Labor Market Power and Factor-Biased Technology Adoption

Michael Rubens[*]

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Abstract

Although monopsony power can induce deadweight loss, it can also incentivize technology adoption of employers by reducing hold-up. Using a structural model that features these two opposing forces, I quantify the net welfare effects of employer monopsony power in the late 19th century Illinois coal mining industry. I find that a one standard deviation increase in employer power would have increased the usage rate of mechanical coal cutters, a new technology, by 13%, thereby lowering marginal costs. However, output would still have decreased by 23%, meaning that the deadweight loss effect dominates the marginal cost reduction due to additional investment. Ignoring endogenous investment leads to overestimating the negative effects of monopsony power on consumer and total surplus by 7% and 17%, respectively.

Keywords: Monopsony, Buyer Power, Investment, Technological Change

JEL codes: L11, L13, J42, N51

1 Introduction

There is increasing empirical evidence for the existence of 'monopsony' or 'buyer power' across various industries, countries, and types of factor markets.[1] Prior research on the welfare consequences of 'classical' monopsony or oligopsony power, such as Berger et al. (2022) and Lamadon et al. (2022), has typically assumed firms' technology choices and investments to be exogenous to the degree of monopsony power. However, employers' investment decisions are endogenous if employers need some degree of monopsony power to recover the fixed costs incurred when investing in human and/or physical capital.

In this paper, I examine the welfare effects of monopsony power by disentangling these two opposing forces. On the one hand, monopsony power leads to deadweight loss because it makes employers cut back on input usage in order to push down input prices. On the other hand, monopsony power can incentivize the adoption of new productivity-enhancing technologies because it allows employers to appropriate more of the rents created by this technology adoption. This is a version of the classical hold-up problem of Williamson (1971). The net effect of monopsony power on equilibrium output, consumer surplus, and total welfare is ambiguous, as it depends on the relative magnitude of the deadweight loss and technology adoption channels. This trade-off between anti-competitive distortions and endogenous human capital investment plays an important role in various debates around labor market power, such as regulation of non-compete agreements (Starr, Prescott, & Bishara, 2021; Shi, 2023), and the role of buyer power in horizontal merger control (Hemphill & Rose, 2017; Loertscher & Marx, 2019)

I start the paper with a theoretical model of labor demand and supply that allows for both monopsony-induced deadweight loss and endogenous investment. Although the model is written in terms of employers and employees, it applies to vertical relationships between buyers and sellers more in general. The model features employers that face upward-sloping

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[1]See literature reviews by Ashenfelter et al. (2010) and Manning (2011), and recent papers by, among many others, Naidu et al. (2016); Berger et al. (2022); Morlacco (2017); Lamadon et al. (2022); Kroft et al. (2020); Rubens (2023); Chambolle et al. (2023).

labor supply curves and negotiate over wages with workers using a linear wage contract in a 'Nash-in-Nash' bargaining model (Horn & Wolinsky, 1988). The model collapses to the classical monopsony model, in which employers unilaterally post wages, if bargaining power lies fully on the employers' side. Employers combine different labor types to produce output using a constant elasticity of substitution (C.E.S.) production function, and choose between a menu of technologies. These technology decisions determine the employers' Hicks-neutral and factor-specific productivity levels, and are incurred at a fixed cost. Employers sell their output on product markets where they face a downward-sloping goods demand curve. Simulating this model, I find that the relationship between equilibrium output and employer power is monotonically decreasing when assuming exogenous technology usage, as only the deadweight loss mechanism is at play. However, when allowing for endogenous technology adoption, the output-employer power relationship becomes an inverted U-shape, as the deadweight loss and endogenous investment mechanisms counteract each other. The output-maximizing bargaining weight depends on the relative size of the curvature of the labor supply curve and of the productivity effects of the technology.

Given that the equilibrium effect of employer power on output is ambiguous, I carry out an empirical application to quantify the relative importance of the deadweight loss and endogenous investment mechanisms. I study how the mechanization of the Illinois coal mining industry between 1884 and 1902 was affected by market power held by firms over their miners. There are two main reasons why this provides a unique and interesting setting to study the relationship between buyer power and innovation. First, the introduction of coal cutting machines in the U.S. in 1882 provides a large observed technological shock. Second, 19th century Illinois coal mining towns are a textbook example of monopsonistic labor markets, with geographically isolated local labor markets, which makes it likely that employers had some market power over their workers.

I implement an empirical version of the model to fit the coal industry setting, and estimate it using a novel and uniquely rich archival dataset on mine-level production, coal prices, input quantities and prices, technology usage, and geological data. I rely on ob-

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served variation in the thickness of coal veins as cost shifters to estimate coal demand, and on international coal price shocks and exporting data to estimate labor supply. The identification of the production function relies, as usual, on timing assumptions on input choices in function of both Hicks-neutral and labor-augmenting productivity shocks. In line with anecdotal historical evidence, I find that cutting machines were unskill-biased, similarly to many other technologies that were developed throughout the 19th century (Mokyr, 1990; Goldin & Katz, 2009). Using the estimated production, labor supply, and coal demand models, I estimate the relative bargaining weights of the employers and of the coal miners. I find that employer power over miners increased substantially throughout the 1890s: in 1890, employers extracted one third of the total rents created in the industry, whereas they extracted almost half of the rents by 1902. Finally, I estimate the fixed costs of cutting machine usage by comparing the variable profit gains from machine adoption to the observed machine usage rates.

Using the estimated model, I numerically solve for output and input quantities, coal prices, miner wages, and machine usage in the observed equilibrium, and in two counterfactual equilibria. In a first counterfactual, I examine how all equilibrium outcomes and welfare would have changed if employer power would have increased by one standard deviation. Second, I examine the same counterfactual exercise, but hold cutting machine usage fixed. This second counterfactual is informative about the relative importance of the endogenous machine usage mechanism compared to the deadweight loss effect. I find that increased employer power would increase cutting machine usage by 13% by the end of the panel in 1902. Hence, both total factor productivity and skill-augmenting productivity would have increased in response to an increase in employer power. However, equilibrium output would have decreased by 22%, because the deadweight loss effect dominates the marginal cost decrease of increased cutting machine adoption. Endogenous capital investment alters the welfare effects of increased labor market power. If capital investment would be exogenous, the increase in employer power would reduce consumer, worker, and total welfare by 23.2%, 38.0 %, and 14.1% respectively. Allowing for endogenous capital

investment reduces these welfare losses to 21.70%, 36.0%, and 12.1%. Hence, assuming exogenous capital investment leads to overestimating the total welfare losses from monopsony power by 17%.

This paper relates to three distinct literatures. First, I contribute to the literature on the welfare consequences of monopsony power by considering endogenous technological change. Existing work on classical monopsony/oligopsony power usually focuses on deadweight loss and/or on misallocation (Berger et al., 2022; Lamadon et al., 2022; Jarosch, Nimczik, & Sorkin, 2019; Morlacco, 2017; Rubens, 2023), but keeps technology choices fixed. In contrast, I show that endogenous technology choices present an additional hannel through which input market power affects welfare. On the other hand, there is work on hold-up in a class of labor search models (Acemoglu & Shimer, 1999; Shi, 2023) and in efficient bargaining models (Abowd & Lemieux, 1993; Van Reenen, 1996; Menezes-Filho & Van Reenen, 2003), but these models do not feature monopsony-induced deadweight loss. I contribute to these literatures by empirically investigating and comparing monopsony-induced deadweight loss to the inefficiency created by hold-up, in order to obtain a net effect of employer power on equilibrium output and welfare.

Second, this paper builds on the vertical relations literature. In contrast to existing work on hold-up (Williamson, 1971; Joskow, 1987; Zahur, 2022), I allow for monopsony distortions by including upward-sloping marginal cost curves of the suppliers, and I also use a model with multiple substitutable inputs, rather than a single input. In contrast to the literature that studies the effects of buyer power on technology choices of suppliers (Just & Chern, 1980; Huang & Sexton, 1996; Köhler & Rammer, 2012; Parra & Marshall, 2021), I focus on its effects on the technology choices of the buyers.

Finally, this paper relates to the literature on labor market power during the late 19th century, such as Boal (1995), Naidu and Yuchtman (2017), and Delabastita and Rubens (2024), and on technological change during the same time period (Atack, Bateman, & Margo, 2008; Goldin & Katz, 1998; Katz & Margo, 2014; ?, ?). I bring these two literatures together by studying how employer power during the late 19th century affected the adoption

of directed technologies, and by quantifying the resulting welfare effects on consumers, producers, and workers.

The remainder of this paper is structured as follows. Section 2 contains the theoretical model. Section 3 discusses the data, the industry background, and the empirical model. Section 4 covers the estimation of the model and the counterfactual simulations.

2   Labor Market Power and Investment

I start with a theoretical model to examine the welfare effects of labor market power when allowing for both deadweight losses and endogenous investment.

2.1   Primitives

Firms f produce output Q_f using two variable inputs, H_f and L_f. I consider a firm to be an employer, and the inputs to be high- and low-skilled labor, but the model can equivalently be interpreted as wholesalers f that purchase various inputs from manufacturers. I rely on the C.E.S. production function (1), in which both inputs are substitutable at a constant elasticity σ. For simplicity, I assume constant returns to scale, but relax this in Appendix C.1. Skill-augmenting productivity is denoted A_f, the low-skilled labor coefficient is β^l, and Hicks-neutral productivity is Ω_f.

$$Q_f = \left((A_f(K_f)H_f)^{\frac{\sigma-1}{\sigma}} + \beta^l L_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \Omega_f(K_f) \tag{1}$$

Firms choose their capital stock K, which enters the production function in two ways. First, capital changes the skill-augmenting productivity term $A_f(K_f)$. Second, capital affects Hicks-neutral productivity $\Omega_f(K_f)$. Firms sell their product at a price P_f. Consumer demand for the good is given by a standard horizontal differentiation demand system, with an average industry-level price P_0, unobserved firm characteristics ξ_f, and a constant de-

mand elasticity η.

$$Q_f = \left(\frac{P_f}{P_0}\right)^\eta \xi_f \tag{2}$$

High-skilled workers have an outside option Z_f which they can earn when choosing not to be employed at firm f. I allow this outside option Z_f to be an upward-sloping curve, with constant inverse elasticity ψ, as shown in Equation (3. Firms are differentiated from the worker's perspective through an amenity term ζ_f. The average industry wage is equal to W_0. In contrast to models with a constant outside option value, such as Abowd and Lemieux (1993), an increasing outside option generates an upward-sloping labor supply curve, which allows for the possibility of monopsonistic behavior by employers. An increasing outside options curve can be rationalized by the fact that workers are heterogeneous in terms of their outside options, and that firms cannot wage-discriminate in function of these worker-specific outside options, as in Berger et al. (2022). Hence, the labor supply curve to each firm is upward-sloping: hiring an extra worker requires a higher wage to compensate the higher outside option of the marginal worker compared to the outside options of the infra-marginal workers.

$$Z_f = \frac{W_0}{1+\psi}\left(\frac{H_f}{\zeta_f}\right)^\psi \tag{3}$$

In contrast, the outside option of low-skilled labor is assumed to be equal to a constant V. This implies that firms pay low-skilled workers a uniform wage V, and that low-skilled labor supply is perfectly elastic.

High-skilled workers are unionized at the firm level. The utility of the labor union is at firm f is denoted Π_f^u, and is defined as the difference between high-skilled earnings and the outside option to high-skilled workers.

$$\Pi_f^u = (W_f - Z_f)Q_f$$

Employer profits are denoted as Π_f^d:

$$\Pi_f^d = P_f Q_f - W_f H_f - V L_f - \phi K_f$$

2.2 Strongly Efficient Bargaining

Behavior and Equilibrium

For illustration purposes, I start with a version of the 'strongly efficient' bargaining model Abowd and Lemieux (1993), in which a labor union and employers collectively bargain over both employment and wages, before moving to the actual model in which they only bargain over wages. The usefulness of the strongly efficient bargaining model is that it does not feature any monopsony distortions, only endogenous technology choices. This makes it a useful benchmark against which the results in the actual model can be compared.

In the strongly efficient bargaining model, employers and unions bargain over both employment and wages in a Nash bargaining protocol, with γ_f indicating union bargaining power.

$$\max_{H_f, L_f, W_f} (\Pi_f^u)^{\gamma_f} (\Pi_f^d)^{1-\gamma_f}$$

The model implies that the union and employers jointly optimize joint profits, and split the surplus according to the bargaining parameters γ_f.

Taking the first order condition for the high-skilled wage results in:

$$W_f = (1 - \gamma_f)Z_f + \gamma_f \left(\frac{P_f Q_f - V L_f}{H_f} \right) \tag{4}$$

The first order conditions for the labor inputs are given by:

$$P_0\Big(\frac{1+\eta}{\eta}\Big)Q_f^{\frac{1}{\eta}}\Big(\frac{Q_f}{H_f}\Big)^{\frac{1}{\sigma}}(\Omega_f A_f)^{\frac{\sigma-1}{\sigma}} = W_0\Big(\frac{H_f}{\zeta_f}\Big)^{\psi} \tag{5}$$

$$P_0\Big(\frac{1+\eta}{\eta}\Big)Q_f^{\frac{1}{\eta}}\Big(\frac{Q_f}{L_f}\Big)^{\frac{1}{\sigma}}(\Omega_f)^{\frac{\sigma-1}{\sigma}}\beta_l = V \tag{6}$$

Equilibrium $(P_f^*, Q_f^*, H_f^*, L_f^*)$ is the solution to the system of equations (1), (2), (5), and (6): the production function, the goods demand curve, and the two input demand equations. Wages are determined in function of the bargaining parameter, as described in Equation (4), and do not have any effect on equilibrium output, inputs, and goods prices as long as capital is held fixed.

An important difference between the model highlighted above and the model of Abowd and Lemieux (1993) is that Abowd and Lemieux (1993) assumes the outside option of workers to be a scalar, whereas I allow the outside option to be increasing. The analog of this feature in models of vertical relations would be that sellers face increasing marginal costs.

Effects of Employer Power: Endogenous Investment

Although employer power $(1 - \gamma_f)$ does not affect equilibrium output when holding the capital stock K_f fixed, employer power optimal investment, which in turn affects marginal costs and, hence, equilibrium output. Suppose firms need to pay a capital cost ϕ per unit of capital K_f, which is a fixed cost as it does not vary with production. We assume that capital increases employer variable profits, which implies that it increases skill-augmenting and/or Hicks-neutral productivity. This is an uncontroversial assumption: if capital would not increase buyer variable profits, firms would never invest unless subsidized to do so. Proposition 1 says that under strongly efficient bargaining, employer power increases technology adoption of firms.

Proposition 1 *Under strongly efficient bargaining, buyer power increases capital invest-*

ment:

$$\frac{\partial K_f}{\partial (1 - \gamma_f)} > 0$$

The proof of this theorem is straightforward. Denoting joint profits as $\Pi^j \equiv \Pi^d + \Pi^u$, the effect of capital on employer profits Π^d is given by:

$$\frac{\partial \Pi_f^d}{\partial K_f} = \frac{\partial \Pi_f^d}{\partial A_f}\frac{\partial A_f}{\partial K_f} - \Phi = (1 - \gamma_f)\frac{\partial \Pi_f^j}{\partial A_f}\frac{\partial A_f}{\partial K_f} - \Phi$$

Taking the derivative with respect to employer power $(1 - \gamma)$ gives:

$$\frac{\partial}{\partial (1 - \gamma_f)}\left(\frac{\partial \Pi_f^d}{\partial K_f}\right) = \frac{\partial \Pi_f^j}{\partial A_f}\frac{\partial A_f}{\partial K_f}$$

This last term is positive under the assumption that the technology is variable profit-enhancing.

The intuition behind Proposition 1 is that buyer power increases the share of the rents created by capital investment that flows to the buyer. Hence, this increases the incentive for the buyer to invest. This a reformulation of the well-known hold-up mechanism from Williamson (1971), which hinges on the assumption that workers and firms can only write incomplete contracts that do not condition on investments by the employer. The wage contracts used in the Illinois coal mining industry are an example of such an incomplete contract.

