

# Oligopsony Power and Factor-Biased Technology Adoption

Michael Rubens\*

April 11, 2022

## Abstract

I show that buyer power of firms could either increase or decrease their technology adoption, depending on the direction of technical change and on which inputs firms have buyer power over. I illustrate this in an empirical application featuring imperfectly competitive labor markets and a large technology shock: the introduction of mechanical coal cutters in the 19th century Illinois coal mining industry. By estimating an oligopsony model of production and labor supply using rich mine-level data, I find that the returns to cutting machine adoption would have increased by 28% when moving from one to ten firms per labor market.

**Keywords:** Oligopsony, Market Power, Innovation, Technological change, Productivity

**JEL codes:** L11, L13, O33, J42, N51

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\*KU Leuven, Department of Economics. Contact: [michael.rubens@outlook.com](mailto:michael.rubens@outlook.com)

This paper previously circulated under the title ‘Monopsony Power and Factor-Biased Technology Adoption’. I thank Jo Van Biesebroeck, Jan De Loecker, Frank Verboven, Chad Syverson, Otto Toivanen, Penny Goldberg, Steve Berry, Suresh Naidu, Daniel Haanwinckel, and Cuicui Chen for feedback and discussion, and participants at the KU Leuven and Yale IO student workshops and various conferences. This is the second chapter of my Ph.D. dissertation at KU Leuven. Financial support from the Belgian American Educational Foundation, the Fulbright program, the Research Foundation Flanders (FWO grant 11A4618N), and the European Research Council (ERC grant 816638) is gratefully acknowledged.

# 1 Introduction

There is increasing empirical evidence for the existence of buyer power across various industries, countries, and types of factor markets.<sup>1</sup> When studying the welfare consequences of such buyer power, prior research has typically assumed that buyer power does not affect firms' technology choices. In contrast to this stands a large literature that studies the effects of imperfect *product* market competition on innovation incentives.<sup>2</sup> This paper fills this gap by examining how buyer power affects innovation. The focus of the paper lies on the *adoption* of new technologies, rather than on their invention, and on process innovations, which affect the cost side of production, rather than on product innovations, which shift the product demand curve.

I start the analysis with a theoretical model of a firm that produces a homogeneous good using two homogeneous inputs, and faces log-linear upward-sloping input supply curves. The firm is both a monopolist downstream and can also exert monopsony power upstream, by setting the price of each input at a markdown below its marginal revenue product. I consider the introduction of a new technology that could have factor-biased effects, by changing the marginal rate of technical substitution, and/or could change Hicks-neutral productivity. A first key result is that the relative change in profits following technology adoption weakly increases with the markdown over the input towards which the technology is biased, but falls with the markdown over the other input. The intuition behind this result is that adopting a technology is more profitable if it increases demand for the factor of which the input price markdown is the highest because that is the factor from which the firm extracts the highest surplus. A second key result is that technology adoption increases with the price markdown of the input towards which the technology is biased. The net effect of the price markdown of the other input on technology adoption is ambiguous, as it depends on the relative size of the rotation and shift of the production isoquant.

Given that the effect of buyer power on technology adoption has an ambiguous sign, and to quantify its size, I turn to an empirical application. I study how the mechanization of the Illinois coal mining industry between 1884 and 1894 was affected by buyer power on the market for coal miners. There are three reasons why this provides an interesting setting to study the relationship between buyer power and innovation. First, 19th century Illinois coal mining towns are a textbook example of classical monopsony/oligopsony power, as local labor markets were isolated and highly concentrated due to prohibitive commuting distances between towns. Up to 1898, wages were set unilaterally by firms, without collective bargaining with labor unions. Second, the introduction of coal cutting machines in the U.S. in 1882, which started the transition from manual to mechanical mining, provides a substantial technological shock. The data set tracks the usage of these cutting machines over time, together with input and output quantities, wages and coal prices, all at the mine level. Third, bitumi-

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<sup>1</sup>See literature reviews by Ashenfelter et al. (2010) and Manning (2011), and recent papers by, among others, Naidu et al. (2016); Berger et al. (2019); Rubens (2020); Morlacco (2017); Lamadon et al. (2019); Kroft et al. (2020).

<sup>2</sup>Examples include, among many others, Schumpeter (1942), Aghion, Bloom, Blundell, Griffith, and Howitt (2005) and Igami and Uetake (2017).

nous coal firms are single-product firms producing a nearly homogeneous product, which facilitates the empirical analysis.

The central counterfactual question of the paper is how changes in labor market competition would have affected cutting machine adoption. In order to answer this question, I construct an empirical model of input supply and demand in the coal mining industry, which has three components. First, I specify a production function for coal with three factors: skilled miners who cut coal, low-skilled other workers who did a variety of tasks such as driving mules and sorting coal, and capital, in the form of cutting machines. I rely on a Cobb-Douglas production function in both labor types, but with output elasticities that are a function of cutting machine usage, and that vary flexibly across firms and over time.<sup>3</sup> This is crucial because anecdotal historical evidence strongly suggests that cutting machines were not Hicks-neutral, but biased towards unskilled workers, similarly to many other technologies throughout the 19th century (James & Skinner, 1985; Mokyr, 1990; Goldin & Katz, 2009). Second, I specify a coal demand model in which coal firms compete along the same railroad in a static Cournot game, assuming their output is undifferentiated given their location. The production function and coal demand model jointly determine the demand for all inputs. Third, I specify a model of oligopsonistic competition on each labor market, as these were concentrated: the median mining town contained merely 2 coal firms. For each labor type, I use a log-linear supply curves of which the elasticity varies flexibly across firms and over time. I assume that firms are homogeneous from the employees' point of view and abstract from search and adjustment frictions, which implies a static Cournot employment-setting game played by the employers.

I estimate the production model with mine-level data on output and input quantities, and rely both on the profit maximization assumption and on input timing assumptions for identification. I find that cutting machines were unskill-biased, which confirms contemporaneous anecdotal evidence, and that they increased Hicks-neutral productivity.<sup>4</sup> The coal demand model is used using market-level price and quantity data, and is identified by exploiting geological variation in the thickness of coal seams as cost shifters that are excluded from consumer utility. Finally, the labor supply model is estimated using labor-market level data on wages and employment, and is identified using seasonal weather variation, which shifts labor demand but is assumed not to shift labor supply. The labor supply estimates reveal a moderate degree of oligopsony power over skilled workers, but no oligopsony power over unskilled workers.<sup>5</sup>

I combine the estimated labor supply and demand model to find the equilibrium, which is a function of labor market structure. Using the estimated model, I conduct the counterfactual exercise of how changes in labor market structure would affect the returns to, and adoption of, new technologies.

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<sup>3</sup>In other words, I allow for the technology to change both  $\beta$  and  $A$  in  $Y = AH^\beta L^{\nu-\beta}$ , and I allow for unobserved variation across firms and time in both  $A$  and  $\beta$ .

<sup>4</sup>With the aforementioned production function  $Y = AH^\beta L^{\nu-\beta}$ , cutting machines lowered  $\beta$  and increased  $A$ .

<sup>5</sup>Miner skills, such as building mine roofs or knowing how thick pillars should be in order to avoid collapse, were not easily transferable to other industries. This explains why coal mines enjoyed some wage-setting power over their skilled laborers, but not over their unskilled laborers, who could switch to other jobs at a lower financial loss.

I carry out this exercise both for the actual production technology, cutting machines, and for two counterfactual technologies: one that is skill-biased, such as the mining locomotive, and another one that is Hicks-neutral. I find that increasing labor market competition would increase the returns to cutting machine adoption: moving from one to ten employers per labor market would increase the average return to cutting machine adoption by 28%. The usage rate of cutting machines would increase by 9% for the same change in labor market concentration, but this change is not statistically significant. If the technology would have been skill-biased rather than unskilled-biased, skilled labor market competition would have the opposite effect on technology returns and usage. Moving from one to ten firms per labor market would then *decrease* the average return to machine adoption by 6%, and technology usage would drop by 17%. Finally, if cutting machines would have been Hicks-neutral moving from one to ten firms per labor market would decrease technology adoption by 12%. Hence, the directed and Hicks-neutral productivity effects of the technology are crucial determinants of how labor market competition affects technology adoption, and of how large this effect is.

Although the empirical setting of the paper is historical, the model has important current-day implications. For instance, it sheds new light on how oligopsony power on labor markets affects automation incentives. Although technologies were mostly unskill-biased throughout the 19th century, they have been skill-biased throughout the last part of the 20th century.<sup>6</sup> Hence, the effects of oligopsony power over low- and high-skilled workers on automation incentives may have inverted between the 19th and 20th centuries. Moreover, oligopsony power over high- and low-skill workers affects automation incentives differently. Knowing both the direction of technical change and the relative wage markdowns for different types of workers is therefore crucial to determine how oligopsonistic labor markets affect technological change today. Especially the latter is a mostly open empirical question: the labor literature has mainly focused on oligopsony power over low-skilled workers, such as Card and Krueger (1994), for instance due to a lack of outside options of workers (Schubert, Stansbury, & Taska, 2020). Non-compete clauses are, however, most frequent among high-skilled jobs in the U.S. (Starr et al., 2020). The model also has implications beyond the study of labor markets. Energy-saving production technologies are another example of directed technological change. If energy-intensive manufacturing firms have some local market power on energy markets, the model can be used to understand how such market power affects the incentives to adopt technologies that are more energy-efficient.

This paper makes three main contributions. First, it contributes to the literature on competition and innovation (Schumpeter, 1942; Aghion et al., 2005; Collard-Wexler & De Loecker, 2015; Hashmi & Van Biesebroeck, 2016; Igami & Uetake, 2017) by studying the effect of *factor* market power on innovation, rather than *product* market power. There are some papers that study how buyer power affects technological change of their suppliers (Just & Chern, 1980; Huang & Sexton, 1996; Köhler & Rammer, 2012; Parra & Marshall, 2021), but I focus on technology adoption by the buyers them-

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<sup>6</sup>Or, or at least, hollowing out the center of the skill and income distribution Autor et al. (2006); Goos and Manning (2007); Goos et al. (2014). (Katz & Margo, 2014) argue this also held for technical change during the second industrial revolution.

selves. The few theory papers that study innovation and investment by firms with buyer power, such as Inderst and Wey (2003) and Loertscher and Marx (2020), do so in bargaining settings with imperfect information and without considering directed technological change, whereas I study unilateral oligopsony power, and provide an empirical application. Another closely related paper is Goolsbee and Syverson (2019), which finds that monopsony power over tenure-track faculty induces universities to substitute these workers for adjunct faculty members. In contrast, I endogenize the choice of the production technology: buyer power does not just let firms move along the input demand curves, but also causes a change of the input demand curves, due to different technology choices.

