Market Power and Wage Inequality[*]

Shubhdeep Deb[†] Jan Eeckhout[‡] Aseem Patel[§] Lawrence Warren[¶]

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Abstract

We propose a theory of how market power affects wage inequality. We ask how goods and labor market power jointly determine the level of wages, the Skill Premium, and wage inequality. We then use detailed microdata from the US Census Bureau between 1997 and 2016 to estimate the parameters of labor supply, technology and the market structure. We find that a less competitive market structure lowers the average wage of high-skilled workers by 11.3%, and of low-skilled workers by 12.2%, contributes 8.1% to the rise in the Skill Premium and accounts for 54.8% of the increase in between-establishment wage variance.

Keywords. Market Power. Wage Inequality. Skill Premium. Technological Change. Market Structure. Endogenous Markups. Endogenous Markdowns.

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[†]UPF Barcelona, shubhdeep.deb@upf.edu

[‡]UPF Barcelona, jan.eeckhout@upf.edu (ICREA-BSE-CREI)

[§]University of Essex, aseem.patel@essex.ac.uk

[¶]US Census Bureau, lawrence.fujio.warren@census.gov

1 Introduction

Wage inequality in the United States has risen sharply since the 1980s. The skill premium, the ratio of the average wage of workers with college education or more over the average wage of workers with up to a high school education, has risen from 50% in 1980 to nearly 100% in recent years.[1] Furthermore, recent work has highlighted the significant role played by heterogeneous firms in shaping the evolution of wage inequality. Most of the rise in wage inequality is due to the increase in between-firm inequality.[2] Over the same period, there has been a corresponding rise in market power.[3]

In this paper, we set out to answer the question: How does market power affect wage inequality? The answer to this question has far-reaching welfare implications and is not merely an intellectual curiosity. If we attribute a substantial role to market power, then absent other frictions, wage inequality is inefficient – there is too much inequality – and there is a role for inequality-reducing policy that is Pareto improving and that raises welfare for all. Instead, if there was no market power, the amount of wage inequality would be Pareto efficient and there would only be a role for policy based on equity grounds and redistribution, without any scope for efficiency enhancing intervention.[4]

The starting point of our analysis is the canonical supply and demand framework of Katz and Murphy (1992), which we augment in two dimensions. First, we depart from the representative firm framework and explicitly account for the role of firm heterogeneity in technology. This setup permits us to study the evolution of wage inequality within *and* between establishments. Second, our economy incorporates oligopolistic output markets as well as oligopsonistic labor markets with heterogeneous markups and markdowns that are determined endogenously. In doing so we develop a tractable, quantitative general equilibrium model where a finite number of firms, each owning a set of heterogeneous establishments, compete in a market. This allows us to measure the macroeconomic im-

[1] See Acemoglu and Autor (2011).

[2] See Song, Price, Guvenen, Bloom, and von Wachter (2018)

[3] See Hall (2018), De Loecker et al. (2020) and Hershbein, Macaluso, and Yeh (2022).

[4] While market power is the only source of inefficiency in our framework, in reality there are other potential sources of inefficiency that increase wage inequality and reduce welfare, such as market incompleteness, uninsurable wage volatility, risk, and frictional reallocation of labor brought about by biased technological change.

plication of market power on the *level* of wages as well as wage *inequality*. To the best of our knowledge, this is the first paper to study the implications of firm heterogeneity, output market power *and* input market power on wage inequality.

Each of these two modifications is crucial for the results we get. First, we adjust the technology with the objective to build a model that can account for the heterogeneity of skill ratios across establishments that we see in the microdata. To that effect, we assume a non-Hicksian, Constant Elasticity of Subsitution (CES) production function where each establishment has skill-specific productivities. For example, some establishments are highly productive with low-skilled workers but not the high-skilled (cleaning and security companies, for example); other establishments are disproportionately productive with high-skilled workers (such as biotech firms); and yet other establishments are productive with workers of both skill types.

Second, those firms owning heterogeneous establishments exert market power by competing in both goods and labor markets with few competitors. Our setup builds on Atkeson and Burstein (2009) to model the goods market and on Berger et al. (2022) for the labor market, where the market structure crucially depends on a finite number of firms competing in a market. Our theoretical and computational contribution is to solve the structural model with *both* goods and labor market power. This gives rise to endogenous, establishment-specific markups and markdowns; therefore, market power in our setup depends not only on the a) household substitutability/preference parameters but also on b) the market structure as well as on c) the dispersion of the technology among competitors. Employment of high and low-skilled workers, together with their wages, is determined in general equilibrium.

Market power in the input and the output market has implications for both the wage levels and wage inequality. On the one hand, the presence of monopsony power induces firms to hire workers at wages lower than their marginal revenue product. On the other hand, even output market power has implications for wages. A firm with market power in the output market sets its price above its marginal cost. This higher price, in conjunction with a downward sloping product demand curve, implies that the equilibrium quantities demanded are lower, which in turn reduces the demand for labor. Therefore, through a general equilibrium effect, wages decline when economy-wide output market power increases.

We estimate each of these determinants of market power using rich establishment-level data from the U.S Census Bureau. We combine data from the US Longitudinal Business Database (LBD) and the Longitudinal Employer-Household Dynamics (LEHD) to construct a database that contains establishment-level employment, wages, and revenue between 1997 and 2016.

One of the main novelties of our approach is that we estimate a stochastic model of the market structure jointly with the technology. Since it is virtually impossible to measure directly how units of input are transformed into quantities of output, it is common practice to use the structure of a model in conjunction with observables in production such as input expenditures and revenues to estimate unobservable technology. Similarly, at a macroeconomic level, it is impossible to measure how firms compete, how many competitors there are, and who competes against whom. Therefore, we take a similar approach to the estimation of the market structure as we do to the estimation of technology. Our model shows a systematic relationship between market structure, revenue, and the wage bill. Both revenue and the wage bill are directly observed in our data. We exploit this structural link by relying on a stochastic model of competition to estimate the market structure.

Our approach of randomly assigning establishments within an industry to compete is a clear shortcut to the standard Industrial Organization (IO) approach that diligently measures and models the identity of the competitors, how they compete, what actions they take and which prices they set. Unfortunately, we cannot apply a similar approach to the macroeconomy with a vast variety of industries, markets and technologies. For example, the market for dry-cleaning services or coffee shops is a neighborhood block, whereas for a furniture retailer like IKEA it is the entire metropolitan area. Our stochastic approach to measuring the market structure is therefore more akin to measuring the economy-wide Solow residual via growth accounting than to the direct measurement of the number of cars produced per worker in an assembly plant.

The main results from our estimation are the following. First, our estimates of market structure highlight declining competition, as measured by the decline in the estimated number of firms competing in a market, which results in an increase in market power. The implied markup distribution shows a sharp increase in the upper tail and a rise in the sales-weighted markup from 1.682 to 2.160 between 1997 and 2016. Meanwhile, the markdowns for high-skill and low-skill workers is virtually unchanged, with a very modest increase from 1.420 to 1.435 and 1.419 to 1.437, respectively. Second, and consistent with the existing literature, we find strong evidence of Skill-Biased Technological Change (SBTC).

In our counterfactual exercise we find that a change in the market structure accounts for 8.1% of the increase in the aggregate skill premium and 54.8% of the increase in between-establishment inequality. Furthermore, we find that the decline in competition leads to a decline in average wages for high-skilled workers by 11.3% and for low-skilled workers by 12.2% relative to their 1997 values.[5] Consistent with Katz and Murphy (1992), we also find strong evidence of SBTC's contribution to aggregate skill premium and wage inequality even when firms are heterogeneous.

We interpret our exercise also as an attempt to explain the fall in the labor share. Explanations for the declining labor share proposed in the literature include: 1. the rise in firm product market power (De Loecker et al. (2018)); 2. the rise in labor market power (Berger et al. (2022)); 3. Automation and technological change (Acemoglu and Restrepo (2019), Karabarbounis and Neiman (2014));[6] 4. Increasing firm inequality with reallocation towards superstar firms (Autor et al. (2020)); 5. rent sharing and the decline in the share accruing to labor due to the demise of unions (Stansbury and Summers (2020)). Our model incorporates elements of each of these explanations with the exception of rent sharing as we do not explicitly model bargaining over surplus.[7] Our quantitative exercise produces estimates regarding the contribution to the labor share of product and labor market power (1. and 2.), the distribution of technologies (3.) and how they evolve over

[5] In related work, De Loecker et al. (2018) and Deb et al. (2022) find similar effects on the wage level from an increase in market power.

[6] Technological change includes the changing price of capital in the presence of capital-skill complementarity as in Krusell et al. (2000).

[7] In our model, declining union membership is likely to be captured either by our estimates of labor substitutability or by the technology parameters.

time. Since market power and the distribution of technologies determines the equilibrium firm size distribution and how it evolves over time, our analysis also includes the rise of firm inequality (4.).

Related literature. A growing literature highlights the role of firms and establishments in the rise of wage inequality.[8] Song et al. (2018) show the increase in the dispersion of earnings *between* firms accounts for two thirds of the increase in wage inequality in the US. Similarly, Barth et al. (2016) find that much of earnings inequality is due to increased dispersion of earnings among establishments. In our setup, in addition to the role of increasing technological differences between establishments in affecting wage inequality, we have skill-specific wages that vary by establishment due to monopsony power. As a result, while changes in technology will have profound implications for wage inequality, our setup also allows us to study how the extent of competition or market structure in the economy affects within and between-establishment inequality.[9]

Our model takes into account both output and input market power and is complementary to the recent literature that examines its role in explaining firm and/or worker-level rents (Kroft, Luo, Mogstad, and Setzler, 2020, Lamadon, Mogstad, and Setzler, 2022), as well as the role of technical change and imperfect competition in the labor market on inequality (Lindner, Muraközy, Reizer, and Schreiner, 2022). The main feature of our model is that markups and markdowns are variable and endogenous, as in Atkeson and Burstein (2009), Melitz and Ottaviano (2008), Edmond et al. (2015), Edmond, Midrigan, and Xu (2023), Amiti, Itskhoki, and Konings (2019), De Loecker et al. (2018) and Baqaee and Farhi (2019) for markups, and Berger, Herkenhoff, and Mongey (2022) and Azkarate-Askasua and Zerecero (2020) for markdowns. Our paper is also related to work on both input and output market power as in Azar and Vives (2021) and Tong and Ornaghi (2022). In our framework, markups and markdowns are heterogeneous and the distribution of

[8] See Card, Heining, and Kline (2013) for Germany, Barth, Bryson, Davis, and Freeman (2016) and Song et al. (2018) for the US, and Håkanson, Lindqvist, and Vlachos (2021) for Sweden. See also Cortes and Tschopp (2020) who argue that an increase in the price sensitivity of consumer demand can lead to an increase in between-firm wage inequality.

[9] Our method using firm-level technologies builds on Patel (2021), who relies on similar tools to analyze Job Polarization in France.

productivities has aggregate implications as in the literature on the granular origins.[10] A key innovation of our model is to solve for heterogeneous markups and markdowns jointly with strategic interaction while allowing for rich heterogeneity in the productivity distribution, in general equilibrium. Finally, our work is also related to estimation of markups and markdowns as in De Loecker et al. (2020), Hershbein et al. (2022), Traina (2022), Tortarolo and Zarate (2018), Mertens (2021).

One of the challenges of the framework proposed by Katz and Murphy (1992) – which assumes perfectly competitive labor and output markets, an aggregate production function with a representative firm, and technological change as the sole driver of wage inequality – is that it does not easily account for the decline or stagnation of real wages. In the last decades, wages for the lowest skilled workers have fallen. SBTC increases the demand for skills, and if SBTC means that there is technological *progress* – skilled workers do not only become more productive *relative* to unskilled workers, all workers become more productive in *absolute* terms – this must necessarily lead to an increase in real wages for all, though relatively more so for the high skilled. It is unlikely that technology has *regressed* and workers have become less productive, especially in the current decades of fast technological innovation. In a model with rising market power, the general equilibrium effect on wages naturally results in a decline in real wages, which is possible even if there is an increase in labor productivity.

In addition to our explanation based on the rise of market power, complementary work has focused on the role of technological change in a competitive setting to explain the fall in real wages relative to productivity and the rise of skill premium. Those explanations build not only on a change in Total Factor Productivity (TFP), but also posit changes in the output elasticities of labor, particularly of low-skilled labor, often due to changing capital prices or automation.[11] Specifically, Krusell, Ohanian, Ríos-Rull, and Violante (2000) show how increased capital intensity by firms directed to high-skill workers can raise the marginal product of high-skill workers relative to that of low-skill workers, lead-

[10] See Gabaix (2011), Grassi et al. (2017), Baqaee and Farhi (2019), Acemoglu et al. (2012), Carvalho and Tahbaz-Salehi (2019), Carvalho and Grassi (2019), and Burstein et al. (2019).

[11] See Krusell et al. (2000), Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), and Acemoglu and Restrepo (2022).

ing to an increase in the skill premium. In recent work, Acemoglu and Restrepo (2022) show how changes in automation and task displacement can account for changes in the US wage structure and explain the rise of skill premium.[12] We view these approaches with competitive markets as complementary to our explanation based on market power. Our main innovation relative to these papers is to highlight the additional channel of market power (both in the output and labor markets) that can simultaneously rationalize stagnating wages and an increase in wage inequality without technological regress. While we do not explicitly model interaction between capital and labor (as in Krusell et al. (2000)) or automation of tasks (as in Acemoglu and Restrepo (2022)), technological differences across producers and its change over time play a central role in the evolution of market power. In addition to these technological differences, we further explore the role of changes in market structure in shaping wage inequality. Therefore, market power in our setup embodies the underlying technological changes along with competitiveness of the economy in determining the evolution of the wage inequality.

2 Model Setup

Environment. We consider a static economy. There are two types of agents: a representative household and heterogeneous establishments. The representative household supplies labor in an oligopsonistic labor market and consumes goods produced in an oligopolistic goods market. Establishments are organized in a continuum of markets indexed by j; the measure of markets is J. Each market contains a finite number of establishments I_j indexed by $i \in \{1, \ldots, I_j\}$ that are owned by N firms indexed by $n \in \{1, \ldots, N_j\}$. The set of establishments i owned by each firm n in market j is denoted as: $\mathcal{I}_{nj} = \{i \mid i \text{ in firm } n, \text{ in market } j\}$.[13] Goods and jobs are differentiated between and within markets, for both output and input markets. An establishment hires two inputs:

[12] In Krusell, Ohanian, Ríos-Rull, and Violante (2000), low-skill wages may decline due to declining price of capital and strong capital-skill complementarity while Acemoglu and Restrepo (2022) show that real wages can stagnate in the presence of rapid automation.

[13] We think of this multi-establishment setup as a metaphor for different ways of modeling market power, including collusion, common ownership, firms with a changing product mix... The modeling choice to have multi-establishment firms is for practical reasons. This setup allows us, first, to change the market structure without changing preferences, and second, to randomly assign establishments under different market structures without changing their number.

high-skilled, H_{inj}, and low-skilled, L_{inj}, workers to produce final goods, Y_{inj}, where subscripts i, n, and j identify the establishment, firm, and market, respectively.

Preferences. The representative household chooses consumption and its supply of labor to both high and low-skill labor markets. The utility of consumption as in Atkeson and Burstein (2009) and the disutility of labor supply as in Berger et al. (2022) have a double nested Constant Elasticity of Substitution (CES) aggregator for quantities within and across markets. Goods i within a market are close substitutes with elasticity η; goods between markets j are relatively less substitutable with elasticity θ. These elasticities are ranked $\eta > \theta$, indicating that the household is more willing to substitute goods within a market (Pepsi vs. Coke) than across markets (soda vs. laundry detergent). Similarly in the labor market, the household has CES preferences over employment in the high-skill and low-skill labor markets.[14] The elasticities of substitution within the market are given by $\{\hat{\eta}_L, \hat{\eta}_H\}$ and between the markets are given by $\{\hat{\theta}_L, \hat{\theta}_H\}$, with $\hat{\eta}_L > \hat{\theta}_L$ and $\hat{\eta}_H > \hat{\theta}_H$, indicating that jobs within a market (barista at two coffee stores) are more substitutable than jobs in different markets (barista vs mechanic). The household maximizes its static utility:

$$\max_{C_{inj}, L_{inj}, H_{inj}} C - \frac{1}{\bar{\phi}_L^{\frac{1}{\phi_L}}} \frac{L^{\frac{\phi_L+1}{\phi_L}}}{\frac{\phi_L+1}{\phi_L}} - \frac{1}{\bar{\phi}_H^{\frac{1}{\phi_H}}} \frac{H^{\frac{\phi_H+1}{\phi_H}}}{\frac{\phi_H+1}{\phi_H}}, \quad \text{s.t. } PC = LW_L + HW_H + \Pi, \tag{1}$$

where C, H and L are the CES indices for aggregate consumption and employment of high and low-skilled workers, respectively. P, W_H and W_L are the CES aggregated indices for the prices of output and wages of skill groups H and L, respectively.[15] Observe that the aggregate and the market specific quantities are normalized by the size of the market to neutralize the love-for-variety effects in the model.

$$C = \left(\int_j J^{-\frac{1}{\theta}} C_j^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}}, \quad C_j = \left(\sum_i I^{-\frac{1}{\eta}} C_{inj}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{2}$$

$$S = \left(\int_j J^{\frac{1}{\hat{\theta}_S}} S_j^{\frac{\hat{\theta}_S+1}{\hat{\theta}_S}} dj \right)^{\frac{\hat{\theta}_S}{\hat{\theta}_S+1}}, \quad S_j = \left(\sum_i I^{\frac{1}{\hat{\eta}_S}} S_{inj}^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}} \right)^{\frac{\hat{\eta}_S}{\hat{\eta}_S+1}}, \quad S \in \{H, L\}. \tag{3}$$

Technology. The starting point is Katz and Murphy (1992), but with a heterogeneous

[14] In what follows, we use employment and jobs interchangeably.

[15] We denote aggregate high and low-skilled labor computed by summing over workers as: $\mathcal{S} = \int_j \sum_i S_{inj} dj, \ S \in \{H, L\}$.

technology that is specific to the establishment and skill type:

$$Y_{inj} = \left[(A_{Linj} L_{inj})^{\frac{\sigma-1}{\sigma}} + (A_{Hinj} H_{inj})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where A_{Hinj} and A_{Linj} are the factor-augmenting technology jointly distributed according to $G(A_{Hinj}, A_{Linj})$ and σ is the elasticity of substitution.

In our framework, the composition of workers across establishments varies for two reasons: 1) technology is factor-specific and 2) there is monopsony power in both labor markets.

Equilibrium. In the decentralized general equilibrium economy, a representative household maximizes utility by choosing consumption of the final good, the price of which is normalized to 1, and supplying high and low-skilled labor to each establishment in the economy. Firms maximize profits by choosing the amount of high and low-skilled labor to hire and supply the goods for the household. The household owns all the firms in the economy and claims all its profits. In equilibrium, the product market, the high-skilled and the low-skilled markets clear. The formal definition of equilibrium is as follows:

Definition 1. *An equilibrium in this economy satisfies:*

1. *Given prices, wages and aggregate profits, the quantities* $\{Y_{inj}\}$*,* $\{H_{inj}\}$ *and* $\{L_{inj}\}$ *maximize the household's utility given the budget constraint;*

2. *Given the inverse demand and inverse labor supply functions from household optimization, the quantities* $\{Y_{inj}\}$*,* $\{H_{inj}\}$*, and* $\{L_{inj}\}$ *maximize firm profits;*

3. *The product market and the high and low-skilled labor markets clear.*

Market structure. Each establishment with productivity (A_{Hinj}, A_{Linj}) belongs to a particular market j and there are I_j establishments in each market j. We define the market structure, N, as the total number of firms competing in a market. Since firms have market power in all three markets: the output market, low-skill and high-skill labor markets, we need to define what is the relevant set of firms competing in each market. A key assumption that makes our model tractable is that the set of firms competing in the goods market and the two labor markets are exactly the same.[16] Finally, we assume that each firm n in market j owns a set of establishments denoted by $\mathcal{I}_{nj}$ that are assigned to a firm stochastically. The key idea is that despite this random assignment of ownership of establishments to firms, the model preserves some key properties as we vary N. Since N measures the extent of competition in a market, a decline in N would translate to an increase in market power in both the output and input markets.

3 Solution

Solution of the household's problem. Given product prices, P_{inj}, and wages, W_{Linj} and W_{Hinj}, the household chooses consumption bundles, C_{inj}, and the labor supply, L_{inj} and H_{inj}, to maximize utility subject to the budget constraint. The household's optimal solution for consumption and labor supply is:

$$C_{inj} = \frac{1}{J}\frac{1}{I}P_{inj}^{-\eta}P_j^{\eta-\theta}P^{\theta}C, \tag{5}$$

$$S_{inj} = \frac{1}{J}\frac{1}{I}W_{Sinj}^{\hat{\eta}_S}W_{Sj}^{\hat{\theta}_S-\hat{\eta}_S}W_S^{-\hat{\theta}_S}S, \tag{6}$$

where $S \in \{H, L\}$. Note that these equilibrium demand and supply functions not only depend on the price (wage) set by the establishment i, but also on its relative magnitude to the market price (wage) index. The aggregate and market price indices are defined as follows:

$$P = \left(\int_j \frac{1}{J}P_j^{1-\theta}dj\right)^{\frac{1}{1-\theta}}, \quad P_j = \left(\sum_i \frac{1}{I}P_{inj}^{1-\eta}\right)^{\frac{1}{1-\eta}}, \tag{7}$$

$$W_S = \left(\int_j \frac{1}{J}W_{Sj}^{1+\hat{\theta}_S}dj\right)^{\frac{1}{1+\hat{\theta}_S}}, \quad W_{Sj} = \left(\sum_i \frac{1}{I}W_{Sinj}^{1+\hat{\eta}_S}\right)^{\frac{1}{1+\hat{\eta}_S}}. \tag{8}$$

From the solutions in equations (5) and (6) we can write the inverse demand function and

[16] We make this assumption to simplify the computation of the model's equilibrium, given the strategic interaction between firms in these markets. In reality, one can imagine a firm n having a different set of competitors in the output market and each of the two labor markets. Recent work by Gutiérrez (2022) makes progress in this direction by allowing distinct boundaries for product and labor markets.

inverse labor supply functions as

$$P_{inj} = \left(\frac{1}{J}\right)^{\frac{1}{\theta}} \left(\frac{1}{I}\right)^{\frac{1}{\eta}} Y_{inj}^{-\frac{1}{\eta}} Y_j^{\frac{1}{\eta}-\frac{1}{\theta}} Y^{\frac{1}{\theta}} P, \tag{9}$$

$$W_{Sinj} = \left(\frac{1}{J}\right)^{-\frac{1}{\theta_S}} \left(\frac{1}{I}\right)^{-\frac{1}{\eta_S}} S_{inj}^{\frac{1}{\eta_S}} S_j^{\frac{1}{\theta_S}-\frac{1}{\eta_S}} S^{-\frac{1}{\theta_S}} W_S. \tag{10}$$

Given that firms compete in Cournot competition in both product and input markets, optimal output prices and wages will also depend on other establishments in the market. In particular, note that P_{inj} and W_{Sinj} will depend on the output choices Y_{-inj} and input choices S_{-inj}, where the subscript $-inj$ denotes all other establishments in a market j except establishment i.