Corrolary 1 *Under strongly efficient bargaining, buyer power increases equilibrium output.*

It follows immediately from Proposition 1 that employer power increases equilibrium output in the strongly efficient bargaining model. Given the strong efficiency assumption, employer power does not affect output conditional on technology adoption K_f. However, employer power increases technology adoption, hence, decreases marginal costs. This marginal cost reduction results in increased equilibrium output.

2.3 Weakly Efficient Bargaining

In reality, employees and employers often do not bargain over both wages and employment, but only over wages. Assuming linear wage contracts, two types of bargaining models are possible. First, it could be that employers choose employment and bargain with workers, which is called the 'weakly efficient' bargaining model in Abowd and Lemieux (1993).[2] Such a model does not allow for monopsony-induced deadweight loss: when all bargaining power goes to the employer, this model converges to the strongly efficient bargaining model, not to the monopsony model with distortions due to wage markdowns. Instead, in this paper I consider a different bargaining protocol: I assume that workers decide how much to work, and that they simultaneously bargain over wages with the employers. There are two reasons for making this modeling assumption. First, this model has the benefit of collapsing to the classical monopsony model when assuming perfect buyer power ($\gamma = 0$), with the ensuing monopsony distortion. Second, as will be discussed more in detail in Section 3, the empirical evidence shows that a large-scale miner's strike in 1898, which resulted in an increased bargaining weight of the miner's union, was followed by increased output, rather than decreased output. This finding aligns with the model in which employers exert monopsony power, whereas it opposes a sequential monopoly model in which miners exert market power.[3]

The labor union decides on how much labor it is willing to supply for any given wage level, in order to maximize union profits Π^u, which leads to the following upward-sloping high-skilled labor supply curve:

$$W_f = W_0 \Big(\frac{H_f}{\zeta_f} \Big)^\psi \tag{7}$$

Wages are bargained over between the labor union and the employers according to their

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[2]In the vertical relations literature, this is similar to models where buyers choose output prices on their product market and simultaneously bargain wholesale prices with their supplier, such as in Crawford and Yurukoglu (2012) and Grennan (2013).

[3]In the latter case, increased bargaining power of the labor union should result in a decreased in equilibrium output, rather than an increase.

relative bargaining power γ_f:

$$\max_{W_f}(\Pi_f^u)^{\gamma_f}(\Pi_f^d)^{1-\gamma_f}$$

The resulting wage equation is given by Equation (8):

$$\gamma_f\Big((1-\frac{\partial Z_f}{\partial W_f})H_f + \frac{\partial H_f}{\partial W_f}(W_f - Z_f)\Big)(P_f Q_f - W_f H_f - V L_f)$$
$$+ (1-\gamma_f)(W_f - Z_f)H_f(P_f\frac{\partial Q_f}{\partial H_f}\frac{\partial H_f}{\partial W_f} - H_f - W_f\frac{\partial H_f}{\partial W_f}) = 0 \quad (8)$$

Finally, low-skilled workers are chosen by the employers to maximize their profits:

$$\max_{L_f}(\Pi_f^d)$$

The low-skilled labor demand function is the same as in the strongly efficient bargaining case, equation (6).

I rely on the 'Nash-in-Nash' equilibrium concept of Horn and Wolinsky (1988). Equilibrium $(Q_f^*, P_f^*, W_f^*, H_f^*, L_f^*)$ is given by equations (1), (2), (6), (7), (8), which are the production, goods demand, low-skilled labor demand, high-skilled labor supply, and wage bargaining equations.

Effects of Employer Power: Endogenous Investment vs. Deadweight Loss

In contrast to the strongly efficient bargaining case, an increase in buyer power $(1-\gamma_f)$ now decreases equilibrium output when holding capital K_f fixed. The reason for this is that employer power allows employers to exercise monopsony power, which creates deadweight loss. In the extreme case when $\gamma_f = 0$, employers set wages at a fixed markdown in function of the labor supply elasticity, which negatively distorts equilibrium labor usage and output.

On the other hand, buyer power still affects capital investment. The effect of capital

investment on buyer profits is given by:

$$\frac{\partial \Pi_f^d}{\partial K_f} = \frac{\partial \Pi_f^d}{\partial A_f}\frac{\partial A_f}{\partial K_f} = (1 - \gamma_f)\frac{\partial \Pi_f^j}{\partial A_f}\frac{\partial A_f}{\partial K_f} - \Phi$$

Taking the derivative with respect to union power γ gives:

$$\frac{\partial}{\partial \gamma_f}\Big(\frac{\partial \Pi_f^d}{\partial K_f}\Big) = -\frac{\partial \Pi_f^j}{\partial A_f}\frac{\partial A_f}{\partial K_f} + (1 - \gamma_f)\frac{\partial}{\partial \gamma_f}\Big(\frac{\partial \Pi_f^j}{\partial A_f}\frac{\partial A_f}{\partial K_f}\Big)$$

The first term is still negative: buyer power increases the buyer's share of the profit increase from technology adoption. The second term is the effect of buyer power on the joint profit effect of capital investment, and is no longer zero given that union power affects equilibrium output and input quantities. Numerically simulating the model reveals that the sign of the second term is ambiguous, as we show below.

As a result, the net effect of buyer power on equilibrium output is ambiguous. On the one hand, increased buyer power decreases output through the monopsony distortion. On the other hand, buyer power increases technology usage, which reduces marginal costs, and hence increases output. Which of these effects dominates depends on the relative magnitude of the deadweight loss and the endogenous investment mechanism. In the empirical application, I will quantify the relative size of these effects in order to examine how counterfactual changes in employer power affect equilibrium output, producer surplus, consumer surplus, and worker welfare.

Simulation

To illustrate the importance of endogenous technology usage for the welfare effects of labor market power, I simulate a parametrized version of the model. The parametrization is specified in Appendix B.1. I calibrate the goods demand elasticity at $\eta = -7$ and the inverse labor supply elasticity at $\psi = 0.25$, following the estimates for U.S. construction workers in Kroft et al. (2020). I consider a new technology that increases H-augmenting productivity A by 5%, and increases TFP Ω by 20%.

Figure 2a plots equilibrium technology usage K against employer power $(1 - \gamma_f)$. The red solid line depicts the model in which technology usage is allowed to change in function of employee bargaining power. As was explained in the theoretical model, technology usage increases with the level of employer power. As a comparison, the blue dashed line depicts the model in which technology usage is exogenous to the degree of employer power. In this model, technology usage is fixed equal to average technology usage in the endogenous adoption model.

Figure 2 shows equilibrium output Q as a function of employer power $(1 - \gamma_f)$. Under the assumption of exogenous technology usage, the blue solid line, output monotonically decreases with employer power. As was explained earlier, this is due to deadweight loss induced by the employer's monopsony power. The wage markdown set by the employer shrinks to zero as employer bargaining power goes to zero, reducing deadweight loss to zero. However, allowing for endogenous capital usage turns the output-bargaining power relationship into an inverted U-shape. At low levels of employer power, the output decrease due to monopsony power is countered by the reduction in marginal costs due to increased technology usage. Under the parametrization of the model, the positive output effect of increased technology usage outweighs deadweight loss until the bargaining weight of the employer is 0.20. Hence, equilibrium output is maximized at this level of employer power. In Appendix B.1, I show that this pattern is robust to various alternative parametrizations.

3   Empirical Model: Illinois Coal Extraction

Simulating the model in the previous section reveals that the relationship between employer power and output is ambiguous, as it depends on the relative magnitude of monopsony-induced deadweight loss and endogenous technology adoption mechanisms. In this section, I quantify the relative magnitude of these forces by estimating the model in the context of the 19th century Illinois coal mining industry.

Figure 1: Bargaining Power, Capital Investment, and Output

(a) Capital Investment
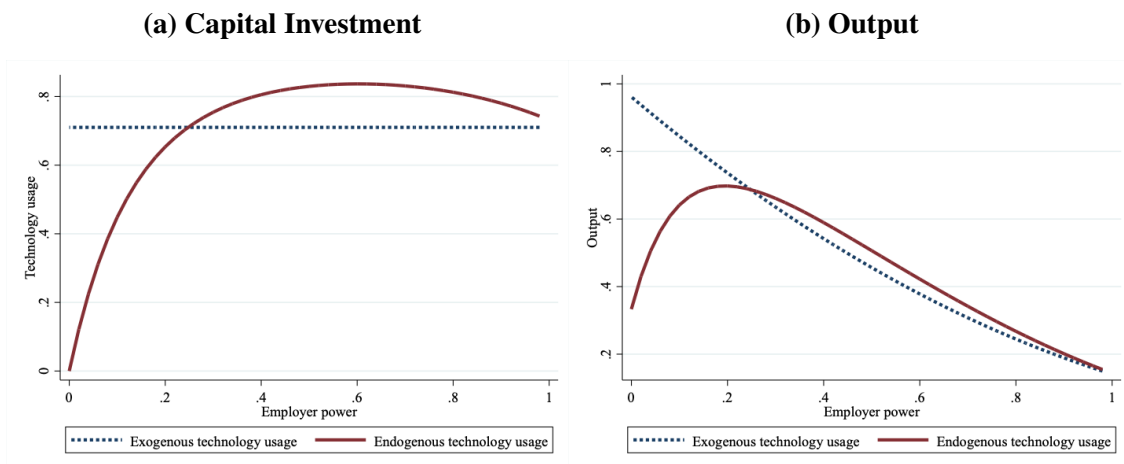
(b) Output

Notes: Panel (a) shows how capital investment changes with the degree of employer power in the simulated model. Panel (b) shows output in function of the employer's bargaining parameter, both when assuming exogenous investment and when letting investment vary with employer power.

3.1 Data

The main dataset is derived from the *Biennial Report of the Inspector of Mines of Illinois*, which was digitized in the context of this project. I observe every bituminous coal mine in Illinois between 1884 and 1902 at two-year intervals, which results in 8356 observations. The dataset records the name of the mine, the mine owner's name, yearly coal extraction, average employee counts for both skilled and unskilled workers, days worked, and a dummy for cutting machine usage per year. Materials are measured as the total number of powder kegs used in a given year. Other technical characteristics are observed for a subset of years, such as dummies for the usage of various other technologies (locomotives, ventilators, longwall machines), and technical characteristics such as mine depth and the mine entrance type (shaft, drift, slope, surface). Not all these variables are used in the analysis, given that some are observed in a small subset of years.[4]

I observe the average piece rate for skilled labor throughout the year and the daily wage for unskilled labor from 1888 to 1896. At some of the mines, 'wage screens' were used,

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[4]A full list of observed variables and the years in which they are observed is in Appendix Table A6.

which means that skilled workers were paid only based on their output of large coal pieces, rather than on their total output. This introduces some measurement error in labor costs. However, the data set reports the usage of wage screens in 1898, and shows that they were used in mines representing merely 2% of total employment. Skilled wages and employment are separately reported for the summer and winter months between 1884 and 1894. For some years I observe additional variables such as mine capacities, the value of the total capital stock and a break-up of coal sales by destination. Wages and employee skill types are not observed in 1896. I deflate all monetary variables using historical CPI estimates from Hoover (1960). The reported monetary values are all in 1884 U.S. dollars.

In addition to the main biennial dataset, I utilize different other datasets. First, the inspection report from 1890 contains monthly data on wages and employment for both types of workers, and monthly production quantities for a sample of 11 mines that covers 15% of skilled and 9% of unskilled workers. Second, town- and county-level information from the 1880 and 1900 population census and the censuses of agriculture and manufacturing are collected as well. Third I collect information on coal cutting machine costs from Brown (1889). I refer to Appendix A for more details regarding the data sources and cleaning procedures.

3.2   Industry Background

The setting of the empirical application is the Illinois coal mining industry between 1884 and 1902. Throughout this time period, the industry grew rapidly: annual output tripled from 10 to 30 megatons between 1884 and 1902. This was both due to an increase in the average mine size and to an increase in the number of mines from 680 to 898 units.

Extraction Process

The coal extraction process consisted of three consecutive steps. First, the coal vein had to be accessed, as it lied below the surface for 98.0% of the mines and 99.4% of output. Second, upon reaching the vein, the coal wall was 'undercut', traditionally by hand, but

from 1882 onward also with coal cutting machines. The mechanization of the cutting process is considered to be the most significant technological change during this time period (Fishback, 1992). Third, coal had to be transported back to the surface and sorted from impurities. The hauling was done using mules or underground locomotives. Mines used two types of intermediate inputs. First, black powder was used to blast the coal wall. This powder and other materials, such as picks, was purchased and brought by the miners. Second, coal itself was used to power steam engines, electricity generators, and air compressors.

Figure 2(b) plots the ratio of total output over total days worked at mines that used cutting machines ('machine mines') and mines that did not ('hand mines'). Daily output per worker increased from 2 to 3.3 tons for hand mines, and from 2.3 to 4.1 tons for machine mines.[5]

Although different coal types exist, the mines in the data set all extract bituminous coal. There might be minor quality differences even within this coal type due to variation in sulfur content, ash yield, and calorific value (Affolter & Hatch, 2002). Most of this variation is, however, dependent on the mine's geographical location and, hence, not a choice variable of the firms conditional on operating in a certain location.
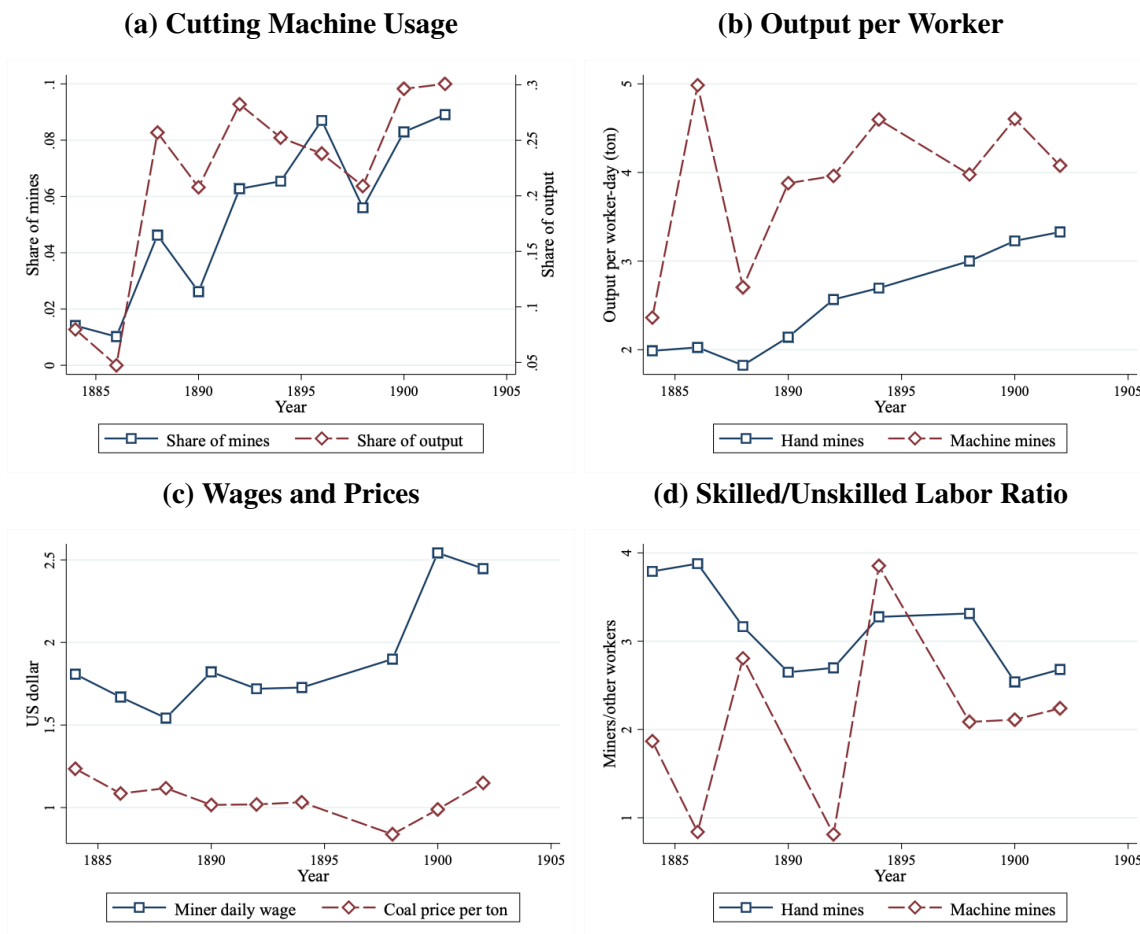
Occupations

Coal mining involved a variety of occupational tasks. The inspector report from 1890 reports wages at the occupation-level, and this subdivision is reported in Appendix Table A1 for the 20 occupations with the highest employment shares, together covering 97% of employment. Three out of five workers were miners, who did the actual coal cutting. This required a significant amount of skill: in order to determine the thickness of the pillars, miners had to trade off lower output with the risk of collapse. The other 40% of workers did a variety of tasks such as clearing the mine of debris ('laborers'), hauling coal to the surface using locomotives or mules ('drivers' and 'mule tenders'), loading coal onto the mine carts ('loaders'), opening doors and elevators ('trappers'), etc. The skills required to carry out these tasks were usually less complex than those of the miners, and were moreover not specific to coal mining: tending mules or loading carts are general-purpose

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[5]This series is adjusted for the reduction of hours per working day in 1898, as explained in Appendix A.