Second, this paper contributes to the literature on directed technological change and factor bias. The seminal models of directed technical change, such as Autor et al. (2003); Acemoglu (2002, 2003) and Antras (2004), assume that input markets are perfectly competitive. Contemporaneous work by Haanwinckel (2018) and Lindner et al. (2019) examine the effects of skill-biased technologies on skill demand and wage inequality with imperfectly competitive labor markets. This paper contributes to this literature by showing that factor-biased technology choices are endogenous to the degree of buyer power. This also relates to the ‘induced innovation’ hypothesis of Hicks (1932), which posits that labor-saving technological change is more likely if wages are high, because cost savings are then higher as well.<sup>7</sup> The induced innovation hypothesis has been empirically studied in a variety of settings, including Popp (2002), Hanlon (2015), and Dechezleprêtre, Hémous, Olsen, and Zanella (2019). As noted in Acemoglu (2002), a critique of the induced innovation hypothesis is that the notion ‘expensive input’ is inconsistent with settings in which factor prices are equal to marginal products (Salter, 1966). In contrast, I do allow for a wedge between factor prices and marginal products, and find that the relevant metric to understand innovation incentives is not which factor has the highest price, but which factor has the highest wedge between its price and marginal product.

Third, I contribute to the literature on labor market power. Manning (2013); Berger et al. (2019); Lamadon et al. (2019) study the distributional and efficiency effects of labor market power keeping technology usage fixed. In contrast, I show that endogenous technology choices present an additional channel through which input market power shapes aggregate outcomes. By studying labor market power in a historical setting, this paper is also related to a body of work on labor market power during the late 19th century, such as Naidu and Yuchtman (2017) and Boal (1995).

The remainder of this paper is structured as follows. Section 2 presents the theoretical model. Section 3 describes the industry background and some stylized facts. Section 4 contains the empirical model and the counterfactuals. Section 5 concludes.

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<sup>7</sup>This theory has been forwarded as a reason why Britain was the first country to experience an industrial revolution (Allen, 2009). This hypothesis that has in turn been criticized by, among others, Humphries (2013).

## 2 Theory

### 2.1 Primitives

#### A Production

Consider a firm  $f$  that produces  $Q_f$  units of a homogeneous product using two variable inputs, of which the quantities are denoted  $H_f$  and  $L_f$ . Production is given by a Cobb-Douglas function, in Equation (1). The output elasticity of input  $V \in \{H, L\}$  at firm  $f$  is denoted  $\beta_f^v$ . Scale returns are parametrized as  $\nu = \beta_f^h + \beta_f^l$ , which is below, above or equal to one if returns to scale are decreasing, increasing, and constant. In the main text, I restrict the analysis to settings with non-increasing returns to scale, but the results are generalized to increasing returns to scale in Appendix B.7. Total factor productivity is denoted  $\Omega_f$ . Firms choose whether to use a technology  $K_f \in \{0, 1\}$  or not, with the technology  $K_f = 1$  having a common fixed cost  $\Phi$ .

$$Q_f = H_f^{\beta_f^h(K_f)} L_f^{\beta_f^l(K_f)} \Omega_f(K_f) \quad (1)$$

Technology usage can affect both the output elasticities and the Hicks-neutral productivity residual. I call the technology  $K$  ‘H-biased’ if  $\frac{\partial \beta_f^h}{\partial K_f} > 0$ , because  $K$  then increases the marginal rate of technical substitution of  $H$  for  $L$ , keeping factor proportions constant.<sup>8</sup> Conversely,  $K$  is an ‘L-biased’ technology if  $\frac{\partial \beta_f^h}{\partial K_f} < 0$ . The technology is ‘neutral’ if  $\frac{\partial \beta_f^h}{\partial K_f} = 0$ , and ‘directed’ otherwise. It is possible that the technology changes only Hicks-neutral productivity  $\Omega_f(K_f)$ , only the output elasticities  $\beta_f^v(K_f)$ , or both. I assume that the technology does not change the degree of returns to scale.

Using a Cobb-Douglas production function with technology-specific output elasticities departs from the canonical models on technical change, which usually rely on a constant elasticity of substitution (CES) production function. Although imposing a Cobb-Douglas elasticity between different types of workers is clearly a strong assumption, I allow for directed technical change by making the output elasticities a function of technology usage, and also allow for flexible variation in output elasticities across both firms and time in the empirical application. The main benefit of the Cobb-Douglas function is that it permits analytical expressions for market equilibrium in the presence of both oligopsonistic and oligopolistic competition.

#### B Markets

A firm  $f$  pays its input suppliers prices  $W_f^h$  and  $W_f^l$ , and cannot price discriminate between different suppliers of the same input. The firm faces the input supply functions in Equation (2), with inverse supply elasticity  $(\psi^h - 1)$  for input  $H$  and  $(\psi^l - 1)$  for input  $L$ . I assume that the supply functions are

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<sup>8</sup>  $MRTS_{hl} \equiv \frac{\frac{\partial Q}{\partial H}}{\frac{\partial Q}{\partial L}} = \frac{\beta^h}{\nu - \beta^h} \frac{H}{L}$

weakly upward-sloping,  $\psi^h \geq 1$  and  $\psi^l \geq 1$ .

$$\begin{cases} W_f^h = H_f^{\psi^h - 1} \\ W_f^l = L_f^{\psi^l - 1} \end{cases} \quad (2)$$

Output is sold at a price  $P_f$ . The firm is a monopolist on the output market, and faces a log-linear demand curve with inverse elasticity  $\eta$ , in Equation (3). I assume that the demand curve is either horizontal or downward-sloping, which implies that  $\eta \leq 0$ .

$$P_f = Q_f^\eta \quad (3)$$

## 2.2 Behavior and equilibrium

### A Behavior

Variable profits are defined as  $\Pi_f \equiv P_f Q_f - W_f^h H_f - W_f^l L_f$ , whereas total profits are  $\Pi_f^{tot} \equiv \Pi_f - \Phi K_f$ . I assume that firms choose the variable input quantities  $H$  and  $L$  that maximize current variable profits, taking the technology  $K$  as given. Depending on how competitive the input markets are, the firm sets the price of each input at a markdown below its marginal revenue product, as parametrized by  $\mu_f^h \in [1, \psi^h]$  and  $\mu_f^l \in [1, \psi^l]$ . If the firm is a monopsonist on the market for  $H$ , the profit-maximizing markdown is equal to the inverse supply elasticity,  $\mu_f^h = \psi^h$ , and similarly for the other input. The labor market equilibrium then lies in the point  $M$  in Figure 1b. If, on the other hand, the market for  $H$  would be perfectly competitive, the price of  $H$  is equal to its marginal product of  $H$ , meaning that  $\mu_f^h = 1$ . This corresponds to the competitive equilibrium on the market for  $H$ , point  $C$  in Figure 1a.

$$\max_{H_f, L_f} (P_f Q_f - W_f^h H_f - W_f^l L_f)$$

Solving the first order conditions of this optimization problem results in the input demand functions in Equation (4):

$$\begin{cases} H_f^* = \frac{P_f Q_f \beta_f^h (1+\eta)}{W_f^h \mu_f^h} \\ L_f^* = \frac{P_f Q_f \beta_f^l (1+\eta)}{W_f^l \mu_f^l} \end{cases} \quad (4)$$

Denote the marginal product of input suppliers  $H$  as  $MR_f^h \equiv \frac{\partial(P_f Q_f)}{\partial H_f} = \beta_f^h P_f Q_f (1 + \eta)$ . By rewriting equation (4), one can see that the markdown parameters  $\mu^h$  and  $\mu^l$  are equal to the ratio of the marginal product of an input over its price:  $\mu_f^h = \frac{MR_f^h}{W_f^h}$ .

## B Equilibrium

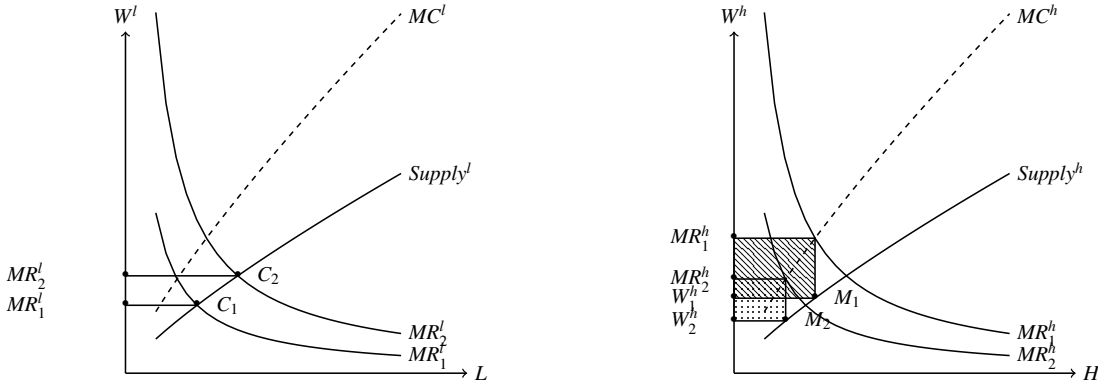
The supply and demand for goods is given by Equations (1) and (3), supply and demand for inputs by Equations (2) and (4). Solving this system of equations yields the equilibrium expression for output  $Q_f^*$  in Equation (5a), at which both the goods and input markets are in equilibrium.

$$Q_f^* = \left[ \left( \frac{\beta_f^h(1+\eta)}{\mu_f^h} \right)^{\frac{\beta_f^h}{\psi_f^h}} \left( \frac{\beta_f^l(1+\eta)}{\mu_f^l} \right)^{\frac{\beta_f^l}{\psi_f^l}} \Omega_f \right]^{\frac{1}{1 - \frac{\beta_f^h(1+\eta)}{\psi_f^h} - \frac{\beta_f^l(1+\eta)}{\psi_f^l}}} \quad (5a)$$

The equilibrium goods price, input prices, and input quantities are functions of this equilibrium quantity. Equilibrium revenue is equal to  $Q_f^{*(1+\eta)}$ . Equilibrium variable profits  $\Pi_f^*$  are equal to the product of equilibrium revenues  $Q_f^{*(1+\eta)}$  and the variable profit margin  $\left( 1 - \frac{\beta_f^h(1+\eta)}{\mu_f^h} - \frac{(\nu - \beta_f^h)(1+\eta)}{\mu_f^l} \right)$ :

$$\Pi_f^* = Q_f^{*(1+\eta)} \underbrace{\left( 1 - \frac{\beta_f^h(1+\eta)}{\mu_f^h} - \frac{(\nu - \beta_f^h)(1+\eta)}{\mu_f^l} \right)}_{\text{variable profit margin}} \quad (5b)$$

**Figure 1: Monopsony power and technology choice**



### 2.3 The returns to technology adoption

With these equilibrium expressions at hand, I now consider how the effect of technology usage  $K$  on variable profits  $\Pi$  depends on the level of competition on each input market.



## A Relative profit return

I start by examining the *relative* profit returns to technology adoption,  $\frac{\Pi(K=1)-\Pi(K=0)}{\Pi(K=0)}$ . For small changes in profits, this ratio is approximated by the log of variable profits  $\log(\Pi)$ . Theorem 1 states that the markdown of an input price increases the relative returns to a technology that is biased towards that input, but decreases the relative returns to a technology that is biased towards the other input.

