model, i.e. it determines the distribution of productivity among operating firms, and therefore will be key for determining concentration and inequality in this model.[22]

As discussed in Appendix C.2, an *increase* in unions' bargaining power (which may be counterfactual given the declining trends of union power that have been documented in many countries) can generate an increase in both concentration and wage inequality. The increase in inequality is intuitive: if bargaining power increases, workers will be able to extract a higher share of value added in younger, more productive firms which pay the decentralized wage. This is not the case in older, less productive (and lower wage) firms, given that these firms pay the market clearing wage – which, as Moene and Wallerstein (1997) show, will fall if unions' bargaining power increases. Hence, wages at young, high wage, high productivity firms will increase relative to old, low wage, less productive firms, so wage inequality will increase.

To understand the increase in concentration, note that due to the decrease in the market clearing wage, older firms that would have otherwise exited are now able to remain in operation. Given the fixed total number of firms, this means that there will be fewer young, high productivity firms and more old, low productivity firms. Hence, aggregate revenues fall. Given that the revenues of a given firm are fixed (as they

[22]Note that in this model all firms produce a homogeneous final good with a common price, so there is no sense in which consumer price sensitivity could vary in this model.

depend only on its age), the fall in aggregate revenues implies that the market share of each individual firm increases. This will tend to push concentration in top firms up. At the same time, the change in the composition of operating firms tends to push concentration down: since there are fewer young, high market share firms, the top 10 (or top 10%) of firms will include additional relatively older, lower market share firms. However, the higher market share of each firm due to the fall in aggregate revenues more than offsets this compositional effect, and concentration increases in response to the increase in unions' bargaining power.

Although increasing unions' power does generate positive co-movements between wage inequality and revenue concentration, it also generates predictions that do not align well with the data. First, as discussed above, the composition of firms in the top decile of productivity will deteriorate when bargaining power increases. The model therefore predicts that this shock unambiguously decreases average revenue in the top decile of the productivity distribution. Moreover, given that in the model each firm employs exactly one worker, each decile of productivity employs exactly 10% of workers in any equilibrium, and therefore average employment in the top decile and overall employment concentration are unchanged. Both of these patterns are at odds with the results that we obtain in Figure 2, which show higher revenues and employment within firms in the top decile of productivity in more concentrated industries.

Another alternative and more concerning reason for the increase in concentration would be the entrenchment of incumbent firms due to barriers to entry, particularly if these entrenched firms are relatively unproductive. De Loecker et al. (2020) 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 again 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.

Overall, even though we do not have a direct measure of changes in competitive pressure or consumer price sensitivity, our empirical evidence is in line with the predictions of the model presented in Section 2, and is inconsistent with other potential shocks. This supports 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.[23] The results show that higher concentration is associated with the best firms in a sector being more dominant and, in spite of their higher dominance, paying higher average wages.

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.[24] The top panel of Table 5 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 5 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.3 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.

Our results therefore 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 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.

[23] 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).

[24] 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.

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), 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	0.900	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 and the variance of firm productivity

	Dep var: Variance of Firm TFP			
	(1)	(2)	(3)	(4)
Concentration (HHI)	9.090	9.158	6.241	6.409
	(0.974)***	(0.987)***	(0.796)***	(0.812)***
Obs.	5659	5659	5583	5583
R^2	0.704	0.709	0.874	0.876
Concentration (top 10)	0.982	0.983	0.685	0.699
	(0.351)***	(0.357)***	(0.272)**	(0.278)**
Obs.	5505	5505	5428	5428
R^2	0.7	0.705	0.873	0.874
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 variance is divided by one million. ***p<0.01,**p<0.05, *p<0.1.