Figure 2: Output, Inputs, and Prices

(a) Cutting Machine Usage

(b) Output per Worker

(c) Wages and Prices

(d) Skilled/Unskilled Labor Ratio

Notes: Panel (a) plots the evolution of cutting machine usage, both as a share of firms and weighted by output. Panel (b) documents the evolution of output per worker at mines where coal is cut manually, and at mines where cutting machines are used. Panel (c) shows the evolution of daily skilled wages and of the coal price per ton in Illinois, weighted by employment and output respectively. Panel (d) shows the evolution of the aggregate ratio of skilled to unskilled workers in Illinois for both hand and machine mines.

tasks, in contrast to undercutting coal walls.

The difference in industry-specific skills are reflected in daily wages: miners earned higher daily wages than any other mining employee type, except for 'pit bosses' (middle managers), and 'roadmen', who maintained and repaired mine tracks, but these two categories of workers represent barely 2% of the workforce. The higher wages of miners cannot be explained as a risk premium, because nearly all other occupations worked below

the surface as well, and were hence subject to the same risks of mine collapse or flooding. From this point onward, I classify workers into two types: miners, which I will denote as 'skilled labor', and all other employees, which are called 'unskilled labor'. This follows the categorization of labor skill levels provided in the data set.

Technological Change

The first prototype of a mechanical coal cutter in the U.S.A. was invented by J.W. Harrisson in 1877.[6] The Harrisson patent was acquired and adapted by Chicago industrialist George Whitcomb, whose 'Improved Harrison Cutting Machine' was released on the market in 1882.[7] As shown in Figure 2a, the share of Illinois coal mines using a cutting machine increased from below 2% to 9% between 1884 and 1902. Mechanized mines were larger: their share of output increased from 7 to 30% over the same time period. The mechanization of the hauling process, which replaced mules with underground locomotives, was another source of technical change, and started during the 1870s. By the start of the panel in 1884, mining locomotives were already widely used in Illinois: the share of output mined in locomotive mines was around 90%.

As was shown in Figure 2(b), output per worker was higher in cutting machine mines. The composition of labor was also different: in Figure 2(d), I plot the ratio of the total number of skilled labor-days over the number of unskilled worker-days per year.[8] Mines without cutting machines used between 3 and 4 skilled labor-days per unskilled labor-days throughout the sample period, compared to 2 to 3 skilled labor-day per unskilled worker-day for machine mines. In every year, except 1894, machine mines used less skilled per unskilled worker. The skilled-unskilled labor ratio was on average 16.5% lower for machine mines compared to hand mines, and this difference is statistically significant. However, this difference is not necessarily a causal effect of cutting machines on skill-augmenting

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[6]Simultaneously, prototypes of mechanical coal cutting machines were invented in Northern England in the late 1870s (Reid, 1876; Ackermann, 1902).

[7]A picture of the patent is in Appendix Figure A5. The spatial diffusion of cutting machines is shown in Appendix Figure A3.

[8]1890 is omitted for machine mines in 1890 due to employment being unobserved for most machine mines in that year.

productivity: mines with higher productivity levels were probably more likely to adopt cutting machines. For estimates of the causal effect of cutting machines on total factor and factor-augmenting productivity levels, I refer to the empirical model in Section 4. Anecdotal evidence suggests that cutting machines led to the substitution of unskilled for skilled workers. In his 1888 report, the Illinois Coal Mines Inspector asserts:

> "Herein lies the chief value of the [cutting] machine to the mine owner. It relieves him for the most part of skilled labor [...] it opens to him the whole labor market from which to recruit his forces [...] The mining machine is in fact the natural enemy of the coal miner; it destroys the value of his skill and experience, and reduces him to the rank of a common laborer" (Lord, 1892).

Labor Markets

Skilled workers received a piece rate per ton of coal mined, whereas unskilled workers were paid a daily wage.[9] Converting the piece rates to daily wages, the net salary of skilled labor was on average 22% higher compared to unskilled labor. 'Net salary' means net of material costs and other work-related expenses. Rural Illinois was, and still is, sparsely populated: the median and average population sizes of the towns in the dataset were 845 and 1706 inhabitants. In the average town, 16% of the population was employed in a coal mine. Considering that women and children under the age of 12 did not work in the mines, this implies that a large share of the local working population was employed in coal mining. Of all the villages, 42% had just one coal firm, and 75% had three or less coal firms. Two-thirds of all employees worked in a village with three or less coal mines. Although most of the villages in the data set were connected by railroad, these were exclusively used for freight: passenger lines only operated between major cities (Fishback, 1992). Given that the average village was 7.4 miles apart from the next closest village, and that skilled workers had to bring their own supplies to the mine, commuting between villages was not an option, and the mining towns can be considered as isolated local labor markets. Most

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[9]Piece rates were an incentive scheme in a setting with moral hazard, as permanent miner supervision would be very costly.

roads were unpaved and automobiles were not yet introduced. In order to switch employers, miners had to migrate to another town.

First attempts to unionize the Illinois coal miners started around 1860, without much success (Boal, 2017). Although Illinois coal miners were unionized, for instance through the *United Mine Workers of America* and the *Knights of Labor*, union power was constrained by the use of 'yellow-dog' labor contracts that forced employees not to join a trade union.[10] A major strike in 1897-1898 led to a modest increase in wages, to a reduction of working hours, and to the introduction of annual wage negotiations, which took place in January (Bloch, 1922). Nevertheless, industrial relations remained tense for the ensuing years (Bloch, 1922).

Wages were bargained over in a tiered negotiation procedure: first, a general agreement was made at the state-industry level, afterwards mine owners individually negotiated wages with miner representatives (Bloch, 1922). There was no minimum wage law. In contrast to other states, the mines in the data set did not pay for company housing of the miners (Lord, 1883, 75), which would otherwise be a labor cost in addition to miner wages.

Figure 2(c) reports the aggregate skilled labor daily wage, defined as the total wage bill spend on skilled labor over the total number of skilled labor-days. The fast growth in labor productivity did not translate into higher wages until 1898, as daily miner wages remained around \$1.8. After the subsequent introduction of wage bargaining, wages rose.

Coal Markets

Coal was sold at the mine gate, and there was no vertical integration with post-sales coal treatment, such as coking. On average 92% of the mines' coal output was either sold to railroad firms or transported by train to final markets. The remaining 8% was sold to local consumers. The main coal destination markets for Illinois mines were St. Louis and Chicago.Railway firms acted as an intermediary between coal firms and consumers, and were also major coal consumers themselves. Historical evidence points to intense

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[10]These contracts were criminalized in Illinois in 1893, with fines of \$100 USD, which was equivalent to on average six months of a miner's wage. (Fishback, Holmes, & Allen, 2009).

competition on coal markets during the last two decades of the 19th century, before the large consolidation wave in the early 1900s (Graebner, 1974). Nevertheless, there was still a considerable transportation cost of coal, which makes that coal markets were likely not entirely integrated. There are large differences in the coal price across Illinois: in 1886, for instance, it varied between 80 cents/short ton at the 10th percentile of the price distribution to 2 dollars/short ton at the 90th percentile, and this price dispersion slightly increased over time. Figure 2(c) shows that the mine-gate coal price per ton, weighted by output shares, fell from $1.2 to $0.9 between 1884-1898, after which it increased again.

3.3 Stylized Facts

In this Section, I present two sets of stylized facts to motivate the assumptions made in the structural model. First, I show that skilled wages co-varied with seasonal labor demand shocks, whereas unskilled wages did not. Second, I show that output increased in response to the 1897-1898 coal strikes at striking mines.

Seasonal Wage Variation

Coal demand was very seasonal: during winters, there was more demand for energy than during summers. As was explained earlier, storage costs meant that firms could not fully arbitrage between winters and summers, and, hence, needed to hire more workers during winter. Joyce (2009) mentions that miners were (partially) unemployed during the summer months. This cyclical pattern provides useful variation to compare wage responses of skilled and unskilled workers to coal demand shocks. In Figure 3(a),I show that skilled wages followed this coal demand cycle: they were higher during winters than during summers. However, this pattern held only for skilled wages, not for unskilled wages. Although the seasonal demand shocks increased both skilled and unskilled labor demand, only skilled wages increased during winter. This is also shown in Figure 3(c), that plots how average daily wages for both skilled and unskilled workers in 1890 change with the monthly num-

ber of worker-days of each type at the mine-month level throughout 1890.[11] Skilled wages were positively correlated with monthly skilled employment, whereas the unskilled worker wage-employment schedule is flat. Moreover, there was a lot of variation in skilled wages across mines and months, but very little cross-sectional and intertemporal variation in unskilled wages.

The fact that skilled wages increased in response to coal demand shocks whereas unskilled wages did not, and the fact that unskilled wages were nearly uniform across Illinois whereas skilled wages were not, suggests an inelastic high-skilled labor supply curve and a fully elastic low-skilled labor supply curve. This implies that firms have the potential to exert monopsony power on the high-skilled labor market, but not on the low-skilled labor market. However, it could be that seasonal employment movements reflected not only labor demand variation, but also labor supply shocks, for instance due to the harvesting season. Moreover, within-year demand shocks trace out a short-run supply curve, whereas labor supply could be more elastic on the longer term. Hence, in the structural model, I will rely on an instrumental variables strategy that relies on international coal price shocks to identify the high-skilled labor supply elasticity.

Output and Investment Response to the 1897-1898 Coal Strikes

During 1897-1898, a large strike broke out in the Illinois coal basin, which became known as the 'Illinois coal war'. Miners went on strike at one quarter of the coal mines in Illinois, and this resulted in a wage increase at 90% of the striking coal mines. Given that the strike was successful at increasing wages, this provides a useful shock to the relative bargaining power of the miner's union. Using a difference-in-differences model, I compare the evolution of log coal output between mines at which miners went on strike in 1898, $I(strike)_f = 1$ to mines where miners did not strike, before and after 1898. I define the strike indicator as mines where miners striked for at least a week during 1898, and I include

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[11]Unlike skilled wages and employment, unskilled wages and employment are not broken down by season in the entire dataset. However, monthly wage and employment data is available for a sample of mines selected by the Illinois Bureau of Labor Statistics across 5 counties in 1890, which covers 16% of skilled employment and 9% of unskilled employment.

Figure 3: Wage-Employment Profile by Skill Type

(a) Wages

(b) Wage-Employment Profile

Notes: Panel (a) shows howthe wages of skilled miners and other mine employees evolved monthly during the year 1890. Panel (b) plots mine-month level wages for both types of workers against monthly employment, again for both types of workers.

both mine fixed effects and a linear time trend. I exclude the year 1898 from the analysis, in order to not take into account the reduction in output during the strike.

$$q_{ft} = a_0 + a_1 I(strike)_f + a_2 I(strike)_f I(t \geq 1898) + a_3 I(t \geq 1898) + a_4 t + \delta_f + e_{ft}$$

I also estimate the same difference-in-difference model, but with cutting machine usage on the left-hand side instead of log output. Rather than a linear model with firm fixed effects, I use a conditional logit model with firm fixed effects because cutting machine usage is a binary variable. In Table 1a, I report the coefficient on the interaction term, a_2. At mines that went on strike, output increased by 27% after 1898 relatively to the mines that did not go on strike. In contrast, machine usage is estimate to decrease relatively at the striking mines, although this effect is not statistically significant.

In Table 1b, I compare pre-trends by estimating the interaction effect between the strike indicators and a linear time trend prior to 1898. Although the pre-trend in output was not signficantly different between mines that went on strike and mines that did not, cutting machine usage grew less prior to the strike at mines that went on strike compared to mines that did not. Hence, the difference-in-difference estimates for cutting machine usage are poten-

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tially invalid. In order to examine the mechanism behind the output and mechanization effects of changes in employer power, and to conduct welfare counterfactuals, a structural model is necessary.

Table 1: Strikes, Output, and Investment

(a) Diff-in-diff results	log(Output)		Machine usage	
	Est.	S.E.	Est.	S.E.
1(Strike)*1(year≥ 1898)	0.233	0.099	-0.143	0.482
Model:	Linear		Logit	
Firm fixed effects:	Yes		Yes	
R-squared	.942		.	
Observations	7415		691	
Firm fixed effects:	No		No	

(b) Pre-trends	log(Output)		Machine usage	
	Est.	S.E.	Est.	S.E.
1(Strike)*yr	0.016	0.019	-0.145	0.036
Model:	Linear		Logit	
R-squared	.192		.	
Observations	5637		5703	

Notes: Panel (a) reports the difference-in-difference estimates of how log output and cutting machine usage changed differently after 1898 between striking and non-striking mines. Panel (b) compares the pre-trend in output and cutting machine usage between the mines that went on strike and those that did not.

3.4   Empirical Model

Production Function

I implement an empirical model of the Illinois coal industry, based on the general model outlined in Section 2. Let f index coal firms per town and let t index all even years between 1884 and 1902. The model is set up at the firm-town-year level: it is plausible that employers optimize at the firm level, rather than at each mine independently. However, I let firms optimize on a labor market-by labor market basis: firms with mines in different labor markets do not internalize the cross-labor market effects of their decisions. This is

consistent with the model, given that it does not feature strategic interaction between firms on the labor market. Annual coal extraction in short tons is denoted Q_{ft}, the number of days worked by high-skilled labor is denoted H_{ft} whereas the number of low-skilled labor-days is L_{ft}. In contrast to the theoretical model, capital investment is modeled as a binary variable: firms choose whether to use cutting machines or not, with usage being denoted $K_{ft} \in \{0, 1\}$. I abstract from other technologies, such as mining locomotives, because they were widely adopted already by the start of the panel, and because they are not observed in all years of the sample.

I maintain the C.E.S. production function from Equation (1), with an elasticity of input substitution σ and low-skilled labor coefficient β^l. Firms differ in terms of their skill-augmenting productivity A_{ft} and in their Hicks-neutral productivity Ω_{ft}. In Appendix C.1, I estimate various extensions of the production model to allow for non-constant returns to scale, the existence of intermediate inputs, and the possibility that cutting machines change scale returns. All these extensions lead to very similar production function estimates. Taking the logs of Equation (1) and adding the time index leads to equation 9, which is the production function I will estimate.

$$q_{ft} = \left(\frac{\sigma - 1}{\sigma}\right) \log\left(\left(H_{ft}A_{ft}(K_{ft})\right)^{\frac{\sigma-1}{\sigma}} + \beta^l L_{ft}\right)^{\frac{\sigma}{\sigma-1}} + \omega_{ft}(K_{ft}) \tag{9}$$

Cutting machine usage K_{ft} is allowed to affect both productivity terms Ω_{ft} and A_{ft}. The logarithms of both these productivity terms, a_{ft} and ω_{ft}, are assumed to evolve as AR(1) processes, as specified in Equations (10) and (11). The productivity terms have serial correlations ρ^a and ρ^ω and are assumed to be affected linearly by cutting machine usage, as parametrized by the coefficients α^k and β^k for labor-augmenting and Hicks-neutral productivity, respectively.[12] Skill-augmenting and Hicks-neutral productivity shocks are denoted

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[12]Although these AR(1) specifications do not allow for richer models of cost dynamics in which current productivity is a function of the total amount of output produced in the past, they do have the benefit of not requiring inversion of the production function, thereby allowing for rich heterogeneity in both productivity terms, markdowns, and markups. I refer to Appendix C.2 for a motivation and discussion of this

e_{ft}^a and e_{ft}^ω.

$$a_{ft} = \alpha^k K_{ft} + \rho^a a_{ft-1} + e_{ft}^a \tag{10}$$

$$\omega_{ft} = \beta^k K_{ft} + \rho^\omega \omega_{ft-1} + e_{ft}^\omega \tag{11}$$

I assume mines do not face a binding capacity constraint. This is consistent with the data: in 1898, the only year for which capacities are observed, merely 1.4% of the mines operated at full capacity, and they were responsible for 1.1% of industry sales.[13] I also abstract from stockpiling of coal, and assume that coal must be sold immediately after extraction: coal storage usualy led to deteriorating coal quality, moreover it was expensive and dangerous (Stoek, Hippard, & Langtry, 1920). As Williams (1901) asserts:

> "The product of a mine can be stored with economy only in the mine itself
>
> [...] Coal must be sold, therefore, as fast as it is mined' (Williams, 1901)

Labor Supply

Adding time subscripts to the inverse labor supply function (7), and inverting it, results in the labor supply equation (12a). The daily wage of high-skilled workers W_{ft} is computed as the piece rate multiplied by daily tonnage per worker. I measure W_{0t} as the average daily wage in year t.