Solution of the firm's problem. Taking as given the inverse demand function in equation (9) and the inverse labor supply function for each type of worker in equation (10), firm n in market j chooses the optimal production plan for each of its establishments with the choice of the quantity of inputs H_{inj} and L_{inj} to maximize profits:

$$\Pi_{nj} = \max_{H_{inj},\, L_{inj}} \sum_{i \in \mathcal{I}_{nj}} \left(P_{inj} Y_{inj} - W_{Hinj} H_{inj} - W_{Linj} L_{inj} \right). \tag{11}$$

There are three important features of the firm's maximization problem. First, as in models of monopolistic and monopsonistic competition, firms internalize the effect of their own quantity choices on their prices and wages. Second, given the multi-establishment setup, firms internalize the ownership structure and take into account interactions between quantity choices across the different establishments owned by it and its effect on prices. Finally, given Cournot competition, firms also internalize the quantity choices of the other$-n$ firms in the market and strategically choose their quantities, such that our equilibrium is characterized by an intersection of best response functions.[17]

[17] Because there is a continuum of other markets $-j$, market j is infinitesimally small relative to the economy and there is no strategic interaction across markets.

The first order condition with respect to a given skill, S_{inj}, $S \in \{H, L\}$ is:

$$\underbrace{\left[P_{inj} + \frac{\partial P_{inj}}{\partial Y_{inj}} Y_{inj} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial P_{i'nj}}{\partial Y_{inj}} Y_{i'nj} \right) \right] \frac{\partial Y_{inj}}{\partial S_{inj}}}_{\text{Marginal Revenue Product of Labor } (MRPL_{Sinj})} = \underbrace{\left[W_{Sinj} + \frac{\partial W_{sinj}}{\partial S_{inj}} S_{inj} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial W_{Si'nj}}{\partial S_{inj}} S_{i'nj} \right) \right]}_{\text{Marginal Cost of Labor } (MC_{Sinj})}, \tag{12}$$

where $\mathcal{I}_{nj} \setminus i$ is the set of all other establishments owned by firm n, except establishment i. Factoring out P_{inj} and W_{Sinj}, we can express the above equation as

$$P_{inj} Y_{ij}^{\frac{1}{\sigma}} A_{Sinj}^{\frac{\sigma-1}{\sigma}} S_{inj}^{-\frac{1}{\sigma}} \left[1 + \varepsilon_{inj}^{P}\right] = W_{Sinj} \left[1 + \varepsilon_{inj}^{S}\right], \tag{13}$$

where ε_{inj}^{P} is the inverse demand elasticity and ε_{inj}^{S} denotes the inverse labor supply elasticity for skill S. In Appendix A.2, we derive each of these elasticities. We further show that the inverse demand elasticity is equal to:

$$\varepsilon_{inj}^{P} \equiv \frac{\partial P_{inj}}{\partial Y_{inj}} \frac{Y_{inj}}{P_{inj}} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial P_{i'nj}}{\partial Y_{inj}} \frac{Y_{i'nj}}{P_{inj}} \right) = - \left[\frac{1}{\theta} s_{nj} + \frac{1}{\eta} (1 - s_{nj}) \right], \tag{14}$$

where $s_{nj} = \sum_{i \in \mathcal{I}_{nj}} s_{inj}$ is the sales share of the firm in market j and $s_{inj} = \frac{P_{inj} Y_{inj}}{\sum_i P_{inj} Y_{inj}}$ is the sales share of establishment i in market j.[18] Similarly, in the labor markets, the inverse labor supply elasticity for each skill satisfies

$$\varepsilon_{inj}^{S} \equiv \frac{\partial W_{Sinj}}{\partial S_{inj}} \frac{S_{inj}}{W_{Sinj}} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial W_{Si'nj}}{\partial S_{inj}} \frac{S_{i'nj}}{W_{Sinj}} \right) = \left[\frac{1}{\hat{\theta}_S} e_{Snj} + \frac{1}{\hat{\eta}_S} (1 - e_{Snj}) \right], \tag{15}$$

where $e_{Snj} = \sum_{i \in \mathcal{I}_{nj}} e_{Sinj}$ is the wage bill share of firm n in market j and $e_{Sinj} = \frac{W_{Sinj} S_{inj}}{\sum_i W_{Sinj} S_{inj}}$ is the wage bill share of establishment i in market j for each input $S \in \{H, L\}$.

The firm's inverse demand elasticity $\varepsilon_{inj}^{p} < 0$ directly determines the markup μ_{inj} which is the ratio of the price over the marginal cost. Similarly, we define the markdown δ_{Sinj} for each skill as the ratio of its marginal revenue product to its wage, which is pinned down by the inverse labor supply elasticity ε_{inj}^{S}:

$$\mu_{inj} = \frac{1}{1 + \varepsilon_{inj}^{P}}, \quad \delta_{Sinj} = 1 + \varepsilon_{inj}^{S}. \tag{16}$$

Note that the markup (markdown) is the same for all the establishments owned by a given firm and is determined by the sum of sales shares (payroll share) of each establishment. The firm faces a non-zero residual inverse demand elasticity, ε_{inj}^{p}, and inverse labor

[18] Throughout, we use capital S to index high and low-skill and small s to refer to sales-share of a firm or an establishment.

supply elasticity, ε^S_{inj}, because it has market power. Under perfect competition, ε^p_{inj} and ε^S_{inj} are zero and the firm sets marginal product equal to the wage. Here, firms that have a large share s_{nj} of revenue in their market j face an inverse demand elasticity $\varepsilon^p_{inj} \approx -\frac{1}{\theta}$. The residual inverse demand is steep as the firm faces virtually no competition within the market and only from goods in other markets, which are not very substitutable. As a result, those firms have high market power. Instead, firms that have a small market share s_{nj} face a relatively flat residual inverse demand with inverse elasticity $\varepsilon^p_{inj} \approx -\frac{1}{\eta}$ (recall that $\eta > \theta$). Those firms face steep competition from firms that produce close substitutes. As a result, their market power is limited. Similar arguments apply in the labor market: firms with a large employment share e_{Snj} for skill S will have a steeper inverse labor supply function with $\varepsilon^S_{inj} = \frac{1}{\hat{\theta}_S}$. While for firms with low employment share, the inverse labor supply function will be flatter with an elasticity $\varepsilon^S_{inj} = \frac{1}{\hat{\eta}_S}$ as $\hat{\eta}_S > \hat{\theta}_S$.

The skill premium in our model is defined as the ratio of the high-skill wage over the low-skill wage. In order to assess how market power affects the skill premium, we take the log-ratio of the first order conditions and get the following equation:

$$\ln\left(\frac{W_{Hinj}}{W_{Linj}}\right) = \ln\left(\frac{\delta_{Linj}}{\delta_{Hinj}}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{A_{Hinj}}{A_{Linj}}\right) - \frac{1}{\sigma}\ln\left(\frac{H_{inj}}{L_{inj}}\right). \tag{17}$$

Equation (17) expresses the establishment-level skill premium, defined as the ratio of high-skill to low-skill wages paid at each establishment. Note that there is no direct role of ε^P_{inj}, and therefore of markups μ_{inj}, in affecting the establishment-specific skill premium. At face value, this equation looks very similar to the skill premium equation that Katz and Murphy (1992) estimate. In particular, with no labor market power, $\delta_{Linj} = \delta_{Hinj} = 1$, and no heterogeneity, it is exactly identical:

$$\ln\left(\frac{W_H}{W_L}\right) = \frac{\sigma-1}{\sigma}\ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\ln\left(\frac{H}{L}\right).$$

However, there are fundamental conceptual differences. First, we explicitly account for heterogeneity in the productivity of skills at each establishment in our framework. Second, equation (17) holds at the establishment level. Third, we allow for input markets to be imperfectly competitive. This implies that in addition to the race between the technology ratio, A_H/A_L, and the skill ratio, H/L, in determining the evolution of the skill premium as postulated by Tinbergen (1974) and later formalized by Katz and Murphy (1992), our model features an additional force that may influence the evolution of the skill premium. The term δ_L/δ_H measures the markdown for low-skill workers relative to that of high-skill workers. The joint implication of these differences is that we have an entire distribution of establishment-specific skill premia in our model, with the additional force of differential monopsony power affecting the evolution of the skill premium.

Finally, in order to calculate the aggregate skill premium, we define the input share-weighted average wages for each skill as $\mathcal{W}_S = \int_j \sum_i S_{inj} W_{Sinj} dj / \mathcal{S}$, where $\mathcal{S} = \int_j \sum_i S_{inj} dj$ denotes the aggregate workers of a given skill. Hence, we define the aggregate skill premium as follows:

$$\kappa = \frac{\mathcal{W}_H}{\mathcal{W}_L} = \frac{\mathcal{L}}{\mathcal{H}} \times \frac{\int_j \sum_i H_{inj} W_{Hinj} dj}{\int_j \sum_i L_{inj} W_{Linj} dj}. \tag{18}$$

The fundamental insight here is that wages $\mathcal{W}_H$ and $\mathcal{W}_L$ adjust in equilibrium to changes in the market structure as well as technology.

Computing the equilibrium. This large economy with heterogeneous establishments, market power and non-Hicks-neutral technology does not have an analytical solution. We therefore solve the economy computationally using the algorithm specified in Appendix A.3. Because in our model the market definitions for labor and product markets coincide, we can solve a system of $I \times 2$ equations, separately for each of the J markets. The algorithm fully specifies the equilibrium allocation of establishment-level quantities, H_{inj}, L_{inj} and Y_{inj}, and establishment-level prices W_{Hinj}, W_{Linj} and P_{inj}, and aggregates them to market and economy-wide prices and quantities. In addition, it allows us to compute establishment-level markups μ_{inj} and markdowns δ_{Linj} and δ_{Hinj}, as well as aggregate them to economy-wide measures of market power.

Model summary. Table 1 summarizes the model variables in 4 categories. Category I lists the exogenous parameters of the model and categories II, III and IV specify the endogenous establishment/firm-level, market-level and economy-wide variables, respectively.

Comparative statics. We compute the economy for a series of comparative statics exercises where we change market structure N and evaluate the impact this has on the key

Table 1: Summary of model variables

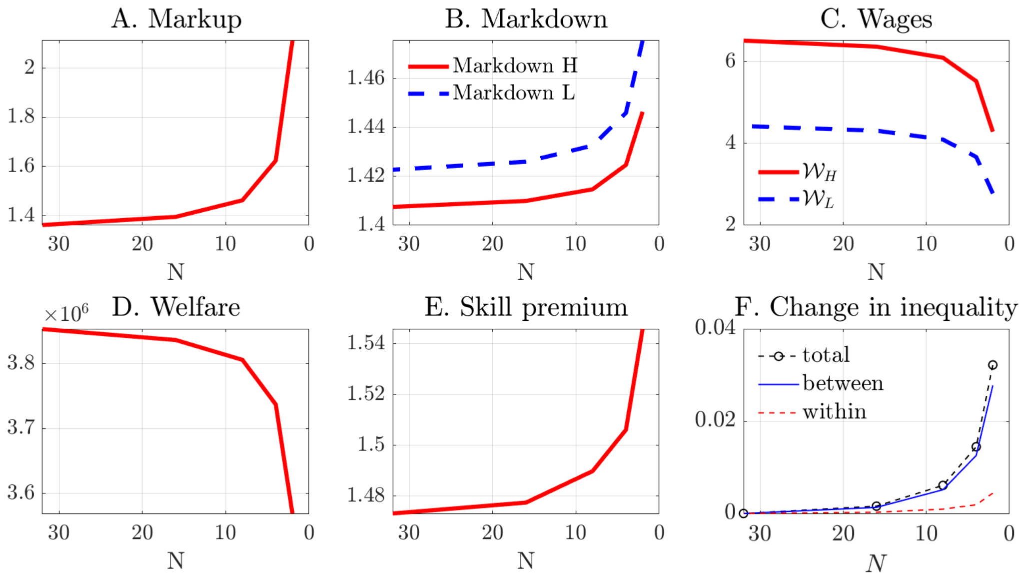
I: Primitives			
η	Output market: within-market substitutability	$\hat{\eta}_S$	Input market: within-market substitutability
θ	Output market: between-market substitutability	$\hat{\theta}_S$	Input market: between-market substitutability
N	Number of firms competing in each market	ϕ_S	Skill S aggregate labor supply elasticity
J	Total number of markets	$\bar{\phi}_S$	Skill S labor supply shifter
I	Total number of establishments in each market	A_{Sinj}	Skill S productivity at establishment i
II: Endogenous variables - Establishment and Firm			
S_{inj}	Employment of skill S at establishment i	Y_{inj}	Output in establishment i
W_{Sinj}	Wage of skill S at establishment i	P_{inj}	Output price in establishment i
e_{Sinj}	Wage bill share of skill S in establishment i	s_{inj}	Sales share of establishment i
e_{Snj}	Wage bill share of skill S in firm n	s_{nj}	Sales share of firm n
δ_{Sinj}	Markdown of skill S in establishment i	μ_{inj}	Markup of establishment i
III: Endogenous variables - Market			
S_j	CES employment skill S in market j	Y_j	CES output in market j
W_{Sj}	CES wages skill S in market j	P_j	CES price in market j
IV: Endogenous variables - Aggregate			
S	CES employment skill S	Y	CES output
W_S	CES wages skill S	P	CES price
δ_S	Skill S specific aggregate markdown	μ	Aggregate markup
$\mathcal{S}$	Total number of skill S workers	Π	Aggregate profit
$\mathcal{W}_S$	Average skill-specific worker-weighted wages		

equilibrium features of the economy.[19]

In Figure 1, we report 6 panels: in panels A and B, we show that as the number of competitors declines, the average sales-weighted markup (aggregate markup) and the average sales-weighted markdowns (aggregate markdowns) increase. As the number of competitors declines, the sales and the wage bill shares of the establishments in the market approach 1 and markups and markdowns approach their respective upper bounds. Panel C shows the average (worker-weighted) wages of high and low-skilled workers, $\mathcal{W}_H$ and $\mathcal{W}_L$, respectively. The decline in wages is a result of an increase in both markups and markdowns. For both skills, when markdowns increase, establishment-specific wages

[19] In the comparative statics exercise, we assume $I_j = I = 32\ \forall j$ and $N_j = N\ \forall j$. In addition, we consider $N \in \{2, 4, 8, 16, 32\}$ such that each firm owns the same number of establishments given by I/N.

Figure 1: Comparative Statics



Notes: These comparative statics are produced using parameter values outlined in Table 2 and Table 3, and with $\log(A_{Sinj}) \sim \mathcal{N}(\mu_S, \sigma_S^2)$ with $\mu_H = 1.2, \mu_L = 1$, $\sigma_H = 1$, and $\sigma_L = 0.8$. We show the effect of a declining N on aggregate markup and aggregate skill-specific markdowns (panels A and B), aggregate skill specific wages (panel C), welfare (panel D), aggregate skill premium (panel E) and change in within and between-establishment inequality (panel F).

decline as establishments charge a larger markdown over wages relative to the marginal revenue product of labor. Meanwhile, an increase in markups leads to a decline in wages through a reduction in aggregate demand for labor as in De Loecker et al. (2018) and Deb et al. (2022), which is a general equilibrium effect. The combined effect of an increase in markups and markdowns in our model is that the average wages of both skills decline. Panel D shows the decline in welfare as an increase in market power reduces the utility from aggregate consumption more than the increase in utility from supplying lower labor in response to the decline in wages.

In panel E, we see that a reduction in the number of competitors N leads to a rise in the aggregate skill premium κ. Similar to the canonical model, an increase in the technology ratio, A_{Hinj}/A_{Linj}, increases the skill premium and an increase in the skill ratio, H_{inj}/L_{inj}, reduces it. However, in addition to these two competing forces our model also allows for market power, such that an increase in the relative monopsony power, $\delta_{Linj}/\delta_{Hinj}$, also increases the skill premium. This increase in the relative monopsony power of firms may come from one of three sources: 1. changes in the technology $G(A_{Hinj}, A_{Linj})$; 2. changes in the substitutability parameters $(\hat{\eta}_S, \hat{\theta}_S)$; 3. changes in market structure N. Furthermore, how a change in N leads to a change in the skill premium will depend on its interaction with the underlying substitutability parameters and productivity distribution.

We first isolate the interaction between N and substitutability parameters in determining the skill premium. We consider a setup with homogeneous establishments where $A_{Hinj} = A_H$ and $A_{Linj} = A_L$ for all establishments while varying only N. Given this, in Proposition 1, we derive a closed form expression for the aggregate skill premium which is a function of productivity ratio A_H/A_L, skill specific labor supply substitutability parameters $(\hat{\eta}_S, \hat{\theta}_S)$, wage bill shares and constants $\{\sigma, \bar{\phi}_S, \phi\}$. Specifically, we use the fact that in the homogeneous establishment case the wage bill shares for each skill can be expressed solely as a function of the number of competitors, given by $1/N$.

Proposition 1. *In homogeneous establishments case, the skill premium is given by:*

$$\kappa = \left[\left(\frac{A_H}{A_L} \right)^{\frac{\sigma-1}{\sigma+\phi}} \times \left(\frac{\bar{\phi}_L}{\bar{\phi}_H} \right)^{\frac{1}{\sigma+\phi}} \right] \times \left[\frac{1 + \frac{1}{\hat{\theta}_L} \frac{1}{N} + \frac{1}{\hat{\eta}_L}(1 - \frac{1}{N})}{1 + \frac{1}{\hat{\theta}_H} \frac{1}{N} + \frac{1}{\hat{\eta}_H}(1 - \frac{1}{N})} \right]^{\frac{\sigma}{\sigma+\phi}}. \tag{19}$$

Then the skill premium elasticity is decreasing, i.e., $\frac{\partial \kappa}{\partial N} / \left(\frac{\kappa}{N} \right) < 0$, *iff*

$$\left(1 + \frac{1}{\hat{\eta}_L}\right) \left(\frac{1}{\hat{\theta}_H} - \frac{1}{\hat{\eta}_H} \right) < \left(1 + \frac{1}{\hat{\eta}_H}\right) \left(\frac{1}{\hat{\theta}_L} - \frac{1}{\hat{\eta}_L} \right).$$

Proof. In Appendix A.5. □

Proposition 1 illustrates, that for identical establishments, a decrease in N results in an increase in the skill premium if $\left(1 + \frac{1}{\hat{\eta}_L}\right) \left(\frac{1}{\hat{\theta}_H} - \frac{1}{\hat{\eta}_H} \right) < \left(1 + \frac{1}{\hat{\eta}_H}\right) \left(\frac{1}{\hat{\theta}_L} - \frac{1}{\hat{\eta}_L} \right)$. The intuition is that as the number of competitors declines, firms increase the markdown for both skills as they constitute a larger share of the labor market for both skills. However, as N declines and firms can exert relatively higher monopsony power over low-skilled workers compared to high-skilled workers, this leads to an increase in the skill premium.

Proposition 1 is holds for homogeneous establishments. With heterogeneous establishments, in addition to the substitutability parameters $\{\hat{\eta}_S, \hat{\theta}_S\}$ the underlying distribution of A_H and A_L within each market also plays an important role in determining the direction of the change in skill premium as N declines. In markets where A_H is much more unequally distributed relative to A_L, a decline in the number of competitors leads to a more than proportional increase in low-skill markdowns δ_L relative to high-skill markdowns δ_H, which results in an increase in skill premium. For instance, consider a market with two establishments, where establishment 1 is more productive in A_H compared to establishment 2, $A_{H1} > A_{H2}$, while both establishments are equally productive in A_L. This implies that establishment 1 hires most of the high-skill workers in the market, resulting in employment shares in the high-skill labor market to be more dispersed than in the low-skill labor market. As a result, establishment 1 has a markdown for high-skill labor close to the upper bound, $\delta_{H1} \approx \frac{\hat{\theta}_H+1}{\hat{\theta}_H}$ while establishment 2 has high-skill markdowns close to the lower bound, $\delta_{H2} \approx \frac{\hat{\eta}_H+1}{\hat{\eta}_H}$.

Now consider a change in the market structure where a single firm owns both these establishments, with an employment share for both skill levels of 1. Since they are owned by a single firm, both establishments have identical markdowns at their respective upper bounds, $\delta_H = \frac{\hat{\theta}_H+1}{\hat{\theta}_H}$ and $\delta_L = \frac{\hat{\theta}_L+1}{\hat{\theta}_L}$.[20] As a result, δ_H increases only for establishment 2 while δ_L increases for both establishments. Consequently, the low-skill wage decreases relatively more than high skill wage, making the skill premium increase. Since we have reason to believe that there is substantial heterogeneity across establishments in our data, we expect both the underlying technology and the substitutability parameters to influence the skill premium as N declines.

Finally, panel F in Figure 1 shows that total log wage inequality, as well as within and between-establishment inequality increases as N declines. The mechanism behind the increase in within-establishment inequality is similar to the intuition for an increasing skill premium since the model has only two skill types at each establishment. For between-establishment inequality, decreasing N increases markups and markdowns for all establishments, but smaller establishments see the largest increases. While this leads to a decline in the aggregate wage in the economy, small establishments reduce their wages more relative to the reduction in the aggregate wage, resulting in a more dispersed log

[20] Overall, the magnitude of increases in δ_L and δ_H and therefore how δ_L/δ_H changes at each establishment depends on the upper bounds of markdowns for each skill.

wage distribution across establishments. While there is also some reallocation of workers from small to large establishments, the large leftward shift at the bottom of the establishment wage distribution dominates such that the between-establishment component of wage inequality increases, as N declines.

4 Quantitative Analysis

In what follows, we proceed with the quantitative analysis, estimating the model parameters and analyzing the determinants of market power. We provide an overview of our data and outline our strategy for the estimation of the skill-specific substitutability parameters in the labor market, the technology distributions, and the market structure. Thereafter, we assess their role in the evolution of wage inequality.