**Theorem 1** *Consider a firm  $f$  that faces log-linear input supply and product demand curves (8)-(9), a production function (1) with weakly decreasing returns to scale,  $\nu \leq 1$ , and is a monopolist on its output market. Then, the price markdown of an input weakly increases the relative variable profit return to a technology that is biased towards that input, but weakly decreases the returns to a technology that is biased towards the other input.*

$$\frac{\partial \beta_f^h}{\partial K_f} \left\{ \begin{array}{l} \geq \\ \leq \end{array} \right\} 0 \Rightarrow \frac{\partial^2 (\ln(\Pi_f))}{\partial \mu_f^h \partial K_f} \left\{ \begin{array}{l} \geq \\ \leq \end{array} \right\} 0$$

**Proof:** see Appendix B.1.

The intuition behind this result becomes clear from Figure 1. Assume that the firm is a price-taker on the market for  $L$ , but a monopsonist on the market for  $H$ . The markdown ratio  $\mu^l$  is equal to one, meaning that the price of  $L$  is equal to its marginal revenue product, whereas the monopsonistic markdown is charged for  $H$ ,  $\mu^h = \psi^h$ . Adopting an  $L$ -biased technology leads to lower usage of  $H$ , but to increased usage of  $L$ . The technology hence decreases profits, as it shifts input usage from the input from which the firm extracts high rents,  $H$ , towards the input from which it extracts zero rents,  $L$ . The firm hence wants to adopt the technology that shifts input usage towards the input from which it extracts the highest markdown, and this incentive increases with the markdown level.

## B Absolute profit return

Theorem 1 explained how markdowns affect the *relative* change in variable profits in response to technology adoption. However, in order to understand technology adoption, we need to know the effects of markdowns on the *absolute* change in *total* profits after machine adoption,  $\Pi(K = 1) - \Pi(K = 0) - \Phi$ . The absolute change in variable profits is written in Equation (6). From Theorem 1, we know that the sign of the relative change in profits, term  $A$ , depends on the direction of technical change and the markdown levels. To understand the effect of markdowns on technology adoption, we need to know the sign of the left hand side of Equation (6),  $\frac{\partial}{\partial \mu_f^h} \left( \frac{\partial \Pi_f}{\partial K_f} \right)$ .

$$\frac{\partial}{\partial \mu_f^h} \left( \frac{\partial \Pi_f}{\partial K_f} \right) = \underbrace{\frac{\partial}{\partial \mu_f^h} \left( \frac{\partial \ln(\Pi_f)}{\partial K_f} \right)}_A \Pi_f + \underbrace{\frac{\partial \Pi_f}{\partial \mu_f^h}}_B \underbrace{\frac{\partial \Pi_f}{\partial K_f}}_C \Pi_f \quad (6)$$

Theorem 2 states that the effect of a markdown on absolute technology returns is positive if the effect on relative technology returns is positive, and ambiguous if the effect on relative technology returns is negative.

**Theorem 2** *The markdown of an input price increases the absolute return to a technology that is biased towards that input. It can increase or decrease the absolute return to a technology that is biased towards the other input.*

**Proof:** see Appendix B.2.

The intuition behind Theorem 2 is as follows. There are two reasons why the result in Theorem 1 will not necessarily translate to the absolute profit difference. First, the higher markdowns are, the lower variable profits. Even if the relative profit change  $\frac{\pi(K=1)-\pi(K=0)}{\pi(K=0)}$  increases with the markdown  $\mu^l$ , still considering an  $L$ -biased technology  $K$ , the absolute profit change  $\pi(K = 1) - \pi(K = 0)$  might be lower with a lower markdown as the baseline profit level  $\pi(K = 0)$  is lower to begin with. Second, if the technology lowers  $\beta^h$ , this reduces the relative demand for  $H$  compared to  $L$ , as can be seen from the input demand function (4). However, if the technology also increases Hicks-neutral productivity  $\Omega$ , it could be that the firm ends up using more of input  $H$  after adopting the technology. In that case, a higher markdown over  $H$  could increase the absolute profit return from the technology.

### C Hicks-neutral vs. factor-biased technology effects

Suppose the markdown decreases the relative return to technology adoption. Which factors then determine whether the effect of the markdown on the absolute return to adoption will be negative or positive? Theorem 3 says that the higher the Hicks-neutral productivity effect of the technology is, the more likely it becomes that markdowns increase the absolute returns to technology adoption. The reason for this is that higher (more positive) Hicks-neutral productivity effects increase the likelihood that the absolute usage of all inputs increases with technology adoption.

**Theorem 3** *The higher the effect of a technology on Hicks-neutral productivity, the more likely that markdowns increase the absolute return to technology adoption.*

**Proof:** see Appendix B.3

In the limiting case of a neutral technology that only increases Hicks-neutral productivity but not the output elasticities, the markdown on any input market increases the absolute return from technology adoption, as is stated in Lemma 1. An increase in Hicks-neutral productivity results in higher equilibrium output produced by the firm. The higher the degree of monopsony power a firm has, the higher profits are, and hence the higher the change in the profit level due to an increase in productivity.

**Lemma 1** *The absolute profit effect of a technology that weakly increases Hicks-neutral productivity but does not change the output elasticity of any input then weakly increases with monopsony power on either input market.*

$$\frac{\partial \beta_f^h}{\partial K_f} = 0 ; \frac{\partial \Omega}{\partial K_f} \left\{ \begin{array}{l} \geq \\ \leq \end{array} \right\} 0 \Rightarrow \frac{\partial^2(\Pi_f)}{\partial \mu_f^h \partial K_f} \left\{ \begin{array}{l} \geq \\ \leq \end{array} \right\} 0$$

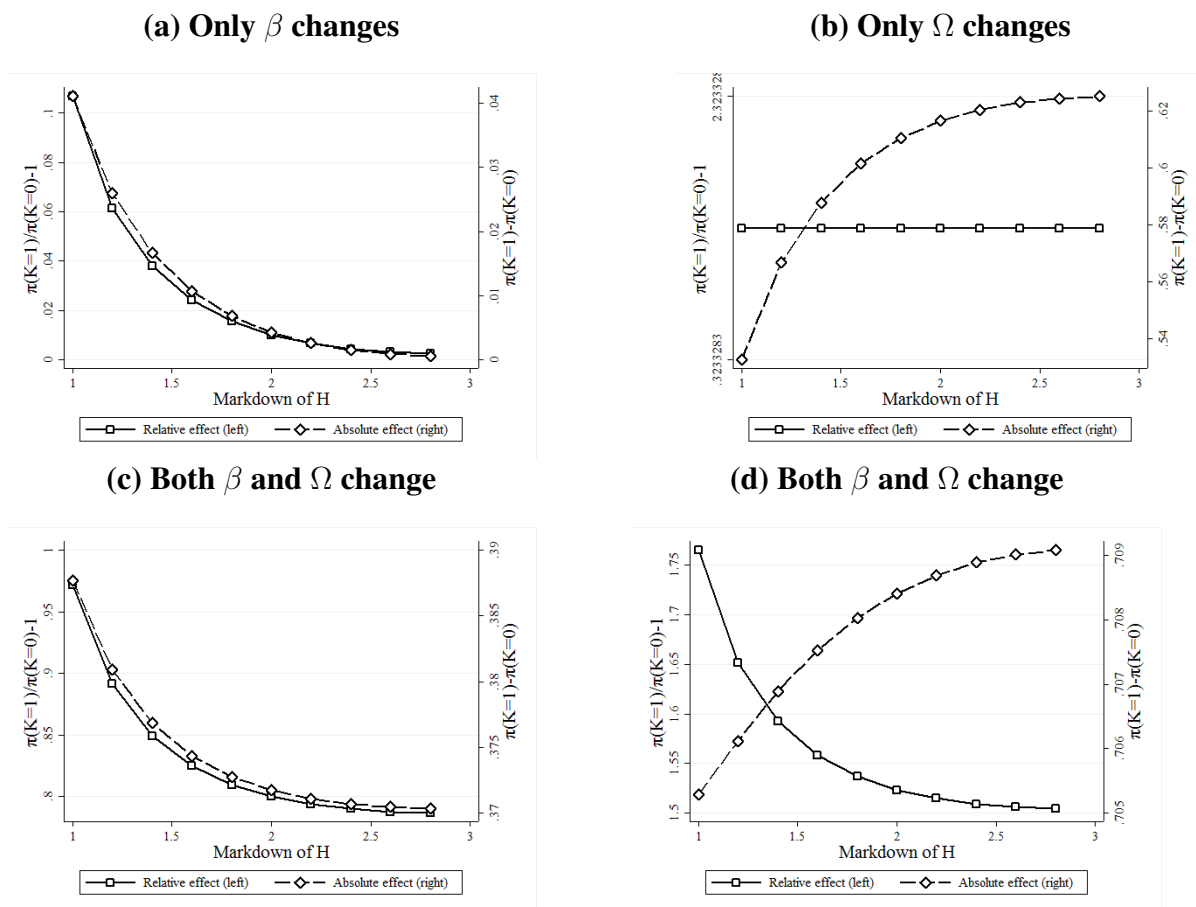
**Proof:** see Appendix B.4.

## D Illustration using the calibrated model

In order to illustrate the above results, I carry out a calibration exercise. Let the degree of scale returns be  $\nu = 0.9$ , and let the output elasticity  $\beta^h$  be drawn from a uniform distribution on the interval  $[0, \nu]$ , with 1000 draws. I let the market-level inverse input supply elasticities be  $\psi_m^h = \psi_n^h = 3$ , which means that a monopsonist pays each of its input suppliers a third of their marginal product. I consider the relative and absolute variable profit effect of a technology at ten different markdowns on the interval  $\mu^h \in [1, \psi^h]$ . I set the inverse demand elasticity to  $\eta = -\frac{1}{3}$ . I consider four technologies. In Figure 2a, the technology reduces the output elasticity of  $H$  by half, and is hence  $L$ -biased, but it does not change Hicks-neutral productivity  $\Omega_f$ . A second technology, in Figure 2b, doubles Hicks-neutral productivity, but does not change the output elasticity  $\beta$ :  $\Omega(K = 1) = 2\Omega(K = 0)$ . A third technology, in Figure 2c, both halves  $\beta$  and doubles  $\Omega$ . A final technology, in Figure 2d, has the same effect on  $\beta$  as technology (c), but triples Hicks-neutral productivity:  $\Omega(K = 1) = 3\Omega(K = 0)$ .