I include observed firm characteristics $\mathbf{X}_{ft}^h$ next to the latent amenity term ζ_{ft}. Specifically, I include a linear time trend, county fixed effects, and the logarithm of the minimal distance of the firm to Chicago and St. Louis as observed characteristics, to account for proximity to the large population centers in the area.

$$H_{ft} = \left(\frac{W_{ft}}{W_{0t}}\right)^{\frac{1}{\psi}} \exp(\mathbf{X}_{ft}^h)^{\psi^x} \zeta_{ft} \tag{12a}$$

---

assumption.

[13]The entire distribution of capacity utilization rates is shown in Figure A4.

I estimate the labor supply equation in logs, which is given by equation (12b).

$$h_{ft} = \frac{1}{\psi}(w_{ft} - w_{0t}) + \boldsymbol{\psi}^x \mathbf{X}_{ft}^h + \log(\zeta_{ft}) \tag{12b}$$

The amenity term ζ_{ft} captures firm differentiation from the miner's perspective. In contrast to Delabastita and Rubens (2024), which relies on a homogeneous employers model, I do allow for firm differentiation because there is substantial variation in skilled wages across mines, even within the same labor markets.[14]

Similarly to the theoretical model, the market for low-skilled labor is perfectly competitive, and low-skilled workers are paid a uniform wage V, which is equal to their outside option. The main reason for this assumption lies in the fact that there was very little variation in unskilled wages across Illinois, and that unskilled wages did not react to seasonal weather shocks, as was shown in Figure 3.

Coal Demand

As was explained in the background section, the coal produced in Illinois mines was a nearly homogeneous product. However, coal firms are differentiated due to their locations, which results in price differences between coal firms. I again include the lowest distance to either Chicago or St. Louis, county fixed effects, and a linear time trend, as these variables could also affect coal demand at each firm.

$$Q_{ft} = \left(\frac{P_{ft}}{P_{0t}}\right)^{\eta} \exp(\mathbf{X}_{ft}^q)^{\boldsymbol{\eta}^x} \xi_{ft} \tag{13}$$

Taking logarithms of Equation (13) results in Equation (14), which is the demand model I estimate.

$$q_{ft} = \eta(p_{ft} - p_{0t}) + \boldsymbol{\eta}^x \mathbf{X}_{ft}^q + \ln(\xi_{ft}) \tag{14}$$

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[14]In Appendix Table A5, I report the R^2 of regressing log daily miner wages on subsequently year, county, town, and firm dummies. Town and year dummies explain only 29% of the variation in skilled miner wages.

Type of Bargaining

I follow the weakly efficient bargaining model in which workers provide labor through an upward-sloping labor supply curve, for three reasons. First, the stylized facts in Section 3.3 showed that output increased in response to strikes. These strikes were a negative shock to employer bargaining power, as I show in Appendix C.2. In the strongly efficient bargaining environment of Section 2.2, output should not change in response to a shock to bargaining power, this would be a mere transfer. In a weakly efficient bargaining environment with a fully elastic labor supply curve and inelastic product demand curve, a decrease in employer power should decrease output, due to double marginalization. In contrast, as was shown in Section 2.3, in a weakly efficient bargaining model with inelastic labor supply, a drop in employer power increases output, as the wage markdown falls. Second, the description of miner union bargaining in Bloch (1922) shows that employers and unions bargained over wages, not employment, which is in line with the weakly efficient bargaining model. Third, the structural model will find evidence for an upward-sloping labor supply curve, which calls for taking monopsony power into consideration.

Variable Input Decisions

I assume firms make decisions in two stages. First, they choose whether to use cutting machines, or not. Second, conditional on this technology choice, they choose high-skilled wages and low-skilled employment. I will discuss these two stages in reverse order, as the estimation of the model will also be done in that order.

In year t, employers negotiate a high-skilled wage rate with the union according to the bargaining protocol specified in Equation (15), which is equivalent to the weakly efficient bargaining model described in Equation (8).

$$\gamma_{ft}\Big((1 - \frac{\partial Z_{ft}}{\partial W_{ft}})H_{ft} + \frac{\partial H_{ft}}{\partial W_{ft}}(W_{ft} - Z_{ft})\Big)(P_{ft}Q_{ft} - W_{ft}H_{ft} - VL_{ft})$$

$$+ (1 - \gamma_{ft})(W_{ft} - Z_{ft})H_{ft}(P_{ft}\frac{\partial Q_{ft}}{\partial H_{ft}}\frac{\partial H_{ft}}{\partial W_{ft}} - H_{ft} - W_{ft}\frac{\partial H_{ft}}{\partial W_{ft}}) = 0 \quad (15)$$

Following the labor supply curve, (12b), this negotiated wage rate results in a certain amount of high-skilled labor being supplied at each coal firm. Coal firms simultaneously choose low-skilled labor as specified in Equation (16). I assume that these variable input decisions happen after the productivity shocks e^ω and e^a are observed by the firm. The combination of low-skilled and high-skilled labor and capital, of which the decisions are specified below, results in coal output Q_f according to the production function (9). The coal demand curve (14) determines the price every firm can charge at that level of coal output.

$$P_{0t}\Big(\frac{1+\eta}{\eta}\Big)Q_{ft}^{\frac{1}{\eta}}\Big(\frac{Q_{ft}}{L_{ft}}\Big)^{\frac{1}{\sigma}}(\Omega_{ft})^{\frac{\sigma-1}{\sigma}}\beta_l = V \tag{16}$$

Fixed Input Choices

In every year t, the equilibrium quantities and prices at every firm can be found by solving the system of equations (9), (12a), (13), (15), and (16): the production function, high-skilled labor supply, coal demand, high-skilled labor demand, and low-skilled labor demand. This delivers equilibrium outcomes $(Q_{ft}^1, P_{ft}^1, H_{ft}^1, L_{ft}^1, W_{ft}^1)$ if the firm uses cutting machines, and different equilibrium outcomes $(Q_{ft}^0, P_{ft}^0, H_{ft}^0, L_{ft}^0, W_{ft}^0)$ if the firm does not use cutting machines. The variable profit gain of the employer from using cutting machines is denoted $\Delta\Pi_{ft}^d$:

$$\Delta\Pi_{ft}^d \equiv (P_{ft}^1 Q_{ft}^1 - W_{ft}^1 H_{ft}^1 - V_t L_{ft}^1) - (P_{ft}^0 Q_{ft}^0 - W_{ft}^0 H_{ft}^0 - V_t L_{ft}^0) \tag{17}$$

The fixed costs of technology usage are denoted Φ_t, so total employer profits are equal to $\Pi_{ft}^d - \Phi_t K_{ft}$. As in Peters, Roberts, Vuong, and Fryges (2017), I parametrize fixed costs as an exponential distribution. I let the rate parameters (ϕ_0, ϕ_1), evolve over time, with ϕ_0 measuring the time-invariant fixed cost of technology usage and ϕ_1 its time trend.

$$\Phi \sim \exp(\phi_0 + \phi_1 t)$$

I assume that prior to observing the productivity shocks e^ω and e^a, firms independently and simultaneously choose whether they will use cutting machines or not. They make this decision by trading off the costs of machine adoption Φ_t with the expected variable profit return $\Delta\Pi^d$. I assume that firms do not choose their cutting machines in a dynamic manner, but optimize their technology mix period-by-period. The main reason for this assumption is that observed entry *and* exit of machine usage is frequent: whereas there are 109 observed instances of cutting machine installation, there are 62 observed instances in which an installed cutting machine is scrapped again. This suggests the existence of an aftermarket for capital.

Using the exponential form of fixed costs, the probability that a firm uses cutting machines $p^k_{ft}(\phi)$ is equal to:

$$p^k_{ft}(\phi_0, \phi_1) = 1 - \exp\left(\frac{-\Delta\Pi^d_{ft}}{\phi_0 + \phi_1 t}\right) \tag{18}$$

4   Identification, Estimation, and Counterfactuals

4.1   Labor Supply Estimation

Although the model is specified at the firm level, the dataset is observed at the mine level. Given that firms are assumed to optimize at the firm-town level, I aggregate all the relevant variables to the firm-town-year-level, as detailed in Appendix A.2.

I start with the identification of the skilled labor supply curve, Equation (12b). The labor supply elasticity $\frac{1}{\psi}$ cannot be recovered by simply regressing skilled labor wages on employment because of the latent firm characteristics ζ_{ft}. Firms with a high ζ_{ft} know they are attractive to miners, which permit them to offer a lower wage to attract the same number of miners. In order to identify the slope of the skilled labor supply curve, a shock to labor demand that is excluded from skilled labor utility is necessary.

I rely on international coal market price shocks for identification. I obtain the average

coal price on international coal markets in Europe in every year from Degrève (1982). I use both this coal price and its interaction term with indicator for whether a mine shipped coal over the railroad network or not as instruments. These instruments imply three assumptions. First, individual Illinois coal mines were too small to have an effect on equilibrium coal prices on the European market. This makes sense given that Illinois produced only around 10% of the total U.S. output, and U.S. bituminous coal mines exported only around 1.2% of their coal in 1898 Graebner (1974). Second, international coal price shocks did affect the demand for Illinois coal. Given that Chicago was one of the destination markets for Illinois coal, and that Chicago also sourced coal by lake steamers from both the East coast and from other coal fields, changes in non-local coal prices affected demand for Illinois coal mines. Third, international coal price shocks affected coal mine demand more if coal mines were shipping their coal over the railroad network compared to coal mines who sold their coal only locally in their own town. This third assumption makes sense given that mines that sold only locally did not compete with coal fields outside of Illinois, given that both these mines and their consumers were not connected to the railroad network, in contrast to mines that did ship coal over the railroad network.

I compute the baseline wage level $w_{0i(f)t}$ as the average miner wage in Illinois. I estimate Equation (12b) with a two-stage least squares estimator using the European coal price and an interaction term of the European coal price and a shipping dummy as instruments for the log relative wage at each firm. I control for whether the firm is a shipping mine or a mine that only sells locally, and include county fixed effects and a linear time trend.

For unskilled wages, I rely on the observed average daily wage for unskilled labor in the Illinois coal industry in every year. Given that I only observe this wage from 1884-1894, I linearly interpolate for the time period 1896-1902 using a loglinear time trend.

The skilled labor supply elasticity is estimated to be 3.799 with a standard error of 1.696, as reported in Table 2(a). This means that in the monopsony case, which corresponds to full employer power $\gamma_{ft} = 0$, skilled labor wages would be set 20.84% below the marginal

revenue product of labor.[15]

Table 2: Model Estimates

(a) Labor supply		Est.	S.E.
Labor supply elasticity	$\frac{1}{\psi}$	3.799	1.696
1(Shipping mine)		1.522	0.324
Year		-0.038	0.005
First-stage F-stat		12.7	
Observations		6497	
(b) Coal demand			
Coal demand elasticity	η	-6.139	0.454
Log(min. distance to big city)		-0.070	0.111
No. railroads		0.240	0.051
Year		0.017	0.005
First-stage F-stat		809.8	
Observations		3192	
(c) Production function			
Input substitution elasticity	σ	0.317	0.063
Skill-augmenting technology effect	α^k	0.204	0.086
Hicks-neutral technology effect	β^k	0.116	0.125
Low-skilled labor coefficient	β^l	0.003	0.005
Serial correlation Hicks-neutral productivity	ρ^ω	0.347	0.092
Serial correlation skill-augmenting productivity	ρ^ω	0.833	0.081
Observations			
(d) Fixed machine costs			
Fixed cost in 1882 ('000 USD)	ϕ_0	21.362	5.449
Fixed cost time trend ('000 USD)	ϕ_1	-2.020	0.627

Notes: Panel (a) reports the skilled labor supply estimates, panel (b) reports the estimates of the coal demand function, panel (c) contains the estimates of the production function, with block-bootstrapped standard errors over 200 iterations. Panel (d) reports the cutting machine fixed cost estimates.

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[15]The wage markdown is equal to $\frac{MRPL-w}{MRPL} = \frac{1}{\psi+1}$.

4.2 Coal Demand Estimation

I estimate the coal demand function in logarithms, Equation (14), using firm-level quantities and prices. I rely on the thickness of the coal vein as a cost shifter: whereas the vein thickness affects the marginal cost of mining, it does not enter consumer utility conditional on the coal price, because vein thickness does not affect coal quality (Affolter & Hatch, 2002). The thickness of the coal vein was the result of geological variation, and hence not a choice variable of the coal firms.

I estimate Equation (14) using a two-stage least squares estimator, with the log average vein thickness in the town as the instrument for coal output. In the observed covariates vector $\mathbf{X}_{ft}^q$, I include the following coal demand shifters: the logarithm of the minimal distance to either Chicago or St. Louis, the number of railroads passing through the mine's town, and a linear time trend. I compute p_{0t} as the average coal price in each year.

The coal demand elasticity is in Table 2(b). The number of observations, 3192, is lower than when estimating labor supply because the thickness of the coal veins is not observed in 1888 and 1890. The demand elasticity is estimated at -6.139 with a standard error of 0.454. This means that firms set coal prices at a markup of 19% above marginal costs. Coal demand is lower in markets that are further away from Chicago or St. Louis, and higher the more railroads pass through the mine's town. Coal demand grows at an average rate of 1.7% per two years throughout the sample period.

4.3 Production Function Estimation

I estimate the production function in two steps. In a first step, I estimate the elasticity of input substitution σ and the skill-augmenting effects of cutting machines, α^k. Second, I estimate all other production function coefficients, β^l and β^k.