Table 4: Heterogeneous relationship between productivity and firm-level outcomes

	Sales	Wages	Employment
	(1)	(2)	(3)
<u>Panel A:</u> *HHI*			
log TFP	1.418	0.365	0.507
	(0.005)***	(0.001)***	(0.004)***
HHI x log TFP	8.505	0.831	9.276
	(0.219)***	(0.064)***	(0.187)***
Obs.	36015	36988	35885
R^2	0.839	0.943	0.66
<u>Panel B:</u> *Top 10*			
log TFP	1.311	0.355	0.392
	(0.005)***	(0.002)***	(0.004)***
Top 10 x log TFP	1.424	0.17	1.544
	(0.027)***	(0.008)***	(0.023)***
Obs.	34931	35888	34836
R^2	0.856	0.945	0.691
Industry x Country x Year FE	Yes	Yes	Yes

Note: Observations are at the country-industry-year-productivity decile level. Sales, Wages and Employment refer to the log mean of the corresponding variable within the country-industry-year-decile cell. 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.

Table 5: Concentration, average wages and sectoral employment

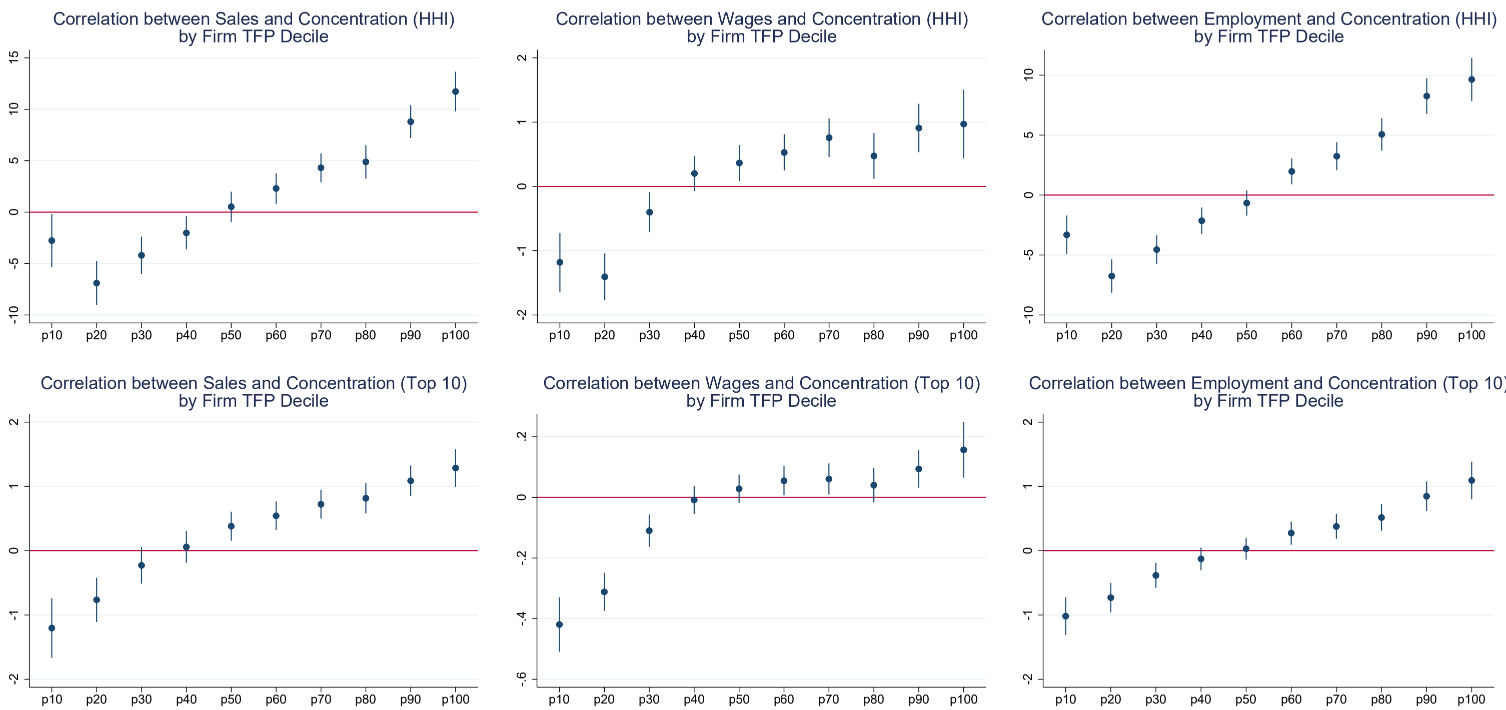
	Dep var: log average firm wages			
	(1)	(2)	(3)	(4)
Concentration (HHI)	0.353	0.303	0.259	0.286
	(0.115)***	(0.105)***	(0.132)**	(0.122)**
Obs.	4178	4178	4123	4123
R^2	0.960	0.969	0.965	0.971
Concentration (top 10)	0.112	0.122	0.103	0.113
	(0.027)***	(0.025)***	(0.029)***	(0.027)***
Obs.	4024	4024	3950	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.