Data. The data we use to estimate our model combines establishment-level information from the Longitudinal Business Database (LBD) with characteristics of the workers at these establishments from Longitudinal Employer-Household Dynamics (LEHD). For our exercise, we use data from LEHD for 20 states to derive measures of the composition of skill types and wages within each firm. We split workers into categories of high education (which we will refer to as "high-skill") as those who attained some college education or above and low education ("low-skill") as those who attain a high school education or less. We take the firm-level ratio of high to low-skill employment and payroll per worker from LEHD and use these measures to split LBD employment and payroll into the same skill-specific ratios, but at the establishment level.[21] This breaks up total payroll and employment in LBD into a measure of skill-specific average wages and employment, along with measures of total revenue, industry classification (NAICS), ownership structure, and geography (MSA) from 1997-2016.[22] For full details about our sample and data, see Appendix B.

[21] We use the education composition of workers via LEHD as a supplement to the LBD establishment-level data. We do not use the worker-level data to measure the response of worker wages to changes in market structure directly, such as in Lamadon et al. (2022).

[22] In what follows, we refer to 2 digit NAICS code (NAICS 2) as a sector, 6 digit NAICS industry code (NAICS 6) as an industry, and the collection of 32 establishments randomly assigned within each NAICS 6 industry as a market. We deflate all values to 2002 dollars.

Market definition. In order to estimate the model, we need to define a market. In the Industrial Organizations literature, this is the key ingredient. Given our interest in the macroeconomics of market power, it is impossible to observe the market structure for each individual firm in different industries and geographies.[23] Since detailed information is unavailable to precisely define a market, we instead rely on the structure of our model and a stochastic notion of market definition. Our market definition is stochastic in that we randomly assign establishments within an industry to define a market. Subsequently, we randomly assign establishments within a market to N competing firms, which we estimate using our model and the data. For instance, even if an industry contains a large number of establishments, if N is small, the extent of the competition is weak. While this approach to defining a market is much less detailed than the traditional approach, it does allow us to make progress in studying market power in the macroeconomy. The main idea is that we remain agnostic about which firms compete and that is something we cannot observe, just like Total Factor Productivity (TFP). But if we observe revenue and costs, we derive the number of competitors consistent with the model that gives rise to those revenues and costs, and hence profits and markups. Just like the Solow residual, we derive the number of competitors as an outcome.

With this random assignment, if the number of firms N competing within a market is smaller, the model predicted markups and markdowns will be higher, firm revenue will be higher, and wages will be lower. The objective is to use the observed revenue and wages from the data to estimate N. As mentioned above, we also make the assumption that the market structure is the same for both the input and output markets.

Quantifying the model. We quantify our model in two steps. First, we estimate the parameters that determine the labor supply elasticity for high and low-skilled workers, namely, $\hat{\eta}_S$ and $\hat{\theta}_S, S \in \{H, L\}$, using the microdata and an instrumental variable strategy. These parameters, along with the ones calibrated externally in Table 2, are held constant for both 1997 and 2016. Second, we *jointly* estimate the non-parametric distribution of technology $G(A_{Hinj}, A_{Linj})$ separately for 1997 and 2016 and our measure of competition

[23] There is too much variation in the market structure across industries and geography and there is mechanical variation over time. For a discussion of the problems with using NAICS codes and geographical areas to pin down the market definition, see Eeckhout (2020).

Table 2: Externally chosen or calibrated parameters

Variable	Value	Description	Source
θ	1.20	Between-market elasticity	De Loecker et al. (2018)
η	5.75	Within-market elasticity	De Loecker et al. (2018)
σ	2.94	Elasticity of substitution	Acemoglu and Autor (2011)
ϕ_H	0.25	High-skilled labor supply elasticity	Chetty et al. (2011)
ϕ_L	0.25	Low-skilled labor supply elasticity	Chetty et al. (2011)
I	32	Total number of establishments	Externally set

in the model, N, in 2016. To estimate the unobservable establishment-level technologies, we leverage the structure of our model which links them to high and low-skill employment – observed directly in the microdata – through the first-order conditions (FOCs). We estimate N such that it matches the moments of the sales-weighted revenue over wage bill distribution between the data and the model using the method of moments.

Step 1. Estimating labor market elasticities. In the first step we estimate $(\hat{\eta}_S, \hat{\theta}_S)$ separately for each of the two skills. The inverse labor supply elasticity $\varepsilon^S_{inj} = \left(1/\hat{\theta}_S\right) e_{Snj} + \left(1/\hat{\eta}_S\right)\left(1 - e_{Snj}\right)$ is a function of a) the within $(\hat{\eta}_S)$ and the between-market $(\hat{\theta}_S)$ labor substitutability parameters and b) the skill-specific establishment-level employment (S_{inj}) in each market j, where $e_{Snj} = \sum_{i \in \mathcal{I}_{nj}} e_{Sinj} = \sum_{i \in \mathcal{I}_{nj}} S_{inj}^{\frac{1+\hat{\eta}_S}{\hat{\eta}_S}} / \sum_{i \in j} S_{inj}^{\frac{1+\hat{\eta}_S}{\hat{\eta}_S}}$. While establishment-level employment is directly observed in the microdata, we need to estimate the two labor substitutability parameters to calculate the elasticity.

We estimate these parameters by relying on the inverse labor supply equation of our model in equation (10). In order to take the model to the data, we add to it an error term and a time subscript, t.[24] Re-writing the expression by taking logs on both sides, we get

$$\ln W^*_{Sinjt} = k_{jt} \; + \; \left(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}\right) \ln S_{jt} \; + \; \frac{1}{\hat{\eta}_S} \ln S_{injt} \; + \; \varepsilon_{Sinjt}, \tag{20}$$

where $\ln W^*_{Sinjt} = \ln W_{Sinjt} + \varepsilon_{Sinjt}$ and $k_{jt} = \ln J_t^{\frac{1}{\hat{\theta}_S}} I_{jt}^{\frac{1}{\hat{\eta}_S}} S_t^{-\frac{1}{\hat{\theta}_S}} W_t$.[25]

The error term, ε_{Sinjt}, in equation (20) has the potential to capture misspecification that may be attributed to non-pecuniary factors such as distance to work or interactions

[24] We add the time subscripts since we will exploit time-series variation in wages and employment at the establishment level and taxes at the state level in our estimation. More details below.

[25] In our estimation exercise, we let the total number of establishments in a market to change, as observed in the data.

with co-workers and supervisors, as argued by Card et al. (2018), or to the impact of labor market institutions that are not accounted for in our model such as the minimum wage.[26] While we remain agnostic about the true source of this misspecification, we account for the fact that the error term is potentially correlated with employment. To address the bias stemming from this correlation, we devise an instrumental variable strategy to estimate our parameters of interest. We build on the recent work of Berger, Herkenhoff, and Mongey (2022) and Giroud and Rauh (2019) and exploit state level corporate taxes as a source of exogenous variation shifting the demand curve in our model. We provide further details about our instrument below. Closest to our approach is the recent work of Felix (2021), who also relies on a similar strategy to estimate the labor substitutability parameters using the labor supply equation directly.[27]

We make the following set of assumptions to identify our parameters of interest:

Assumption 1. $\varepsilon_{Sinjt} = \alpha_{Sinj} + \epsilon_{Sinjt}$

Assumption 2. $\varepsilon_{Sinjt} \perp\!\!\!\perp \tau_{X(i)t}$

Assumption 3. $\nu_{jt} \perp\!\!\!\perp \bar{\tau}_{jt}$*, where* $k_{jt} = k_j + k_t + \nu_{jt}$ *and* $\bar{\tau}_{jt} = \frac{1}{I_j}\sum_{i\in j}\tau_{X(i)t}$

$\tau_{X(i)t}$ denotes the corporate tax faced by an establishment i in state X at time t and $\bar{\tau}_{jt}$ denotes the average tax rate of a given market j at time t.[28] Assumption 1 states that the error term is composed of an establishment fixed effect, α_{Sinj}, and an establishment and time-specific error term, ϵ_{Sinjt}. We rely on this assumption to exploit within-establishment variation over time in estimating $\hat{\eta}_S$. Assumptions 2 and 3 are our key identifying assumptions. Assumption 2 is required for the exogeneity of our tax instrument, $\tau_{X(i)t}$, that it is uncorrelated with the error term. Finally, Assumption 3 implies that the average

[26] In a slight abuse of notation, ε_{Sinj} denotes measurement error in log wages for skill S, while ε^S_{inj} denotes the inverse labor supply elasticity for skill S.

[27] In Appendix C, we show identification of the labor substitutability parameters in the simpler case without endogeneity. We also provide results from Monte Carlo experiments that demonstrates the ability of our estimator to parse out the true structural parameters in simulations.

[28] We use corporate taxes to estimate the labor substitutability parameters in our model, relying on insights from Giroud and Rauh (2019). However, we remain agnostic on the channels through which corporate taxes affect firm level labor demand. Interested readers can refer to Berger et al. (2022) Section 2 (Estimation), who model financing of capital through debt as one potential mechanism of how taxes may affect labor demand.

market-level taxes are independent of ν_{jt}. Assumptions 2 and 3 extend the exogeneity of our instrument to the estimation of the across-market substitutability parameter $\hat{\theta}_S$.

Under these assumptions, we can identify $\hat{\eta}_S$ and $\hat{\theta}_S$ using the following moments in the data:[29]

$$\hat{\eta}_S = \frac{\mathbb{E}(\widetilde{S}_{injt} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{W^*}_{Sinjt} \times \tau_{X(i)t})}, \quad \hat{\theta}_S = \left[\frac{\mathbb{E}(\{\overline{\Omega}_{Sjt} - (k_j + k_t)\} \times \bar{\tau}_{jt})}{\mathbb{E}(\ln S_{jt} \times \bar{\tau}_{jt})} + \frac{\mathbb{E}(\widetilde{W^*}_{Sinj} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{S}_{inj} \times \tau_{X(i)t})} \right]^{-1}, \tag{21}$$

where we denote

$$\widetilde{S}_{injt} = \ln S_{injt} - \frac{1}{I_j} \sum_{i \in j} \ln S_{injt}, \qquad \widetilde{W^*}_{Sinjt} = \ln W^*_{Sinjt} - \frac{1}{I_j} \sum_{i \in j} \ln W^*_{Sinjt},$$

$$\Omega_{Sinjt} = \ln W^*_{Sinjt} - \frac{1}{\hat{\eta}_S} \ln S_{injt}, \qquad \overline{\Omega}_{Sjt} = \frac{1}{I_j} \sum_{i \in j} \Omega_{Sinjt}.$$

Estimation. We use Two-Stage Least Squares (2SLS) on the following equation to get the estimate of $\hat{\eta}_S$ and $\hat{\theta}_S$.

$$\ln W^*_{Sinjt} = k_{jt} \; + \; \gamma_S \ln S_{jt} \; + \; \beta_S \ln S_{injt} \; + \; \underbrace{\alpha_{Sinj} \; + \; \epsilon_{Sinjt}}_{\varepsilon_{Sinjt}}, \tag{22}$$

where we define $\beta_S = \frac{1}{\hat{\eta}_S}$ and $\gamma_S = \left(\frac{1}{\hat{\theta}_S} - \beta_S\right)$. From equation (22), we notice that while we observe wages and employment in the data, we do not directly observe the establishment fixed effect α_{Sinj} and market-year specific constants, k_{jt} and S_{jt}, which are both functions of our structural parameter $\hat{\eta}_S$ and $\hat{\theta}_S$. We need to control for these unobserved variables to avoid omitted variable bias stemming from them. We control for α_{Sinj} by including establishment fixed-effects in our estimation. To control for k_{jt} and S_{jt}, we include an interaction of market and year fixed-effects. Together, these two controls allow us to exploit within-establishment variation while controlling for time shocks that vary by market. Finally, to control for endogeneity arising from correlation between the log of employment and the error term, we instrument $\ln S_{injt}$ with state corporate taxes, $\tau_{X(i)t}$. We think of the time-series variation in taxes as an exogenous shock to a firm's labor demand which help us identify the parameters of the labor supply equation faced by the firm.

[29] Refer to Appendix C for derivation.

Once we get an estimate of β_S (and implicitly $\hat{\eta}_S$) from equation (22), we proceed to estimate γ by relying on the following equation:

$$\overline{\Omega}_{Sjt} = k_{jt} + \gamma_S \ln S_{jt} + \bar{\varepsilon}_{Sjt} = k_j + k_t + \gamma_S \ln S_{jt} + \tilde{\nu}_{jt}, \tag{23}$$

where $k_{jt} = k_j + k_t + \nu_{jt}$, $\tilde{\nu}_{jt} = \nu_{jt} + \bar{\varepsilon}_{Sjt}$ and $\bar{\varepsilon}_{Sjt} = \mathbb{E}_{jt}(\varepsilon_{Sinjt})$.

We control for k_j and k_t by including market and year fixed effects, respectively, in our specification.[30] To address the issue of endogeneity due to potential correlation between $\ln S_{jt}$ and $\tilde{\nu}_{jt}$, we instrument $\ln S_{jt}$ by $\bar{\tau}_{jt}$, the average tax-rate in a given market j. Intuitively, we exploit plausibly exogenous variation in market-level average tax rates over time to estimate γ_S.

Next, to estimate the labor disutility parameter, we rely on the aggregate labor supply equation of the household for each skill, written in logs as follows:[31]

$$\ln W_{st} = \frac{1}{\phi_S} \ln \frac{1}{\bar{\phi}_{St}} + \frac{1}{\phi_S} \ln S_t. \tag{24}$$

We calibrate the value of the Frisch elasticity, ϕ_S, to be equal to 0.25 (see Chetty et al. (2011)) for both high and low-skilled workers. This allows us to estimate the value of $\bar{\phi}_{St}$, one for each year, by inverting equation (24).

Finally, once all the key parameters of interest are estimated, and given the skill-specific employment observed in the microdata, we calculate wages by using equation (10). The difference between the model implied wages and the ones observed in the data is precisely the measurement error denoted in equation (20).

Estimation sample. To estimate the within and between-market substitution parameters, we rely on the panel dimension of our merged LBD-LEHD data. We estimate these parameters for the tradeable sector between 1997 and 2011.[32] We extend our stochastic assignment procedure to account for the panel dimension of our data. To do so, we first

[30] Notice that if we were to control for k_{jt} by including an interaction of market-year fixed-effects, we would no longer be able to identify γ_S as there will not be any variation in $\ln S_{jt}$. Giroud and Rauh (2019) have argued that market size (I_j) may be correlated with taxes, which can be a threat to the identification of γ_S in our framework. However, this correlation is unlikely to hold in our data since we define a market as a NAICS 6 industry, which contain multiple states as opposed to a single state. In our framework, given that we control for market and year fixed effects, we only require $\tilde{\nu}_{jt}$ to be uncorrelated with taxes for identification of γ_S to hold.

[31] We assume there is no measurement error in aggregate wages, i.e. $\ln W^*_{st} = \ln W_{st}$.

[32] We do not have state tax data beyond 2011.

randomly assign establishments to markets, conditional on NAICS 6 in 1997, such that there are at most 32 establishments in each market. Once assigned to a market, the establishment always remains in it as long as we observe it in the data. For every subsequent year starting from 1997, we again randomly assign the establishments that we did not observe previously (i.e., the new entrants) to one of the existing markets created in 1997. As a result, the size and the composition of the markets evolve randomly over time given the entry and exit of establishments from markets. Our baseline estimates are based on this sample.[33]

Clustering. We provide two sets of estimates for the standard error. The first estimate does not cluster the standard error at any level, while the second estimate clusters the standard error at the state level for the estimate of $\hat{\eta}_S$ and the market level for the estimate of $\hat{\theta}_S$.[34] The clustering for $\hat{\eta}_S$ takes into account the possibility that unobserved shocks may be correlated across establishments within a state and over time while the market level clustering of $\hat{\theta}_S$ accounts for the potential correlation of market-specific shocks over time.

Step 2. Estimating the distribution of technologies and N. Equipped with the estimates of within and across market labor substitutability parameters, we proceed to jointly estimate N, the total number of firms competing in a market, and the distribution of productivities, $G(A_{Hinj}, A_{Linj})$.

To do so, we guess a value for the total number of competitors in each market, denoted N^g. Conditional on N^g, we randomly assign I establishments to N^g firms within each market and back out the joint distribution of technology using the FOCs stated in equation (25). Finally, we estimate the optimal number of competitors, denoted N^*, using Simulated Method of Moments (SMM).

We begin by outlining how we back out the technology distribution conditional on N^g and then provide further details concerning SMM. Our approach to estimating the technology distribution non-parametrically, starts from the FOCs in equation (25), for

[33] To see our estimation results without random assignment, refer to Appendix D.

[34] We cluster at the state level to estimate $\hat{\eta}_S$ since our instrument's variation (i.e. state level taxes) is at that level, as suggested by Abadie, Athey, Imbens, and Wooldridge (2023). We would like to acknowledge an anonymous referee for bringing this to our attention.

each skill:

$$P_{inj}Y_{inj}^{\frac{1}{\sigma}}A_{Sinj}^{\frac{\sigma-1}{\sigma}}S_{inj}^{-\frac{1}{\sigma}}\left[1+\varepsilon_{inj}^{P}\right]=W_{Sinj}\left[1+\varepsilon_{inj}^{S}\right],\quad S\in\{H,L\}. \tag{25}$$

Observe that we can re-write the FOCs solely in terms of employment, S_{inj}, time-invariant model parameters and skill-specific technology parameters, A_{Sinj}. To do so, we first replace output market elasticity (ε_{inj}^{P}) and input market elasticities (ε_{inj}^{S}) in the FOCs by equation (14) and equation (15), respectively. These elasticities are functions of the revenue share (s_{nj}) and the wage bill share (e_{Snj}) which can be expressed as a function of output and employment, as follows:

$$s_{nj}=\frac{\sum_{i\in\mathcal{I}_{nj}}P_{inj}Y_{inj}}{\sum_{i}P_{inj}Y_{inj}}=\frac{\sum_{i\in\mathcal{I}_{nj}}Y_{inj}^{\frac{\eta-1}{\eta}}}{\sum_{i}Y_{inj}^{\frac{\eta-1}{\eta}}},\quad e_{Snj}=\frac{\sum_{i\in\mathcal{I}_{nj}}W_{Sinj}S_{inj}}{\sum_{i}W_{Sinj}S_{inj}}=\frac{\sum_{i\in\mathcal{I}_{nj}}S_{inj}^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}{\sum_{i}S_{inj}^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}.$$

Finally, we substitute out prices (P_{inj}), wages (W_{Sinj}) and output (Y_{inj}) from the two FOCs by using equations (9), (10) and (4).

Consequently, for each establishment i, we have two FOCs, one for each skill. Given our assumption that there are I establishments in each market, we have a system of $2\times I$ equations to pin down $2\times I$ unknown values of A_{Hinj} and A_{Linj} within each market j. We solve this system of equations for each market $j\in\{1,\ldots,J\}$ to pin down an estimate of $G(A_{Hinj},A_{Linj})$. Since we estimate the model for 1997 and 2016, we get a different estimate of $G(A_{Hinj},A_{Linj})$ for each year. The algorithm that we use in practice that helps us achieve this objective is outlined in Appendix A.4.

Our procedure allows us to back out a distribution of technology that is consistent with the equilibrium value of employment for each establishment observed in the micro-data. Note that the technology distribution that we estimate allows us to perfectly match the distribution of employment in the data. Using the estimated technology distribution, we can calculate revenues, prices, output and wages in the model. While prices and output are not directly observed in the data, revenue and wages are. Unlike employment, which is directly obtained from the data, revenues and wages differ between the model and the data as the model revenues and wages are obtained from solving for the model equations using the *estimated* productivity parameters and other structural parameters.

To estimate N, we start from the aforementioned observation that for every guess of $N^g \in \{2, 4, 8, 16, 32\}$, we recover a distribution of technology that is consistent with the distribution of employment in the data.[35] Thereafter, holding employment and wages fixed, our theory suggests a monotonically declining relationship between the ratio of revenue over wage-bill and N. To see this, note that the revenue over wage bill for each establishment in the model can be written as:

$$\frac{R_{inj}}{W_{Hinj}H_{inj} + W_{Linj}L_{inj}} \equiv \psi_{inj} = \left[\omega_{Hinj} \times \mu_{inj} \times \delta_{Hinj}\right] + \left[\omega_{Linj} \times \mu_{inj} \times \delta_{Linj}\right], \qquad (26)$$

where $\omega_{Sinj} = \frac{W_{Sinj}S_{inj}}{W_{Hinj}H_{inj}+W_{Linj}L_{inj}}$ denotes the wage bill share of skill S in the establishment. Equation (26) says that holding employment at each establishment fixed at their level observed in the data and the corresponding wages implied by the labor supply function, a decline in N leads to an increase in the revenue share s_{nj} and the skill-specific wage bill share e_{Snj} of each firm. This is because each firm now owns a greater number of establishments in its market. For any given values of within and between-market substitutability in the product and the labor markets, this increase leads to an increase in the market power of firms in both the input and the output markets and increases the wedge between revenue and wage bill.[36] Consequently, we estimate N by minimizing the distance between the sales-weighted revenue over wage bill in the data and the model:

$$N^* = \min_{N \in \{2,\,4,\,8,\,16,\,32\}} \left[\int_j \sum_i m^D_{inj}\psi^D_{inj} dj - \int_j \sum_i m^M_{inj}(N)\psi^M_{inj}(N) dj \right]^2, \qquad (27)$$

where $m^D_{inj} = \frac{R_{inj}}{\int_j \sum_i R_{inj} dj}$ denotes the sales-share of establishment i in the data while m^M_{inj} denotes the same quantity in the model.

[35] We consider only 5 values of N as $N = 2^k$ where $k \in \{1, 2, 3, 4, 5\}$ for two main reasons. First, given Cournot competition the model is already close to a competitive economy at high values of N above 16. Second, while this characterization of N is coarse, this allows us to compute the economy for only symmetric patterns of ownership where each firm owns I/N establishments within a market yielding a computationally feasible estimation of N and a clean counterfactual.

[36] To gain some intuition for how we identify the number of competitors, in the simplest setting with Cournot competition amongst identical firms, there is a direct relation between the margin ($(p-c)/p$ with price p and marginal cost c) and the inverse of the number of firms and the consumer price elasticity in absolute value (see Horowitz (1971)). For a given elasticity, an increase in the measured margins implies a decline in the number of firms competing.