Elasticity of Substitution

The elasticity of substitution is usually estimated by taking the ratio of the input demand functions from the employer's profit maximization first order conditions, e.g. in Doraszelski and Jaumandreu (2018). In the bargaining model, however, the marginal revenue product of high-skilled labor is not equal to its wage as long as $\gamma < 1$. Setting γ to zero in equation (8), which implies perfect monopsony power, gives:

$$\frac{\partial R_{ft}}{\partial H_{ft}} = w_{ft}(1 + \psi)$$

Conversely, if γ becomes one, which implies that the labor union has all the bargaining power, the wage of high-skilled workers is equated to their marginal revenue product:

$$\frac{\partial R_{ft}}{\partial H_{ft}} = w_{ft}$$

These two first order conditions for extremes of the bargaining parameter γ_f can be linearly interpolated using the bargaining parameter γ_{ft}, which results in a linear approximation of the first order conditions:

$$\frac{\partial R_{ft}}{\partial H_{ft}} = w_{ft}(1 + (1 - \gamma_{ft})\psi) \tag{19}$$

Working out the first order conditions (6) and (19), and dividing (6) by (19), results in Equation (20). This equation is a variant of the first stage regression from Doraszelski and Jaumandreu (2018), with the difference that the labor supply elasticity enters into the first order conditions, as in Rubens, Wu, and Xu (2024).

$$l_{ft} - h_{ft} = \sigma(w_{ft} - v + \ln(1 + (1 - \gamma_{ft})\psi)) + \underbrace{\sigma \ln(\beta^l) + (1 - \sigma)a_{ft}}_{\equiv \tilde{a}_{ft}} \tag{20}$$

Given that Equation (10) specifies an AR(1) process for the factor-augmenting productivity term a_{ft}, the residual $\tilde{a}_{ft}$ also evolves as an AR(1). Hence, taking ρ^a differences of (20)

isolates the productivity shock e_{ft}^a as a function of the coefficients ρ^a, σ, and α^k. Using the previously stated assumptions that capital is chosen prior to observing the skill-augmenting productivity shock e_{ft}^a, but variable inputs are chosen afterwards, the moment conditions (21) can be specified to estimate the elasticity of input substitution σ, the skill-augmenting productivity effect of cutting machines α^k, and the serial correlation in skill-augmenting productivity ρ^a:

$$\mathbb{E}\left[e_{ft}^a(\rho^a, \alpha^k, \sigma) \Big| \begin{pmatrix} K_{ft-r} \\ L_{ft-r-1} \\ H_{ft-r-1} \end{pmatrix} \right]_{r=0}^{T-1} = 0 \tag{21}$$

Second-Stage Production Function Coefficients

From Equation (20), the log factor-augmenting productivity residual a_{ft} can be written as a function of the estimated parameters σ and ψ, and the yet to be estimated parameters β^l and β^k:

$$a_{ft} = \left(\frac{l_{ft} - h_{ft}}{1 - \sigma} \right) - \frac{\sigma}{1 - \sigma} \left(\ln(\beta^l) \right) - \frac{\sigma}{1 - \sigma} \left(w_{ft} - v_t + \ln(1 + (1 - \gamma_{ft})\psi) \right)$$

Substituting this factor-augmenting productivity term into the log production function gives:

$$q_{ft} = \frac{\sigma}{\sigma - 1} \ln \left(\left(H_{ft} \exp \left(\frac{l_{ft} - h_{ft}}{1 - \sigma} - \frac{\sigma}{1 - \sigma} \ln(\beta^l) - \frac{\sigma}{1 - \sigma} (w_{ft} - v_t + \ln(1 + (1 - \gamma_{ft})\psi))) \right) \right)^{\frac{\sigma - 1}{\sigma}} \right.$$

$$\left. + \beta^l L_{ft}^{\frac{\sigma}{\sigma - 1}} \right) + \omega_{ft} \tag{22}$$

I define the first linear term in the log production function as $B_{ft}(.)$:

$$B_{ft} \equiv \frac{\sigma}{\sigma - 1} \ln \left(\left(H_{ft} \exp \left(\frac{l_{ft} - h_{ft}}{1 - \sigma} - \frac{\sigma}{1 - \sigma} \ln(\beta^l) - \frac{\sigma}{1 - \sigma} (w_{ft} - v_t + \ln(1 + (1 - \gamma_{ft})\psi))) \right) \right)^{\frac{\sigma-1}{\sigma}} \right.$$

$$\left. + \beta^l L_{ft}^{\frac{\sigma}{\sigma-1}} \right)$$

Using the productivity transition in Equation (11), taking ρ^ω differences isolates the Hicks-neutral productivity shock e_{ft}^ω as a function of the parameters $(\rho^\omega, \beta^k, \beta^l)$:

$$e_{ft}^\omega = q_{ft} - \rho^\omega q_{ft-1} - \beta^k (k_{ft} - \rho^\omega k_{ft-1}) - (B_{ft} - \rho^\omega B_{ft-1})$$

Making use of the timing assumption that employers choose capital prior to the realization of the Hicks-neutral productivity shock, but choose low-skilled labor and bargain over wages after the realization of this shock leads to the moment conditions in Equation (23). I estimate this model using lags of up to one time period.

$$\mathbb{E} \left[e_{ft}^\omega (\rho^\omega, \beta^k, \beta^l) \mid \begin{pmatrix} K_{ft-r} \\ L_{ft-r-1} \\ H_{ft-r-1} \end{pmatrix} \right]_{r=0}^{T-1} = 0 \tag{23}$$

4.4   Bargaining Weights

Adding time subscripts to the wage bargaining first order condition, Equation (15), and rearranging terms in function of the union bargaining weights γ_{ft}, leads to Equation (24). I estimate the bargaining parameters using this equation, of which all variables are either observed or have been estimated in the production, labor supply, and goods demand models.

$$\gamma_{ft} = \frac{(W_{ft} - Z_{ft})(\frac{\partial R_{ft}}{\partial H_{ft}} \frac{\partial H_{ft}}{\partial W_{ft}} - H_{ft} - W_{ft} \frac{\partial H_{ft}}{\partial W_{ft}})}{(W_{ft} - Z_{ft})(\frac{\partial R_{ft}}{\partial H_{ft}} \frac{\partial H_{ft}}{\partial W_{ft}} - H_{ft} - W_{ft} \frac{\partial H_{ft}}{\partial W_{ft}}) - (\frac{\psi H_{ft}}{1+\psi} + \frac{\partial H_{ft}}{\partial W_{ft}}(W_{ft} - Z_{ft}))(\frac{\Pi_{ft}^d}{H_{ft}})} \tag{24}$$

Fixed point algorithm

In order to estimate both the first and second stages of the production function estimation, Equations (20) and (22), the bargaining parameters γ_{ft} need to be known, as they enter in the first order condition for high-skilled labor demand. However, estimating the bargaining parameters γ_{ft} requires knowing the production function coefficients, as is clear from Equation (24). I proceed by estimating the production function and bargaining parameters using a fixed point algorithm. I start with an initial value of $\gamma_{ft} = 0.5$ to estimate the production function and bargaining parameters. Then, I use the resulting bargaining parameter to re-estimate the production function and the bargaining parameter. I continue this estimation loop until the production function coefficients converge, up to a sensitivity level of 0.001. I find that the estimated quickly converge to a fixed point.

Results

The production function estimates are reported in Table 2(c). The elasticity of substitution between skilled and unskilled miners is estimated at 0.317, which implies that these two types of workers are gross complements. It is not surprising that this elasticity is relatively low, given that skilled miners were used for cutting coal whereas unskilled miners were used mainly for hauling coal, two tasks that complements rather than substitutes. Cutting machines are estimated to increase skill-augmenting productivity by 22.6%, so cutting machines are a skill-augmenting technology. Given that skilled and unskilled labor are gross complements, this makes cutting machines an unskill-biased technology (Acemoglu, 2002), similarly to many other technologies that were developed throughout the 19th century, which were also unskill-biased (Mokyr, 1990; Goldin & Katz, 2009). The finding that cutting machines were unskill-biased is consistent with the fact that cutting machines automated the cutting process, which was reliant on skilled miners, in contrast to the hauling process, which was mainly reliant on unskilled workers. Besides increasing skill-augmenting productivity, cutting machines also increased Hicks-neutral productivity by 12.3%, although this effect is not statistically significant. The low-skilled labor parameter

Figure 4: Bargaining Parameter Estimates

(a) Employer Power: Distribution	(b) Employer Power: Evolution
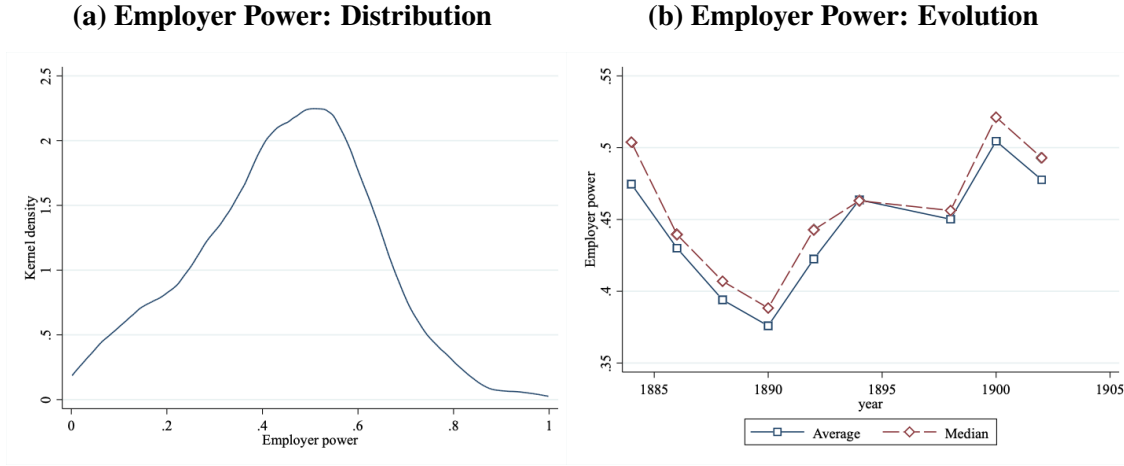
β^l is estimated at 0.003, but is estimated imprecisely. Easier to interpret are the corresponding output elasticities of low- and high-skilled labor, which are estimated at 0.675 and 0.325, respectively. Finally, both skill-augmenting and Hicks-neutral productivity are serially correlated, with serial correlations of 0.347 and 0.833.

The employer's bargaining weight was on average 0.445 and 0.458 at the median firm, so bargaining power was roughly split equally between mine owners and the miners' union. I keep only the bargaining parameter values that range in between zero and one, as values outside of this range are meaningless in the context of the bargaining model. This reduces the number of observations by 11%. Figure 4a shows the entire distribution of employer power, Figure 4b shows the evolution of employer power on average and at the median firm. After an initial decrease in the first years of the sample, employer power increased by more than one third between 1890 and 1902. This coincided with an aggregate decline in both nominal and real wages in the United States during the 1890s (Douglas & Lamberson, 1921).

Table 3 regresses the logarithm of the employer bargaining parameter over high-skilled workers $(\ln(1 - \gamma_f))$ on firm and market characteristics. The first two columns do not include firm fixed effects, the last two do. In both specifications, employers with higher market shares on the high-skilled worker market had more bargaining power. Moreover,

employer power was increasing at a rate of 0.6%-0.9% per year. Employers in markets with more immigrants and a higher population share of African Americans have more bargaining power. This is consistent with the worse bargaining power faced by both immigrants and African Americans, and with the use of 'strike-breakers' from the Southern United States to the decrease the bargaining ability of the labor unions. Finally, firms in counties with higher manufacturing wages have less bargaining power, as this provides a more favorable negotiation position for miners. Although the 1897-1898 strikes did not succeed in countering the overall rise in employer power, employer power did fall relatively at the striking mines compared to the mines that did not go on strike.[16]

Table 3: Employer Power: Covariates

| | log(Employer bargaining power) | | | |
	Est.	S.E.	Est.	S.E.
High-skilled employment market share	0.262	0.021	0.162	0.036
Low-skilled employment market share	-0.284	0.021	-0.188	0.043
Year	0.009	0.002	0.006	0.003
Pop. share foreigners	0.735	0.271		
Pop. share Afro-Americans	2.264	0.641		
Log(manufacturing wage)	-0.166	0.064		
Firm FE:	No		Yes	
R-squared	.063		.677	
Observations	3565		3565	

Notes: In this table, I regress $\ln(1 - \gamma_f)$ on firm and market characteristics.

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[16]I document this in Appendix C.2.

4.5 Cutting Machine Fixed Costs

Solving for Market Equilibrium Conditional on Machine Usage

Using the estimated model, I solve the system of equations (9), (12a), (13), (15), and (16) for every firm in every year, both if using cutting machines and if not using cutting machines. Given that this system of equations is nonlinear, and cannot be solved analytically, I solve for equilibrium numerically.[17] For every outcome variable $Y \in \{Q, P, H, L, W\}$, this yields an equilibrium outcome if the firms uses cutting machines, which is denoted as Y_{ft}^1, and if it does not, denoted as Y_{ft}^0.

Estimation of Fixed Costs

Using the estimated equilibrium, the cutting machine probabilities at each firm in each year, $p_{ft}^k(\phi)$, can be computed using Equation (18), up to the unknown fixed cost parameters (ϕ_0, ϕ_1). I estimate these fixed cost parameters using a maximum likelihood estimator. Using Equation (18), the log likelihood function of using cutting machines $\ln(\mathcal{L}_{ft}(\phi)$ can be written as:

$$\ln(\mathcal{L}_{ft}(\phi)) = \sum_{f,t} [K_{ft} \ln(p^k(\phi)) + (1 - K_{ft}) \ln(1 - p_{ft}^k(\phi))]$$

I estimate the fixed cost parameters (ϕ_0, ϕ_1) by maximizing the log likelihood function $\ln(\mathcal{L}_{ft}(\phi))$. Because the number of observed capital usage decisions is sparse, I do not rely on the observed capital usages K_{ft} in the raw data, but rather estimate a conditional choice probability $\tilde{K}_{ft}$ first by running a probit model of cutting machine usage on log Hicks-neutral and labor-augmenting productivity, the labor supply shifter, and the coal demand shifter. I estimate this model on the entire sample and obtain predicted usage rates of cutting machines for every firm in every year. Next, I use these predicted usage rates in the log likelihood function to estimate cutting machine fixed costs. The resulting estimates are

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[17]I use the Matlab optimizer `fsolve` with function tolerance 10^{-3}, 10^5 maximum iterations, and 600 maximum function evaluations.

in Table 2(d). The fixed cost of using a cutting machine is estimated to be $21,362 in 1882, and is estimated to fall by $2,020 every two years throughout the sample period. This decline in machine fixed cost is in line with the falling costs of many new technologies. External cost information for cutting machines in 1889 is obtained from Brown (1889), which reports a purchasing cost of $8,000 for eight cutting machines. The average firm in the data set also used 8 cutting machines, so the estimated fixed cost in 1888 of $5,202 is lower than the external cost estimate, although in the same order of magnitude.

Solving for Market Equilibrium and Equilibrium Machine Usage

Using Equation (18), I estimate equilibrium cutting machine usage for every firm in every year. I compute the equilibrium values $\hat{Y}_{ft}$ for variables $Y \in \{Q, P, H, L, W\}$ as the weighted average of the value when the firm uses machine usage and when if does not, weighted by the probability of using cutting machines:

$$\hat{Y}_{ft} = Y_{ft}^0 Pr(K_{ft} = 0) + Y_{ft}^1 Pr(K_{ft} = 1) \tag{25}$$

Appendix B.2 discusses how the predicted equilibrium values $\hat{\mathbf{Y}}_{ft}$ compare to the observed variables $\mathbf{Y}_{ft}$. As shown in Appendix Figure A2, the model closely tracks the observed evolution of all equilibrium variables, despite the fact that the estimation procedure does not explicitly target any of these moments, except for machine usage rates.

4.6 Counterfactual: Welfare Effects of Labor Market Power

In order to examine the effects of employer power, I compute how all equilibrium outcomes and welfare would have changed if bargaining power of employers would increase by one standard deviation, which is denoted as a counterfactual bargaining parameter $\tilde{\gamma}_{ft}$.

Welfare

In both the actual and counterfactual equilibria, I compute consumer surplus CS_{ft} as the area in between the demand curve and the equilibrium price:

$$CS_{ft} \equiv \int_0^{\hat{Q}_{ft}} (P_0 \Big(\frac{Q_{ft}}{\xi_{ft}}\Big)^{\frac{1}{\eta}} - \hat{P}_{ft}) dQ_{ft} = \Big(\frac{-1}{\eta+1}\Big) \frac{P_0}{\xi^{\frac{1}{\eta}}} (\hat{Q}_{ft})^{\frac{\eta+1}{\eta}}$$

Similarly, I compute worker surplus WS_{ft} as the area between the labor supply curve and the equilibrium wage $\hat{W}_{ft}$:

$$WS_{ft} \equiv \int_0^{\hat{H}_{ft}} (\hat{W}_{ft} - W_{0,i(f)t} \Big(\frac{H_{ft}}{\zeta_{ft}}\Big)^{\psi}) dH_{ft} = \Big(\frac{\psi}{\psi+1}\Big) \frac{W_0}{\zeta_{ft}^{\psi}} (\hat{H}_{ft})^{\psi+1}$$

Finally, producer surplus is equal to variable employer profits:

$$PS_{ft} \equiv \hat{P}_{ft}\hat{Q}_{ft} - \hat{H}_{ft}\hat{W}_{ft} - \hat{L}_{ft}V_t$$

Counterfactual Results

Table 4a reports the equilibrium effects of a one standard deviation increase in employer power. If capital investment would be exogenous, coal output would decrease by 26.8%, because the exertion of monopsony power induces deadweight loss. However, capital investment does not remain fixed: the increase in employer power results in an increase in the cutting machine usage of 13.8%.[18] As a result, the output decline due to monopsony power is lower, at 24.6%, when taking into account endogenous cutting machine usage, given that increased investment lowers marginal costs. The net effect on equilibrium output is still negative because the deadweight loss effect dominates the reduction in marginal costs due to higher technology adoption. Similarly, the exogenous investment model overestimates the decline in employment and wages, and the increase of the coal price. Both

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[18]The usage rate of 8.4% in the observed equilibrium is lower as the usage rate of 11% in Figure A2e because the comparison table conditions on the equilibrium being solved in both the actual and counterfactual equilibrium. This leads to a different sample selection with slightly lower capital usage rates.