Appendix for:

Rising Concentration and Wage Inequality

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Appendix A Detailed results from the Helpman et al. (2010) framework

A.1 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 $\frac{\overline{\theta}}{\theta_d} = \mu^{-\frac{1}{z}}$. Replacing the latter equation in (A.1) we obtain an expression for the share of revenues accruing to firms in the top μ% 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 μ% 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 $\frac{\delta\Gamma z}{\beta k}$.

A.2 Impacts of an Increase in Consumer Price Sensitivity

A.2.1 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.

A.2.2 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 μ% 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]

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

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

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

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

[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

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

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]

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

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

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

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 B 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 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:

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

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

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

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:

$$C_{h,\ell} = \mu^{1-\frac{\beta}{\Gamma z}(1-k_\ell/\delta)} \tag{B.2}$$

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.

Appendix C Alternative Frameworks

C.1 Models with upward sloping labor supply curves

In this Appendix we provide intuition for the impact of an increase in consumer price sensitivity within the class of models that feature an upward sloping labor supply curve to the firm.

Various versions of this class of models are discussed by Card et al. (2018), including a version in which, as in our model, firms face a downward sloping product demand curve (see Card et al., 2018, p. S50). The main underlying assumption in these models is that workers have heterogeneous idiosyncratic and unobservable valuations of different workplaces. In particular, in the framework developed by Card et al. (2018), worker utility is given by:

$$u_{ij} = \beta \ln w_j + a_j + \epsilon_{ij}$$

where w_j is the wage offered by firm j, a_j is a firm-specific amenity common to all workers, and ϵ_{ij} reflects idiosyncratic preferences of worker i for working at firm j.[4]

Assuming that workers draw ϵ_{ij} independently from a type I extreme value distribution, and assuming that the number of firms J is very large, one can obtain firm-specific labor supply functions which exhibit a positive relationship between firm-level employment and firm-level wages. Specifically, the firm-specific labor supply function is given by:

$$\ln L_j = \ln(\ell\lambda) + \beta \ln w_j + a_j \tag{C.1}$$

where ℓ is the total number of workers in the economy and λ is a constant common to all firms.

One can easily show that, as long as $0 < \beta \leq 1$,

$$\frac{\partial w_j}{\partial L_j} > 0 \text{ and } \frac{\partial^2 w_j}{\partial L_j^2} \geq 0$$

Hence, as long as there are decreasing or constant marginal returns to (log) wages in the utility function, we have that, in order to increase employment, firms have to offer wage increases, and especially so if their baseline employment level is higher.

In the context of our shock, since more productive firms are already larger at base-

[4] We have made the simplification of assuming that there is only one type of worker, and that the outside option of the worker is equal to zero.

line, and they experience an increase in (relative) demand which leads them to increase their (relative) employment, they must increase their wages (relatively) more than less productive firms. In the case where $\beta = 1$, their higher (relative) wage increase is simply because they expand employment by a larger (relative) amount. In the case where $\beta < 1$, this is compounded by the fact that in order to attract workers they must increase their wages more, even for the same change in employment.