Finally, as our production function abstracts from capital and intermediate inputs, we adjust the revenue in the data to make it comparable to our model. To do so, we multiply the revenue in the data by a constant α_N such that $R^{Adj,Data}_{inj} = \alpha_N \times R^{Data}_{inj}$, where $R^{Adj,Data}_{inj}$ denotes the adjusted revenue in the data and R^{Data}_{inj} is the unadjusted revenue in the data.[37] We pin down the value of α_N such that $N = 16$ in 1997.[38] In 2016, we hold the value of α_N constant and estimate N by matching the sales-weighted distribution of revenue over wage bill in the data and the model.[39] Our estimate of α_N is 0.314 which is in line with the estimates found in the literature on production function estimation.[40]

5 Results

In this section, we present the results of our analysis, including the estimates of labor market substitutability parameters for each skill, and the findings related to the distribution of establishment-specific technology and market structure, respectively. We find evidence that low-skilled workers have a lower substitutability within and across markets. We also find evidence of Skill-Biased Technological Change amidst a broad decline in competition.

Estimates of labor substitutability parameters. In Table 3, Panel A, we present the OLS and the IV estimates of our reduced form parameters $\beta_S = \frac{1}{\hat{\eta}_S}$ and $\gamma_S = \frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}$. For both the skills and for both $\hat{\eta}_S$ and $\hat{\theta}_S$, we find that the OLS estimates of parameters are biased

[37] We assume that the gross revenue in the data is generated using a Cobb-Douglas production function. The function takes the form $\widetilde{Y}_{inj} = Y^{\alpha_N}_{inj} K^{\alpha_K}_{inj} M^{\alpha_M}_{inj}$, where $Y_{inj} = \left[\left(A_{Hinj} H_{inj}\right)^{\frac{\sigma-1}{\sigma}} + \left(A_{Linj} L_{inj}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$. In this function, K_{inj} represents capital, M_{inj} represents materials, and $\alpha_N + \alpha_K + \alpha_M = 1$. Gross revenue can be expressed as $\widetilde{R}_{inj} = \mu_{inj}\delta_{Linj}W_{Linj}L_{inj} + \mu_{inj}\delta_{Hinj}W_{Hinj}H_{inj} + \mu_{inj}P^M M_{inj} + \mu_{inj}P^K K_{inj} = \alpha_N \widetilde{R}_{inj} + \alpha_M \widetilde{R}_{inj} + \alpha_K \widetilde{R}_{inj}$. In our model where only labor is considered as input, the revenue R_{inj} is given by $\mu_{inj}\delta_{Linj}W_{Linj}L_{inj} + \mu_{inj}\delta_{Hinj}W_{Hinj}H_{inj}$. In this case, we have $R_{inj} = \alpha_N \widetilde{R}_{inj}$.

[38] Given the monotonic relation between revenue over wage bill in the model and N, there exists an α_N such that the sales-weighted revenue over wage bill in the data (after adjustment using α_N) exactly equals the sales-weighted revenue over wage bill in the model.

[39] Note that in our framework, α_N, the output elasticity of labor, is held fixed for the duration of our analysis. This is in line with the evidence by De Loecker et al. (2020) who show that the output elasticity of Cost of Goods Sold (COGS), which includes labor and materials, is roughly constant between 1997 and 2016 for US Compustat data. However, we note that the elasticity could have changed over time, due to increased automation in production for example.

[40] Closest to our specification is the work of De Loecker (2011) and Doraszelski and Jaumandreu (2013), both of whom rely on a Cobb-Douglas production function with capital, intermediate inputs, and labor. Both find the output elasticity of labor to be in the range of 0.17 and 0.334.

downward compared to the IV. More importantly, the OLS estimate for β_S is not consistent with the theory as it shows a negative relationship between wages and employment. The IV corrects for the bias and shows that the corresponding structural parameters in Panel B of Table 3 are in line with the theory: $\hat{\eta}_L > \hat{\theta}_L$ and $\hat{\eta}_H > \hat{\theta}_H$, i.e., within-market substitutability is greater than the between-market substitutability.

We find that the estimate of the within-market substitutability parameter for high-skilled workers, $\hat{\eta}_H$, is n 2.53 while that of low-skilled workers, $\hat{\eta}_L$, is 2.42. These estimates imply that jobs within a market have similar substitutability for high and low-skilled workers. Furthermore, we find that the estimate of between-market substitutability for the high-skilled worker, $\hat{\theta}_H$, is 2.02 while that of the low-skilled worker, $\hat{\theta}_L$, is 1.85. This implies that jobs across markets are less substitutable for low-skill workers, which can be interpreted as indicating that the mobility cost for low-skilled workers to move across markets is relatively high compared to that of high-skilled workers.

Berger et al. (2022) also estimate a model of oligopsony in the labor market without the distinction between high and low skill types. Their estimate for the within-market substitutability is equal to 10.85 while for between-market substitutability is 0.42. To get to their estimates, they rely on Indirect Inference.[41] In contrast, we take a different approach. While we use the same instrument, we exploit the log-linearity of the labor supply function to estimate the substitutability parameters. This is similar to the approach adopted by Felix (2021), who relies on a) the import tariff reductions as an exogenous variation to estimate the within-market substitutability parameter and b) cross-market variation in import competition to estimate the between-market substitutability parameter in a model of oligopsonistic labor markets.

Finally, Table 3, Panel C provides the first-stage estimates of our IV. In both cases we find that the first-stage is negative and statistically significant. In the case of the estimation of β_S, when we use taxes as an instrument for changes in labor demand we find that taxes

[41] Apart from the methodological difference in the estimation, three additional differences lead to different estimates of the labor substitutability parameters between our work and the results in Berger et al. (2022). First, because we have no information on the market, we randomly assign our firms to markets drawn from industry classifications instead of assuming the market is a particular industry classification. Second, our estimates of the labor supply function are at the establishment level while Berger et al. (2022) estimate it at the firm level. Lastly, in our baseline, our labor markets are considered to be national while Berger et al. (2022) consider local labor markets defined by NAICS 3 x MSA.

are negatively correlated with employment at the establishment level. This reduced-form relationship between employment and taxes is consistent with the evidence presented in Giroud and Rauh (2019) and Berger et al. (2022). We also find a similar relationship when we estimate γ_S, where in the first stage we find a negative correlation between average market employment and average market-level taxes.

Robustness of elasticity estimates. The baseline model estimates the labor substitutability parameters by randomly assigning establishments to markets within a given NAICS 6, without considering the interactions between geography (e.g. MSA) and NAICS. These choices could lead to two concerns: First, the estimates of the labor substitutability parameters could be influenced by the random assignment itself, and second, labor markets may not be correctly specified. To address these concerns, we conduct two robustness exercises in Appendix D. In both of these exercises, we change the method of assignment of establishments to markets. In the first exercise, a market is defined as the entire NAICS 6 industry, while in the second, a market is defined as NAICS 3 x MSA. We find similar estimates; although when markets are defined as NAICS 3 x MSA, without random assignment, the estimate of $\hat{\eta}_S$ loses statistical significance when we cluster standard errors at the state-level.

TFP distribution. In Table 4, we report aggregate moments of the estimated skill-specific technology. We show that there is an increase in the level and variance of these technologies over time, for both high and low-skill workers. The variance of the distribution of productivities for high-skilled workers is *higher* compared to low-skilled workers in both years. In Figure A6 in Appendix E, we plot the density of $\ln A_{Hinj}$ and $\ln A_{Linj}$.[42] Inspection of the distributions of skill-specific technologies confirms this increasing variance and significant heterogeneity. The variance of technology and its increase over time have an important implication for heterogeneity in establishment-level markups and markdowns as well as trends in wage inequality. We explore the quantitative implications of these results in our counterfactual experiments in Section 6.

We also decompose the total variance of $\ln A_{Hinj}$ and $\ln A_{Linj}$ into within and between

[42] We also plot the densities of skill-specific employment, $\ln H_{inj}$ and $\ln L_{inj}$ in Figure A5 in Appendix E as they are the primary heterogeneous input used in the estimation of the model.

Table 3: Estimates of reduced-form parameters: Tradeables with Random Sampling

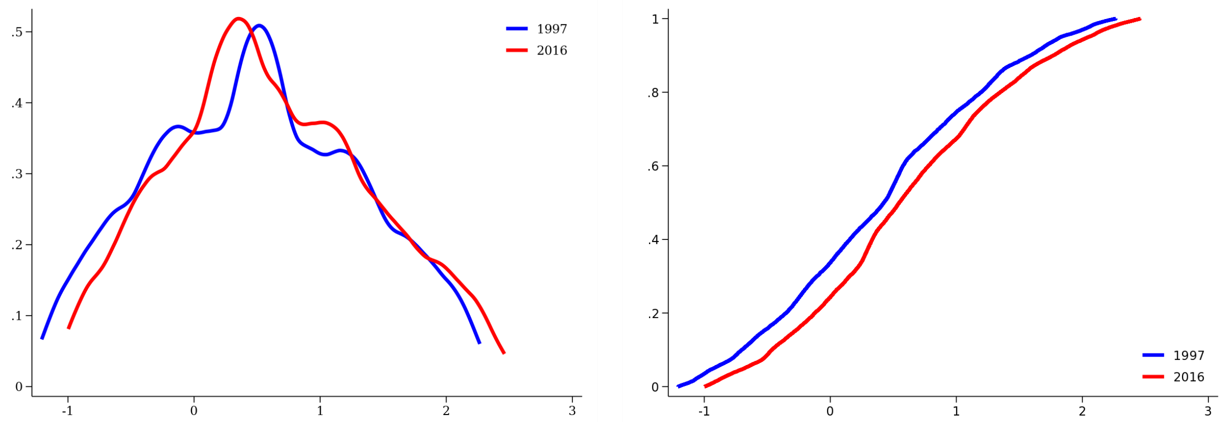
A. OLS and Second-Stage IV Estimates					
	OLS	IV		OLS	IV
	(1)	(2)		(3)	(4)
β_H	-0.180***	0.396***	γ_H	0.111***	0.100***
SE	0.0007	0.062	SE	0.0003	0.005
State level SE	(0.002)	(0.104)	Market SE	(0.003)	(0.041)
β_L	-0.110***	0.414***	γ_L	0.072***	0.127***
SE	0.0007	0.057	SE	0.0003	0.005
State level SE	(0.003)	(0.116)	Market SE	(0.003)	(0.041)
Market x Year FE	Yes	Yes	Market FE	Yes	Yes
Establishment FE	Yes	Yes	Year FE	Yes	Yes
B. Structural Parameters					
$\hat{\eta}_H$	-5.55	2.53	$\hat{\theta}_H$	-14.37	2.02
$\hat{\eta}_L$	-9.10	2.42	$\hat{\theta}_L$	-26.24	1.85
C. First-stage Regressions for the IV					
$\tau^H_{X(i)t}$	-	-0.012***	$\bar{\tau}^H_{jt}$	-	-0.061***
SE		0.0009	SE		0.0008
State level SE		(0.004)	Market SE		(0.009)
$\tau^L_{X(i)t}$	-	-0.014**	$\bar{\tau}^L_{jt}$	-	-0.066***
SE		0.0009	SE		0.0008
State level SE		(0.006)	Market SE		(0.009)
Market x Year FE	-	Yes	Market FE	-	Yes
Establishment FE	-	Yes	Year FE	-	Yes
No. of obs (High-Skilled)	1,147,000	1,147,000		70,000	70,000
No. of obs (Low-Skilled)	1,147,000	1,147,000		70,000	70,000

Notes: *** p < 0.01, ** p<0.05, *p<0.1. Non-clustered standard errors, denoted SE, are reported without parenthesis while clustered standard errors are reported with parenthesis. The significance stars correspond to clustered standard errors. Estimates of γ_S in columns 3 and 4 are conditional on the estimates of columns 1 and 2, respectively. Number of observations are common for both the first and the second-stage. The number of observations reflects rounding for disclosure avoidance. $\tau^S_{X(i)t}$ denotes the coefficient infront of taxes in the first-stage regression for the estimate of β_S. The same instrument is used separately, first to estimate β_H and then to estimate β_L.

NAICS 6 industries in Table 4. The details of the decomposition are provided in Appendix E.2. We find that in 1997, roughly one-third of the total variance in $\ln A_{Hinj}$ and $\ln A_{Linj}$ is within NAICS 6 industries, while the remaining two-thirds is attributed to between NAICS 6 industries. In 2016, the contribution of between-industry variance in produc-

Figure 2: Estimated Distribution of Relative Skill-Specific Technology

(a) PDF of $\ln \frac{A_{Hinj}}{A_{Linj}}$ (b) CDF of $\ln \frac{A_{Hinj}}{A_{Linj}}$



Notes: Panels (a) and (b) show the probability density function and the cumulative density function of the ratio of $\ln \frac{A_{Hinj}}{A_{Linj}}$, respectively. For the distributions of $\ln A_{Hinj}$ and $\ln A_{Linj}$ as well as the underlying skill-specific employment distributions $\ln H_{inj}$ and $\ln L_{inj}$, see Appendix E.1. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

tivity increases to roughly three-fourths of the total variance. More importantly, we find that between 1997 and 2016, we have observed an increase in total variance of $\ln A_{Hinj}$ and $\ln A_{Linj}$. This increase is exclusively due to an increase in between-industry variance in establishment-level productivity and a mild decline in within-industry productivity differences. This is supportive of the recent evidence by Haltiwanger et al. (2022), who show that of the total change in the variance of earnings, the between-industry change in variance explains about 62%. Our results provide a rationale for their finding: the rise in between-industry earnings is potentially due to a rise in between-industry dispersion in technology.

Consistent with the literature, we also find strong evidence in support of Skill-Biased Technological Change. In Figure 2a, we show that the mean of the distribution of relative productivities in 2016 increased compared to 1997. The mean of $\ln(A_{Hinj}/A_{Linj})$ has increased from 0.50 to 0.63 and the variance has remained effectively unchanged as shown in Table 4. Meanwhile, in Figure 2b, we show that the 2016 CDF of relative productivities first-order stochastically dominates the distribution in 1997.

Table 4: Moments of the Technology Distribution

	$\ln A_{Hinj}$				$\ln A_{Linj}$				$\ln \frac{A_{Hinj}}{A_{Linj}}$	
	Mean	Variance			Mean	Variance			Mean	Variance
		Total	Within	Between		Total	Within	Between		
1997	8.70	21.71	7.23	14.48	8.20	21.33	7.34	13.99	0.50	1.11
2016	8.89	28.54	7.13	21.41	8.26	26.11	7.07	19.04	0.63	1.12

Notes: We decompose the total variance for $\ln A_{Linj}$ and $\ln A_{Hinj}$ into within and between NAICS 6 industries. More details about the decomposition are provided in Appendix E.2.

Estimated market structure, markups and markdowns. Table 5 reports that our estimated value of N has declined substantially between the two endpoints of our data: N was 16 in 1997 while it has declined to 4 in 2016, implying that any given firm competes with fewer other firms, on average, in a market.[43] We remain agnostic about the source of this decline. For example, this decline in N can be due to a rise in common ownership – large investors owning shares in competing firms. In their recent work, Ederer and Pellegrino (2022) show that in the US the "network of common ownership has a hub-and-spoke structure with a large proportion of firms sharing significant overlap and the remainder of largely unconnected firms at the periphery." This evidence is in line with the declining estimate of N that we document in the paper.

We find that the estimated N in 2016 is low relative to 1997. We rationalize this finding as follows. Our model has two forces that can drive the wedge between revenue over the wage bill, which has increased over time, as shown in Table 6. These forces are technological change and N. While there has been an increase in the variance of the distribution of technology over time, the underlying heterogeneity cannot fully explain the increase in the wedge between revenue and the wage bill.[44] The residual increase in this wedge is explained by a decline in N which leads to higher market power for firms.[45] Recently, De Loecker et al. (2018) also estimate a model of imperfect competition with strategic in-

[43] The decline in N is also consistent with the evidence of increasing concentration as measured by the Herfindahl-Hirschman Index (HHI). See for example Autor et al. (2020).

[44] In our estimation strategy, the distribution of technology is a function of both the underlying employment distribution in the data and the market structure N.

[45] The effect of N on the wedge is highly non-linear in a model with Cournot competition. In other words, the increase in the wedge when N moves from 16 to 8 is lower than its increase when N moves from 8 to 4. Consequently, N needs to be as low as 4 for our model to match the observed wedge in the data.

Table 5: Estimates of the Market Power and Labor Supply Parameters

	N	$\bar{\phi}_H$	$\bar{\phi}_L$	Average Markup	Average Markdown	
					High-Skilled	Low-Skilled
1997	16	166900	180800	1.682	1.420	1.419
2016	4	96430	64760	2.160	1.435	1.437

Notes: The average markup is the sales-weighted average markup estimated from our model. The average markdown is the sales-weighted markdowns for high and low-skilled workers.

teraction in the output market and show that competition in the aggregate economy has declined.

Table 5 shows that this decline in competition which we estimate leads to an increase in sales-weighted average markup from 1.682 in 1997 to 2.160 in 2016. While markdowns for both skills are substantial, we find that they increase only marginally.[46] One of the main factors contributing to the higher increase in markups compared to markdowns is the difference in the within and across market substitutability parameters between the product and labor markets. These parameters indicate that the range between the upper and lower bounds of markups is significantly larger than that of markdowns.[47]

Figures A8a, A8b, and A8c in Appendix E show the distribution of unweighted establishment level markups and the markdowns for each skill level. The distributions of markups and markdowns have shifted to the right in 2016 compared to 1997, with a much more substantial shift for markups compared to the markdowns. The main insight is that the variance of markups has increased substantially.

Model fit. Our model does reasonably well matching the level and the change of skill premium between 1997 and 2016 (Table 6). The model underpredicts the levels slightly, but tracks the data closely when it comes to the change over time. Furthermore, in Figure

[46] Qualitatively speaking, this increase in markup is consistent with the rise of markup documented by De Loecker et al. (2020), who use Compustat data and rely on the production function estimation to get their results. With regards to markdowns, we observe a marginal increase in the sales-weighted markdowns, while Hershbein et al. (2022), using the Census of Manufacturers (CMF), find a more pronounced increase in average markdowns since 1997.

[47] In addition, the functional forms of markups and markdowns in the model differ. In our model, markups are defined as, $\mu_{inj} = \left[1 - \frac{1}{\theta} s_{nj} - \frac{1}{\eta}(1 - s_{nj})\right]^{-1}$, while markdowns for a given skill $S \in \{H, L\}$, are defined as $\delta_{Sinj} = \left[1 + \frac{1}{\tilde{\theta}_S} e_{snj} + \frac{1}{\tilde{\eta}_S}(1 - e_{snj})\right]$. When comparing these two expressions, it is evident that even if the wage bill share and the sales share were identical, the implied markups and markdowns would differ due to differences in the functional form.

Table 6: Model Fit

	1997		2016		Δ	
	Data	*Model*	*Data*	*Model*	*Data*	*Model*
Skill Premium	1.515	1.468	1.734	1.642	0.219	0.174
Inverse Wage Bill Share	2.524	2.524	3.290	3.444	0.766	0.920
Total Log Wage Variance	0.285	0.308	0.366	0.336	0.081	0.028
Within Establishment	0.046	0.047	0.052	0.050	0.006	0.003
Between Establishment	0.238	0.261	0.314	0.286	0.075	0.025

Notes: The Inverse Wage Bill Share is defined as $\int_j \sum_i m_{inj} \frac{R_{inj}}{\sum_S W_{Sinj} S_{inj}} dj$, where $m_{inj} = \frac{R_{inj}}{\int_j \sum_i R_{inj} dj}$ is the revenue weight and $\frac{R_{inj}}{\sum_S W_{Sinj} S_{inj}}$ denotes the revenue over the wage bill share for a given establishment. For the data value, $R_{inj} = R_{inj}^{Adj,Data} = \alpha_N R_{inj}^{Data}$ where $\alpha_N = 0.314$. Section 6 outlines the decomposition of the overall log wage variance into a within-establishment component and a between-establishment component.

A7 in Appendix E we show that the model skill premium distribution has a close fit to the data in both 1997 and 2016.

For the sales-weighted average of the revenue over the wage bill, the relevant comparison is for the year 2016 since we match this quantity between the data and the model in 1997 by construction to estimate α_N, the output elasticity of labor. This is the key moment that we target to estimate N. As shown earlier, the wedge between revenue and the wage bill informs us about the market power of firms in their market. We find that the model provides a reasonable fit for this moment in the data.

Finally, we evaluate our model's fit to the data with respect to the variance of log wages. We find that our model generates 34.6% of the total change in the variance in log wages, 50% of the change in within-establishment variance, and 33% of the change in between-establishment variance.

6 Counterfactuals

Given the estimated parameters of the model, we perform a set of counterfactual experiments to quantify the effect of market structure and technological change to wage inequality. We show in Tables 7 and 8 how these factors contribute to the changes in aggregate skill premium, wage levels, and between-establishment inequality.

To do so, we hold fixed the assignment of establishments to markets that we applied to back out the skill-and-establishment-specific productivity distributions in Section 4. Because in each counterfactual we investigate the role of different market structures, we need to reassign establishments to firms within a given market. To account for the possible influence of this random assignment, we employ a bootstrap-style procedure.[48]

Quantifying the effect of N. To quantify the effect of N, we perform the following experiment: we hold all parameters of the model fixed to their estimated values in 1997 and change N from its value of 16 in 1997 to its estimated value of 4 in 2016. We find that the skill premium goes up from 1.468 to 1.480 in this counterfactual, implying that the change in the market structure accounts for 8.1% of the rise in the skill premium. Intuitively, a decline in N leads to an increase in average markdowns for high and low-skilled workers. However, this increase is relatively larger for low-skilled workers, which translates to an increase in the aggregate skill premium.

We find that the decline in competition in both output and input markets has significant effects on the *level* of average high and low-skilled worker-weighted wages. Our results show that if only 4 firms were competing in 1997 instead of 16, average high-skilled workers' wages would decrease by 11.3% and average low-skilled workers' wages would decrease by 12.2% relative to their 1997 levels. The level of wages drops despite the small changes in the average markdown of high and low-skilled workers because of the general equilibrium effect of the rise in the market power of firms in the product market. Since firms are exerting monopoly power in the goods market, the resulting increase in markups leads to a fall in the demand for goods and therefore labor. In Deb et al. (2022), we take this insight further and show that the rise in output market power of firms accounts for 75% of the wage stagnation, and can account for the decoupling of productivity and wage growth in the US.