For technology (a), moving from a competitive to a monopsonistic markdown lowers the relative return to technology adoption from 11% to 0%, in line with Theorem 1. The absolute return drops from 0.04 units to 0 units, but as explained by theorem 2, this effect could go in the other direction depending on the parametrization of the model. For technology (b), which only changes Hicks-neutral productivity, the relative returns to technology adoption do not change with the markdown, in line with Theorem 1, and the absolute returns to adoption increase with the markdown. Lemma 1 says that is true more in general. Technologies (c) and (d) both decrease the output elasticity of  $H$ , but also increase Hicks-neutral productivity, by respectively 100% and 200%. For technology (c), the absolute returns to technology adoption still fall with the markdown, but for technology (d), higher markdowns lead to higher returns to innovation. This is a result of Theorem 3: for technology (c), the Hicks-neutral productivity effect is too small to dominate the factor-biased effect of the technology, and markdowns decrease returns to innovation, whereas the Hicks-neutral effect dominates for technology (d), making markdowns increase the absolute return to innovation.

**Figure 2: Returns to an L-biased technology: calibration**



**Notes:** Each panel plots the relative and absolute returns to mechanization,  $\frac{\Pi(K=1) - \Pi(K=0)}{\Pi(K=0)}$  and  $\Pi(K=1) - \Pi(K=0)$ , for an  $L$ -biased technology  $K$  against the markdown of input  $H$  by step of 5 percentiles. Panel (a) considers a technology that only changes the output elasticity  $\beta$  but not Hicks-neutral productivity  $\Omega$ . Panel (b) lets  $\Omega$  change but not  $\beta$ . Panel (c) lets both  $\Omega$  and  $\beta$  change, with  $\Omega(K=1) = 2\Omega(K=0)$ . Panel (d) increases the Hicks-neutral effect to  $\Omega(K=1) = 3\Omega(K=0)$ .

### 3 Coal mining in Illinois (1884-1902)

In this section, I complement the theoretical results from the previous section with an empirical application, for two reasons. First, following Theorems 2 and 3, the sign of the effect of markdowns on technology usage is ambiguous and depends on both the directed and Hicks-neutral productivity effects of the technology, and on which input market the firm has market power. Empirical analysis is required to know these primitives. Second, we are not just interested in the sign of the effect of markdowns on innovation, but also on its size. In the application, I study how employer power on labor markets affected the adoption of coal cutting machines in the Illinois coal mining industry between 1884 and 1902. This is an interesting setting because it features isolated labor markets in the form of mining towns, which are likely to feature some oligopsony power, with a large factor-biased technological innovation due to the invention of coal cutting machines. Before presenting the empirical

model, I discuss the most important industry characteristics and the data sources.

### 3.1 Industry background

#### A Extraction process

The coal extraction process consisted of three consecutive steps. First, the coal seam had to be accessed, which usually required either a vertical ‘shaft’, a diagonal ‘slope’ or a horizontal ‘drift’, depending on the geography of the mine. As large parts of Illinois are flat, 60% of the mines were ‘shaft’ mines.<sup>9</sup> Second, upon reaching the seam, the coal wall was ‘undercut’, traditionally manually using picks, 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).<sup>10</sup> Third, coal had to be transported back to the surface and sorted from impurities. The hauling was done using mules or underground locomotives. Over 90% of output was hauled using locomotives. Mines used two types of intermediate inputs. First, black powder was used to blast the coal wall. This was purchased by the miners, not by the firm. Second, coal itself was used to power steam engines, electricity generators, and air compressors.<sup>11</sup>

#### B Technological change: the coal cutting machine

The first mechanical coal cutter in the U.S.A. was invented by J.W. Harrison in 1877, but it was merely a prototype.<sup>12</sup> The Harrison patent was acquired and adapted by Chicago industrialist George Whitcomb, whose ‘Improved Harrison Cutting Machine’ was released in 1882, of which the patent is pictured in Figure A4a. An illustration of how the coal cutting machine was used is in Figure A4b. Ninety percent of the cutting machines in the dataset are of this type. The spatial diffusion of cutting machines is shown in Figure A1. As shown in Figure 3, the share of mines using a coal 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 this same time period. The mechanization of the hauling process, which replaced mules with underground locomotives, was another source of technical change. This was largely accomplished in Illinois: the share of output mined in locomotive mines was above 90%.

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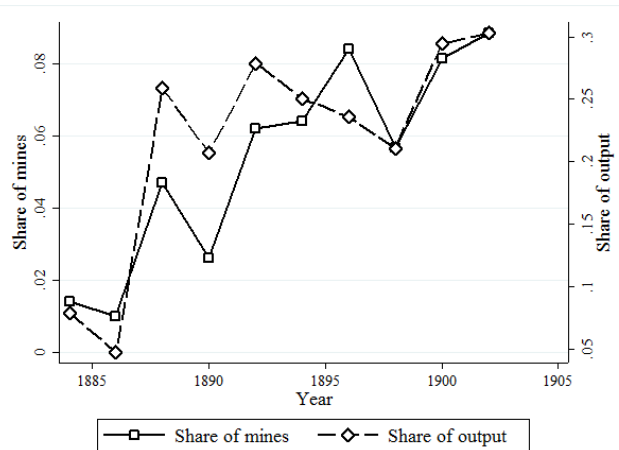
<sup>9</sup>Less than 2% of the mines were surface mines that did not require any digging.

<sup>10</sup>Two techniques existed to cut the coal: nine out of ten mines used a ‘rooms and pillars’ technique in which miners excavated everything except pillars, which were left to sustain the roof. The other mines used so-called ‘longwall’ techniques in which miners temporarily constructed an artificial roof and allowed the room to collapse in a controlled way.

<sup>11</sup>A fraction of the mine’s coal output was re-used as an energy input. I only observe reused coal inputs in 1902, and the fraction of output that was re-used as an input was on average 5%, and 0% for the median mine. As I do not observe this variable in all years, I do not take it into account in the model.

<sup>12</sup>Simultaneously, prototypes of mechanical coal cutting machines were invented in Northern England in the late 1870s (Reid, 1876; Ackermann, 1902).

**Figure 3: Cutting machine adoption**



**Notes:** This graph plots the share of Illinois coal mines using at least one cutting machine (solid line, left axis) and the share of output produced by mines with at least one cutting machine (dashed line, right axis) over time.

## C Occupations

Coal mining involved a wide variety of different 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 tasks, in contrast to undercutting coal walls.<sup>13</sup>

The difference in industry-specific skills are reflected in daily wages: miners earned an average daily wage of \$2.3, which was higher than any other employees 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.

The biennial mine-level data set I will rely on for the model classifies workers into two types: miners and all other employees. Henceforth, I will call miners 'skilled labor', and other workers 'unskilled labor'.

<sup>13</sup>Some unskilled workers eventually became skilled, such as boys who started out as trappers but became miners at an older age. I abstract from such dynamic considerations on the labor supply side in the model.

## D Labor markets

Skilled workers received a piece rate per ton of coal mined, whereas unskilled workers were paid a daily wage.<sup>14</sup> Converting the piece rates to daily wages, the net salary of skilled labor was on average 23% higher compared to unskilled labor. ‘Net salary’ means net of material costs and other work-related expenses. At some of the mines, ‘wage screens’ were used, 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 merely 4 out of 52 counties, at mines that jointly represented merely 2.3% of employment.<sup>15</sup>

Rural Illinois was, and still is, sparsely populated: the median and average population sizes of the towns in the dataset were 1067 and 3090 inhabitants, and on average a third of the population were coal miners. Considering that women and children under the age of 12 did not work in the mines, almost the entire working population was employed in coal mining in most villages. Of all the villages, 50% had just one coal mine, and another 30% had two or three. 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 roads were unpaved and automobiles were not yet introduced. In order to switch employers, miners had to migrate to another town.<sup>16</sup>

First attempts to unionize the Illinois coal miners started around 1860, without much success (Boal, 2017). Unionism was countered by employers in various ways, for instance by including non-membership of a labor union as a requirement in labor contracts. These so-called ‘yellow-dog’ 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). In 1886, 15% of miners in Illinois were members of trade unions. The first successful labor union in Illinois was the *United Mine Workers of America*, founded in 1890. A major strike in 1897-1898 had important consequences: wages were raised and working hours reduced to a maximum of eight hours per day. Even more importantly, wages were determined during annual wage negotiations between the unions and a state-wide representation of employers after 1898, which took place in January (Bloch, 1922). Wage-setting was therefore done by each mine independently until 1898, and through collective bargaining afterwards. 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

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<sup>14</sup>Piece rates were an incentive scheme in a setting with moral hazard, as permanent miner supervision would be very costly.

<sup>15</sup>Nevertheless, I test the robustness of the results for the non-inclusion of counties in which wage screens were used in Appendix C.4.

<sup>16</sup>Some more evidence supporting the isolated mining towns assumption is in Appendix C.3.

in addition to miner wages.

## **E 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 93% of the mines' coal output was either sold to railroad firms or transported by train to final markets. The remaining 7% was sold to local consumers. The main coal destination markets for Illinois mines were St. Louis and, to a lesser extent, Chicago, which was supplied with cheaper coal from fields in Ohio, Pennsylvania, and West Virginia using lake steamers (Graebner, 1974). Railway firms acted as an intermediary between coal firms and consumers, and were also major coal consumers themselves. Historical evidence points to intense 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 90 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.

### **3.2 Data**

I observe every bituminous coal mine in Illinois between 1884 and 1902 at two-year intervals, which results in 8356 observations. The data are obtained from the *Biennial Report of the Inspector of Mines of Illinois*. The dataset covers all mines, of which the yearly number fluctuated between 683 and 919. I observe the name of the mine, the mine owner, yearly coal extraction, average employee counts for both skilled and unskilled workers, days worked, and a dummy for cutting machine usage in every two-year period. 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 of these variables are used in the analysis, given that some of these are observed in a small subset of years.

I observe the average piece rate for skilled labor throughout the year and the daily wage for unskilled labor from 1888 to 1896. 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 of production quantities are given for a sample of 11 mines that covers 15% of skilled and 9% of un-



skilled workers. Second, monthly free-of-board bituminous coal prices in the harbor of New York are collected for the years 1890-1900 from the NBER Macrohistory Database (National Bureau of Economic Research, n.d.). Third, town- and county-level information from the 1880 and 1900 population census and the censuses of agriculture and manufacturing are collected as well. Fourth, 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.

### 3.3 Key facts

**Fact 1** *Output and labor productivity increased, but skilled wages stagnated until 1898.*

The Illinois coal mining industry grew rapidly during the last two decades of the 19th century. Annual output, in Figure 4a, 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 700 to 900. Daily output per worker, in Figure 4b, increased from 2 to 3.3 tons for hand mines, and from 2.3 to 4.1 tons for machine mines.<sup>17</sup> Until 1898, this growth in output and productivity did not translate into higher wages: the daily wage of skilled labor remained around \$ 1.8 until 1898, as can be seen in Figure 4c. After the large strikes in 1897-1898 and the introduction of centralized wage bargaining, wages rose. Coal prices per ton fell from \$1.2 to \$0.9 between 1884-1898, after which they increased again.