C.2 Vintage Capital Model

In this section we derive concentration, wage inequality and outcomes in the top decile of the productivity distribution within the Moene and Wallerstein (1997) vintage capital framework. In this model, firm productivity is directly linked to firm age and wages are determined via either centralized or decentralized bargaining. Our goal is to examine the implications of increasing union's power, denoted α, within the decentralized bargaining regime.

Employment per firm is fixed to one, hence the model is not designed to generate differential employment growth across firms. Value-added of a firm built at time t is given by:

$$p(t) = p_0 e^{\Upsilon t}, \tag{C.2}$$

where $\Upsilon > 0$ captures technical progress and p_0 denotes the price. Since firms operate in a small open economy, the price is fixed and exogenous. Equation (C.2) highlights that newer firms are more productive and have higher output. The equation also highlights that, conditional on p_0 and Υ, the revenues of a firm born at t are fixed forever. Thus, union's power has no effect on revenues and any impact on concentration has to take place via the entry and exit of firms.

Aggregate output at time s is:

$$Q(s) = \int_{s-\Theta(s)}^{s} p(t)n(t)dt,$$

where $\Theta(s)$ denotes the age of the oldest firm at time s and $n(t)$ is the number of firms built at time t. Both objects are endogenously determined.

In steady state, the age of the oldest firm in operation and the number of entrants in each period are constant over time, i.e. $\Theta(s) = \Theta$ and $n(t) = n$.[5] In particular, we have that $n\Theta = N$ and $\Theta = \Theta(\alpha, \Upsilon)$, where N is the total number of firms and α, the worker share of value added, represents union's power. In the decentralized bargaining regime (our case of interest), N is fixed, implying that the number of firms by age category falls as the age of the oldest firm increases. Moreover, as shown in Moene and Wallerstein (1997), the age of the oldest firm increases with both union's power and technical progress, i.e. $\partial\Theta/\partial\alpha > 0$ and $\partial\Theta/\partial\Upsilon > 0$ in the decentralized regime.

Concentration Measure We measure concentration (C_r) as the share of revenues accruing to firms in the top μ% of the productivity distribution. Let Θ_μ be the age of the firm corresponding to the $(100 - \mu)$th percentile of the productivity distribution. Given that in steady state there is a uniform distribution of firms of all ages, $\Theta_\mu = \mu\Theta$.[6] Thus, $\partial\Theta_\mu/\partial\Theta > 0$ and the age of firms at the $(100-\mu)$th percentile of the productivity distribution increases as the age of the oldest firm goes up.

Using steady state conditions together with equation (C.2), aggregate output is:

$$Q(s) = \frac{Np_0}{\Upsilon} e^{\Upsilon s} \frac{\left(1 - e^{-\Upsilon\Theta}\right)}{\Theta} \tag{C.3}$$

and the amount of output concentrated in firms built between s and $s - \Theta_\mu$ is:

$$\int_{s-\Theta_\mu}^{s} p(t)n(t)dt = \frac{Np_0}{\Upsilon} e^{\Upsilon s} \frac{\left(1 - e^{-\Upsilon\mu\Theta}\right)}{\Theta}. \tag{C.4}$$

Since $\frac{\partial}{\partial\Theta}\left[\frac{1-e^{-\Upsilon\Theta}}{\Theta}\right] < \frac{\partial}{\partial\Theta}\left[\frac{1-e^{-\Upsilon\mu\Theta}}{\Theta}\right] < 0$, both aggregate output and the output concentrated in firms built between s and $s - \Theta_\mu$ fall as the age of the oldest firm increases.[7]

Combining equations (C.3) and (C.4) the share of revenues accruing to firms in the top μ% of the productivity distribution is given by:

$$C_r = \frac{1 - e^{-\Upsilon\mu\Theta}}{1 - e^{-\Upsilon\Theta}}. \tag{C.5}$$

[5]As discussed by Moene and Wallerstein (1997), the fact that $\Theta(s) = \Theta$ and $n(t) = n$ comes from the following three assumptions: (i) the relative price of output and capital is constant, (ii) technical change is labor-augmenting and (iii) the supply of labor is fixed.