[48] Specifically, within each market, we randomly reassign establishments to firms 41 times. In each assignment we divide the 32 establishments within each market into N firms. For each of these reassignments, we calculate our counterfactual experiments of interest. We then rank these assignments based on the change in total wage inequality between 1997 and 2016. We present the results corresponding to the assignment with the median change in total wage inequality. To account for the variability arising from random assignments, we have added supplementary tables in Appendix F. These additional results present the 5th and 95th percentiles for each of the counterfactual scenarios we conducted.

Table 7: Counterfactual Exercises on Skill Premium and Wages

	Skill Premium			
	Level	% Contr.	$\mathcal{W}_H$	$\mathcal{W}_L$
	(1)	(2)	(3)	(4)
1997	1.468	0.00	100.00	100.00
N	1.480	8.05	88.71	87.85
A_{Hinj}, A_{Linj}	1.934	268.97	231.49	175.48
$\bar{\phi}_H, \bar{\phi}_L$	1.242	-128.74	93.71	110.59
N and A_{Hinj}, A_{Linj}	1.956	281.61	204.57	153.28
N and $\bar{\phi}_H, \bar{\phi}_L$	1.255	-121.26	83.16	97.15
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	1.631	94.83	218.58	196.51
2016	1.642	100.00	193.20	171.60

Notes: Column (2) (titled % Contribution) is constructed as follows: $\frac{\kappa^{CF}-\kappa^{R}_{1997}}{\kappa_{2016}-\kappa_{1997}} \times 100$, where κ denotes the level of the skill premium and κ^{CF} denotes the counterfactual under consideration. κ^{R}_{1997}, $\mathcal{W}_H$ and $\mathcal{W}_L$ denote, respectively, the level of the skill premium, high and low-skill wages, of the seed that corresponds to the median change in the total variance of wage inequality in Table 8. $\mathcal{W}_H$ and $\mathcal{W}_L$ are normalized to 100 in 1997. Values in column (1) are rounded to three decimal points.

Quantifying the effect of A_{Hinj} and A_{Linj}. As previously mentioned, the parameters of the model were fixed to their values in 1997 and the technology distribution estimated in 2016 was subsequently fed into the model. We find that this shift in the technology distribution accounts for approximately 269.0% of the total change in the skill premium. Changes in the productivity distributions are an important source of wage growth for both high and low-skilled workers, and relatively more for high-skilled. This evidence is in line with the previous literature highlighting the role of Skill-Biased Technological Change as being an important driver of the rise in the skill premium.

With regard to the level of wages, our counterfactual exercise demonstrates that the average wage for high-skilled workers would have increased by 131.5%, while the average wage for low-skilled workers would have increased by 75.5%. These increases in wages stem from improved productivity for both high- and low-skilled workers, as outlined in Table 4. To answer the question of how much market power is impeding wage gains from productivity improvements, we shift both technology and N jointly and compare it to the counterfactual where we only shift the technology distribution. We find that

Table 8: Counterfactual Exercises on Within and Between-Establishment Inequality

	Levels			% Contribution of total change		
	Total	Within	Between	Total	Within	Between
	(1)	(2)	(3)	(4)	(5)	(6)
1997	0.308	0.047	0.261	0.00	0.00	0.00
N	0.329	0.048	0.282	51.79	29.67	54.80
A_{Hinj}, A_{Linj}	0.400	0.087	0.313	305.71	1337.67	181.60
$\bar{\phi}_H, \bar{\phi}_L$	0.293	0.027	0.266	-76.43	-656.67	-6.80
N and A_{Hinj}, A_{Linj}	0.416	0.089	0.327	360.36	1399.33	235.60
N and $\bar{\phi}_H, \bar{\phi}_L$	0.308	0.028	0.280	-25.71	-642.67	48.40
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	0.356	0.050	0.306	145.36	99.33	150.80
2016	0.336	0.050	0.286	100.00	100.00	100.00

Notes: Columns (4)-(6) are calculated as follows: $\frac{d^{CF}-d^{R}_{1997}}{d_{2016}-d_{1997}} \times 100$, where $d \in \{\text{Total}, \text{Within}, \text{Between}\}$ and CF denotes the counterfactual under consideration. d^{R}_{1997} in the numerator denotes the level of total, within or between-establishment inequality pertaining to the seed that corresponds to the median change in the total variance of wage inequality. Total^{R}_{1997} is equal to 0.315, Within^{R}_{1997} is equal to 0.047 and $\text{Between}^{R}_{1997}$ is equal to 0.268. Values in columns (1)-(3) are rounded to three decimal points.

the increase in average high and low-skilled wages would have been 104.6% and 53.3%, respectively, instead of 131.5% and 75.5%. This implies that market power impedes wage gains by 26.9 percentage points (pp) for high-skilled workers and 22.2 pp for low-skilled workers.

Labor supply. In addition to technology and market structure, wages in our model are determined by endogenous labor supply. The parameter $\bar{\phi}_S$ captures the disutility cost of the household from supplying one additional unit of labor, and the estimated values reflect the increase in the relative supply of high-skilled workers. In the absence of technological change and market structure, our results suggest that changes in labor supply would have led to an increase in low-skill wages, a decrease in high-skill wages, and a decline in the aggregate skill premium.

Within and Between-establishment inequality. We perform the same decomposition as Song et al. (2018) at the establishment level to quantify how much of the change in within and between-establishment inequality can be attributed to changes in market structure and technology. We focus primarily on between-establishment inequality since our measure of within-establishment inequality is incomplete. Specifically, our measure depends exclusively on one dimension of worker heterogeneity, which is high and low skill.[49]

Let log wages of a worker z, in establishment i, in period t, be denoted by w_{zit}.[50] Then, the decomposition can be written as follows:

$$\mathbb{V}ar_z(w_{zit}) = \underbrace{\sum_i \omega_{it} \left\{ \frac{H_{it}(w_{Hit} - \overline{w}_{it})^2 + L_{it}(w_{Lit} - \overline{w}_{it})^2}{H_{it} + L_{it}} \right\}}_{\text{Within establishment}} + \underbrace{\sum_i \omega_{it}[\overline{w}_{it} - \overline{w}_t^A]^2}_{\text{Between establishment}}, \tag{28}$$

where ω_{it} is the employment share of establishment i in the economy, $\overline{w}_{it}$ is the average establishment wage and $\overline{w}_t^A$ is the average wage in the economy.

The variance of (log) earnings increases over time, both in our model and in the data. Roughly 10.7% of the total increase in the variance of earnings is due to an increase in within-establishment inequality, compared to 7.4% in the data, while the remaining 89.3% of the increase is due to an increase in between-establishment inequality, compared to 92.6% in the data.[51]

To isolate the role of N and the technology distribution in explaining the rise in within and between-establishment inequality, we perform the same counterfactual experiments as in Table 7. As noted earlier, our model explains 34.6% of the variation in log wages, half of the variation in the within-establishment component and one-third of the variation in the between-establishment component in the data. Of this increase, we find that the decrease in N can explain 29.7% of the total change in within-establishment inequality and 54.8% of the total change in between-establishment inequality in our model.[52] We also find that Skill-Biased Technological Change has increased within-establishment inequal-

[49] Our analysis does not include other sources of heterogeneity, such as human capital and efficiency, which may account for differences in within-establishment wages and changes therein. Therefore, we collapse a lot of the within-establishment inequality which leads to such small numbers in Table 6.

[50] To simplify notation, we remove subscripts n and j that indicate the firm and the market to which establishment i belongs. In equation (28) we sum over all establishments in the economy.

[51] The within-establishment inequality constitutes a small part of total inequality as we collapse all wage heterogeneity within an establishment to just two wages, of high and low skill workers, both in the data and the model.

[52] Given that these counterfactuals stem from our specific structural model, our findings are contingent on our choice of the production technology. Specifically, while we integrate a significant level of heterogeneity into our production function with two skill inputs and an establishment-specific TFP parameter for each skill, we abstract from alternate advancements in the literature which account for capital-skill complementarity (Krusell et al. (2000)), automation of tasks (Acemoglu and Restrepo (2022)), and complementarities among coworkers within the firm (Freund (2022)) which can also contribute to rising wage inequality.

ity by 1337.7% and between-establishment inequality by 181.6% - contributing to the bulk of the observed increase in between-establishment inequality.[53]

7 Conclusion

In this paper, we address the question of how the rise in market power affects wage inequality. We provide a theoretical model that augments the canonical supply-demand framework of Katz and Murphy (1992) to incorporate rich heterogeneity between firms, as well as market power through strategic interaction in the product and labor markets. In addition to the race between the technology and the relative skill supply as postulated by Tinbergen (1974), our model highlights an additional channel that affects the skill premium: the relative monopsony power over different skills. This enables us to show how an increase in market power, through declining competition, affects the skill premium and wage inequality.

To quantify the effect of market power, we take our model to microdata from the US Census Bureau. We estimate the parameters pertaining to within and between-market substitutability of workers directly from the upward-sloping labor supply equation faced by establishments.

Furthermore, in our estimation approach we remain agnostic about the true definition of a market. The key restriction we face is that it is impossible to observe which firms are competing with whom in the macroeconomy. To address these issues, we estimate a stochastic model of competition by randomly assigning establishments to markets and firms within industry classification. When we apply our framework to the micro data, we can estimate an economy-wide productivity distribution consistent with the observed employment distribution. Our estimates provide evidence of increased dispersion in technology, Skill-Biased Technological Change, and a less competitive market structure between 1997 and 2016.

Our counterfactual exercises show that a less competitive market structure alone explains 8.1% of the rise in the skill premium as well as a decline in average equilibrium

[53] Note that the large percentage increase in within-establishment inequality is due to a very small change in that measure over time.

wage level for high-skilled workers by 11.3% and for low-skilled workers by 12.2%. This large effect of market power on the wage level is arguably the biggest impact of market power on wages and the distribution of income between firm owners and workers. Finally, we also find that a decline in competition explains 54.8% of the total change in between-establishment inequality in our model.

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Online Appendix

A Derivations

A.1 Household's optimization

Optimum consumption functions: Representative Household maximize the following utility function subject to the budget constraint

$$\max_{C_{inj},L_{inj},H_{inj}} C - \frac{1}{\bar{\phi}_L^{\frac{1}{\phi_L}}} \frac{L^{\frac{\phi_L+1}{\phi_L}}}{\frac{\phi_L+1}{\phi_L}} - \frac{1}{\bar{\phi}_H^{\frac{1}{\phi_H}}} \frac{H^{\frac{\phi_H+1}{\phi_H}}}{\frac{\phi_H+1}{\phi_H}}, \quad \text{s.t.} \quad PC = LW_L + HW_H + \Pi.$$

We solve the problem in two-steps. First, we derive the household's market level demand function and then we derive the establishment-level demand function. The solution to household's market-level demand function is a solution to

$$\max_{Y_j} \quad \left(\int_j J^{\frac{-1}{\theta}} Y_j^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}}, \text{ s.t } \int_J P_j Y_j dj \leq Z. \tag{A29}$$

Then the optimal allocation is given by

$$\frac{\theta}{\theta-1} \left(\int_j J^{\frac{-1}{\theta}} Y_j^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}-1} J^{\frac{-1}{\theta}} \frac{\theta-1}{\theta} Y_j^{\frac{\theta-1}{\theta}-1} = \lambda P_j. \tag{A30}$$

This can be simplified as $J^{\frac{-1}{\theta}} Y^{\frac{1}{\theta}} Y_j^{\frac{-1}{\theta}} = \lambda P_j$. Next, multiply each side by Y_j and integrate across J to get $Y = \lambda \int_j P_j Y_j dj$. We define the market price index P such that $PY = \int_j P_j Y_j dj$ which would imply that $\lambda = P^{-1}$. Then plugging this into the first order condition delivers the market specific demand function:

$$Y_j = \left(\frac{1}{J}\right) \left(\frac{P_j}{P}\right)^{-\theta} Y. \tag{A31}$$

The aggregate price index can be recovered by multiplying both sides by P_j and integrating across markets:

$$P = \left[\frac{1}{J}\int_J P_j^{1-\theta} dj\right]^{\frac{1}{1-\theta}}. \tag{A32}$$

We can apply a similar formulation to derive the establishment specific demand function, $Y_{inj} = \frac{1}{I}\left(\frac{P_{inj}}{P_j}\right)^{-\eta} Y_j$, and the market price index, $P_j = \left(\frac{1}{I}\sum_i P_{inj}^{1-\eta}\right)^{\frac{1}{1-\eta}}$. Then, the establishment specific demand function is given by:

$$Y_{inj} = \frac{1}{J}\frac{1}{I}\left(\frac{P_{inj}}{P_j}\right)^{-\eta}\left(\frac{P_j}{P}\right)^{-\theta} Y. \tag{A33}$$

To derive the market specific inverse demand function we can write, $P_j = J^{-\frac{1}{\theta}}\left(\frac{Y_j}{Y}\right)^{-\frac{1}{\theta}} P$, and similarly at the establishment level as $P_{inj} = I^{-\frac{1}{\eta}}\left(\frac{Y_{inj}}{Y_j}\right)^{-\frac{1}{\eta}} P_j$. Combining the last two equations we can get the establishment-specific inverse demand curve as

$$P_{inj} = \left(\frac{1}{J}\right)^{\frac{1}{\theta}}\left(\frac{1}{I}\right)^{\frac{1}{\eta}} Y_{inj}^{-\frac{1}{\eta}} Y_j^{\frac{1}{\eta}-\frac{1}{\theta}} Y^{\frac{1}{\theta}} P. \tag{A34}$$

Optimum labor supply functions: To derive equation (6), we follow Berger et al. (2022) and adjust for the love for variety by scaling the utility function. The household's aggregate labor supply function for each skill $S \in \{H, L\}$ can be derived from

$$\max_S \quad C - \frac{1}{\bar{\phi}_L^{\frac{1}{\phi_L}}}\frac{L^{\frac{\phi_L+1}{\phi_L}}}{\frac{\phi_L+1}{\phi_L}} - \frac{1}{\bar{\phi}_H^{\frac{1}{\phi_H}}}\frac{H^{\frac{\phi_H+1}{\phi_H}}}{\frac{\phi_H+1}{\phi_H}}, \quad \text{s.t. } PC = LW_L + HW_H + \Pi.$$

Then, the first order condition for $S \in \{H, L\}$ is

$$\frac{W_S}{P} = \overline{\phi}_S^{-\frac{1}{\phi_S}} S^{\frac{1}{\phi_S}} \iff S = \overline{\phi}_S\left(\frac{W_S}{P}\right)^{\phi_S},$$

which gives the aggregate labor supply function. The households optimum choice of allocation of labor across markets can be written as the solution to

$$\min_{S_j} \quad \left[\int_j \left(\frac{1}{J}\right)^{\frac{-1}{\hat{\theta}_S}} S_j^{\frac{\hat{\theta}_S+1}{\hat{\theta}_S}} dj \right]^{\frac{\hat{\theta}_S}{\hat{\theta}_S+1}}, \text{ s.t } \int_J W_{Sj} S_j dj \geq Z. \tag{A35}$$

Then, the optimal allocation is given by

$$\frac{\hat{\theta}_S}{\hat{\theta}_S+1}\left(\int_j \left(\frac{1}{J}\right)^{\frac{-1}{\hat{\theta}_S}} S_j^{\frac{\hat{\theta}_S+1}{\hat{\theta}_S}} dj \right)^{\frac{\hat{\theta}_S}{\hat{\theta}_S+1}-1} \left(\frac{1}{J}\right)^{\frac{-1}{\hat{\theta}_S}} \frac{\hat{\theta}_S+1}{\hat{\theta}_S} S_j^{\frac{\hat{\theta}_S+1}{\hat{\theta}_S}-1} = \lambda W_{Sj}. \tag{A36}$$

This can be simplified as $\frac{1}{J}^{\frac{-1}{\hat{\theta}_S}} S^{\frac{-1}{\hat{\theta}_S}} S_j^{\frac{1}{\hat{\theta}_S}} = \lambda W_{Sj}$. Next, multiply each side by S_j and integrate across J to get $S = \lambda \int_j W_{Sj} S_j dj$. We define the aggregate wage index W such that $WS = \int_j W_j S_j dj$ which would imply that $\lambda = W^{-1}$. Then, plugging this into the first order condition delivers the market specific labor supply equation as a function of wage levels and aggregate labor supply:

$$S_j = \left(\frac{1}{J}\right) \left(\frac{W_{Sj}}{W_S}\right)^{\hat{\theta}_S} S. \tag{A37}$$

The aggregate wage index can be recovered by multiplying both sides by W_j and integrating across markets:

$$W_S = \left[\frac{1}{J} \int_J W_{Sj}^{1+\hat{\theta}_S} dj \right]^{\frac{1}{1+\hat{\theta}_S}}. \tag{A38}$$

We can apply a similar formulation to derive the establishment-level labor supply, $S_{inj} = \left(\frac{1}{I}\right) \left(\frac{W_{Sinj}}{W_{Sj}}\right)^{\hat{\eta}_S} S_j$ and the market specific wage index is $W_{Sj} = \left[\left(\frac{1}{I}\right) \sum_i W_{Sinj}^{1+\hat{\eta}_S} \right]^{\frac{1}{1+\hat{\eta}_S}}$. Then the establishment-level labor supply curve is given by

$$S_{inj} = \left(\frac{1}{J}\right) \left(\frac{1}{I}\right) \left(\frac{W_{Sinj}}{W_{Sj}}\right)^{\hat{\eta}_S} \left(\frac{W_{Sj}}{W_S}\right)^{\hat{\theta}_S} S \tag{A39}$$

To derive the market specific inverse labor supply function, write $W_{Sj} = \left(\frac{1}{J}\right)^{-\frac{1}{\hat{\theta}_S}} \left(\frac{S_j}{S}\right)^{\frac{1}{\hat{\theta}_S}} W_S$

and similarly at the establishment level as $W_{inj} = \left(\frac{1}{I}\right)^{-\frac{1}{\hat{\eta}_S}} \left(\frac{S_{inj}}{S_j}\right)^{\frac{1}{\hat{\eta}_S}} W_{Sj}$. Combining these two equations we can get the establishment-level inverse labor supply curve as

$$W_{Sinj} = \left(\frac{1}{J}\right)^{-\frac{1}{\hat{\theta}_S}} \left(\frac{1}{I}\right)^{-\frac{1}{\hat{\eta}_S}} S_{inj}^{\frac{1}{\hat{\eta}_S}} S_j^{\frac{1}{\hat{\theta}_S}-\frac{1}{\hat{\eta}_S}} S^{-\frac{1}{\hat{\theta}_S}} W_S. \tag{A40}$$

A.2 Solving the equilibrium

Optimal firm solution: There are N firms indexed by n in each market. A firm owns I/N establishments. An establishment's sales share and wage bill share are denoted by s_{inj} and e_{Linj}, e_{Hinj}, respectively. As a result, the firm's sales share and wage bill share can be expressed as $s_{nj} = \sum_{i \in \mathcal{I}_{nj}} s_{inj}$ and $e_{Lnj} = \sum_{i \in \mathcal{I}_{nj}} e_{Linj}$ for the low-skilled and $e_{Hnj} = \sum_{i \in \mathcal{I}_{nj}} e_{Hinj}$ for the high-skill, respectively. Firm's problem here is to choose an employment level L_{inj}, H_{inj} for each establishment i simultaneously to maximize its profit. The FOC for input L_{inj} is derived below:

$$\left[P_{inj} + \frac{\partial P_{inj}}{\partial Y_{inj}} Y_{inj} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial P_{i'nj}}{\partial Y_{inj}} Y_{i'nj}\right)\right] \frac{\partial Y_{inj}}{\partial L_{inj}} = \left[W_{Linj} + \frac{\partial W_{Linj}}{\partial L_{inj}} L_{inj} + \sum_{i' \in \mathcal{I}_{nj} \setminus i} \left(\frac{\partial W_{Li'nj}}{\partial L_{inj}} L_{i'nj}\right)\right]. \tag{A41}$$

Note that $\frac{\partial P_{inj}}{\partial Y_{inj}} Y_{inj} = \left[-1/\eta + (1/\eta - 1/\theta) s_{inj}\right] P_{inj}$, and

$$\begin{aligned}
\frac{\partial P_{i'nj}}{\partial Y_{inj}} Y_{i'nj} &= \frac{\partial P_{i'nj}/P_{i'nj}}{\partial Y_{inj}/Y_{inj}} \frac{P_{i'nj} Y_{i'nj}}{P_{inj} Y_{inj}} P_{inj}, \\
&= \frac{\partial \log P_{i'nj}}{\partial \log Y_{inj}} \frac{s_{i'nj}}{s_{inj}} P_{inj}, \\
&= \left[\left(\frac{1}{\eta} - \frac{1}{\theta}\right) s_{inj}\right] \frac{s_{i'nj}}{s_{inj}} P_{inj}, \\
&= \left(\frac{1}{\eta} - \frac{1}{\theta}\right) s_{i'nj} P_{inj}.
\end{aligned} \tag{A42}$$

and similarly, $\frac{\partial W_{Linj}}{\partial L_{inj}} L_{inj} = \left[1/\hat{\eta}_L + (1/\hat{\theta}_L - 1/\hat{\eta}_L) e_{Linj}\right] W_{Linj}$, and

$$\frac{\partial W_{Li'nj}}{\partial L_{inj}} L_{i'nj} = \left(\frac{1}{\hat{\theta}_L} - \frac{1}{\hat{\eta}_L} \right) e_{Li'nj} W_{Linj}. \tag{A43}$$

Combining these the FOC can be rewritten into

$$\left[1 - \frac{1}{\theta} s_{nj} - \frac{1}{\eta}(1 - s_{nj}) \right] P_{inj} \frac{\partial Y_{inj}}{\partial L_{inj}} = \left[1 + \frac{1}{\hat{\theta}_L} e_{Lnj} + \frac{1}{\hat{\eta}_L}(1 - e_{Lnj}) \right] W_{Linj}, \tag{A44}$$

where markup and markdown are defined as

$$\begin{aligned} \mu_{inj} &= \frac{1}{1 + \varepsilon^P_{inj}} = \left[1 - \frac{1}{\theta} s_{nj} - \frac{1}{\eta} \left(1 - s_{nj}\right) \right]^{-1}, \\ \delta_{Linj} &= 1 + \varepsilon^L_{inj} = \left[1 + \frac{1}{\hat{\theta}_L} e_{Lnj} + \frac{1}{\hat{\eta}_L} \left(1 - e_{Lnj}\right) \right]. \end{aligned} \tag{A45}$$

We can similarly derive the FOC for H_{inj} to get

$$\delta_{Hinj} = 1 + \varepsilon^H_{inj} = \left[1 + \frac{1}{\hat{\theta}_H} e_{Hnj} + \frac{1}{\hat{\eta}_H} \left(1 - e_{Hnj}\right) \right]. \tag{A46}$$