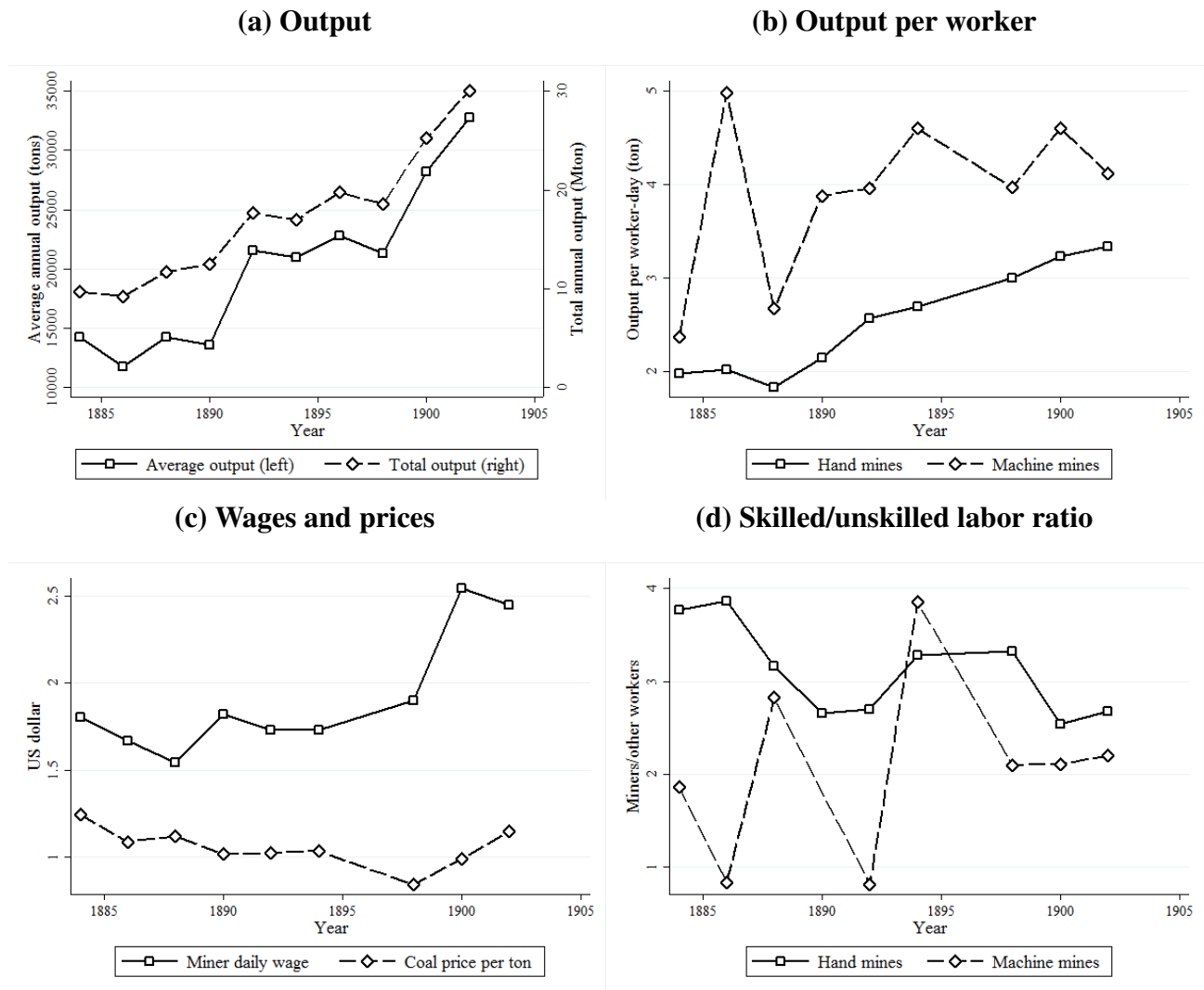
**Fact 2** *Mechanized mines used less skilled workers per unskilled worker.*

As was shown in Figure 4b, output per worker was higher in machine mines. The composition of labor was also different: in Figure 4d, I plot the ratio of the total number of skilled labor-days over the number of unskilled worker-days in per year. 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 between 11% and 22% lower at a certainty of 90%. However, this difference is not necessarily a causal effect of cutting machines on skill-augmenting productivity: mines with higher productivity levels were probably more likely to adopt cutting machines. For the causal effects of cutting machines on total factor and factor-augmenting productivity levels, I refer to the empirical model in the next section. 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.” (Lord, 1888, 340)

<sup>17</sup>This series is adjusted for the reduction of hours per working day in 1898, as explained in Appendix A.

**Figure 4: Aggregate quantities and prices**



**Notes:** Panel (a) plots average output per mine-year and total mine output in Illinois over time. Panel (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’). Panel (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, and the aggregate price, defined as total revenue over total output, in the Illinois coal mining industry. The reduction in working hours in 1898 is taken into account. The coal price per ton is the mine-gate price. Panel (d) plots the ratio of total skilled worker-days over total unskilled worker-days at hand and machine mines. 1890 is omitted for machine mines in 1890 due to employment being unobserved for most machine mines in that year.

Along the same lines, the State Inspector of Mines of Illinois wrote:

“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, 1888, 339)

**Fact 3** *Skilled labor wages varied seasonally, unskilled labor wages did not.*

Coal demand was seasonal: during the cold winter months, energy demand increased compared to the warm summer months. As can be seen in Figure 5a, which plots average monthly skilled labor-days in 1890, skilled employment follows the coal demand cycle.<sup>18</sup> From August to February, employment is high, as coal for the cold winter months is extracted. Given that transporting coal to the final market took some time, coal demand already began to increase around August. Panel 5b shows that skilled wages followed this coal demand cycle: during summer, skilled wages fell compared to the other months. There is a lag between the wage and employment cycle of around a month, which might be due to the fact that wages are paid with a lag. In contrast unskilled worker wages did not co-vary with product and labor demand throughout the year.<sup>19</sup> Panel 5c also shows this by plotting monthly wages for both skilled and unskilled workers against the monthly number of worker-days of each type at the mine-month level throughout 1890. Skilled wages were positively correlated with monthly skilled employment, whereas the unskilled worker wage-employment schedule is flat. Moreover, there was a large variation in skilled wages across mines and months, but very little variation in unskilled wages

Skilled workers were paid piece rates, whereas unskilled workers were paid daily rates. If skilled workers were more productive during months of peak demand, this could be the reason that skilled wages co-vary with employment, rather than other explanations, such as monopsony power. However, as can be seen in Figure 5d, this is not the case. During the winter months, output per skilled worker-day was on average 2.53 tons, whereas it was 2.61 tons during summer. There is also a significant difference in skilled labor piece rates (wage per ton mined) between summer and winter: the wage per ton earned by a skilled worker was on average \$0.780 during summer and \$0.817 during winter, so it was 4.7% higher during the winter. This difference is significantly large than zero: the difference between summer and winter piece rates lies between 0.026 and 0.049 with a probability of 90%.

## 4 Empirical model

### 4.1 Model

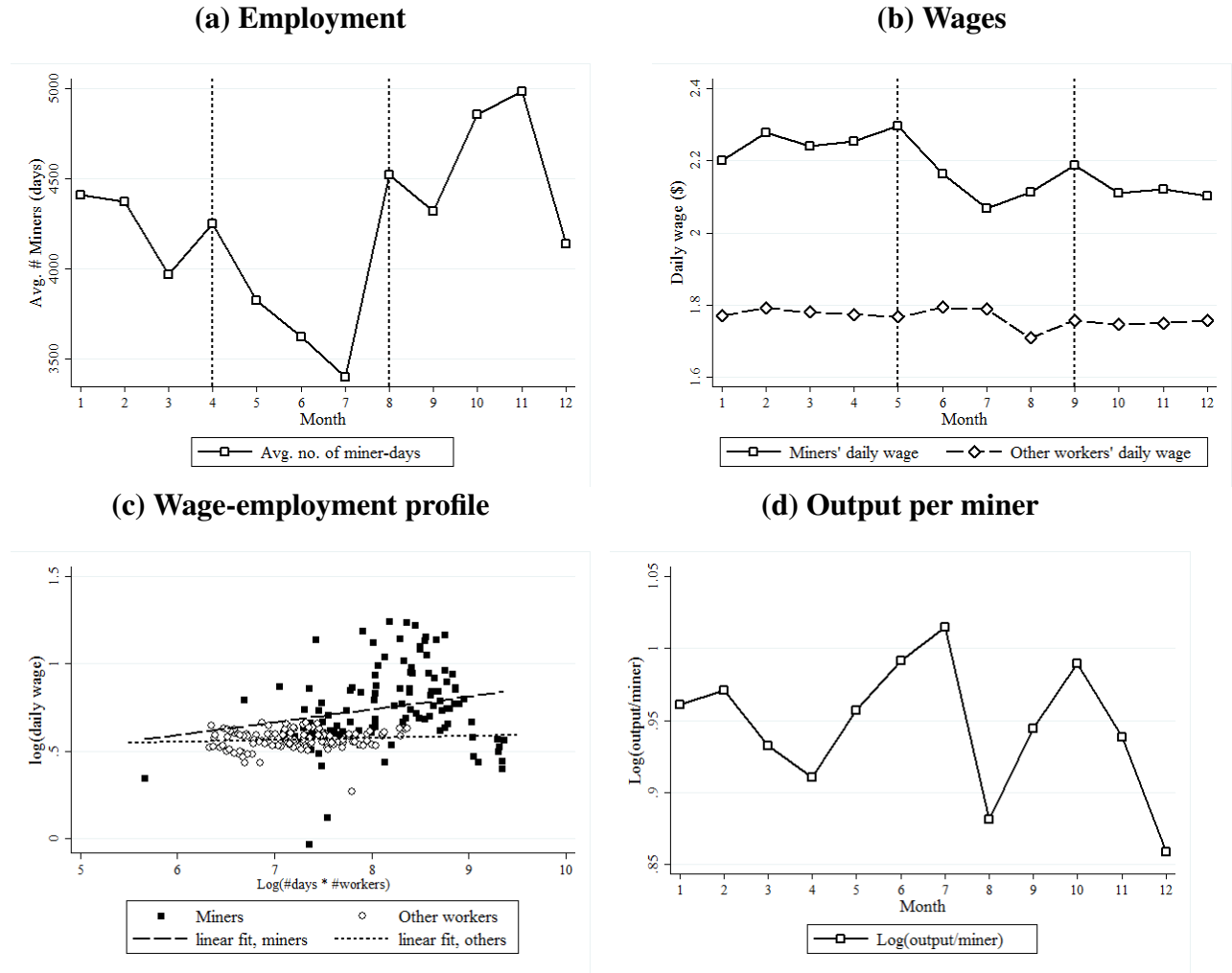
In this section, I model labor demand and supply in the coal mining industry by implementing an empirical version of the model in Section 2 with a concrete model of competition on both input and product markets. This serves as an input to the counterfactual exercise of understanding the effects of monopsony power on innovation in section 4.4.

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<sup>18</sup>This monthly data is based on 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.

<sup>19</sup>As for coal prices, FOB coal prices in the Harbor of New York did not seem to fluctuate between months, but mine-gate coal prices in Illinois might have fluctuated. I have no data on monthly coal prices in Illinois.