[6]In fact, $\mu = \frac{\int_{s-\Theta_\mu}^{s} n(t)dt}{\int_{s-\Theta}^{s} n(t)dt} = \frac{n\int_{s-\Theta_\mu}^{s} dt}{n\int_{s-\Theta}^{s} dt} = \frac{\Theta_\mu}{\Theta}$.

[7]This is because $e^{-x}(1 + x) - 1 < 0 \ \forall x > 0$.

Hence, steady state concentration is constant at any given point s and entirely depends on technical progress γ and union's power (via Θ).

Finally, $\partial C_r/\partial\Theta$ is given by:

$$\frac{\partial C_r}{\partial \Theta} = \frac{\Upsilon\mu e^{-\Upsilon\mu\Theta}(1-e^{-\Upsilon\Theta}) - \Upsilon e^{-\Upsilon\Theta}(1-e^{-\Upsilon\Theta\mu})}{(1-e^{-\Upsilon\Theta})^2}. \tag{C.6}$$

For values of $\mu \in (0, 1/2)$, $\Upsilon > 0$ and $\Theta > 0$, we have that $\mu e^{-\Upsilon\mu\Theta} + (1-\mu)e^{-\Upsilon\mu\Theta-\Upsilon\Theta} - e^{-\Upsilon\Theta} > 0$. Therefore,

$$\partial C_r/\partial\Theta > 0 \quad \text{and} \quad \partial C_r/\partial\alpha > 0,$$

which implies that increasing union's power in the decentralized regime rises concentration in the top decile of the productivity distribution. This result comes from the fact that the fall in revenues is larger in the aggregate than at the top decile of the productivity distribution.

Wage Inequality In the decentralized bargaining regime, at time s the wage of a firm born at time t is:

$$w(s,t) = \begin{cases} \alpha p(t) & \text{for} \quad t \le s \le t + \overline{\Theta} \\ r(s) & \text{for} \quad t + \overline{\Theta} \le s \le t + \Theta, \end{cases}$$

where α is the relative worker share in value added and where $r(s)$ represents the market clearing wage. Hence, firms born between s and $s - \overline{\Theta}$ pay the bargained wage while older firms pay the market clearing wage. At age $\overline{\Theta}$, both the market clearing and decentralized wage are identical, which implies that $r(s) = \alpha p_0 e^{\gamma(s-\overline{\Theta})}$. In this model, $\overline{\Theta} = \Theta + \frac{\ln \alpha}{\Upsilon}$, where $\ln \alpha < 0$.

We look at firm wages at different percentiles of the distribution to examine how wage inequality responds to a change in α. Given the discontinuity in the wage profile, we consider two cases, one where both percentiles are given by the decentralized wage and another one where the bottom percentile corresponds to the market clearing wage.[8] In either case, wage inequality is increasing in union's bargaining power.

[8]The wage of firm at the $(100-\mu)$th percentile of the wage distribution is given by $w(s,t)_\mu = \alpha p_0 e^{\Upsilon(s-\mu\Theta)}$. Symmetrically, the wage of a firm at the bottom μth percentile of the wage distribution is given by either the decentralized wage $w(s,t)_{1-\mu} = \alpha p_0 e^{\Upsilon[s-(1-\mu)\Theta]}$ or the market clearing wage $r(s)_{1-\mu} = \alpha p_0 e^{\Upsilon(s-\overline{\Theta})}$.

In the first scenario where both percentile wages are given by the decentralized wage, the top-to-bottom wage ratio is given by:

$$\frac{w(s,t)_{\mu}}{w(s,t)_{1-\mu}} = e^{\Upsilon\Theta(1-2\mu)}. \tag{C.7}$$

Given that $1-2\mu > 0$, wage inequality unambiguously increases with the age of the oldest firm, and consequently, with union's power.