Solving the model. Start from the first order condition for low-skilled worker:

$$Y^{\frac{1}{\sigma}}_{inj} A^{\frac{\sigma-1}{\sigma}}_{Linj} L^{-\frac{1}{\sigma}}_{inj} \left[1 - \frac{1}{\theta} s_{nj} - \frac{1}{\eta}(1 - s_{nj}) \right] P_{inj} = \left[1 + \frac{1}{\hat{\theta}_L} e_{L,nj} + \frac{1}{\hat{\eta}_L}(1 - e_{Lnj}) \right] W_{Linj}. \tag{A47}$$

Similarly, we have a similar equation for a high-skilled worker:

$$Y^{\frac{1}{\sigma}}_{inj} A^{\frac{\sigma-1}{\sigma}}_{Hinj} H^{-\frac{1}{\sigma}}_{inj} \left[1 - \frac{1}{\theta} s_{nj} - \frac{1}{\eta}(1 - s_{nj}) \right] P_{inj} = \left[1 + \frac{1}{\hat{\theta}_H} e_{Hnj} + \frac{1}{\hat{\eta}_H}(1 - e_{Hnj}) \right] W_{Hinj}. \tag{A48}$$

By plugging into the inverse labor supply and inverse demand functions, we can re-write each of these two conditions into:

$$\frac{1}{J}^{\frac{1}{\theta}}\frac{1}{I}^{\frac{1}{\eta}}(Y_{inj})^{-\frac{1}{\eta}}\left[\left(\frac{1}{I}^{\frac{1}{\eta}}\sum_i (Y_{inj})^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}\frac{(\theta-\eta)}{\eta\theta}}\right]\left[1-\frac{1}{\theta}\frac{\sum_{i\in\mathcal{I}_{nj}}(Y_{inj})^{\frac{\eta-1}{\eta}}}{\sum_i (Y_{inj})^{\frac{\eta-1}{\hat{\eta}}}}-\frac{1}{\eta}\left(1-\frac{\sum_{i\in\mathcal{I}_{nj}}(Y_{inj})^{\frac{\eta-1}{\eta}}}{\sum_i (Y_{inj})^{\frac{\eta-1}{\eta}}}\right)\right]\frac{\partial Y_{inj}}{\partial S_{inj}}Z_S \tag{A49}$$

$$=\frac{1}{J}^{\frac{-1}{\hat{\theta}_S}}\frac{1}{I}^{\frac{-1}{\hat{\eta}_S}}(S_{inj})^{\frac{1}{\hat{\eta}_S}}\left[\left(\frac{1}{I}^{\frac{-1}{\hat{\eta}_S}}\sum_i (S_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}\right)^{\frac{\hat{\eta}_S}{\hat{\eta}_S+1}\frac{(\hat{\eta}_S-\hat{\theta}_S)}{\hat{\eta}_S\hat{\theta}_S}}\right]\left[1+\frac{1}{\hat{\theta}_S}\frac{\sum_{i\in\mathcal{I}_{nj}}(S_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}{\sum_i (S_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}+\frac{1}{\hat{\eta}_S}\left(1-\frac{\sum_{i\in\mathcal{I}_{nj}}(S_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}{\sum_i (S_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}}}\right)\right],$$

where $S \in \{H, L\}$, $Z_S = W_S^{-1} S^{1/\hat{\theta}_S} Y^{1/\theta}$ is the skill specific aggregate and the aggregate price P is normalized to 1. Finally, we replace Y_{inj} in the above expression by the production function which gives us two first order conditions that are functions of H_{inj} and L_{inj}. We use these two equations to solve the model computationally using the following algorithm.

A.3 Algorithm to solve the model

Given model primitives outlined in Table 1, we proceed to compute the equilibrium of our economy using the following algorithm:

1. Guess three aggregates: $\{W_H^k, W_L^k, Y^k\}$, where k is the index of iteration.

2. Given those three initial values, solve the $2 \times I$ first order conditions, market-by-market, and calculate H_{inj}, L_{inj} and Y_{inj} for each establishment.

3. Compute $W_{H,inj}$, $W_{L,inj}$ and P_{inj} for each establishment using the inverse labor supply function for each skill and inverse demand function. Then, aggregate the establishment wages W_{Hinj}, W_{Linj} into W_H^{k+1}, W_L^{k+1} and establishment output Y_{inj} to Y^{k+1} using the respective CES aggregators.

4. Update the initial guess and iterate until all three aggregates converge $W_H^{k+1} = W_H^k$, $W_L^{k+1} = W_L^k$ and $Y^{k+1} = Y^k$ to get the equilibrium aggregates W_H^*, W_L^* and Y^*.

A.4 Algorithm to back out technology shocks

In order to backout the A_{Hinj} and A_{Linj} from the microdata, we proceed as follows:

1. Given that we can express the two first order conditions for each establishment only as a function of $A_{Sinj},\ S_{inj}\ \forall i \in j$ in equation (A49) of Section (A.2), we begin by solving for $Z_S = W_S^{-1} S^{1/\hat{\theta}_S} Y^{1/\theta}$. We first use the aggregate labor supply function to substitute out W_S as a function of S using $W_S = \frac{S^{1/\varphi_S}}{\overline{\varphi}_S^{1/\varphi_S}}$.

2. Given our estimation of the labor supply function from Steps 1 and 2 in Section 4, we have estimates of $\hat{\eta}_S, \hat{\theta}_S, \overline{\varphi}_S$. Now $Z_S = S^{1/\hat{\theta}_S - 1/\varphi_S} Y^{1/\theta} \overline{\varphi}_S^{1/\varphi_S}$ where we only need to solve for Y. To do so, we use a two-step procedure.

   (a) **Step 1:** We guess $Y = \widetilde{Y}$ and solve for the $A_{Sinj},\ \forall i$. At this stage we identify the $\mu^*_{inj}, \delta^*_{Sinj}, W^*_{Sinj}$, and S^*_{inj}, where * denotes the equilibrium value of these quantities. S^*_{inj} are establishment-level skill specific employment which we use from the data, W^*_{Sinj} are model wages from the labor supply function and $\mu^*_{inj}, \delta^*_{Sinj}$ are independent of aggregate Y as they only depend on the relative A_{Sinj} within a market.

   (b) **Step 2:** In Step 1, we identify $Y^* = \int_j \sum_i P_{inj} Y_{inj} dj$, as the establishment-level revenues are independent of the guess $\widetilde{Y}$. Therefore, we can solve the model a second time using Y^* to retrieve the estimated A^*_{Sinj} distribution.[54]

A.5 Proofs

Proof of Proposition 1. *In homogeneous establishment case, the skill premium is given by:*

$$\kappa = \left[\left(\frac{A_H}{A_L} \right)^{\frac{\sigma-1}{\sigma+\phi}} \times \left(\frac{\bar{\phi}_L}{\bar{\phi}_H} \right)^{\frac{1}{\sigma+\phi}} \right] \times \left[\frac{1 + \frac{1}{\hat{\theta}_L}\frac{1}{N} + \frac{1}{\hat{\eta}_L}(1 - \frac{1}{N})}{1 + \frac{1}{\hat{\theta}_H}\frac{1}{N} + \frac{1}{\hat{\eta}_H}(1 - \frac{1}{N})} \right]^{\frac{\sigma}{\sigma+\phi}}. \tag{A50}$$

Then the skill premium elasticity is decreasing, i.e., $\frac{\partial \kappa}{\partial N} / \left(\frac{\kappa}{N}\right) < 0$, iff $\left(1 + \frac{1}{\hat{\eta}_L}\right)\left(\frac{1}{\hat{\theta}_H} - \frac{1}{\hat{\eta}_H}\right) < \left(1 + \frac{1}{\hat{\eta}_H}\right)\left(\frac{1}{\hat{\theta}_L} - \frac{1}{\hat{\eta}_L}\right)$.

[54] An alternate way to solve for the aggregate Y^* would be to loop over guess $\widetilde{Y}$ until the goods market is in equilibrium.

Proof. From first order conditions, we know:

$$\begin{aligned}\kappa \equiv \kappa_{ij} &= \frac{A_{H,ij}^{\frac{\sigma-1}{\sigma}} H_{ij}^{-\frac{1}{\sigma}} \delta_{L,ij}}{A_{L,ij}^{\frac{\sigma-1}{\sigma}} L_{ij}^{-\frac{1}{\sigma}} \delta_{H,ij}}, \\ &= \left(\frac{A_H}{A_L}\right)^{\frac{\sigma-1}{\sigma}} \cdot \left[\frac{1+\frac{1}{\hat{\theta}_L} e_{L,nj} + \frac{1}{\hat{\eta}_L}(1-e_{L,nj})}{1+\frac{1}{\hat{\theta}_H} e_{H,nj} + \frac{1}{\hat{\eta}_H}(1-e_{H,nj})}\right] \cdot \left(\frac{H}{L}\right)^{-\frac{1}{\sigma}}, \\ &= \left(\frac{A_H}{A_L}\right)^{\frac{\sigma-1}{\sigma}} \cdot \left[\frac{1+\frac{1}{\hat{\theta}_L} e_{L,nj} + \frac{1}{\hat{\eta}_L}(1-e_{L,nj})}{1+\frac{1}{\hat{\theta}_H} e_{H,nj} + \frac{1}{\hat{\eta}_H}(1-e_{H,nj})}\right] \cdot \left(\frac{\bar{\phi}_L}{\bar{\phi}_H}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{W_L}{W_H}\right)^{\frac{\phi}{\sigma}}.\end{aligned}$$

By rearranging, we get the aforementioned expression.[55] Now we have following properties:

1. From equation (A50), when $N > 1$ it is clear that: $\partial\kappa/\partial\hat{\theta}_L < 0$, $\partial\kappa/\partial\hat{\eta}_L < 0$, $\partial\kappa/\partial\hat{\theta}_H > 0$ and $\partial\kappa/\partial\hat{\eta}_H > 0$. In addition it can be shown that $\partial\kappa/\partial A_H > 0$ and $\partial\kappa/\partial A_L < 0$.

2. With respect to the change in skill premium when changing N, we have:

$$\frac{\partial\kappa}{\partial N} / \left(\frac{\kappa}{N}\right) = \frac{\sigma}{\sigma+\phi} \frac{N\left[\left(1+\frac{1}{\hat{\eta}_L}\right)\left(\frac{1}{\hat{\theta}_H}-\frac{1}{\hat{\eta}_H}\right) - \left(1+\frac{1}{\hat{\eta}_H}\right)\left(\frac{1}{\hat{\theta}_L}-\frac{1}{\hat{\eta}_L}\right)\right]}{\left[N\left(1+\frac{1}{\hat{\eta}_H}\right)+\frac{1}{\hat{\theta}_H}-\frac{1}{\hat{\eta}_H}\right]\left[N\left(1+\frac{1}{\hat{\eta}_L}\right)+\frac{1}{\hat{\theta}_L}-\frac{1}{\hat{\eta}_L}\right]}.$$

   A sufficient condition for this term to be negative is:

$$\left(1+\frac{1}{\hat{\eta}_L}\right)\left(\frac{1}{\hat{\theta}_H}-\frac{1}{\hat{\eta}_H}\right) < \left(1+\frac{1}{\hat{\eta}_H}\right)\left(\frac{1}{\hat{\theta}_L}-\frac{1}{\hat{\eta}_L}\right).$$

   .

□

[55] We denote $\kappa = \frac{W_H}{W_L} = \frac{\mathcal{W}_H}{\mathcal{W}_L}$ and assume that $\phi_L = \phi_H = \phi$.

B Data Appendix

In this section, we discuss the steps we took in the creation and cleaning of our data. We first outline the broad overview of our data cleaning and construction. We discuss some of the quality and coverage issues we face with our data and provide some insight into the different decisions we made in constructing our data for the analysis. Then we discuss the mapping of our model to the data.

Longitudinal Business Database. The data we use to estimate our model combines establishment-level data from the Longitudinal Business Database (LBD) with characteristics of the workers at these establishments from Longitudinal Employer-Household Dynamics (LEHD) data. The frame of the LBD comes from the Census Business Register, which is populated from the quinquennial economic census and from administrative sources. LBD is an establishment level dataset containing information on payroll, employment, revenue, ownership structure, geography (MSA), and industry classification (NAICS). We consider the LBD to be the frame of our sample, and augment this frame with information on worker composition.

Longitudinal Employer-Household Dynamics. The Longitudinal Employer Household Dynamics (LEHD) data provides information on workers and firms in each state at quarterly frequency from unemployment insurance records. This data allows us to observe about 96% of workers and the identities of their employers (via tax identifiers) for a sample of 20 states, going back to 1997.[56] The LEHD infrastructure files include demographic information on workers from decennial censuses and the American Community Survey as well as administrative records, including age, sex, race and ethnicity, and education. We use the LEHD to construct measures of the education composition of each firm in our data.

[56]Our sample includes CA, CO, CT, ID, IL, KS, LA, ME, MD, MN, MO, MT, NJ, NM, NC, OR, RI, TX, WA, and WI.

B.1 Education

Skill definition. For our exercise, we use the LEHD to derive measures of the composition of skill types and wages within each firm. We label individuals with some college education or greater as "high-skill" and we label individuals with a high school diploma or less as "low-skill" workers. The concept of a firm in LEHD is the State Employer Identification Number (SEIN) under which a firm typically reports its employment and payroll for all of its employees at all establishments within the state.

Earnings. Since we observe only earnings rather than wages in our data and only at quarterly frequency, we limit our measurement of earnings and employment to full-quarter observations where for time t, we require the worker is also employed at the firm in quarters $t-1$ and $t+1$ so we know the job existed for the duration of the entire quarter. To further limit marginal employment and outlier observations, we drop any earnings from workers at the firm below an earnings threshold equivalent to 130 hours worked (averaging 10 hours/week) at the federal minimum wage for that quarter. We also truncate worker earnings at the 99th percentile and restrict our earnings observations to prime age workers, between the ages of 25 and 65.

We aggregate these employment and earnings observations at the firm level by high (and low) skill workers' share of employment, i.e. their skill ratio. Similarly, we measure the high (and low) skill workers' ratio of payroll per worker (skill premium) for each SEIN. Using the linkage of workers to employers in LEHD, we split the establishment-level payroll and employment in LBD by using the firm-level ratio of high to low-skill workers and payrolls we observed in LEHD. This provides us with our high and low-skill employment, H_{inj}, L_{inj} and wages (payroll per worker) W_{Hinj}, W_{Linj}.

Define the skill ratio of the firm in LEHD as $SR_{LEHD} = \frac{H_{LEHD}}{H_{LEHD}+L_{LEHD}}$ where H_{LEHD} and L_{LEHD} are full-quarter employment by skill type in LEHD. Then, skill-specific employment in LBD is $H_{inj} = SR_{LEHD}Emp_{LBD}$ and $L_{inj} = (1 - SR_{LEHD})Emp_{LBD}$. Similarly, define skill premium as $SP_{LEHD} = W_{H,LEHD}/W_{L,LEHD}$ where $W_{S,LEHD}$ is payroll per worker by skill type for full-quarter employment in each firm in LEHD. Using the definition of payroll as $Payroll_{LBD} = W_{Hinj}H_{inj} + W_{Linj}L_{inj}$ and the skill premium, the formula for the wage (payroll per worker) in our sample is

$$W_{Hinj} = \frac{Payroll_{LBD}}{H_{inj} + \frac{L_{inj}}{SP_{LEHD}}} \quad W_{Linj} = \frac{Payroll_{LBD}}{L_{inj} + (SP_{LEHD}H_{inj})}.$$

Given our formula for H_{inj} and L_{inj}, we can write W_{Sinj} in terms of our skill ratio, skill premium, employment, and payroll as

$$W_{Hinj} = \frac{Payroll_{LBD}}{SR_{LEHD}Emp_{LBD} + (1 - SR_{LEHD})Emp_{LBD}/SP_{LEHD}}$$
$$W_{Linj} = \frac{Payroll_{LBD}}{(1 - SR_{LEHD})Emp_{LBD} + (SP_{LEHD}SR_{LEHD}Emp_{LBD})}.$$

Coverage. While coverage of demographic information such as age and race is high in LEHD, the coverage of educational attainment data is lower than that of other individual characteristics. Education is available for workers in LEHD who were at least 25 years of age when surveyed in the 2000 decennial long form survey or the American Community Survey (ACS) and covers 27.6% of workers in our sample in 1997 and 16.9% in 2016. Because of the higher coverage of the 2000 decennial long form survey relative to ACS, education is observed for more workers in our sample in 1997 than in 2016. For workers without observed education, this value is imputed. The education imputation in LEHD is stationary, however, and poorly matches the time trends in educational attainment and skill premium observed in other datasets such as ACS and CPS. We would like to limit our use of education in LEHD to observed cases, however, this causes another issue of biasing our sample to only larger firms. To balance the representativeness of our establishment sample and also retain the trends in college attainment and skill premium in our sample, we use only observed data for any firm with at least one linked high-skill and low-skill worker with full-quarter earnings. For firms where we cannot observe at least one high-skill and one low-skill worker using observed education values, we use the imputed education values of the firm's full-quarter workers to get payroll and employment by skill level for the employer.

We merge the LBD to the LEHD by firm identifier, which provides each establishment within that firm with the same measure of skill ratio and payroll ratio from LEHD. For each establishment within the firm in a state, we split the LBD employment and payroll for that establishment by the skill ratio and payroll ratios we measured for the linked employer in LEHD. This approach preserves the establishment employment and payroll distribution within LBD. We show that our resulting measures using full-quarter earnings and employment, restricting our use of imputed education information, and applying the measures of skill ratio and payroll ratio to the LBD establishments gives us a sample which accurately reflects establishment counts and size as well as the trends in educational attainment and relative wages by skill.[57]

Matching trends and the size distribution. Table A1 shows the summary statistics of our baseline sample in comparison to our same sample construction if we used only observed worker information without any imputations, and our sample if we used all worker information including the observed and imputed worker education for all observations. We can see that using some imputed information maintains the coverage of our sample and the average establishment size, while restricting our use of imputed workers in large firms helps to preserve the skill composition and skill premium trends of the observed sample.

B.2 Revenues

Allocating firm revenue to the establishments. As outlined in Section 4, the last step in our estimation procedure requires us to estimate the market structure. To do so, we need aggregate moments of the distribution of establishment-level revenue and payroll. Of course, our measure of sales which we can link to LBD is a firm-level measure derived from administrative tax data. To get at an establishment distribution, we follow Tanaka et al. (2023) and impute the revenue to the establishment by using the establishment's share of payroll within its firm. While imputing revenue to the establishment based on

[57] Our estimated elasticities are qualitatively similar when we restrict to only using observed educational attainment. We have also established robustness of our elasticity estimates with different categorizations of skills.

Table A1: Sample Summary Statistics by Education Impute Usage

	Hybrid		**Observed**		**All Workers**	
	1997	**2016**	**1997**	**2016**	**1997**	**2016**
Total Employment	52.2	70.6	70.3	90.3	52.5	70.9
Skill Ratio	0.493	0.609	0.492	0.618	0.509	0.560
Skill Premium	1.52	1.73	1.52	1.77	1.45	1.46
$\mathcal{W}_H$	\$46,960	\$67,100	\$47,960	\$69,340	\$45,880	\$64,970
$\mathcal{W}_L$	\$30,980	\$38,690	\$31,590	\$39,290	\$31,630	\$44,560
Establishment Count	72,000	27,000	47,000	17,000	72,500	27,000

Notes: Hybrid refers to our sample methodology where imputed workers are only used in the absence of at least one observed high and low-skill worker. The skill ratio is the establishment-level mean of the share of employment with high skill (some college education or more), weighted by employment. Total Employment refers to the average establishment size in the sample. $\mathcal{W}_H$ and $\mathcal{W}_L$ denote the employment-weighted mean of establishment payroll per worker for high and low-skill workers, respectively. Note that the skill premium is slightly different from the data values in Table 6 as the samples in this table are constructed in the same manner as our estimation of labor supply elasticities, however it includes establishments with missing revenue information.

payroll shares is imperfect relative to a direct establishment-level measurement, we only use an aggregate moment for our market structure estimation.

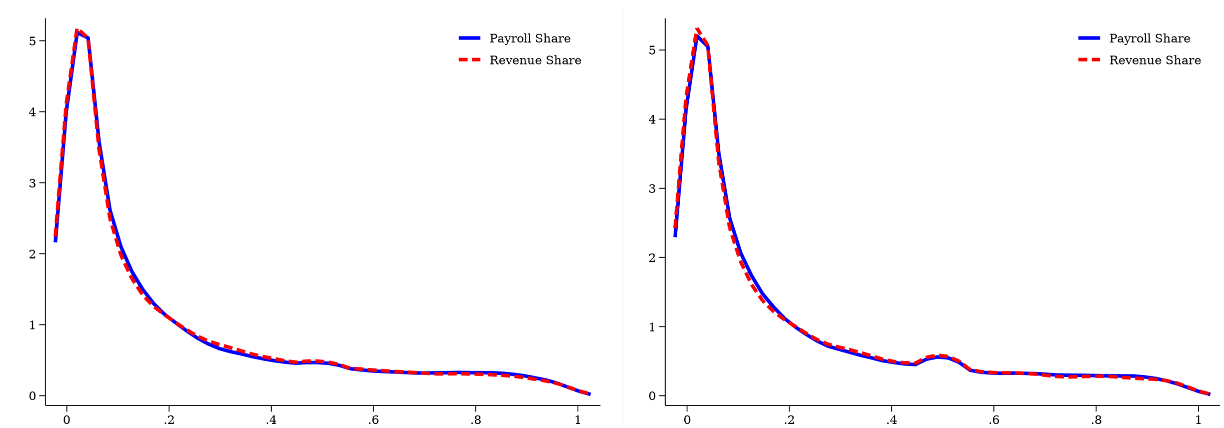
Validation using CMF. It is impossible to get the exact establishment-level distribution of revenues for all sectors in our dataset, but it is possible to assess our imputation method by making a comparison between our payroll-share imputed revenue and a direct measure of establishment sales for the manufacturing sector in Economic Census years. We take the Census of Manufactures for the years 1997 and 2017 and apply similar restrictions to the payroll and revenue variables for establishments in our sample (non-missing and strictly positive payroll and revenue, and truncation of revenue at the 99th percentile). To check the quality of our impute, we focus on the sample of establishments within multi -establishment firms, as these are the units which we impute based on our payroll share. Figure A1 shows that the establishment-level payroll and revenue share distribution is nearly identical.[58]

We can further assess the revenue impute by comparing the difference between the directly measured establishment-level revenue to our payroll-imputed revenue measure.