**Figure 5: Seasonality in employment and wages**



**Notes:** Panel (a) plots average monthly skilled employment per month for a sample of 11 mines in 1890. Panel (b) does the same for average daily wages of skilled and unskilled employees. Panel (c) plots mine-level monthly employment against daily wages for both worker types across mines in 1890. Panel (d) plots total output per skilled worker per month during 1890.

## A Coal extraction

Let  $f$  index firms and  $t$  bi-yearly intervals. Biennial coal extraction is  $Q_{ft}$  tons, the amount of skilled labor (in days worked) is  $H_{ft}$ , and unskilled labor-days is  $U_{ft}$ . Cutting machine usage is denoted  $K_{ft} \in \{0, 1\}$ . The model is written at the level of the firms  $f$ , which are observed in the data. The production function in logs is given by Equation (7a), denoting logarithms of variables in lowercases. I use a Cobb-Douglas production function in both labor types, but allow for the output elasticity of skilled labor  $\beta_{ft}$  to vary flexibly across mines and years. The scale parameter  $\nu$  is equal to the sum of the output elasticities of skilled and unskilled workers, and is assumed to be a constant. The

Hicks-neutral productivity residual in logs is denoted  $\omega_{ft}$ .

$$q_{ft} = \beta_{ft}h_{ft} + (\nu - \beta_{ft})l_{ft} + \omega_{ft} \quad (7a)$$

Besides labor, mines also use cutting machines, the usage of which is indicated by a dummy variable  $K_{ft} \in \{0, 1\}$ . Both the output elasticity of skilled workers  $\beta_{ft}$  and the productivity residual  $\omega_{ft}$  are assumed to be AR(1) processes, Equations (7b) and (7c), with serial correlations  $\sigma^\beta$  and  $\sigma^\omega$ . This specification does not allow for some forms of cost dynamics in which current productivity is a function of the total amount of output produced in the past.<sup>20</sup> Both the output elasticity and Hicks-neutral productivity level are assumed to be linear functions of current machine usage  $K_{ft}$  and a vector of other control variables  $\mathbf{X}_{ft}$ . I include a linear time trend, a constant, and the quantity of black powder used to this controls vector: both Hicks-neutral productivity and the output elasticity of workers could differ depending on how much black powder was used to blast the coal veins. The effects of using cutting machines on the output elasticity of skilled labor is parametrized by the coefficient  $\alpha^\beta$ , their effect on Hicks-neutral productivity is  $\alpha^\omega$ . The residual shocks to the skilled labor output elasticity and Hicks-neutral productivity are denoted  $\gamma_{ft}^\beta$  and  $\gamma_{ft}^\omega$ . By using these parametric specifications, I assume that there is no heterogeneity across mines or time in the Hicks-neutral and factor-biased effects of cutting machines.

$$\beta_{ft} = \alpha^\beta K_{ft} + \sigma^\beta \mathbf{X}_{ft} + \rho^\beta \beta_{ft-1} + \gamma_{ft}^\beta \quad (7b)$$

$$\omega_{ft} = \alpha^\omega K_{ft} + \sigma^\omega \mathbf{X}_{ft} + \rho^\omega \omega_{ft-1} + \gamma_{ft}^\omega \quad (7c)$$

Although the assumption of unitary substitution between both inputs in the Cobb-Douglas model is strong, and goes against the canonical models in the labor literature, the model does better than usual Cobb-Douglas formulations in empirical work by allowing for unobserved heterogeneity in output elasticities of inputs across mines and time, and by allowing these output elasticities to be conditional on technology usage, which is crucial when studying non-Hicks neutral technological change.

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. The entire distribution of capacity utilization rates is shown in Figure A3.

## B Coal demand

In contrast to the general model in Section 2, most coal firms were not monopolists on the coal market. Each firm operates on a single coal market, indexed by  $m$  with a market share  $s_{ft}^q \equiv \frac{Q_{ft}}{Q_{mt}}$  and market-level output  $Q_{mt} \equiv \sum_{f \in m} Q_{ft}$ . Coal markets will be defined in Section 4.2. The market-level coal

<sup>20</sup>I refer to Appendix C.2 for a motivation and discussion of this assumption.

demand curve is given by Equation (8), with a market-level mine-gate coal price  $P_{mt}$ , an inverse demand elasticity  $\eta$ , and a residual  $\zeta_{mt}$  which reflects differences in coal prices across markets due to variation in local demand conditions, transport costs, etc. In the baseline model, I assume that all markets face the same coal demand elasticity.

$$P_{mt} = (Q_{mt})^\eta \exp(\zeta_{mt}) \quad (8)$$

Coal is assumed to be a homogeneous product. 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 can be absorbed into a market fixed effect. Regressing coal prices on market and year fixed effects yields an R-squared of 0.73.

### C Input supply

Each firm operates on exactly one labor market  $n$  with skilled and unskilled labor market shares  $s_{ft}^h$  and  $s_{ft}^l$ . More information on how labor markets are defined is in Section 4.2. Skilled labor in a market  $n$  earns a daily wage  $W_{nt}^h$ , unskilled labor earns a daily wage  $W_{nt}^l$ . I convert the piece rates paid to skilled workers into daily wages in order to be comparable to the unskilled worker wages. Firms are assumed not to wage-discriminate in terms of skilled labor piece rates. Mine-employee-level wage data from the 1890 report show indeed that there was very little heterogeneity in both piece rates and daily wages across miners within firms at a certain point in time. A firm  $f$  has an input market share  $s_{ft}^h \equiv \frac{H_{ft}}{H_{mt}}$  on the market for  $H$  and input market share  $s_{ft}^l \equiv \frac{L_{ft}}{L_{mt}}$  on the market for  $L$ , with market-level employment  $H_{mt} \equiv \sum_{f \in m} H_{ft}$  and  $L_{mt} \equiv \sum_{f \in m} L_{ft}$ . The market-level supply curve for both types of workers is given by equation (9). The inverse wage elasticity of skilled labor is  $\psi_{nt}^h = \frac{\partial W_{nt}^h}{\partial H_{nt}} \frac{H_{nt}}{W_{nt}^h} + 1$  and for unskilled workers as  $\psi_{nt}^l = \frac{\partial W_{nt}^l}{\partial L_{nt}} \frac{L_{nt}}{W_{nt}^l} + 1$ . The error terms  $\xi_{nt}^h, \xi_{nt}^l$  explains variation in wages across markets that cannot be explained by market size, which includes the outside options available to the workers in each market.

$$\begin{cases} W_{nt}^h &= H_{nt}^{\psi_{nt}^h - 1} \exp(\xi_{nt}^h) \\ W_{nt}^l &= L_{nt}^{\psi_{nt}^l - 1} \exp(\xi_{nt}^l) \end{cases} \quad (9)$$

Figure 5c revealed that unskilled worker wages were much less dispersed compared to skilled wages, and did not change in response to seasonal labor demand shocks. Therefore, I assume that unskilled labor supply is perfectly elastic, meaning that  $\psi_{nt}^l = 1 \forall f$ . There are, of course, other possible explanations for the fact that wages did not react to labor demand shocks, such as behavioral reasons, as shown in (Kaur, 2019). The key thing to note here is, however, that monthly wage profiles were only flat for unskilled labor, not for skilled labor. Although wage contracts differed between skilled

and unskilled labor because skilled labor received a piece rate rather than a daily wage, both of these contracts were limited to monthly durations or less; it is hence not the case that unskilled wages did not respond to seasonal demand shocks because they were pre-negotiated for the entire year. In contrast, I allow for the elasticity of skilled labor supply,  $\psi_{nt}^h$ , to be above one. Although the log-linearity of Equation (9) imposes a strong functional form assumption, I allow the slope  $\psi_{nt}^h$  to vary flexibly across markets and time, as local labor market conditions vary. I assume that cutting machines  $K$  are sold on competitive markets, and that their prices are exogenous to each individual mine.

I assume that employers are homogeneous ‘products’ from the point of view of the workers: when choosing which firm to work for within a town, miners only care about the wage rate, not about other firm characteristics. The motivation for this assumption is that there is very little dispersion in wages within towns in a given year: town and year dummies explain 86% of the variation in skilled wages.

I do not formally model how employees gather their skills, and whether employees can move from being unskilled to skilled worker types. I do assume that firms cannot invest to turn unskilled workers into skilled workers - this would imply a dynamic input demand problem that does not fit the static input demand conditions that are outlined below.

## D Firm behavior

Using the terminology of Akerberg et al. (2015), I assume that skilled and unskilled workers are both variable and static inputs. They are *variable* because they can be flexibly adjusted: as shown earlier, employment was adjusted throughout the year on a monthly basis, and wages were determined in short-term contracts until 1898.<sup>21</sup> Both labor types are also *static* because current labor choices do not affect future profits, i.e. there are no hiring or firing costs. Cutting machines are, in contrast, a *fixed* input. Firms need to make their cutting machine adoption decision one period in advance. Let the capital accumulation equation be given by the following equation, with machine acquisitions being denoted as  $A_{ft-1} \in \{0, 1\}$ . Depreciation  $\delta \in \{0, 1\}$  takes the value of either zero or one. If there is no depreciation, meaning that  $\delta = 1$ , firms can only acquire a cutting machine if they do not already own one, and such an acquisition is permanent. If  $\delta = 0$ , machines fully depreciate within two years, and firms re-make the capital adoption decision every time period.

$$K_{ft} = \delta K_{ft-1} + A_{ft-1}(1 - \delta K_{ft-1}) \quad (10)$$

Cutting machines have both a common fixed cost component  $\Phi$ , which is the capital cost of acquiring the machine, and a common variable cost component  $W^k$ , due to the usage of electricity. Mine-level variable profits are denoted  $\Pi_{ft} \equiv P_{ft}Q_{ft} - W_{mt}^h H_{ft} - W_{mt}^l L_{ft} - W^k K_{ft}$ . Other intermediate input expenditure is not part of the mine’s profit function, as these inputs were purchased and brought by the miners. I assume zero sunk costs of cutting machine usage, as the adoption model will be static. Hence, total mine profits are defined as  $\Pi_{ft}^{tot} \equiv \Pi_{ft} - \Phi K_{ft}$ .

<sup>21</sup>As explained further below, I will only consider the period 1884-1894 when estimating the structural model.

I assume that firms make their input decisions in two phases. At time  $t - 1$ , before the productivity residuals  $\omega_{ft}$  and  $\omega_{ft}^h$  are observed, firms simultaneously choose their cutting machine usage for the next period,  $K_{ft}$ . At time  $t$ , after the productivity residuals  $\omega_{ft}$  and  $\omega_{ft}^h$  are observed, firms simultaneously choose their optimal amounts of both labor types conditional on their capital technology, which was chosen earlier.