In the second scenario where the bottom percentile wage is given by the market clearing wage, the top-to-bottom wage ratio is given by:

$$\frac{w(s,t)_{\mu}}{r(s)_{1-\mu}} = e^{\Upsilon\Theta(1-\mu)+\ln\alpha}. \tag{C.8}$$

Here as well, wage inequality unambiguously increases with both Θ and α.

Average Revenue, Wage and Employment in the Top Decile The average revenue in the top μ% of the productivity distribution is:

$$\overline{r(t)}_{\mu} \quad = \quad \frac{\int_{s-\Theta_{\mu}}^{s} p(t)n(t)dt}{n_{\mu}}, \tag{C.9}$$

where $n_{\mu} = \mu N$ is the number of firms in the top μ% of the productivity distribution.[9] Using steady state conditions we obtain:

$$\overline{r(t)}_{\mu} = \frac{p_0 e^{\Upsilon s}}{\Upsilon\mu}\frac{\left(1-e^{-\Upsilon\mu\Theta}\right)}{\Theta}. \tag{C.10}$$

Therefore,

$$\partial\overline{r(t)}_{\mu}/\partial\Theta < 0 \quad \text{and} \quad \partial\overline{r(t)}_{\mu}/\partial\alpha < 0,$$

implying that the average revenue in the top decile of the productivity distribution falls as union's bargaining power increases. Since n_{μ} is constant, this effect is driven by the

[9]The number of firms in the top μ% of the productivity distribution is given by:

$$n_{\mu} = \int_{s-\Theta_{\mu}}^{s} n(t)dt = n\Theta_{\mu} = \mu N.$$

Hence, $\partial n_{\mu}/\partial\Theta = 0$ and the number of firms in the top μ% of the productivity distribution is fixed. However, since $\partial\Theta_{\mu}/\partial\Theta$, the composition (and hence the average age) of firms in that decile goes down.

fact that aggregate revenues in the top decile fall.

Similarly, the average wage in the top $\mu\%$ of the productivity distribution is given by:

$$\overline{w(t)}_\mu = \frac{p_0 N e^{\Upsilon s}}{\Upsilon \mu} \alpha \frac{\left(1 - e^{-\Upsilon \mu \Theta}\right)}{\Theta}. \tag{C.11}$$

Here, the effect of an increase in α is ambiguous. On the one hand, increasing α shifts the decentralized wage curve up. This has a direct positive effect on the average wage $\overline{w(t)}_\mu$. On the other hand, the age corresponding to the top μ productivity percentile shifts up, meaning that older firms (which pay relatively lower wages) will join the top percentile. Hence, by shifting Θ_μ, an increase in α has an indirect negative effect on $\overline{w(t)}_\mu$. The net effect on the average wage in the top $\mu\%$ of the productivity distribution then depends on the dominating force.

Finally, since employment in every firm is fixed at 1, the average employment in the top $\mu\%$ of the productivity distribution does not change with α.

Other Implications The model also allows us to examine the implications of changing bargaining regime. Given that there is no wage dispersion in the centralized regime, shifting to the decentralized bargaining regime increases wage inequality. Moene and Wallerstein (1997) show that, holding union's power constant, decentralizing bargaining increases the age of the oldest firm Θ. For this reason, decentralizing bargaining unambiguously increases C_r and redues $\overline{r(t)}_\mu$.