Hicks-neutral and skill-augmenting productivity increase on average when employer power increases, due to higher capital investment.

The welfare counterfactuals are reported in Table 4b. Consumer surplus is estimated to fall by 23.2% on average in the exogenous investment model, which reduces to a 21.7% drop in the endogenous investment model. Similarly, the reduction in labor surplus changes from 38.0% to 36.0% once endogenous capital usage is taken into account.

Under increased employer power, consumers and workers experience a drop in surplus, although consumer surplus could in theory have increased if the technology adoption mechanism would dominate the deadweight loss effect. In contrast, producer surplus obviously increases when employers gain bargaining power. Assuming exogenous investment, producer surplus would increase by 9.35%, which increases to 11.83% under endogenous investment. The increased producer surplus is insufficient to compensate the losses to consumer and labor surplus, as total surplus falls by 12.1%. However, assuming exogenous investment would predict a total surplus drop of 14.1%, which is an overestimate of the true welfare loss of 16.5%.

Factor Intensity and Monopsony Power

The equilibrium employment changes in Table 4a reveal that increased employer power leads to a reduction of the high- to low-skilled labor ratio from 2.84 to 2.75. This reduction in relative high-skilled labor usage is due to a combination of two effects. First, the increase in employer power affects employer bargaining power only over high-skilled workers, not over low-skilled workers which are supplied on a perfectly competitive market. Hence, increased monopsony power over high-skilled workers increases the marginal cost for these workers, and induces employers to substitute low-skilled workers for high-skilled workers. This is the mechanism documented in Goolsbee and Syverson (2019).

However, a second mechanism is at play. The increase in employer power results in higher cutting machine adoption, which is an unskill-biased technology. This leads to an additional substitution of low-skilled for high-skilled workers. Comparing the exogenous to the endogenous investment counterfactual shows that 76.5% of the reduction in the high-

Table 4: Counterfactual: Increased Employer Power

(a) Equilibrium		Exogenous K		Endogenous K	
	Actual	C.F.	%dif	C.F.	%dif
Output	1444.738	1058.002	-26.769	1090.018	-24.553
Price	1.685	1.769	4.973	1.766	4.838
High-skilled labor	602.522	439.061	-27.130	445.810	-26.009
Low-skilled labor	212.053	158.325	-25.337	161.984	-23.611
High-skilled wage	1.828	1.679	-8.170	1.682	-8.011
Cutting machine usage	0.084	0.084	0.000	0.095	13.781
Hicks-neutral productivity	1.524	1.524	0.000	1.525	0.062
Skill-augmenting productivity	4.774	4.774	0.000	4.784	0.209
(b) Welfare		Exogenous K		Endogenous K	
	Actual	C.F.	%dif	C.F.	%dif
Consumer surplus	373.115	286.461	-23.224	292.201	-21.686
Producer surplus	363.860	397.863	9.345	406.904	11.830
Worker surplus	215.499	133.568	-38.019	137.833	-36.040
Total surplus	952.474	817.892	-14.130	836.938	-12.130

Notes: Panel (a) reports averages for all equilibrium outcomes in 1902 in the observed equilibrium (the left column) and in the counterfactual equilibrium where employer power does not increase (the center and right columns). The center column keeps cutting machine usage exogenous, whereas the right column allows cutting machine usage to be endogenous to the degree of bargaining power held by employers.

to-low skilled labor ratio was due to the monopsony-induced substitution effect, whereas the remaining 23.5% was due to increased cutting machine adoption.

5   Conclusion

In this paper, I investigate the welfare effects of employer power by studying the trade-off between monopsony distortions and endogenous investment. Using a model of production and labor supply that allows for monopsony power, wage bargaining, and imperfectly com-

petitive goods markets, I find that an increase in employer power could either increase or decrease output and total welfare, depending on the relative size of the monopsony distortion, of the marginal cost reduction due to endogenous investment, and on the initial level of employer power. In the empirical context of the mechanization of the late 19th century Illinois coal mining industry, I find that an increase in employer power lowers equilibrium output because the monopsony distortion dominates the marginal cost reduction that is due to additional coal cutting machine adoption. Although total welfare declines when employer power increases, this decline is 14.2% smaller than one would find when holding capital investment fixed. Hence, the model and the results show that taking into account endogenous capital quantitatively matters for assessing the welfare effects of labor market power.

References

Abowd, J. A., & Lemieux, T. (1993). The effects of product market competition on collective bargaining agreements: The case of foreign competition in canada. *The Quarterly Journal of Economics*, *108*(4), 983–1014.

Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies*, *69*(4), 781–809.

Acemoglu, D., & Shimer, R. (1999). Holdups and efficiency with search frictions. *International Economic Review*, *40*(4), 827–849.

Ackermann, A. (1902). *Coal-cutting by machinery in America* (No. 16). The Colliery Guardian Company Limited.

Affolter, R. H., & Hatch, J. R. (2002). Characterization of Quality of Coals from the Illinois Basin. In R. H. Affolter & J. R. Hatch (Eds.), (Vol. 1625, p. 1-227). U.S. Geological Survey.

Ashenfelter, O. C., Farber, H., & Ransom, M. R. (2010). Labor market monopsony. *Journal of Labor Economics*, *28*(2), 203-210.

Atack, J., Bateman, F., & Margo, R. A. (2008). Steam power, establishment size, and labor productivity growth in nineteenth century american manufacturing. *Explorations in Economic History*, *45*(2), 185–198.

Benkard, C. L. (2000). Learning and forgetting: the dynamics of aircraft production. *American Economic Review*, *90*(4), 1034-1054.

Berger, D., Herkenhoff, K., & Mongey, S. (2022). Labor market power. *American Economic Review*, *112*(4), 1147–93.

Bloch, L. (1922). *The Coal Miners' Insecurity: Facts about Irregularity of Employment in the Bituminous Coal Industry in the United States* (No. 7). Russell Sage Foundation.

Boal, W. M. (1995). Testing for employer monopsony in turn-of-the-century coal mining. *RAND Journal of Economics*, *26*(3), 519-536.

Boal, W. M. (2017). What did Unions do? The case of Illinois Coal Mining in the 1880s. *Journal of Labor Research*, *38*(4).

Brown, W. (1889). *Transactions of the federated institution of mining engineers* (Tech. Rep. No. 1). Federated Institution of Mining Engineers.

Chambolle, C., Christin, C., & Molina, H. (2023). Buyer power and exclusion: A progress report. *International Journal of Industrial Organization*, 102969.

Crawford, G. S., & Yurukoglu, A. (2012). The welfare effects of bundling in multichannel television markets. *American Economic Review*, *102*(2), 643–685.

Degrève, D. (1982). *Le commerce extérieur de la Belgique, 1830-1913-1939: Présentation critique des données statistiques* (Vol. 1b). Brussels: Palais des Académies.

Delabastita, V., & Rubens, M. (2024). Colluding against workers. *Available at SSRN*.

Doraszelski, U., & Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, *126*(3), 1027-1084.

Douglas, P. H., & Lamberson, F. (1921). The movement of real wages, 1890-1918. *The American Economic Review*, *11*(3), 409–426.

Fishback, P. V. (1992). *Soft coal, hard choices: The economic welfare of bituminous coal miners, 1890-1930*. Oxford University Press.

Fishback, P. V., Holmes, R., & Allen, S. (2009). Lifting the curse of dimensionality: measures of states' labor legislation climate in the United States during the progressive era. *Labor History*, *50*(3), 313-346.

Goldin, C., & Katz, L. F. (1998). The origins of technology-skill complementarity. *The Quarterly journal of economics*, *113*(3), 693–732.

Goldin, C., & Katz, L. F. (2009). *The race between education and technology*. harvard university press.

Goolsbee, A., & Syverson, C. (2019). *Monopsony power in higher education: a tale of two tracks* (Tech. Rep.). National Bureau of Economic Research.

Graebner, W. (1974). Great expectations: The search for order in bituminous coal, 1890-1917. *The Business History Review*, 49–72.

Grennan, M. (2013). Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review*, *103*(1), 145–177.

Hemphill, C. S., & Rose, N. L. (2017). Mergers that harm sellers. *Yale LJ*, *127*, 2078.

Hoover, E. D. (1960). Retail prices after 1850. In *Trends in the American economy in the nineteenth century* (pp. 141–190). Princeton University Press.

Horn, H., & Wolinsky, A. (1988). Bilateral monopolies and incentives for merger. *The RAND Journal of Economics*, 408–419.

Huang, S.-Y., & Sexton, R. J. (1996). Measuring returns to an innovation in an imperfectly competitive market: Application to mechanical harvesting of processing tomatoes in Taiwan. *American Journal of Agricultural Economics*, *78*(3), 558–571.

Jarosch, G., Nimczik, J. S., & Sorkin, I. (2019). *Granular search, market structure, and wages* (Tech. Rep.). National Bureau of Economic Research.

Joskow, P. L. (1987). Contract duration and relationship-specific investments: Empirical evidence from coal markets. *The American Economic Review*, 168–185.

Joyce, R. (2009). *The Early Days of Coal Mining in Northern Illinois.* Illinois Labor History Society. (Accessed through http://www.illinoislaborhistory.org/labor-history-articles/early-days-of-coal-mining-in-northern-illinois)

Just, R. E., & Chern, W. S. (1980). Tomatoes, technology, and oligopsony. *The Bell Journal of Economics*, 584–602.

Katz, L. F., & Margo, R. A. (2014). Technical change and the relative demand for skilled labor: The United States in historical perspective. In *Human capital in history: The American record* (pp. 15–57). University of Chicago Press.

Köhler, C., & Rammer, C. (2012). Buyer power and suppliers' incentives to innovate. *ZEW-Centre for European Economic Research Discussion Paper*.

Kroft, K., Luo, Y., Mogstad, M., & Setzler, B. (2020). *Imperfect competition and rents in labor and product markets* (Tech. Rep.). National Bureau of Economic Research.

Lamadon, T., Mogstad, M., & Setzler, B. (2022). Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review*, *112*(1), 169–212.

Loertscher, S., & Marx, L. M. (2019). Merger review for markets with buyer power. *Journal of Political Economy*, *127*(6), 2967–3017.

Lord, J. S. (1883). *Statistics of Coal Production in Illinois, 1883: A Supplemental Report of the State Bureau of Labor Statistics*.

Lord, J. S. (1892). *Coal in Illinois, 1884-1892* (Biennial Reports No. 2-7).

Manning, A. (2011). Imperfect competition in the labor market. In *Handbook of labor economics* (Vol. 4, pp. 973–1041). Elsevier.

Menezes-Filho, N., & Van Reenen, J. (2003). Unions and innovation: a survey of the theory and empirical evidence. *International handbook of trade unions*, 293–334.

Mokyr, J. (1990). *Twenty five centuries of technological change: An historical survey* (Vol. 35). Taylor & Francis.

Morlacco, M. (2017). *Market power in input markets: theory and evidence from French manufacturing* (Tech. Rep.).

Naidu, S., Nyarko, Y., & Wang, S.-Y. (2016). Monopsony power in migrant labor markets. *Journal of Political Economy*, *124*(6), 1735-1792.

Naidu, S., & Yuchtman, N. (2017). Labor market institutions in the gilded age of american

history. *The Oxford Handbook of American Economic History*, *Forthcoming*.

Parra, A., & Marshall, G. (2021). *Monopsony power and upstream innovation* (Tech. Rep.).

Peters, B., Roberts, M., Vuong, V. A., & Fryges, H. (2017). Estimating Dynamic R&D Demand: An Analysis of Costs and Long-Run Benefits. *RAND Journal of Economics*, *48*(2), 409-437.

Reid, A. (1876). *Transactions of the North of England Institute of Mining and Mechanical Engineers*. North of England Institute of Mining and Mechanical Engineers.

Rubens, M. (2023). Market structure, oligopsony power, and productivity. *American Economic Review*, *113*(9), 2382–2410.

Rubens, M., Wu, Y., & Xu, M. (2024). *Exploiting or augmenting labor?* (Tech. Rep.).

Shi, L. (2023). Optimal regulation of noncompete contracts. *Econometrica*, *91*(2), 425–463.

Starr, E., Prescott, J. J., & Bishara, N. (2021). Noncompetes in the us labor force. *Journal of Law and Economics*.

Stoek, H., Hippard, C., & Langtry, W. (1920). Bituminous coal storage practice. *Bulletin of the University of Illinois Engineering Experiment Station*, *116*, 1-142.

Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of uk companies. *The Quarterly Journal of Economics*, *111*(1), 195–226.

Whitcomb, G. D. (1882, 08 8). *Coal mining machine* (No. 262225).

Williams, T. (1901). The anthracite coal crisis. *The Atlantic*, *April*.

Williamson, O. E. (1971). The vertical integration of production: market failure considerations. *The American Economic Review*, *61*(2), 112–123.

Zahur, N. B. (2022). Long-term contracts and efficiency in the liquefied natural gas industry. *Available at SSRN 4222408*.

Appendices

A   Appendix: Data

A.1   Sources

Mine Inspector Reports

The main data source is the biennial report of the Bureau of Labor Statistics of Illinois, of which I collected the volumes between 1884 and 1902. Each report contains a list of all mines in each county, and reports the name of the mine owner, the town in which the mine is located, and a selection of variables that varies across the volumes. An overview of all the variables (including unused ones), and the years in which they are observed, is in Tables A6 and A7. Output quantities, the number of miners and other employees, mine-gate coal prices, and information on the usage of cutting machines are reported in every volume. Miner wages and the number of days worked are reported in every volume except 1896. The other variables, which includes information about the mine type, hauling technology, other technical characteristics, and other inputs, are reported in a subset of years.

Census of Population, Agriculture, and Manufacturing

I use the 1880 population census to have information on county population sizes, demographic compositions, and areas. I also observe the county-level capital stock and employment in manufacturing industries from the 1880 census of manufacturing, and the number of farms and improved farmland area from the 1880 census of agriculture.

Monthly Data

The 1888 report contains monthly production data for a selection of 11 mines in Illinois, across 6 counties. I observe the monthly number of days worked and the number of skilled and unskilled workers. I also observe the net earnings for all skilled and unskilled workers per mine per month, and the number of tons mined per worker per month. This allows me

to compute the daily earnings of skilled and unskilled workers per month.

A.2 Data Cleaning

Employment

In every year except 1896, workers are divided into two categories, 'miners' and 'other employees'. In 1896, a different d istinction is made, between 'underground workers' and 'above-ground workers'. This does not correspond to the miner-others categorization because all miners were underground workers, but some underground workers were not miners (e.g. doorboys, mule drivers, etc.). Hence, I do not use the 1896 data. From 1888 to 1896, boys are reported as a separate working category. Given that miners (cutters) were adults, I include these boys in the 'other employee' category. The number of days worked is observed for all years. The average number of other employees per mine throughout the year is observed in every year except 1896; in 1898 it is subdivided into underground other workers and above-ground other workers, which I add up into a single category. The quantity of skilled and unskilled labor is calculated by multiplying the number of days worked with the average number of workers in each category throughout the year. Up to and including 1890, the average number of miners is reported separately for winters and summers. I calculate the average number of workers during the year by taking the simple average of summers and winters. If mines closed down during winters or, more likely, summers, I calculate the annual amount of labor-days by multiplying the average number of workers during the observed season with the total number of days worked during the year.