The second stage of the decision problem, the labor demand problem, is given by Equation (11). Taking capital usage as given, each mine  $f$  independently chooses the amount of skilled and unskilled labor that maximizes its current variable profits. By choosing the amount used of both labor types, firms also choose their output  $Q_{ft}$ .

$$\max_{H_{ft}, L_{ft}} (\Pi_{ft}) \quad (11)$$

In the first stage, firms choose their capital investment  $A_{ft} \in \{0, 1\}$  that maximizes discounted total profits, with a common discount factor  $\delta$ . In the application, I will assume full depreciation of capital within two years, meaning that  $\delta = 0$ , in order to keep the cutting machine adoption problem static. This means that firms re-choose their capital stock in every two-year period, and do so by maximizing the profits in the next period.

$$\max_{A_{ft}} \Pi_{f,t+1}^{tot} + \mathbb{E}_t \sum_{r=2}^{\infty} (\delta^{r-1} \Pi_{f,t+r}^{tot}) \quad (12)$$

In contrast to labor choices by firms, which happen in a Cournot game, capital investment is assumed to be a single-agent problem, similarly to Olley and Pakes (1996). Firms do not take into account that their technology choices affect wages and markdowns at other firms in the same market, and hence technology choices of these other firms.

## E Equilibrium

By solving the first order conditions for the profit maximization problem in (11), the equilibrium expressions for all endogeneous static variables ( $Q, P, H, L, W^h, W^l$ ) can be solved for. These equilibrium expressions can be found in Appendix B.6. The skilled labor wage markdown charged by the firm is equal to  $1 + s_{ft}^h (\psi_{nt}^h - 1)$ :

$$\frac{\partial(P_{mt}Q_{ft})}{\frac{H_{ft}}{W_{mt}^h}} = 1 + (\psi_{mt}^h - 1)s_{ft}^h$$

The markdown parameter  $\mu_f$  from the theoretical model hence corresponds to the markdown  $1 + (\psi_{mt}^h - 1)s_{ft}^h$  in the empirical model. If the labor market share of the firm is equal to one, the actual markdown is equal to the monopsonistic markdown  $\psi_{nt}^h$ . If the firm is atomistically small, the markdown goes toward 1 in the limit, meaning that skilled laborers earn their marginal product of labor.



Due to the Cournot coal market assumption, the markup is equal to  $\mu_{ft} = (1 + s_{ft}^q \eta)^{-1}$ .

## 4.2 Identification and estimation

I now turn to the identification and estimation of the model. Six latent variables need to be identified: the market-level inverse elasticity of skilled labor supply  $\psi_{nt}^h$ , in Equation (9), the inverse elasticity of coal demand  $\eta$ , in Equation (8), the entire distribution of output elasticities of skilled labor  $\beta_{ft}^h$ , in Equation (7a), the effects of cutting machines on the output elasticity of skilled labor and on Hicks-neutral productivity, in Equations (7b-7c), and fixed cutting machine costs. Although the model is specified at the firm-bi-year level, the dataset comes at the mine-bi-year level. I aggregate all the relevant variables from the mine- to the firm-level.<sup>22</sup> I restrict the panel to the time period 1884-1894 when estimating the model and conducting the counterfactual exercises, because wage and price data are missing in 1896, and because annual collective bargaining over wages between unions and coal firms was instituted in 1898, which does not fit the unilateral oligopsony framework of the model.

### A Labor supply

**Identification** I start with the identification of the skilled labor supply function. Taking the logarithm of Equation (9) for skilled labor, and denoting logs as lowercases, gives equation (13).

$$w_{nt}^h = (\psi_{nt}^h - 1)h_{nt} + \xi_{nt}^h \quad (13)$$

The supply elasticity  $\psi_{nt}^h$  cannot be recovered by simply regressing skilled labor wages on employment because of the latent outside options  $\xi_{nt}^h$ . Firms in labor markets with an unattractive outside option  $\xi_{nt}^h$  can offer a lower wage to attract the same number of skilled laborers. 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 the seasonal character of coal demand as a source of labor demand variation. As explained in section 3.1, coal demand rises during the fall and winter due to low temperatures. Denote skilled employment in town  $n$  during winter and summer months as  $H_{nt}^{WIN}$  and  $H_{nt}^{SUM}$ , and the corresponding daily skilled wages as  $W_{nt}^{h,WIN}$  and  $W_{nt}^{h,SUM}$ . The supply residuals during winter and summer are  $\xi_{nt}^{h,WIN}$  and  $\xi_{nt}^{h,SUM}$ . I assume that the outside option  $\xi^h$  is the same during winters and summers:  $\xi_{nt}^{h,WIN} = \xi_{nt}^{h,SUM}$ . Under these assumptions, the slope of the skilled labor supply curve can then be calculated using equation (14):

$$\psi_{nt}^h = \frac{w_{nt}^{h,WIN} - w_{nt}^{h,SUM}}{h_{nt}^{WIN} - h_{nt}^{SUM}} + 1 \quad (14)$$

The main argument in favor of these two assumptions is that the monthly wage profile of unskilled workers did not fluctuate between the different seasons, as shown in Figure 5. It could be that outside

<sup>22</sup>Details on how I aggregate to the firm-level are in Appendix A.2.

options varied seasonally, for instance due to increased agricultural labor demand during the harvest season. This would, however, be consistent with higher wages during the summer, while lower summer wages are observed. Also, we would expect unskilled labor wages to fluctuate seasonally as well, which they did to a much lesser extent than skilled labor wages. Working conditions, such as mine safety, could vary seasonally, but were less easily adjustable than wages. Anecdotal sources mention that most skilled workers were (partially) unemployed during the summer months in Northern Illinois coalfields (Joyce, 2009), which is consistent with increased monopsony power over these workers during the summer.

**Labor market definition** Workers did not own cars yet, and railroads were only used for freight cargo except between large cities. Miners could hence only work in their own mining town or commute by foot to another town. Of the 448 towns reported in the data set, 75% were located more than 3 miles in a straight line from their closest mining town (town with at least one mine), and the average town was 5.6 miles away from the closest mining town. Given that miners had to bring their own equipment to the mines and that until 1898, they often worked 10 hours per day, it seems safe to assume that any town further than 3 miles apart is not a viable commuting option, as it would imply 2h30 of daily commuting time by foot.<sup>23</sup> In order to ensure isolated labor markets, I merge the towns that are closer than 3 miles from each other.<sup>24</sup> This results in 350 labor markets that lied on average 6.4 miles from the next nearest town.

**Estimation** I calculate the slope of the skilled labor supply curve for each town using equation (14). Skilled wages are reported separately for winters and summers between 1884-1894.<sup>25</sup> The reported wage rates are piece rates, in wages per ton. Equation (14) was, however, written using daily wages per worker and days of employment, because workers care only about their daily wage, not their wage per tons of coal mined. I transform the piece rates that are observed in the data into daily wages by multiplying by the ton of coal mined per skilled labor-day at each mine. Next, I aggregate employment and daily wages to the town-year-level in order to estimate the town-level inverse skilled labor supply elasticity using Equation (14). This results in a skilled labor supply elasticity that can flexibly vary both across towns and over time.

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<sup>23</sup>Taking a 10% sample of the town pairs to google maps shows that 3 miles of bird's eye distance corresponds on average to 3.9 miles by today's roads, and 77 minutes of walking (without equipment) one-way.

<sup>24</sup>More information is in Appendix A.2

<sup>25</sup>Summer and winter skilled employment is reported only up to 1890. However, the maximum number of workers is reported next to the average in 1892 and 1894. For these two years, I assume that the maximum number of employees coincides with the amount of workers during winter, and that the average number of workers throughout the year is a simple average between the summer and winter employment averages. This allows me to back out summer and winter worker averages for 1892 and 1894 as well.

## B Coal demand

**Identification** Taking logarithms of the coal demand function (8) results in  $p_{mt} = \eta q_{mt} + \mathbf{X}_{mt} + \xi_{mt}$ . As firms with attractive features  $\xi_{mt}$ , such as a convenient location, will set higher coal prices, this equation cannot be identified by regressing coal prices on quantities. I rely on the thickness of the coal seam as a cost shifter: whereas the seam thickness affects the marginal cost of mining, consumers do not care about it as it does not affect coal quality (Affolter & Hatch, 2002). Seam thickness was the result of geological variation, and hence plausibly exogenous to coal firms conditional on their location. A key driver of coal quality in Illinois was the mine's depth (Affolter & Hatch, 2002), so I include the average mine depth in market  $m$  into the observable market characteristics  $\mathbf{X}_{mt}$ .

**Coal market definition** Coal firms either sold their output locally near the mine, or sold it to railroad firms who either transported it to final markets, or used it themselves to power their locomotives. I define coal markets  $m$  as follows. If a mining town was not located on a railroad line, I infer that coal was sold locally, and define the coal market similarly to labor markets, being the town unless towns are located less than 3 miles from each other. If towns were connected to the railroad network, I let the railroad line be the market: as railroad firms were the main coal buyers, coal firms presumably competed against each other on the same railroad line, but did not compete against coal firms operating on different railroad lines.<sup>26</sup> Defining coal markets in this way results in 249 coal markets, of which 26 railroad lines and 223 local markets. Coal firms on markets not connected to the railroad network have an average coal market share of 38%, compared to 5.8% for firms selling through the railroad network.

**Estimation** I estimate Equation (8) in logs by 2SLS using the log average vein thickness in the town and the log average mine depth in each year as instruments for the total coal quantity sold. I include the distance to Chicago and St. Louis, a dummy of whether a town was located on a railroad and whether it was located on a crossing of railroads, and year dummies as observable market-specific coal demand shifters  $\mathbf{X}_{mt}$ . I also control for log mine depth, as mentioned earlier.

## C Output elasticities of labor

**Identification** As explained earlier, both labor inputs are assumed to be variable, static inputs. Working out the input demand conditions from Equation (11), the output elasticity of skilled labor is equal to the product of its revenue share, its wage markdown, and its coal price markup.

$$\beta_{ft}^h = \frac{W_{nt}^h H_{ft} ((\psi_{nt}^h - 1) s_{ft}^h + 1)}{P_{mt} Q_{ft} (1 + \eta s_{ft}^a)} \quad (15)$$

---

<sup>26</sup>Details are in Appendix A.2.