Table A.1: Concentration and wage inequality – Robustness checks

	Dep var: log 90-10 ratio of wage bill per worker			
	(1)	(2)	(3)	(4)
Panel A:				
Excl. France, the Netherlands and Italy:				
Concentration (HHI)	0.395	0.470	0.436	0.553
	(0.055)***	(0.05)***	(0.064)***	(0.058)***
Obs.	6744	6737	6728	6720
R^2	0.834	0.870	0.854	0.888
Concentration (top 10)	0.197	0.242	0.189	0.228
	(0.03)***	(0.027)***	(0.034)***	(0.03)***
Obs.	6105	6098	6086	6077
R^2	0.838	0.876	0.855	0.891
Panel B:				
Excl. countries with unconsolidated enterprises:				
Concentration (HHI)	0.065	0.065	0.395	0.411
	(0.084)	(0.071)	(0.099)***	(0.082)***
Obs.	5662	5655	5595	5588
R^2	0.560	0.700	0.647	0.772
Concentration (top 10)	0.287	0.196	0.287	0.191
	(0.043)***	(0.035)***	(0.045)***	(0.036)***
Obs.	5570	5563	5507	5500
R^2	0.600	0.746	0.673	0.799
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. Panel A excludes countries that may be affected by cross-country comparability problems related to the unit of observation (i.e. definition of a firm) according to CompNet (2018). Panel B excludes countries where the data is based on unconsolidated enterprises, namely Finland, Croatia, Lithuania and Romania. ***p<0.01,**p<0.05, *p<0.1.

Table A.2: Wage and Size effects

	log Wage	log Wage
	(1)	(2)
Log Employment	0.339	0.399
	(0.002)***	(0.003)***
HHI x log Employment	-1.354	
	(0.06)***	
Top 10 x log Employment		-.318
		(0.009)***
Obs.	35863	34814
R^2	0.897	0.901
Industry x Country x Year FE	Yes	Yes

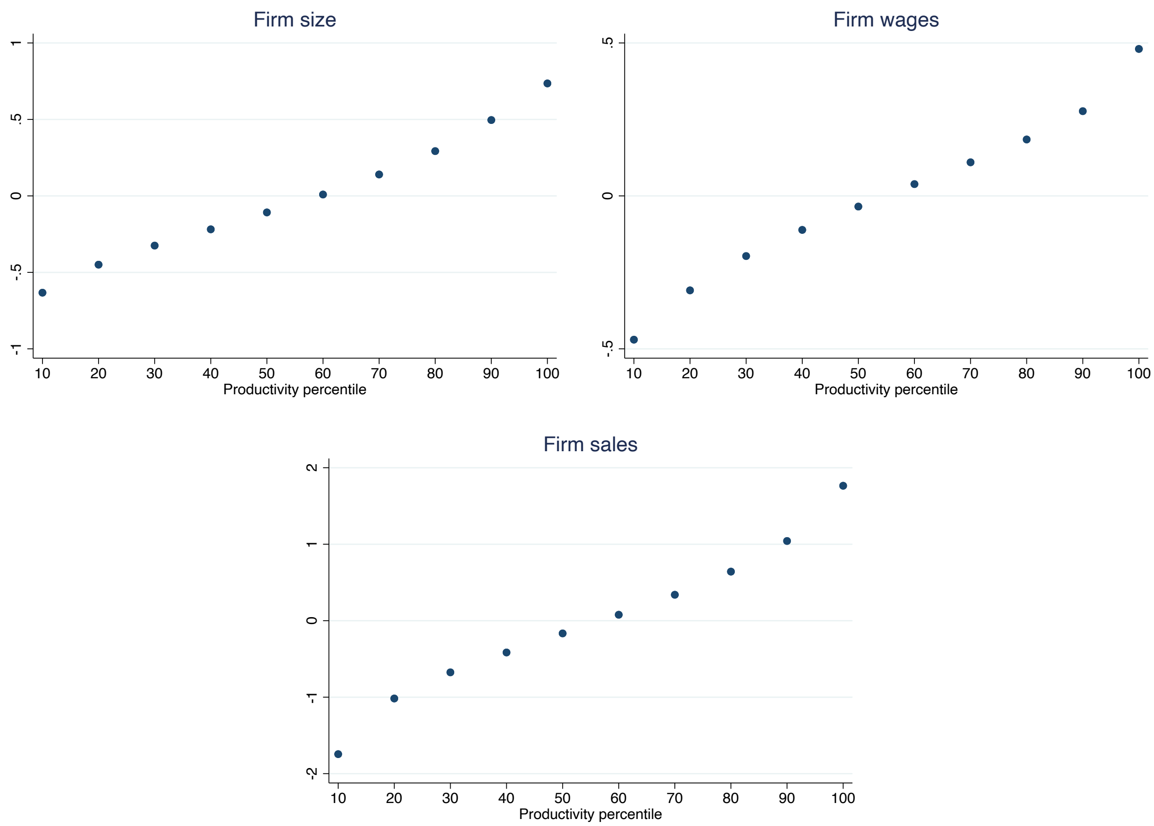
Note: Observations are at the country-industry-year-productivity decile level. Log Wage and Log Employment refer to the log mean of the corresponding variable within the country-industry-year-decile cell. All regressions are weighted using each industry's time-averaged share of total value added in each country. ***p<0.01,**p<0.05, *p<0.1.