Wages

Only miner wages are consistently reported over time at the mine level. The piece rate for miners is reported. Up to 1894, miner wages per ton of coal are reported separately for summers and winters. I weight these seasonal piece rates wages using the number of workers employed in each season for the years 1884-1890. In 1892 and 1894, seasonal

employment is not reported, so I take simple averages of the seasonal wage rates. In 1896, wages are unobserved. From 1898 onwards, wages are no longer reported seasonally, because wages were negotiated biennially from that year onwards. For these years, wages are reported separately for hand and machine miners. In the mines that employed both hand and machine miners, I take the average of these two piece rates, weighted by the amount of coal cut by hand and cutting machines.

Output Quantity and Price

The total amount of coal mined is reported in every year, in short tons (2000 lbs). Up to and including 1890, the total quantity of coal extraction is reported, without distinguishing different sizes of coal pieces. After 1890, coal output is reported separately between 'lump' coal (large pieces) and smaller pieces, which I sum in order to ensure consistency in the output definition. Mine-gate prices are normally given on average for all coal sizes, except in 1894 and 1896, where they are only given for 'lump' coal (the larger chunks of coal). I take the lump price to be the average coal price for all coal sizes in these two years. There does not seem to be any discontinuity in the time series of average or median prices between 1892-1894 or 1896-1898 after doing this, which I see as motivating evidence for this assumption.

Cutting Machine Usage

Between 1884 and 1890, the number of cutting machines used in each mine is observed. In between 1892 and 1896, a dummy is observed for whether coal was mined by hand, using cutting machines, or both. I categorize mines using both hand mining and cutting machines as mines using cutting machines. In 1898, I infer cutting machine usage by looking at which mines paid 'machine wages' and 'hand wages' (or both). In 1888, the number of cutting machines is reported by type of cutting machine as well. Finally, in 1900 and 1902, the output cut by machines and by hand is reported separately for each mine, on the basis of which I again know which mines used cutting machines, and which did not.

Deflators

I deflate all monetary variables using the consumer price index from the *Handbook of Labor Statistics* of the U.S. Department of Labor, as reported by the Minneapolis Federal Reserve Bank website.[19]

Hours Worked

In 1898, eight-hour days were enforced by law, which means that the 'number of days' measure changes in unit between 1898 and 1900. As the inspector report from 1886 shows that ten-hour days were the standard, I multiply the number of working days after 1898 by 80% in order to ensure consistency in the meaning of a 'workday', i.e. to ensure that in terms of the total number of hours worked, the labor quantity definition does not change after 1898. Given that the model is estimated on the pre-1898 period, this does not affect the model estimates, only the descriptive evidence.

Mine and Firm Identifiers

The raw dataset reports mine names, which are not necessarily consistent over time. Based on the mine names, it is often possible to infer the firm name as well, in the case of multi-mine firms. For instance, the Illinois Valley Coal Company No. 1 and Illinois Valley Coal Company No. 2 mines clearly belong to the same company. For single-mine firms, the operator is usually mentioned as the mine name, (e.g. 'Floyd Bussard'). For the multi-mine firms, mine names were made consistent over time as much as possible.

Town Identifiers and Labor Market Definitions

The data set contains town names. I link these names to geographical coordinates using Google Maps. I calculate the shortest distance between every town in the data. For towns that are located less than 3 miles from each other, I merge them and assign them randomly the coordinates of either of the two mines. This reduces the number of towns in the dataset from 448 to 374. The resulting labor markets lie at least 3 miles from the nearest labor

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[19]https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1800-

market.

Coal Market Definitions

Using the 1883 Inspector Report, I link every coal mining town to a railroad line, if any. Some towns are located at the intersection of multiple lines, in which case I assign the town to the first line mentioned. I make a dummy variable that indicates whether a railroad is located on a crossroad of multiple railroad lines. Towns not located on railroads are assumed to be isolated coal markets. For the connected towns, the market is defined as the railroad line on which they are located, of which there are 26. Given that data from 1883 is used, expansion of the railroad network after 1883 is not taken into account. However, the Illinois railroad network was already very dense by 1883.

Aggregation from Mine to Firm Level

I aggregate labor from the mine-bi-year- to firm-bi-year level by taking sums of the number of labor-days and labor expenses for both types of workers, both per year and per season. I calculate the wage rates for both types per worker by dividing firm-level labor expenditure on the firm-level number of labor-days. I also sum powder usage, coal output and revenue to the firm-level and calculate the firm-level coal price by dividing total firm revenue by total firm output. I aggregate mine depth and vein thickness by taking averages across the different mines of the same firm. I define the cutting machine dummy at the firm-level as the presence of at least one cutting machine in one of the mines owned by the firm. I define 'firm' as the combination of the firm name in the dataset and its town (the merged towns that are used to define labor markets), as firms are assumed to optimize input usage on a town-by-town basis.

B   Appendix: Simulations and Model Fit

B.1   Simulating the Theoretical Model

Baseline Parametrization

In Section 2.3, I simulate the theoretical model with the following parameters values. I use the estimates from Kroft et al. (2020) for the U.S. construction industry to set the product demand elasticity to $\eta = -7$ and the labor supply elasticity to $\psi = 0.25$. I calibrate the elasticity of substitution between high- and low-skilled labor at $\sigma = 0.7$. I normalize most parameters at one: $\xi = 1$, $\zeta = 1$, $w_0 = p_0 = v = 1$, $\omega = 1$, $a = 1$. I set the low-skilled production coefficient at 0.2: $\beta^l = 0.1$. I simulate a dataset with 50 observations, in which the bargaining parameter γ_f is distributed uniformly between 0 and 1. I let fixed technology costs be distributed as an exponential distribution with its mean being 0.05.

Under these parametrizations, I solve the system of equations (1), (2), (7), (6), (8) for equilibrium (Q, P, W, H, L).

Alternative Parametrizations

In Figure A1, I compare the baseline calibration of the structural model to various alternative parametrizations. First, I let labor supply be more inelastic. Second, I increase the productivity effects of the new technology.

B.2   Model Fit

Figure A2 compares the model-predicted equilibrium outcomes against the observed outcomes in the data. The model is not estimated to target any of these outcomes, except for capital invetment, through the maximum likelihood estimation of fixed technology costs. Nevertheless, the model generates a very similar evolution of average wages, prices, employment, output, and investment between the predicted and observed outcomes. Although the model performs well in terms of generating the observed evolution of these variables

over time, it performs slightly less well in terms of absolule magnitudes. The model-predicted output and employment levels are underestimated compared to the truth, and coal prices are overestimated.

C   Appendix: Extensions and Robustness Checks

C.1   Alternative Production Function Specifications

Non-Constant Returns to Scale

In the main text, the production function (1) relied on constant returns to scale. In contrast, Equation (28) allows for non-constant returns to scale, as parametrized by ν.

$$Q_f = \left((A_f(K_f)H_f)^{\frac{\sigma-1}{\sigma}} + \beta^l L_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\nu\sigma}{\sigma-1}} \Omega_f(K_f) \tag{26}$$

The first step of the production function estimation procedure, the estimation of Equation (20) remains the same. However, the second step of the estimation procedure needs to estimate the scale parameter ν in addition to the other production function coefficients ρ^ω, β^l, and β^k. Given that we have four instruments (lagged employment for both labor types, current and lagged capital), the model is still identified.

$$q_{ft} = \frac{\nu\sigma}{\sigma-1} \ln \left(\left(\exp \left((\frac{l_{ft} - h_{ft}}{1-\sigma}) - \frac{\sigma}{1-\sigma}(\ln(\beta^l)) - \frac{\sigma}{1-\sigma}(w_{ft} - v_t + \ln(1 + (1-\gamma_{ft})\psi)) \right) H_{ft} \right)^{\frac{\sigma-1}{\sigma}} \right.$$
$$\left. + \beta^l L_{ft}^{\frac{\sigma}{\sigma-1}} \right) + \omega_{ft}$$

The results are in the first column of Table A4. The scale parameter is estimated at 1.039, which indicates modestly increasing returns to scale, but is not significantly different from 1. Hence, the assumption of constant returns to scale cannot be rejected. The other production coefficients look very similar to the estimates in the main model that assumes constant returns to scale.

Adding Materials

As a second robustness check, I add the materials to the production function as a third production input. I use the number of kegs of black powder to measure materials, as this is the

main intermediate input that is measured in the dataset. This implies that a fifth coefficient, β^m needs to be estimated. I assume that changing the stock of black powder requires adjustment costs: black powder is a durable good but needs to be safely stored. Hence, it is conceivable that there was an adjustment cost when increasing the stock of black powder, as additional storage space needed to be added. Conform with this assumption, I include current and lagged materials as an additional instrument when estimating the production function.

$$Q_f = \left((A_f(K_f)H_f)^{\frac{\sigma-1}{\sigma}} + \beta^l L_f^{\frac{\sigma-1}{\sigma}} + \beta^m M_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\nu\sigma}{\sigma-1}} \Omega_f(K_f) \tag{27}$$

The estimates are in the second column of Table A4. The material coefficient is estimated to be very close to zero, which means that ignoring materials in the main production model does not matter much. The remaining production coefficient look very similar to the previous ones, with the exception of the serial correlation in TFP, which increases to 0.571.

Capital and Returns to Scale

It could be that the degree of returns to scale changed when firms adopted cutting machines. To test this, I interact the returns to scale parameter with the cutting machine indicator variable, thereby allowing returns to scale to differ between firms that do and do not use cutting machines. Now, an additional instrument is needed to identify all six parameters in the production function. I rely on non-fatal accident rates as shifters of labor supply, which should affect input usage but not productivity directly. I measure the probability of non-fatal accidents as the ratio of the number of such accidents over total employment at the mine, in days worked.

$$Q_f = \left((A_f(K_f)H_f)^{\frac{\sigma-1}{\sigma}} + \beta^l L_f^{\frac{\sigma-1}{\sigma}} + \beta^m M_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{(\nu_0+\nu_1 K_f)\sigma}{\sigma-1}} \Omega_f(K_f) \tag{28}$$

The estimates are in the third column of Table A4. The interaction effect between re-

turns to scale and cutting machines is close to zero and not statistically significant. Hence, the null hypothesis that returns to scale are invariant to cutting machine usage cannot be rejected.

C.2 Additional Results

Strikes and Employer Power

In this appendix, I repeat the difference-in-differences analysis from Section 3.3, but now use the log of the estimated bargaining parameter γ_{ft} as the left-hand side variable, in order to examine how employer power changed in response to the 1897 strike. In the left column of Table A3, I compare all firms with strikes to the non-striking firms. Union power is estimated to increase by 3%, although this effect is not statistically significant. When only considering the striking firms at which wages increased after the strike, the increase in union bargaining power is higher, at 8.5%, and this change is statistically significant.

Cost Dynamics

In Table A2, I test for cost dynamics by regressing labor productivity, measured as output per labor day, on log cumulative output. This is in the same spirit of Benkard (2000). I find that when not taking mine fixed effects, cumulative past output correlates with higher productivity. However, this is likely due to a selection effect: more productive mines exist longer and produce more. As soon as I include mine fixed effects and look at time series variation in productivity within mines, the relationship between log cumulative output and labor productivity vanishes. This suggests that cost dynamics are not a key feature to be included in the model.
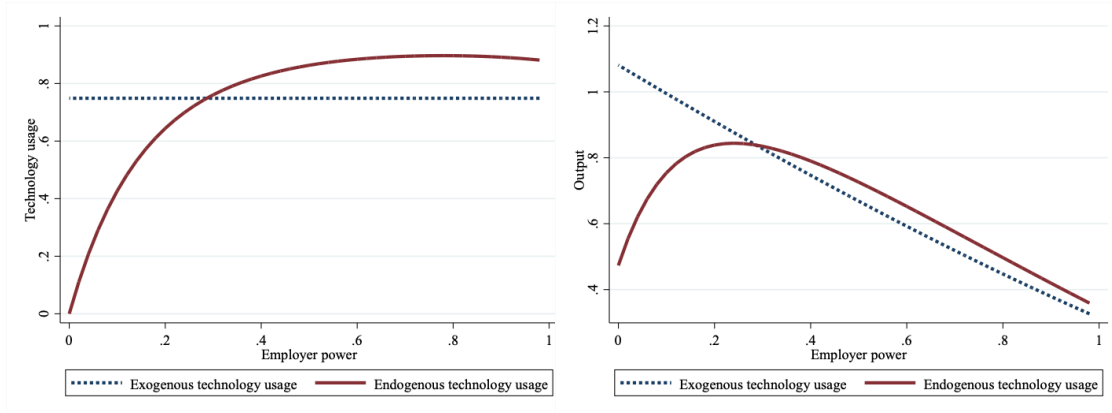
C.3 Appendix Tables and Figures

Figure A1: Simulations: Alternative Parametrization
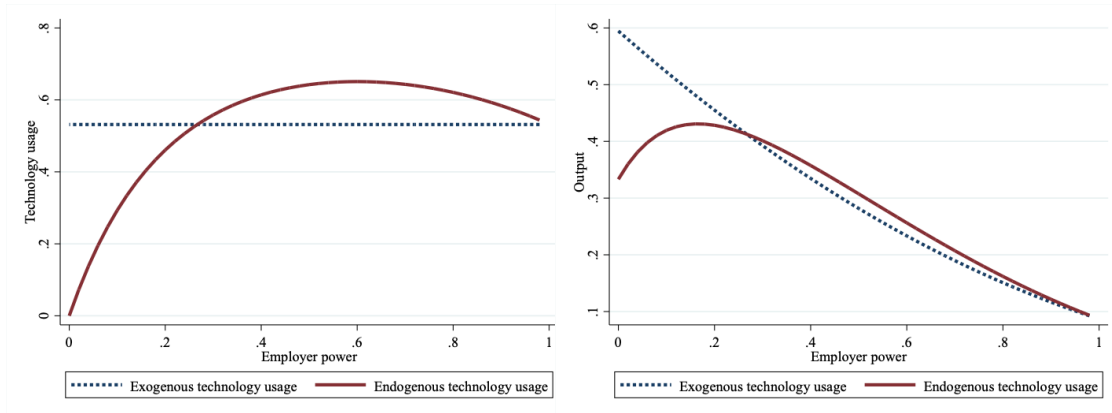
(a) Baseline: $\psi = 0.25, \beta^k = 0.2$
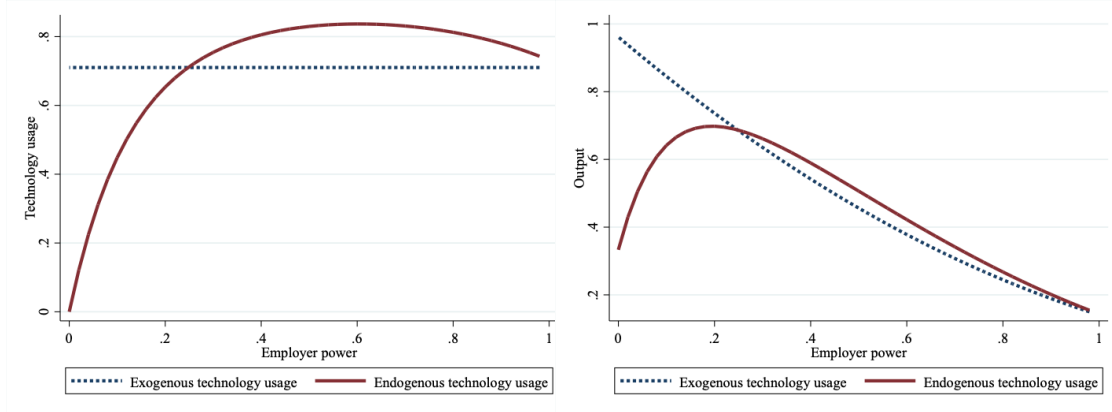
(b) $\psi = 0.5, \beta^k = 0.2$