[58] We deflate revenue to 2002 dollars.

Figure A1: Payroll Shares and Revenue Shares of Establishments in Multi-unit Firms

(a) 1997 (b) 2017

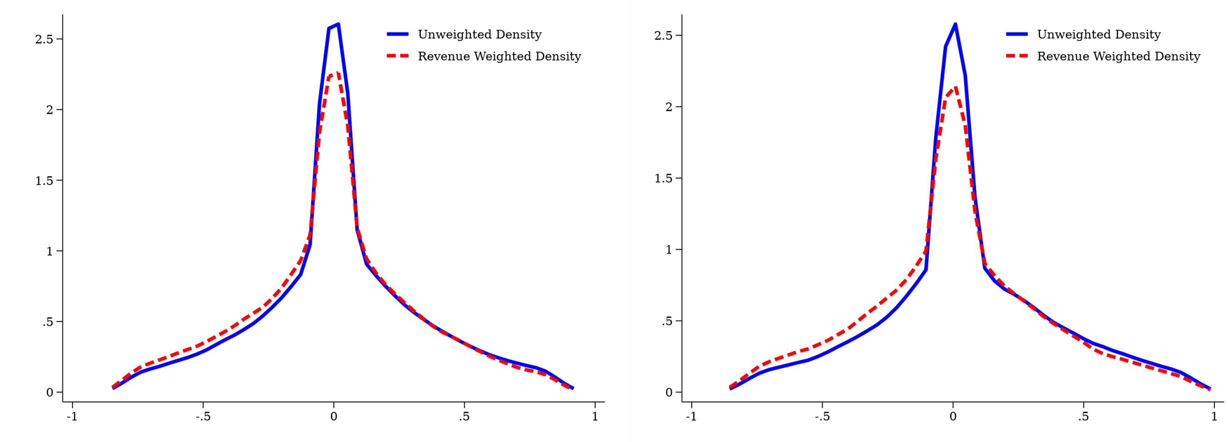


Notes: Kernel density plot of establishment payroll share and revenue share for establishments in multi-unit firms in CMF. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

In Figure A2, we plot the distribution of the difference in logged imputed revenue minus the observed log of establishment revenue. The distribution of errors is symmetric and centered at 0. Looking at the revenue-weighted difference relative to the unweighted difference, the weighted distribution has a thicker left tail, suggesting that the imputed revenue is lower than the observed revenue especially for high-revenue establishments. When we look at our moment of interest, the sales-weighted distribution of revenue over payroll, we see that the distribution of observed revenue over payroll has a fatter tail than the imputed measure.[59] However, this error does not seem to affect the trends in our measure over time. The change in the sales-weighted establishment-level mean of revenue over payroll from 1997 to 2017 is nearly identical when using our imputed measure or the direct establishment measure, as can be seen in the last row of Table A2.

[59] The heavier tail is not so obvious in the plotted distributions due to the truncation of the kernel densities at the 5th and 95th percentiles. However, the comparison of the weighted means in Table A2 are consistent with more skewed distribution for the observed vs. imputed measure.

Figure A2: Log Difference of Imputed Revenue - Observed Revenue

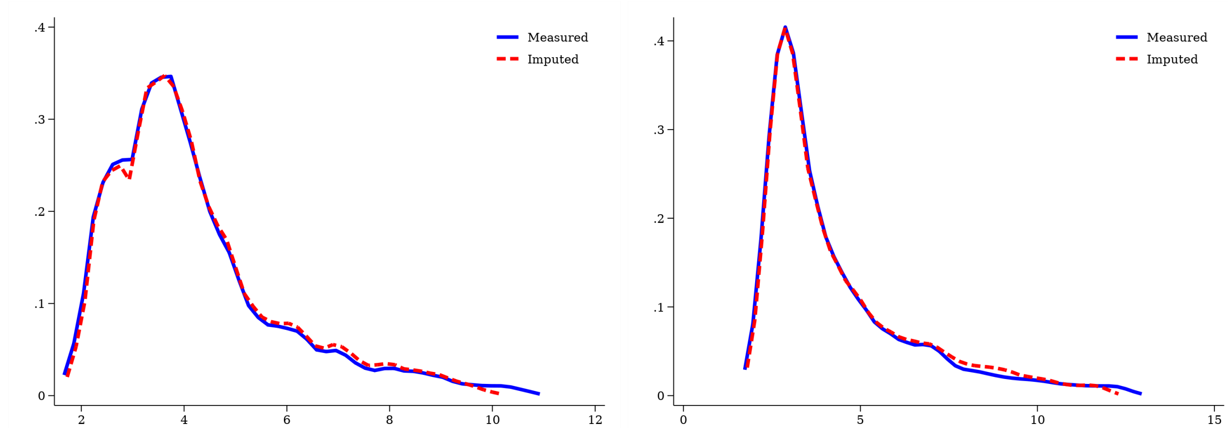


(a) 1997 (b) 2017

Notes: Distributions of log differences in the imputed revenue and observed revenue at the establishment level for multi-unit establishments in CMF. This figure plots the differences for multi-unit firms, as these are the establishments which require imputation. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

Figure A3: Distribution of Revenue over Payroll

(a) 1997 (b) 2017



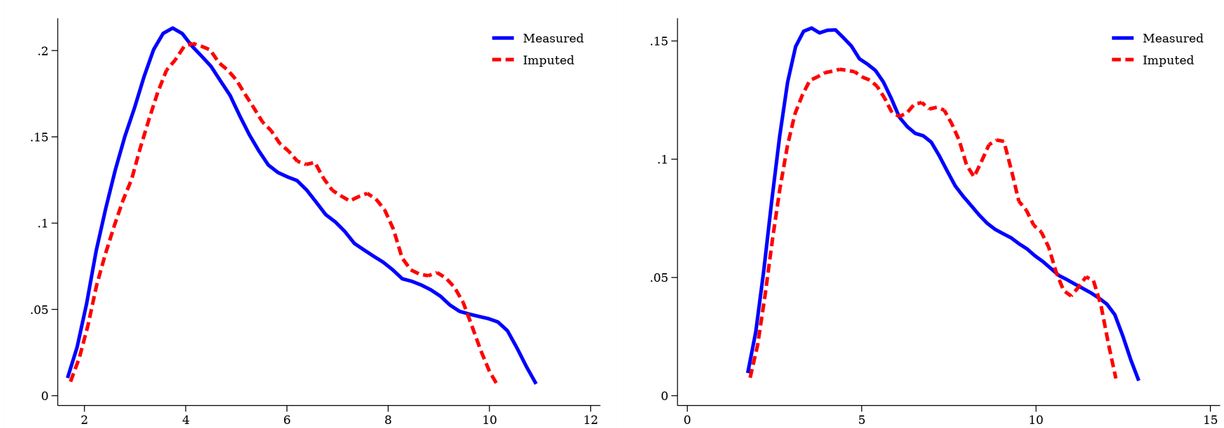
Notes: Unweighted distributions of revenue over payroll using imputed revenue and observed revenue at the establishment level for multi-unit establishments in CMF. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

B.3 Market definition

In order to estimate the model, we need to define a market. Our approach is to stochastically define markets and use the structure of our model to estimate the scope of our

Figure A4: Distribution of Revenue over Payroll (sales-weighted)

(a) 1997 (b) 2017



Notes: Revenue-weighted distributions of revenue over payroll using imputed revenue and observed revenue at the establishment level for multi-unit establishments in CMF. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

Table A2: Revenue over Payroll

	Revenue over Payroll						
	Measured	Imputed	Measured	Imputed			
	Mean	Mean	Wgt Mean	Wgt Mean	MU_N	SU_N	Estab. Count
1997	4.87	4.70	8.87	7.49	68,000	326,000	394,000
2017	5.27	5.13	12.39	11.04	59,000	233,000	292,000
Change	0.40	0.43	3.52	3.55			

Notes: The weighted mean in this table is weighted by observed establishment revenue. MU_N and SU_N are the rounded counts of establishments in multi-unit and single-unit firms, respectively. Imputations are only necessary for establishments within multi-unit firms.

markets. Practically, we start by defining a broad set of potential competitors as a NAICS 6 industry.[60] In order to define a market within each NAICS 6 industry, we first randomly assign establishments to markets of size I. Once we select those I establishments that form a market, thereafter we randomly establish the identity of the firms that compete, and how many firms N are active within a market by randomly assigning these I establishments into N subsets of size I/N. We drop the remainder of establishments in each industry that cannot be assigned to a full market of I establishments. In our exercise, we

[60] In Appendix D, we condition on geography and we define the broad set of competitors as those within NAICS 3 industry x MSA.

choose I to be 32.

Our baseline estimation uses NAICS 6 industry as the basis for our random market assignment to best match the features of the product market. Since our tax variation is at the state level, markets within a state will not have any variation in tax rates which makes it difficult for us to condition on geography. Therefore, we use Tradeables and narrowly defined national industries (NAICS 6) as our baseline.[61] We could alternatively choose to match on characteristics of the labor market, however we lack information such as occupation to satisfactorily define labor markets. Since our model assumes identical product and labor markets, our choice to match on product market characteristics implies that our labor markets are also national. In Appendix D, we perform robustness exercises where we eliminate random assignment of establishments to markets and where we segment our industries by geography (MSA) so that we are likely to be closer to the relevant boundary of the market for labor at the expense of the product market.

Ownership assignment. Note that we do not use the ownership structure of firms and establishments from the data in our exercise. This discards some useful information about changes in the distribution of establishments and firms. Firm growth, especially at the tail, is documented by Cao et al. (2020) to be largely driven by increases in the number of establishments a firm operates. However, we remain agnostic about the process of establishment birth, death, and consolidation. The primary reasons for our use of a stochastic ownership structure is that this allows a level of symmetry which is useful in our counterfactual analysis.

B.4 Summary of Data Cleaning

We have two samples which we use in our estimation process. For our backing out of technology and estimation of the market structure, we use cross-sections of establishments for the years 1997 and 2016. For this sample, we assign establishments to markets (and firms) stochastically as described above. We also require revenue information so we restrict the sample to establishments with non-missing revenue and truncate revenue at

[61] Using Tradeables also helps our results to be comparable to Berger et al. (2022).

the 99th percentile.

For our estimation of labor supply elasticities, we use a panel of establishments from 1997-2011 as we have state-level corporate tax rates through 2011 from Giroud and Rauh (2019). In order to stochastically assign establishments to markets and retain a panel structure, we first randomly assign establishments to markets, conditional on NAICS 6, in 1997 such that there are at most 32 establishments in each market. Once assigned to a market, the establishment always remains in that market as long as we observe it in the data. For every subsequent year starting from 1997, we again randomly assign the establishment unobserved previously (i.e., the new entrants) to one of the existing markets created in 1997. As a result, the size and the composition of the markets evolve randomly over time given the entry and exit of establishments from markets. Our baseline elasticity estimates are based on this sample. Since we want to estimate labor supply elasticities using the entire wage and earnings distribution, we do not restrict the sample based on revenue as we do when estimating market structure.

Our final data cleaning steps are common to both samples. Our sample is the subset of our LBD sample of establishments where the firm links to at least one SEIN in our 20 state LEHD sample. We drop firms in LBD where they account for less than 5 percent of the employment when measured at the linked firm in LEHD to drop some outlier firms in our linkage. We drop establishments with missing county. We keep only establishments of C-corporation firms for our tax instrument in the elasticity estimation. We use establishments in tradeable sectors (11, 21, 31, 32, 33, and 55) as defined in Delgado et al. (2014). We drop establishments with five or fewer total employees, and for which we do not have at least one high and one low-skill employee and positive payroll for each skill type. We winsorize establishment employment and average high and low-skill payroll per worker, W_{Hinj}, W_{Linj}, at the 1st and 99th percentile.

C Identification

C.1 Derivation of equation (21)

To derive equation (21) in the main text, we proceed as follows. We start from the labor supply equation (re-written below for convenience)

$$\ln W^*_{Sinjt} = k_{jt} \; + \; (\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}) \ln S_{jt} \; + \; \frac{1}{\hat{\eta}_S} \ln S_{injt} \; + \; \varepsilon_{Sinjt}$$

where $\ln W^*_{Sinjt} = \ln W_{Sinjt} + \varepsilon_{Sinjt}$ and $k_{jt} = \ln J_t^{\frac{1}{\hat{\theta}_S}} I_{jt}^{\frac{1}{\hat{\eta}_S}} S_t^{-\frac{1}{\hat{\theta}_S}} W_t$.

We construct sector-time average of the labor supply function to remove the sector-time fixed terms from the labor supply equation.

$$\overline{\ln W}^*_{Sjt} = k_{jt} \; + \; \left(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}\right) \ln S_{jt} \; + \; \frac{1}{\hat{\eta}_S} \overline{\ln S}_{jt} \; + \; \bar{\varepsilon}_{Sjt}$$

where $\overline{\ln W}^*_{Sjt} = \frac{1}{I_j} \sum_{i \in j} \ln W^*_{Sinjt}$, $\overline{\ln S}_{jt} = \frac{1}{I_j} \sum_{i \in j} \ln S_{injt}$ and $\bar{\varepsilon}_{Sjt} = \frac{1}{I_j} \sum_{i \in j} \varepsilon_{injt}$.
Getting rid of sector-time components from the labor supply equation we get

$$\ln W^*_{Sinjt} - \overline{\ln W}^*_{Sjt} = \frac{1}{\hat{\eta}_S} (\ln S_{injt} - \overline{\ln S}_{jt}) \; + \; (\varepsilon_{Sinjt} - \bar{\varepsilon}_{Sjt})$$

Finally, we rely on the following moment conditions implied by Assumption 3 to get our equation of interest for $\hat{\eta}_S$:

$$0 = \mathbb{E}[(\varepsilon_{Sinjt} - \bar{\varepsilon}_{Sjt}) \times \tau_{X(i)t}] = \mathbb{E}\left[\left\{ \left(\ln W^*_{Sinjt} - \overline{\ln W}^*_{Sjt}\right) - \frac{1}{\hat{\eta}_S}(\ln S_{injt} - \overline{\ln S}_{jt}) \right\} \times \tau_{X(i)t}\right]$$

$$\mathbb{E}\left[\left(\ln W^*_{Sinjt} - \overline{\ln W}^*_{Sjt}\right) \times \tau_{X(i)t}\right] = \frac{1}{\hat{\eta}_S} \mathbb{E}\left[(\ln S_{injt} - \overline{\ln S}_{jt}) \times \tau_{X(i)t}\right]$$

$$\hat{\eta}_S = \frac{\mathbb{E}(\widetilde{S}_{injt} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{W^*}_{Sinjt} \times \tau_{X(i)t})}$$

where $\widetilde{S}_{injt} = \ln S_{injt} - \overline{\ln S}_{jt}$ and $\widetilde{W^*}_{Sinjt} = \ln W^*_{Sinjt} - \overline{\ln W}^*_{Sjt}$.

In order to derive the expression for $\hat{\theta}_S$ in equation (21), we proceed as follows.

Equipped with the estimate of $\hat{\eta}_S$, we re-write the labor supply function as follows

$$\ln W^*_{Sinjt} \;-\; \frac{1}{\hat{\eta}_S} \ln S_{injt} \equiv \Omega_{Sinjt} = k_{jt} \;+\; (\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}) \ln S_{jt} \;+\; \varepsilon_{Sinjt}$$

Taking sector-time average on both sides, we get

$$\overline{\Omega}_{Sjt} = k_j \;+\; k_t \;+\; (\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}) \ln S_{jt} \;+\; \nu_{jt} \;+\; \bar{\varepsilon}_{Sjt}$$

where $k_{jt} = k_j + k_t + \nu_{jt}$ and $\overline{\Omega}_{Sjt} = \frac{1}{I_j} \sum_{i \in j} \Omega_{Sinjt}$.

Using the following moment implied by Assumption 3, we can calculate our expression of interest for $\hat{\theta}_S$

$$\mathbb{E}(\bar{\varepsilon}_{Sjt} \times \bar{\tau}_{jt}) = \mathbb{E}\big[\big(\overline{\Omega}_{Sjt} - k_{jt} \;-\; (\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}) \ln S_{jt}\big) \times \bar{\tau}_{jt}\big] = 0$$

$$\mathbb{E}\big[\big(\overline{\Omega}_{Sjt} - k_{jt}\big) \times \bar{\tau}_{jt}\big] = \mathbb{E}\big[\big(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S}\big) \ln S_{jt} \times \bar{\tau}_{jt}\big]$$

$$\hat{\theta}_S = \left[\frac{\mathbb{E}(\{\overline{\Omega}_{Sjt} - k_{jt}\} \times \bar{\tau}_{jt})}{\mathbb{E}(\ln S_{jt} \times \bar{\tau}_{jt})} + \frac{\mathbb{E}(\widetilde{W^*}_{Sinj} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{S}_{inj} \times \tau_{X(i)t})}\right]^{-1}$$

$$\hat{\theta}_S = \left[\frac{\mathbb{E}(\{\overline{\Omega}_{Sjt} - (k_j + k_t + v_{jt})\} \times \bar{\tau}_{jt})}{\mathbb{E}(\ln S_{jt} \times \bar{\tau}_{jt})} + \frac{\mathbb{E}(\widetilde{W^*}_{Sinj} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{S}_{inj} \times \tau_{X(i)t})}\right]^{-1}$$

$$\hat{\theta}_S = \left[\frac{\mathbb{E}(\{\overline{\Omega}_{Sjt} - (k_j + k_t)\} \times \bar{\tau}_{jt})}{\mathbb{E}(\ln S_{jt} \times \bar{\tau}_{jt})} + \frac{\mathbb{E}(\widetilde{W^*}_{Sinj} \times \tau_{X(i)t})}{\mathbb{E}(\widetilde{S}_{inj} \times \tau_{X(i)t})}\right]^{-1}$$

where $\bar{\tau}_{jt} = \frac{1}{I_j} \sum_{i \in j} \tau_{X(i)t}$. To go from line 3 to 4, we rely on the fact that $k_{jt} = k_j + k_t + \nu_{jt}$. Finally, to go from line 4 to 5, we rely on Assumption 3 outlined in the main text which implies $\mathbb{E}(\nu_{jt} \times \bar{\tau}_{jt}) = 0$.

C.2 Identification without Endogeneity

In this section we show that, under the assumption that the error term is *uncorrelated* with employment, we can identify $\hat{\eta}_S$ and $\hat{\theta}_S$ using the following moments.

$$\hat{\eta}_S = \left(\frac{\mathbb{C}ov(\widetilde{S}_{inj},\ \widetilde{W^*}_{Sinj})}{\mathbb{V}ar(\widetilde{S}_{inj})} \right)^{-1} \tag{A51}$$

$$\hat{\theta}_S = \left[\left(\frac{\mathbb{C}ov(\ln S_j,\ \overline{\Omega}_{Sj})}{\mathbb{V}ar(\ln S_j)} \right) + \left(\frac{\mathbb{C}ov(\widetilde{S}_{inj},\ \widetilde{W^*}_{Sinj})}{\mathbb{V}ar(\widetilde{S}_{inj})} \right) \right]^{-1} \tag{A52}$$

where we denote

$$\widetilde{S}_{inj} = \ln S_{inj} - \overline{\ln S_j}, \qquad \widetilde{W^*}_{Sinj} = \ln W^*_{Sinj} - \overline{\ln W^*_{Sj}}, \qquad \overline{\ln X_j} = \frac{1}{I} \sum_{i \in j} \ln X_{inj}$$

$$\Omega_{Sinj} = \ln W^*_{Sinj} - \frac{1}{\hat{\eta}_S} \ln S_{inj}, \qquad \overline{\Omega}_{Sj} = \frac{1}{I} \sum_{i \in j} \Omega_{Sinj}.$$

The moment condition in equation (A51) is equivalent to regressing the difference of log employment from the mean of market level log-employment on difference of log wages from the mean of market log wages. The moment condition in equation (A52) is equivalent to regressing the market level employment CES index on average market level wages (after removing the effect of average sectoral employment). Given that the sectoral CES index is a function of $\hat{\eta}_S$, we need to construct moments in equation (A51) and equation (A52) sequentially, starting with first retrieving the estimate of $\hat{\eta}_S$.

Deriving the moment conditions. To derive the moment conditions in equation (A51) and equation (A52), start by differencing out the market-specific mean wages and mean employment from equation (20) to get the following expression:

$$\ln W^*_{Sinj} - \overline{\ln W^*_{Sj}} = \frac{1}{\hat{\eta}_S} (\ln S_{inj} - \overline{\ln S_j}) + (\varepsilon_{Sinj} - \overline{\varepsilon}_{Sj}) \tag{A53}$$

An OLS regression of equation (A53) helps us retrieve $\hat{\eta}_S$ and equation (A51) specifies the moments that helps us pin it down. Equipped with the estimate of $\hat{\eta}_S$, we can construct S_j, the CES index of market-level employment. In the second step, we can then estimate the between-market substitution parameter $\hat{\theta}_S$ by relying on equation (20) and subtracting $\frac{1}{\hat{\eta}_S} \ln S_{inj}$ from $\ln W^*_{Sinj}$.

$$\ln W^*_{Sinj} - \frac{1}{\hat{\eta}_S} \ln S_{inj} \equiv \Omega_{Sinj} = k + \left(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S} \right) \ln S_j + \varepsilon_{Sinj} \tag{A54}$$

where $k = \ln J^{\frac{1}{\hat{\theta}_S}} I^{\frac{1}{\hat{\eta}_S}} S^{-\frac{1}{\hat{\theta}_S}} W$.