Table A.3: 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

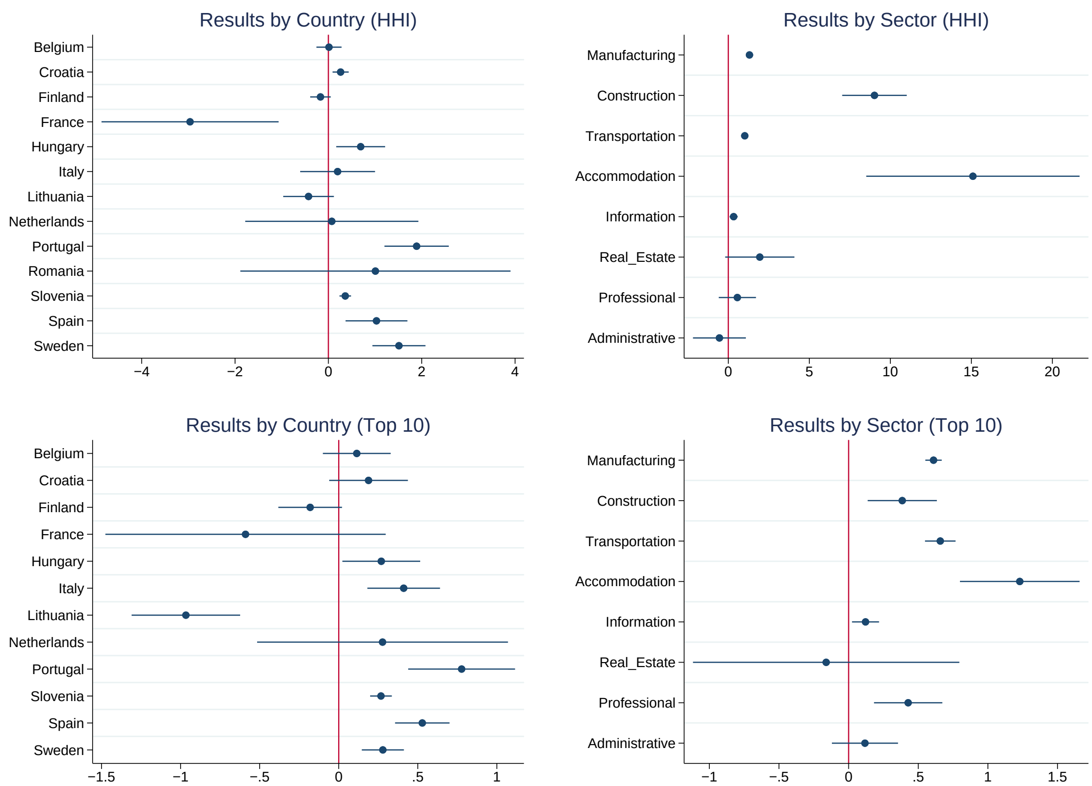
Note: Regressions are based on the restricted sample (industry-country-year cells for which information for firms at all deciles of the TFP distribution is available). Observations are at the country-industry-year level. All regressions are weighted using each industry's time-averaged share of total 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. For this sector, the estimated coefficient and 95% confidence interval (CI) are -61 ($CI = [-82, -40]$) and -2.7 ($CI = [-3.4, -1.9]$) when using HHI and Top 10 as concentration measures, respectively.