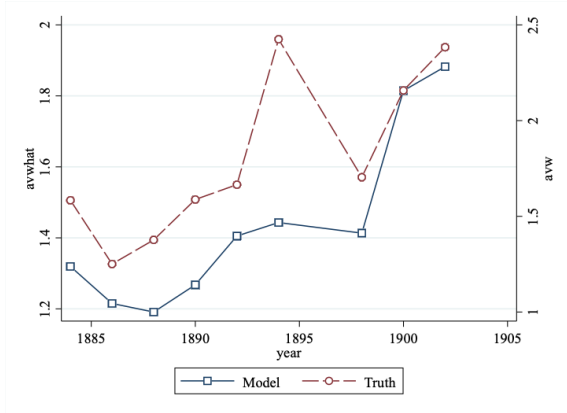
(c) $\psi = 0.25, \beta^k = 0.05$

Figure A2: Model Fit

(a) High-Skilled Wage

(b) Coal Price
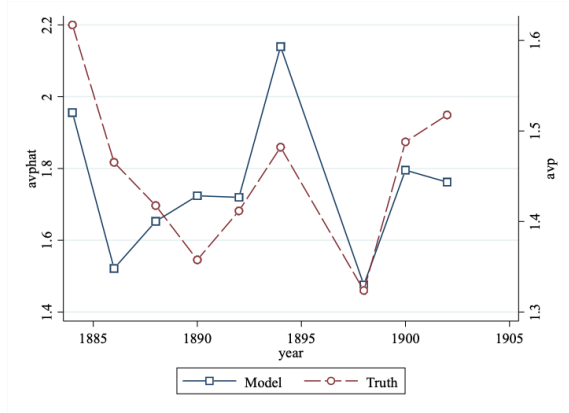
(c) High-Skilled Labor
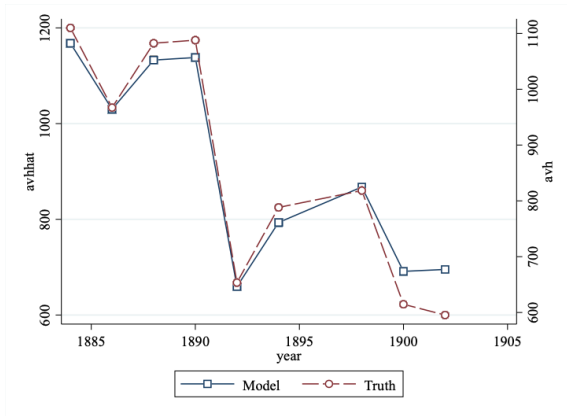
(d) Low-Skilled Labor
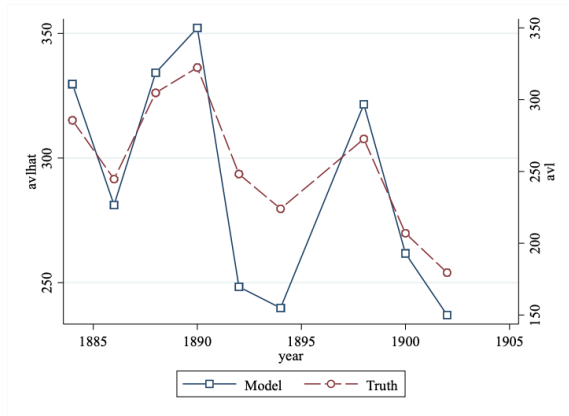
(e) Technology Usage
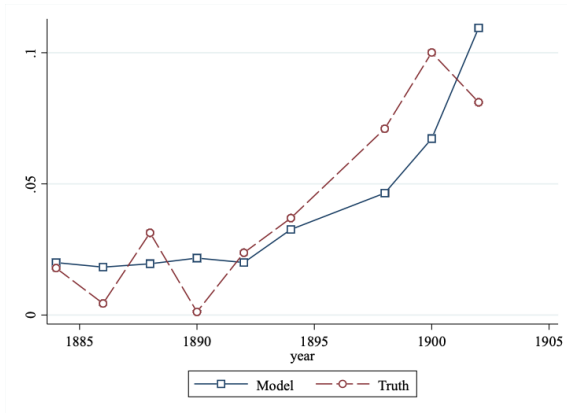
(f) Output
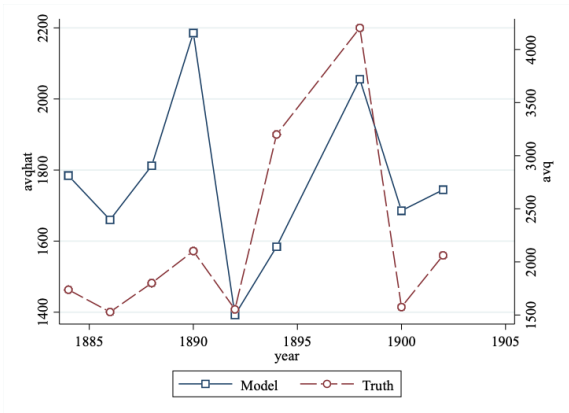
Notes: Figures compare the average equilibrium variables between their observed values and the predicted values from the model, for each year.

Figure A3: Geographical Spread of Cutting Machines
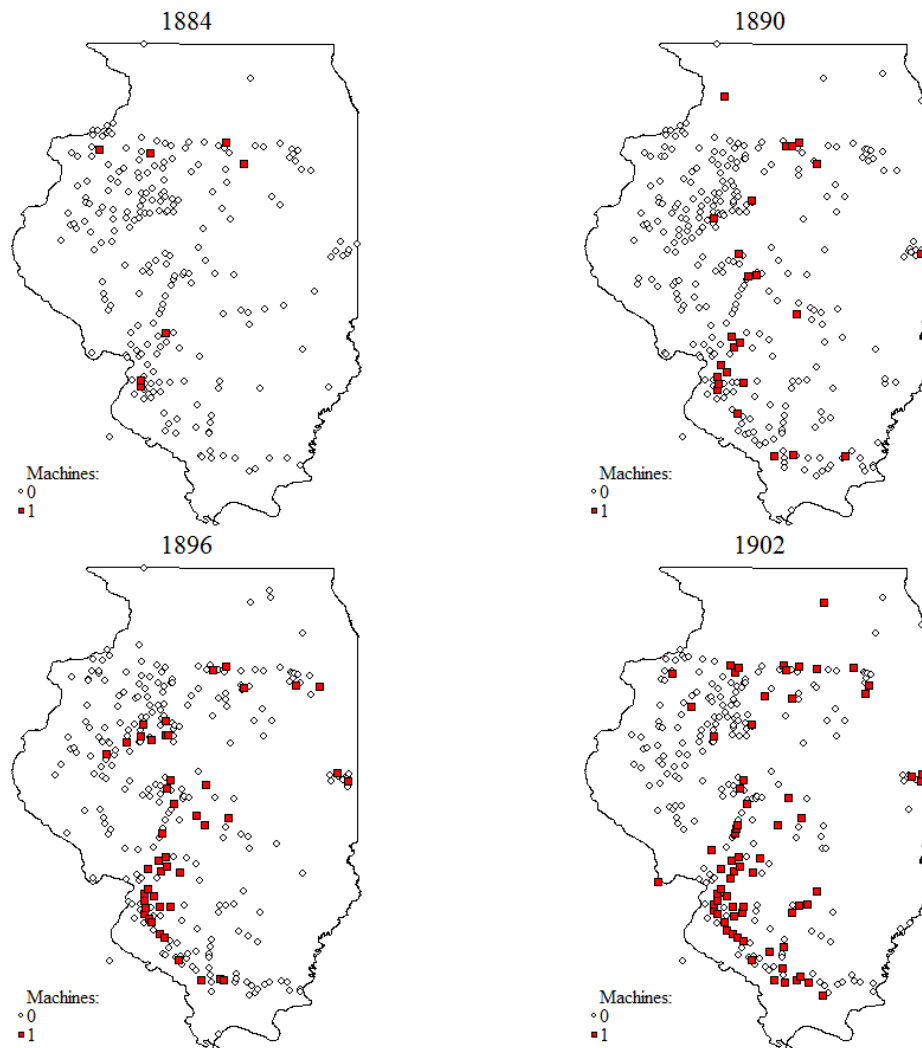
Notes: The dots indicate mining towns, each of which can contain multiple mines. Villages with squares contain at least one machine mine.

Figure A4: Capacity Utilization
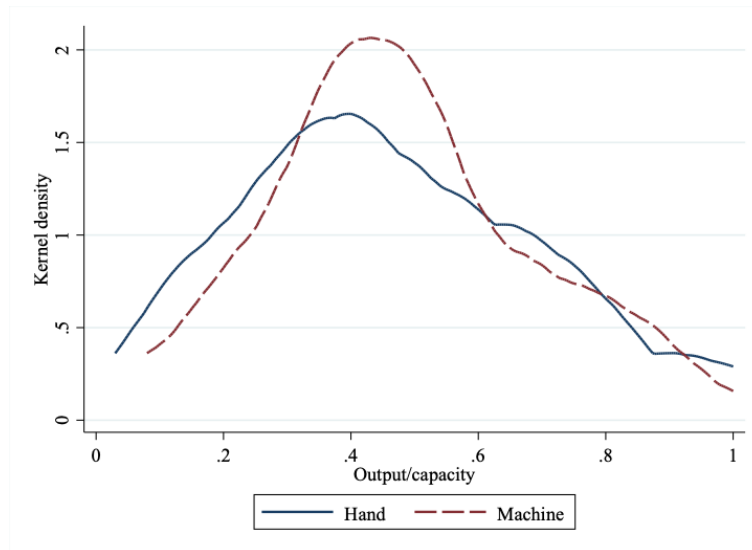
Notes: This graph plots the distribution of capacity utilization, defined as annual mine output over annual mine capacity, across mines in 1898. A distinction is made between hand mines, which did not use cutting machines, and machine mines, which did so.

Figure A5: Patent of the Harrison Cutting Machine
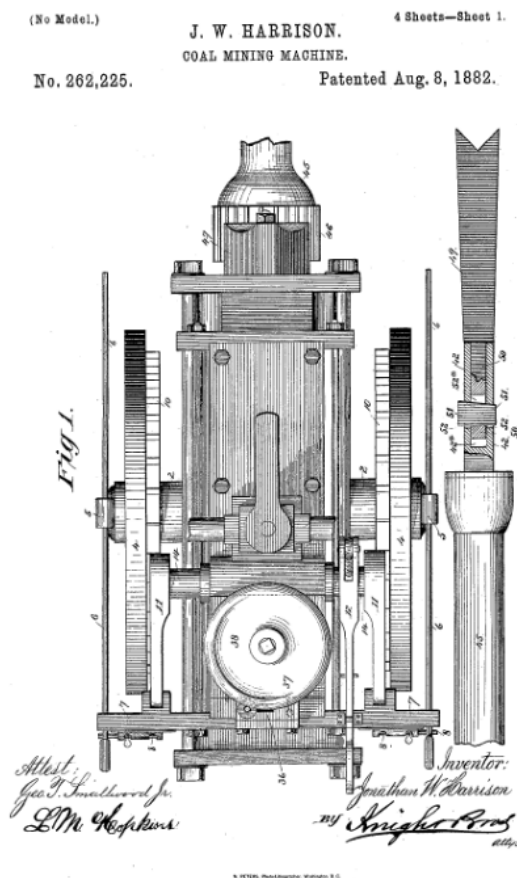
Notes: U.S. patent of the 1882 Improved Harrison Coal Cutting Machine (Whitcomb, 1882). This was the most frequently used coal cutting machine in the data set.

Table A1: Occupations and Wages

	Daily wage (USD)	Employment share (%)
Miner	2.267	61.5
Laborers	1.76	14.30
Drivers	1.83	5.91
Loaders	1.74	3.63
Trappers	0.80	1.86
Timbermen	2.02	1.68
Roadmen	2.36	1.46
Helpers	1.70	0.92
Brusher	2.06	0.75
Cagers	1.87	0.70
Engineer	2.11	0.61
Firemen	1.60	0.57
Entrymen	2.01	0.56
Pit boss	2.70	0.56
Carpenter	2.09	0.53
Blacksmith	2.08	0.46
Trimmers	1.50	0.36
Dumper	1.68	0.36
Mule tender	1.65	0.31
Weighmen	1.95	0.29

Notes: Occupation-level data for the top-20 occupations by employment share in the 1890 sample of 11 mines in Illinois. The 20 occupations with highest employment shares together cover 97% of coal mining workers in the sample.

Table A2: Cost Dynamics

| | log(Output/(labor-days)) | | | |
	Est.	S.E.	Est.	S.E.
log(Cum. output)	0.124	0.004	-0.009	0.017
Mine FE	No		Yes	
Observations	3717		3717	
R-squared	.327		.811	

Notes: Regression of log output per worker-day against log cumulative output (lagged by one time period) at the mine-year level. Sample only includes mines for which lagged output is observed.

Table A3: Union Power and Strikes

| | log(Union bargaining power) | | | |
	Est.	S.E.	Est.	S.E.
1(Strike)*1(year≥ 1898)	0.089	0.079	0.175	0.068
Strike indicator:	Any		Successful	
R-squared	.701		.651	
Observations	3466		3915	

Notes: This table re-estimates the difference-in-differences model for the 1897-1898 strikes, but using the log of the labor union's bargaining power, $\ln(\gamma_{ft})$, as the left-hand side variable instead of log output. The left column compares all mines that went on strike, the right column only the mines at which strikes resulted in wage increases.

Table A4: Production Function: Extensions

	Non-constant RTS		Adding materials		Capital and RTS	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
Returns to scale	1.039	0.075	1.049	0.293	0.979	.
Labor coefficient	0.005	0.011	0.007	0.012	0.001	.
Capital coefficient	0.062	0.177	-0.042	0.223	0.738	.
Serial corr. TFP	0.406	0.112	0.571	0.278	0.431	.
Materials coefficient		.	0.000	0.000	0.000	0.000
Returns to scale * K		.		.	-0.010	.
Observations	711		324		324	

Notes: This table reports the estimates for the various extensions of the production function. Standard errors are block-bootstrapped with 200 iterations.

Table A5: Wage Variation

	R^2	R^2	R^2	R^2
Log(Daily skilled miner wage)	0.099	0.185	0.290	0.736
Year F.E.	X	X	X	X
County F.E.		X	X	X
Town F.E.			X	X
Firm F.E.				X

Notes: The four columns report the R^2 of regressing log wages on, alternatively, year, county, town, and firm fixed effects.

Table A6: All Variables per Year

Year	1884	'86	'88	'90	'92	'94	'96	'98	'00	'02
Output Quantities										
Total	X	X	X	X	X	X	X	X	X	X
Lump					X	X	X	X	X	X
Mine run									X	X
Egg									X	X
Pea									X	X
Slack									X	X
Shipping or local mine					X	X	X			
Shipping quantities										X
Input Quantities										
Miners, winter	X	X	X	X						
Miners, summer	X	X	X	X						
Miners, avg entire year					X	X		X	X	X
Miners, max entire year					X	X				
Other employees	X	X	X	X	X	X		X	X	X
Other employees, underground								X		
Other employees, above ground								X		
Other employees winter							X			
Other employees summer							X			
Boys employed underground			X	X	X	X	X			
Mules		X								
Days worked	X	X	X	X	X	X		X	X	X
Kegs powder	X	X	X	X	X	X		X		X
Men killed	X	X	X	X	X	X		X		X
Men injured	X	X	X	X	X	X		X		X
Capital (in dollar)	X									

Table A7: All Variables per Year (cont.)

Year	1884	'86	'88	'90	'92	'94	'96	'98	'00	'02
Output Price										
Price/ton at mine	X	X	X	X	X			X	X	X
Price/ton at mine, lump						X	X	X		
Input prices										
Miner piece rate (summer)	X	X	X	X	X	X				
Miner piece rate (winter)	X	X	X	X	X	X				
Miner piece rate (hand)								X	X	X
Miner piece rate (machines)								X	X	
Piece rate dummy					X					
Payment frequency						X	X	X	X	
Net/gross wage							X			
Oil price							X			
Technical information										
Type (drift, shaft, slope)	X	X			X	X	X	X		
Hauling technology	X	X			X	X		X		
Depth	X	X			X	X	X	X	X	
Thickness	X	X			X	X	X	X	X	
Geological vein type	X	X			X	X		X		
Longwall or PR method	X	X			X	X	X		X	
Number egress places	X	X								
Ventilation type	X	X								
New/old mine					X	X				
# Acres					X	X	X			
Mine capacity								X		
Mined or blasted								X		
Cutting Machines										
Cutting machine dummy					X	X	X	X		
# Cutting machines	X	X	X	X						
# Tons cut by machines									X	X
# Cutting machines, by type			X							