To construct the moment in equation (A52), take market-specific averages of both sides on equation (A54) and regress $\ln S_j$ on $\overline{\Omega}_{Sj}$ to retrieve the estimate of θ.

$$\overline{\Omega}_{Sj} = k + \left(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S} \right) \ln S_j + \bar{\varepsilon}_{Sj} \tag{A55}$$

C.2.1 Monte Carlo Simulation

To see if our proposed estimator is able to recover the true structural parameters, we perform the following Monte Carlo simulation. First, we simulate the labor supply equation as follows:[62]

$$\ln W^*_{Sinj} = k \; + \; \underbrace{\left(\frac{1}{\hat{\theta}_S} - \frac{1}{\hat{\eta}_S} \right)}_{\gamma_S} \ln S^*_j \; + \; \underbrace{\frac{1}{\hat{\eta}_S}}_{\beta_S} \ln S^*_{inj} \; + \; \underbrace{\epsilon^W_{inj} \; + \; \epsilon^S_{inj}}_{\epsilon_{inj}} \tag{A56}$$

$$\ln W^*_{Sinj} = \ln W_{Sinj} + \epsilon^W_{inj}$$

$$\ln W_{Sinj} = k \; + \; \gamma_S \ln S_j \; + \; \beta_S \ln S_{inj}, \quad \ln S_{inj} \sim \mathbb{N}(0,1), \quad S_j = \left(\sum_i I^{\frac{1}{\hat{\eta}_S}} S_{inj}^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}} \right)^{\frac{\hat{\eta}_S}{\hat{\eta}_S+1}}$$

$$\ln S^*_{inj} = \ln S_{inj} + \rho \times \epsilon^S_{inj}, \quad S^*_j = \left(\sum_i I^{\frac{1}{\hat{\eta}_S}} (S^*_{inj})^{\frac{\hat{\eta}_S+1}{\hat{\eta}_S}} \right)^{\frac{\hat{\eta}_S}{\hat{\eta}_S+1}}$$

$$\epsilon^S_{inj} \sim \mathbb{N}(0,1), \;\; \epsilon^W_{inj} \sim \mathbb{N}(0,1)$$

where ϵ^W_{inj} denotes the measurement error in wages and ϵ^S_{inj} denotes the measurement error in employment if $\rho \neq 0$. We assume that ϵ^W_{inj} and ϵ^S_{inj} are independent. Finally, we

[62]We simulate only a cross-section and assume that each market has I establishments. We omit the time notation as we work with a cross-section.

Table A3: Monte Carlo Simulation

		$\hat{\eta}_S$	$\hat{\theta}_S$	$\bar{\phi}_S$
True Value		3.00	1.50	10.00
$\rho = 0$	Mean	3.00	1.50	10.00
	Std. Dev	0.07	0.07	0.11
$\rho = 0.5$	Mean	3.75	2.02	16.80
	Std. Dev	0.10	0.12	0.70
$\rho = 1.5$	Mean	9.78	6.80	968.56
	Std. Dev	0.44	0.72	205.37

Notes: In simulation, we assumed that $J = 500$ and $I = 32$ and ran 1000 trials for each value of ρ.

also assume that $\ln S_{inj}$ is independent of ϵ_{inj}^{W}.

Given this data generating process, we first verify that the estimator is able to recover the true structural parameters if $\rho = 0$. This implies that there is a zero correlation between ϵ_{inj} and $\ln S_{inj}$. The results of this exercise are provided in Table A3. We find that under this assumption OLS can retrieve the true structural parameters $\hat{\eta}_S$ and $\hat{\theta}_S$ using cross-sectional data on employment and wages as outlined in equation (A53) and equation (A55).

In order to understand the role of endogeneity bias, we perform additional simulations where we assume that $\rho \neq 0$. This implies that $\ln S_{inj}$ is correlated with ϵ_{inj} in equation (A56). In practise, we pick $\rho \in \{0.5, 1.5\}$. As before, we try to recover the estimates of $\hat{\eta}_S, \hat{\theta}_S$ and $\bar{\phi}_S$ using OLS. The results of this exercise are also presented in Table A3. We find that as ρ deviates from 0, it leads to an upward bias in the estimates of $\hat{\eta}_S, \hat{\theta}_S$ and $\bar{\phi}_S$, with the bias increasing as ρ increases.

D Robustness of the estimates of labor substitutability parameters

This Appendix presents two cases where we deviate from our baseline estimates in which we randomly assigned establishments to markets within NAICS 6. The main aim is to eliminate the influence of the random assignment of establishments into markets and explore the robustness of our estimates to potential misspecification of the labor market definition. Under each scenario in the robustness, the market size is allowed to vary based on the total number of establishments within each market and is entirely determined by the fixed market definition and the underlying microdata.

In Table A4, the results of the parameters for labor substitutability are presented when establishments are no longer randomly assigned to markets and when product and labor markets are defined as NAICS 6. In Table A5, the results of labor substitutability are shown when we redefine our product and labor markets to be NAICS 3 x MSA and did not randomly assign establishments to markets.

In Table A4, the estimates of the $\hat{\eta}_H$ and $\hat{\eta}_L$ are 2.70 and 2.50 respectively, as compared to our baseline values of 2.53 and 2.42. On the other hand, the estimates of $\hat{\theta}_H$ and $\hat{\theta}_L$ are 1.93 and 1.87, respectively, as compared to 2.02 and 1.85. These estimates are statistically significant at 1% when we cluster the standard errors at the state level.

In Table A5, we find the value of the substitutability parameters for both high and low-skilled workers increases (relative to the benchmark) and the difference between $\hat{\eta}_S - \hat{\theta}_S$ widens. For instance, the estimates of $\hat{\eta}_H$ and $\hat{\eta}_L$ are 5.40 and 6.41, respectively and that of $\hat{\theta}_H$ and $\hat{\theta}_L$ are 2.92 and 3.43. However, we find that the second stage estimates of $\beta_S = 1/\hat{\eta}_S$ is no longer statistically significant when we cluster at the state level.[63] In conclusion, we find that the baseline results are robust if the random assignment of establishments to markets is eliminated and the market is defined as NAICS 6. However, the estimate of $\hat{\eta}_S$ loses statistical significance if the market is defined as NAICS 3 x MSA.

[63] The only difference with regard to the baseline specification is that we do not include establishment fixed-effects in our regression. When we include the establishment fixed effect, we find that the estimates of labor substitutability parameters are theory inconsistent.

Table A4: Estimates of Labor Substitutability Parameters: NAICS-6, Tradeables, without Random Sampling

A. OLS and Second-Stage IV Estimates					
	OLS	IV		OLS	IV
	(1)	(2)		(3)	(4)
β_H	-0.177***	0.371***	γ_H	0.146***	0.148***
SE	0.0007	0.057	SE	0.0002	0.001
State level SE	(0.002)	(0.113)	Market SE	(0.023)	(0.043)
β_L	-0.108***	0.399***	γ_L	0.123***	0.136***
SE	0.0007	0.051	SE	0.0002	0.001
State level SE	(0.003)	(0.097)	Market SE	(0.025)	(0.041)
Market x Year FE	Yes	Yes	Market FE	Yes	Yes
Establishment FE	Yes	Yes	Year FE	Yes	Yes
B. Structural Parameters					
$\hat{\eta}_H$	-5.64	2.70	$\hat{\theta}_H$	-31.37	1.93
$\hat{\eta}_L$	-9.30	2.50	$\hat{\theta}_L$	64.2	1.87
C. First-stage Regressions for the IV					
$\tau^H_{X(i)t}$	-	-0.013***	$\bar{\tau}^H_{jt}$	-	-0.015***
SE		0.0008	SE		0.0009
State level SE		(0.004)	Market SE		(0.001)
$\tau^L_{X(i)t}$	-	-0.015***	$\bar{\tau}^L_{jt}$	-	-0.276***
SE		0.0009	SE		0.0008
State level SE		(0.006)	Market SE		(0.059)
Market x Year FE	-	Yes	Market FE	-	Yes
Establishment FE	-	Yes	Year FE	-	Yes
No. of obs (High-Skilled)	1,166,000	1,166,000		5900	5900
No. of obs (Low-Skilled)	1,166,000	1,166,000		5900	5900

Notes: *** p < 0.01, ** p<0.05, *p<0.1. Non-clustered standard errors are reported without parenthesis while clustered standard errors are reported with parenthesis. The significance stars correspond to clustered standard errors. Estimates of γ_S in columns 3 and 4 are conditional on the estimates of columns 1 and 2, respectively. Number of observations are common for both the first and the second-stage. The number of observations reflects rounding for disclosure avoidance. $\tau^S_{X(i)t}$ denotes the co-efficient infront of taxes in the first-stage regression for the estimate of β_S. The same instrument is used separately, first to estimate β_H and then to estimate β_L.

Table A5: Estimates of Labor Substitutability Parameters: NAICS 3 x MSA, without Random Sampling

A. OLS and Second-Stage IV Estimates					
	OLS	IV		OLS	IV
	(1)	(2)		(3)	(4)
β_H	0.079***	0.185	γ_H	0.063***	0.157***
SE	0.0006	0.063	SE	0.0004	0.002
State level SE	(0.003)	(0.189)	Market SE	(0.013)	(0.044)
β_L	0.029***	0.156	γ_L	0.080***	0.136***
SE	0.0007	0.086	SE	0.0004	0.001
State level SE	(0.005)	(0.310)	Market SE	(0.013)	(0.044)
Market x Year FE	Yes	Yes	Market FE	Yes	Yes
Establishment FE	Yes	Yes	Year FE	Yes	Yes
B. Structural Parameters					
$\hat{\eta}_H$	12.62	5.40	$\hat{\theta}_H$	7.05	2.92
$\hat{\eta}_L$	34.98	6.41	$\hat{\theta}_L$	9.23	3.43
C. First-stage Regressions for the IV					
$\tau^H_{X(i)t}$	-	0.031***	$\bar{\tau}^H_{jt}$	-	-0.110***
SE		0.004	SE		0.0005
State level SE		(0.008)	Market SE		(0.022)
$\tau^L_{X(i)t}$	-	0.024**	$\bar{\tau}^L_{jt}$	-	-0.127***
SE		0.004	SE		0.0005
State level SE		(0.011)	Market SE		(0.023)
Market x Year FE	-	Yes	Market FE	-	Yes
Establishment FE	-	Yes	Year FE	-	Yes
No. of obs (High-Skilled)	497,000	497,000		5800	5800
No. of obs (Low-Skilled)	497,000	497,000		5800	5800

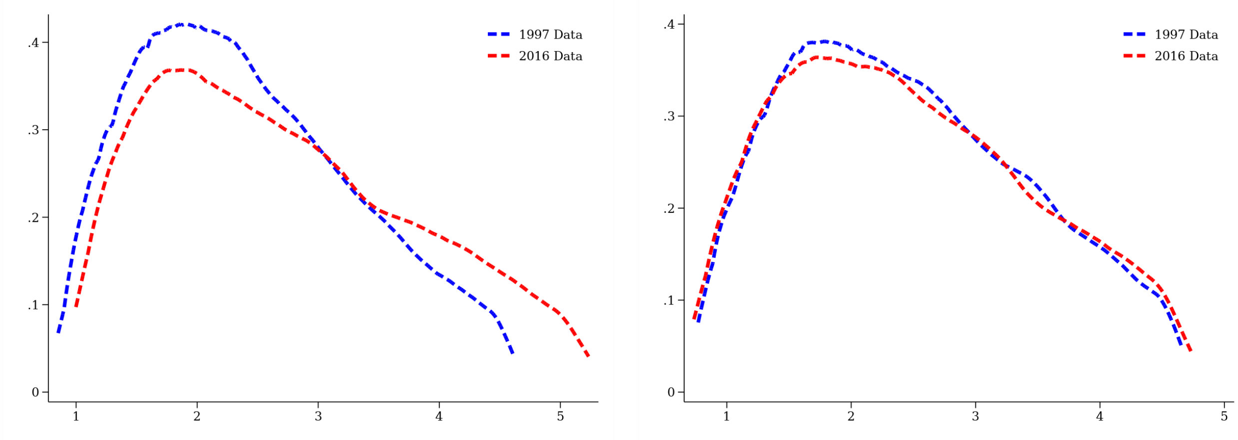
Notes: *** $p < 0.01$, ** $p<0.05$, *$p<0.1$. Non-clustered standard errors are reported without parenthesis while clustered standard errors are reported with parenthesis. The significance stars correspond to clustered standard errors. Estimates of γ_S in columns 3 and 4 are conditional on the estimates of columns 1 and 2, respectively. Number of observations are common for both the first and the second-stage. The number of observations reflects rounding for disclosure avoidance. $\tau^S_{X(i)t}$ denotes the co-efficient infront of taxes in the first-stage regression for the estimate of β_S. The same instrument is used separately, first to estimate β_H and then to estimate β_L.

E Additional Results

E.1 Distributions

Figure A5 plots the distributions of log employment by skill level, $\ln H_{inj}$ and $\ln L_{inj}$. The employment distribution increases in variance, especially for high-skill workers. Fig-

Figure A5: Distribution of Employment by Skill



(a) PDF of $\ln H_{inj}$ (b) PDF of $\ln L_{inj}$

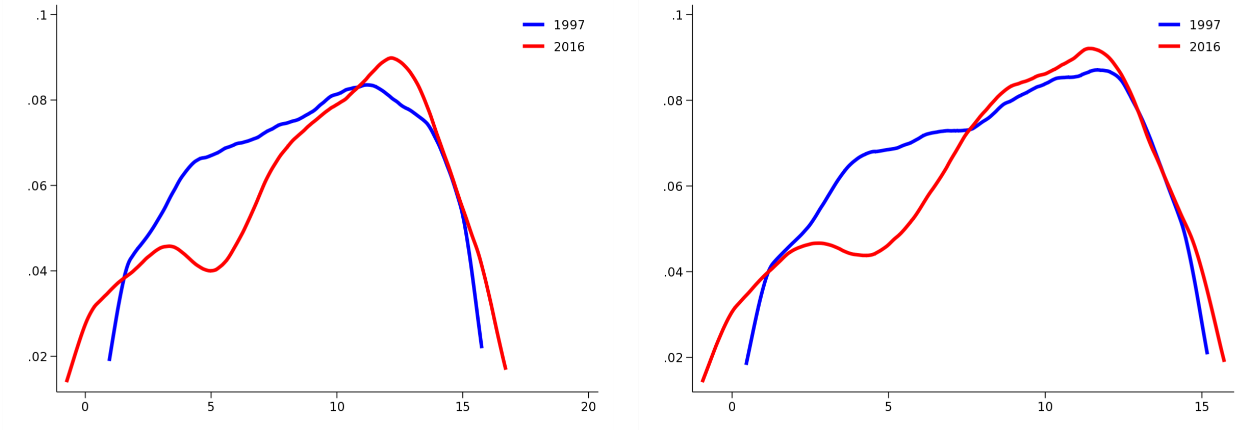
Notes: Panels (a) and (b) show the probability density function of productivities of $\ln A_{Hinj}$ and A_{Linj}, respectively, for 1997 and 2016. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

ure A6 plots the distributions of log technology by skill level, $\ln A_{Hinj}$ and $\ln A_{Linj}$. It is worthwhile to note that while employment is the primary source of establishment-level heterogeneity in the model inputs, the distribution of technology reflects the model structure, key parameters such as N and elasticities, as well as the market assignment.

Figure A7 shows that our estimated model matches the establishment-level distribution of skill premium remarkably well. Not only do we replicate the change in skill premium, but our model generates the substantial heterogeneity in the establishment-level skill premia we observe in the data.

Figure A8 plots the unweighted establishment-level distributions of the markup and skill-specific markdowns from our estimated model. Note that we observe a shift in all three distributions from 1997 to 2016. While we observe an increase in variance for both markdowns and markups, the upper bound for markdowns moves relatively little compared to the upper bound for markups. There is a much larger increase in the variance of markups over time.

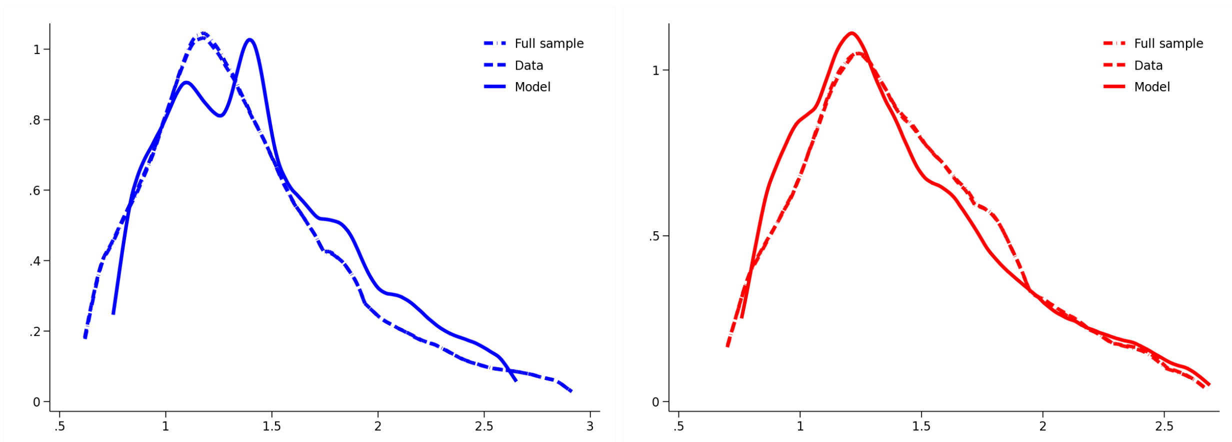
Figure A6: Estimated Distribution of Skill-Specific Technology



(a) PDF of $\ln A_{Hinj}$ (b) PDF of $\ln A_{Linj}$

Notes: Panels (a) and (b) show the probability density function of productivities of $\ln A_{Hinj}$ and $\ln A_{Linj}$, respectively, for 1997 and 2016. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

Figure A7: Distribution of Skill Premium

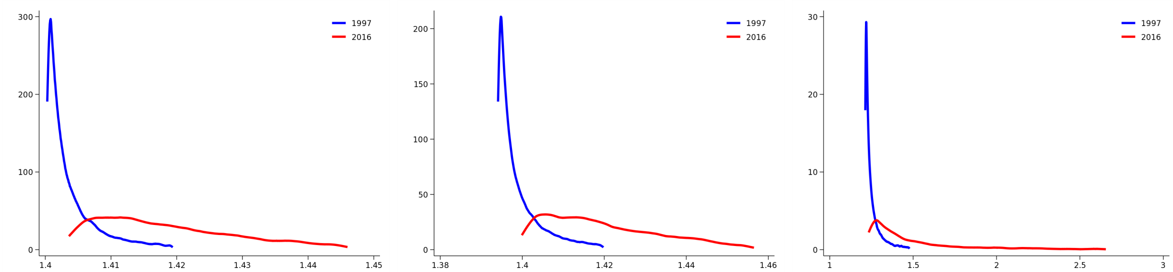


(a) 1997 (b) 2016

Notes: Full sample corresponds to the set of establishments in the data where we observe high and low-skill wage. Data refers to the subset of full sample after the assignment of establishments to markets of size I. Model corresponds to the model-predicted skill premium for the same set of establishments in the Data sample. Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

Figure A8: Estimated Markup and Markdown distribution

(a) Distribution of δ_{Hinj} (b) Distribution of δ_{Linj} (c) Distribution of μ_{inj}



Notes: Variables are truncated at the 5th and 95th percentiles before plotting kernel densities.

E.2 Decomposing estimated productivity

In Table 4, we decomposed the total variance in $\ln A_{Linj}$ and $\ln A_{Hinj}$ into within and between NAICS 6 industries. To do so, we denote industry as $k \in \{1, \ldots, K\}$, the total number of establishment in a given industry k as $\tilde{I}_k$ and the total number of establishments in the economy as $\tilde{I} = \sum_{k=1}^{K} \tilde{I}_k$. Additionally, we denote $\ln A_{Sik} = a_{Sik},\ S \in \{H, L\}$. We can then decompose the $\mathbb{V}ar(a_{Sik})$ as follows:

$$\mathbb{V}ar(a_{ik}) = \underbrace{\frac{1}{\tilde{I}} \sum_{i=1}^{\tilde{I}} (a_{ik} - \bar{a}_k)^2}_{\text{Within NAICS 6}} + \underbrace{\frac{1}{\tilde{I}} \sum_{k=1}^{K} \tilde{I}_k (\bar{a}_k - \bar{a})^2}_{\text{Between NAICS 6}}$$

F Additional Tables pertaining to Randomization

In order to deepen our understanding of the influence of randomness in our main findings presented in Tables 7 and 8, we present additional evidence in this Appendix. As highlighted in the main text, to conduct counterfactual simulations, we randomized establishment assignments to firms a total of 41 times. For each counterfactual scenario, we provide estimates of the 5th and 95th percentiles in Tables A6 and A7 to capture the range of possible outcomes.

Table A6: Confidence Intervals for Counterfactual Results of Table 7

	Level (1)	5th Percentile (2)	95th Percentile (3)
N	1.480	1.475	1.482
A_{Hinj}, A_{Linj}	1.934	1.931	1.940
$\bar{\phi}_H, \bar{\phi}_L$	1.242	1.241	1.243
A_{Hinj}, A_{Linj} and N	1.956	1.942	1.959
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	1.631	1.628	1.635
N and $\bar{\phi}_H, \bar{\phi}_L$	1.255	1.250	1.256

Notes: Column 1 denotes the level of the skill premium for each of the counterfactuals presented in Table 7. These values correspond to the seed that produces the median change in the total variance of wage inequality in Table 8. Columns 2 and 3 provide the estimates of the 5th and the 95th percentiles for each of the counterfactuals we performed.

Table A7: Confidence Intervals for Counterfactual Results of Table 8

	Level	5th Pctile	95th Pctile
	(1)	(2)	(3)
	Total		
N	0.329	0.327	0.330
A_{Hinj}, A_{Linj}	0.400	0.401	0.403
$\bar{\phi}_H, \bar{\phi}_L$	0.293	0.293	0.294
A_{Hinj}, A_{Linj} and N	0.416	0.413	0.418
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	0.356	0.356	0.358
N and $\bar{\phi}_H, \bar{\phi}_L$	0.308	0.306	0.308
	Within		
N	0.048	0.048	0.048
A_{Hinj}, A_{Linj}	0.087	0.087	0.087
$\bar{\phi}_H, \bar{\phi}_L$	0.027	0.027	0.027
A_{Hinj}, A_{Linj} and N	0.089	0.088	0.089
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	0.050	0.050	0.050
N and $\bar{\phi}_H, \bar{\phi}_L$	0.028	0.028	0.028
	Between		
N	0.282	0.280	0.282
A_{Hinj}, A_{Linj}	0.313	0.314	0.315
$\bar{\phi}_H, \bar{\phi}_L$	0.266	0.266	0.267
A_{Hinj}, A_{Linj} and N	0.327	0.324	0.329
A_{Hinj}, A_{Linj} and $\bar{\phi}_H, \bar{\phi}_L$	0.306	0.306	0.308
N and $\bar{\phi}_H, \bar{\phi}_L$	0.280	0.278	0.281

Notes: Column 1 (titles Level) denotes the level of total, within or between-establishment wage inequality for each of the counterfactual presented in Table 8. These values correspond to the seed that produces the median change in the total variance of wage inequality in Table 8. Columns 2 and 3 provide the estimates of the 5th and the 95th percentiles over all seeds for each of the counterfactuals we performed.