The output elasticity of unskilled labor is then known up to the scale returns constant  $\nu$ :  $\beta_{ft}^l = \nu - \beta_{ft}^h$ . Relying on the first order conditions from the labor demand problem to identify the output elasticities of skilled and unskilled labor follows Hall (1988); Foster et al. (2008); Hsieh and Klenow (2009), with the difference that I allow for endogenous input prices. This approach has the benefit of allowing for flexible heterogeneity in the output elasticities of labor across firms and time, while still allowing for imperfectly competitive input markets. The intuition behind (15) is that after netting out any markup and markdown variation, the residual variation in revenue shares should be due to variation in output elasticities. Taking this approach does come at the cost of having to impose a fixed parameter for the degree of returns to scale and a model of competition both upstream and downstream. Appendix C.1, presents an alternative approach which also estimates the markup and scale returns, without having to impose a model of downstream competition, but which allows for less unobserved heterogeneity in output elasticities. The resulting average markup is very similar to the one estimated using the Cournot model.<sup>27</sup>

**Estimation** The full distribution of output elasticities of skilled and unskilled labor across firms and time can be readily computed from Equation (15) given that the revenue share of skilled labor is observed, and that the inverse skilled labor elasticity  $\psi_{ft}^h$  was estimated earlier. However, doing so requires a calibration of the degree of scale returns  $\nu$ . I assume that there are decreasing returns to scale in coal mining extraction, because of three reasons. First, nearly all the mines produced far below their full capacity, despite coal markets being perfectly competitive. If there would be constant or increasing returns to scale and perfect competition downstream, firms without monopsony power on labor markets should produce at full capacity. Whereas half of the firms have a horizontal skilled labor supply function, and hence no monopsony power, merely 2% of firms produce at full capacity, and 90% of firms use less than four-fifths of their capacity. Second, the monthly production data, which were discussed in Section 3, show that aggregate output per worker and output are negatively correlated across months within a year. Output per worker was 3% lower during winters compared to summers. This is consistent with decreasing returns to scale, as output was higher during winter. Third, in Appendix C.1, I specify an extension to the model in which I estimate the degree of returns to scale while imposing more structure on the distribution of output elasticities of inputs across firms, which yields an estimated scale parameter of 0.908. I calibrate the scale parameter to be  $\nu = 0.9$ , but conduct robustness checks with different values for  $\nu$  in Appendix C.4.

## D Factor-biased and Hicks-neutral effects of cutting machines

**Identification** Finally, the effects of cutting machines on both the output elasticity of skilled labor and on Hicks-neutral productivity, Equations (7b) and (7c), need to be identified. Simply regressing

<sup>27</sup>In principle, imposing a model of competition downstream would not be required in any case, as one could net out markdowns from *cost* share variation across firms, rather than from *revenue* share variation across firms. However, in this paper, unskilled labor costs are unobserved, which rules out this approach.

the output elasticity of skilled labor  $\beta_{ft}^h$  or Hicks-neutral productivity  $\Omega_{ft}$  on cutting machine usage is subject to simultaneity bias, as both Hicks-neutral and factor-augmenting productivity affect input demand, an argument also made by Doraszelski and Jaumandreu (2017). I follow the production function identification literature by relying on timing assumptions to identify the cutting machine effects  $\beta_1$  and  $\beta_2$  (Olley & Pakes, 1996; Akerberg et al., 2015). Following Blundell and Bond (2000) I take  $\rho$ -differences of Equation (7c), such that the skilled labor productivity shock can be written as  $\gamma_{ft}^\beta = \alpha^\beta(K_{ft} - \rho^\beta K_{ft-1}) + \sigma^\beta(\mathbf{X}_{ft} - \rho^\beta \mathbf{X}_{ft-1})$ , and the Hicks-neutral productivity shock as  $\gamma_{ft}^\omega = \alpha^\omega(K_{ft} - \rho^\omega K_{ft-1}) + \sigma^\omega(\mathbf{X}_{ft} - \rho^\omega \mathbf{X}_{ft-1})$ . Given that cutting machines are assumed to be a dynamic and fixed input, I assume that firms decide on cutting machine usage prior to the realization of both productivity shocks  $\gamma_{ft}^1$  and  $\gamma_{ft}^2$ , which allows to identify the coefficients  $\beta$ ,  $\rho$ , and  $c$  by imposing that current and lagged capital usage are orthogonal to  $\gamma_{ft}^\beta$  and  $\gamma_{ft}^\omega$ . As both labor inputs and black powder are variable inputs, they are chosen after the productivity shocks  $\gamma_{ft}^\beta$  and  $\gamma_{ft}^\omega$  are observed, but their lagged values are orthogonal these shocks. Hence, the moment conditions are:

$$\mathbb{E} \left[ \gamma_{ft}^\beta(\rho^\beta, \alpha^\beta, \sigma^\beta) \begin{pmatrix} K_{ft} \\ K_{ft-1} \\ \mathbf{X}_{ft-1} \\ h_{ft-1} \\ l_{ft-1} \end{pmatrix} \right] = 0 \qquad \mathbb{E} \left[ \gamma_{ft}^\omega(\rho^\omega, \alpha^\omega, \sigma^\omega) \begin{pmatrix} K_{ft} \\ K_{ft-1} \\ \mathbf{X}_{ft-1} \\ h_{ft-1} \\ l_{ft-1} \end{pmatrix} \right] = 0$$

**Estimation** I estimate Equations (7b) and (7c) using GMM with the moment conditions above. In the vector of controls  $\mathbf{X}$ , I include a constant, a linear time trend, and the logarithm of the number of powder kegs used by the firm, adding one within the logarithm to include firms that did not use any powder at all.

## E Fixed costs of cutting machines

As mentioned before, I assume a discount rate of  $\delta = 0$ , which implies that machines fully depreciate after two years, in order to make the adoption problem static. I assume fixed machine costs  $\Phi$  are common across firms and time, and estimate  $\Phi$  by matching the average observed machine usage rate to the predicted machine usage rate under this fixed cost. I re-estimate fixed costs in every bootstrapping iteration.

## F Bootstrapping

The entire estimation procedure that has been described in this section happens sequentially. First, I estimate the firm-bi-year-level inverse skilled labor supply elasticities  $\psi_{ft}^h$ . Next, I estimate the market-level inverse coal demand elasticity  $\eta$ . Third, I estimate the firm-level output elasticities  $\beta_{ft}^h$ , which requires knowledge of both  $\psi_{ft}^h$  and  $\eta$ . Fourth, I estimate the transition equations for the output elasticity of skilled labor  $\beta$  and for Hicks-neutral productivity,  $\omega$ , in order to obtain the cutting

machine effects  $\alpha^\beta$  and  $\alpha^\omega$ . Finally, I estimate the level of fixed machine costs  $\Phi$ . In order to obtain the correct standard errors, I block-bootstrap this entire estimation procedure while resampling within firms over time, with 250 iterations.

### 4.3 Results

A summary of the key model estimates are in Table 1, I refer to Appendix Table A4 for the full list of coefficient estimates. The market-level skilled labor supply estimates are in Table 1a. The number of observations is 1,116 because the skilled wage markdown is estimated at the labor market-bi-yearly level on the subset of the panel for which seasonal wages are observed (1884-1894). The mean town-level inverse skilled labor supply elasticity  $\psi_{nt}^h$  is 1.164. This implies that a monopsonist would set the marginal product of skilled laborers at 16.4% above their wage, but a firm with a labor market share of  $s_{ft}^h$  would set the marginal product at  $s_{ft}^h * 16.4\%$  above the skilled wage. The average firm charges a markdown of 3.5%. The average market-level inverse skilled labor supply elasticity lies in a 90% confidence interval of [1.136, 1.176] and hence lies significantly above one.<sup>28</sup>

The market-level coal demand elasticities are in Table 1b. The number of observations is lower, at 453, because there are fewer coal markets than labor markets and because vein thickness (the instrument) is not observed in 1888 and 1890. The inverse demand elasticity is estimated to be -0.465, with a 90% confidence interval on [-0.671; -0.362]. The remaining coefficient estimates are in Appendix Table A4. The first-stage regression of the coal quantity on vein thickness has an F-statistic of 51.3. Coal demand is higher in markets that are connected to the railroad network and located on railroad crossings, and decreases with the distance to both St. Louis and Chicago. The distribution of firm-level markup ratios is plotted in Figure A5a. The average firm charges a price of 14.8% above its marginal cost, but the median firm only charges a price that is 2.2% above its marginal cost. Coal market power is hence skewed considerably towards large firms.

Table 1c contains the estimated output elasticities of skilled labor. The number of observations is 3,723, given that this output elasticity is estimated at the firm-bi-yearly level. The output elasticity of skilled labor is on average 0.727, with a 90% confidence interval of [0.675; 0.773]. The average output elasticity of unskilled labor is, mechanically, 0.173. The distribution of output elasticities across firms and time is plotted in Figure A5b.

The factor-biased effects of cutting machines are in Table 1d. Although this model is estimated at the firm-year level too, the number of observations is lower, at 1133, because lagged values of all variables are needed to estimate the equation of motion for the output elasticities. The output elasticity of skilled labor is estimated to fall by 0.143 units due to the usage of cutting machines, which is a relative drop of 20% on average. The 90% confidence interval lies on [-0.186 and 0.005] so the coefficient is not significantly below zero at the 95% confidence level, but is at the 90% confidence

<sup>28</sup>Appendix C.3 discusses how the markdown estimates are correlated with town and county characteristics. The distribution of firm-level markdown ratios, as opposed to the market-level skilled labor supply elasticity, is plotted in Figure A5a.

**Table 1: Model estimates**

<i>(a) Miner supply (town-level)</i>		Estimate	CI05	CI95
Inverse elasticity of miner supply	$\psi^h$	1.164	1.136	1.176
Observations			1116	
<i>(b) Coal demand (county-level)</i>				
Coal demand elasticity	$\eta$	-0.465	-0.671	-0.362
Observations			453	
R-squared			.191	
<i>(c) Output elasticities</i>				
Output elasticity of miners (avg.)	$\beta^h$	0.727	0.675	0.773
Observations			3723	
<i>(d) Factor-biased productivity transition</i>				
1(Cutting machine)	$\alpha^\beta$	-0.143	-0.186	0.005
Observations			1133	
R-squared			.007	
<i>(e) Hicks-neutral productivity transition</i>				
1(Cutting machine)	$\alpha^\omega$	0.242	-0.112	0.396
Observations			1050	
R-squared			.204	
<i>(f) Fixed machine costs</i>				
Fixed machine cost (USD)	$\Phi$	3590.797	1849.541	14107.491

**Notes:** Panel (a) reports the estimates of the labor supply function, Equation (14). Panel (b) reports the estimates of the coal demand function, Equation (8). Panel (c) reports the output elasticity of skilled labor, using Equation (15). Panels (d)-(e) report the estimated transition equations for the output elasticity of skilled labor and for Hicks-neutral productivity, Equations (7b)-(7c). Panel (f) reports estimates fixed cutting machine costs. Standard errors are block-bootstrapped with 250 iterations.

level. The finding that cutting machines were unskill-biased is consistent with the anecdotal historical evidence presented earlier, in Section 3. The effect of cutting machines on Hicks-neutral productivity is in Table 1e. The point estimate of 0.242 implies that cutting machines increased Hicks-neutral

productivity by 27%, but this effect is very imprecisely estimated. Finally, the fixed machine cost is in Table 1f, and is estimated to be \$3591, which is almost equal to the average variable profit of a coal mine (\$3456), but 8.5 times higher than the median mine's variable profit (\$422).

## 4.4 Counterfactuals

Using the estimated model, I now examine how technology returns and usage would change under different levels of labor market competition, and under different directions of technological change.

### A Computation of the equilibrium

Let  $X \in \{Q, H, L, W^h, W^l, P, \Pi, \Pi^{tot}\}$  be an endogenous variable in the model. I denote  $X_{ft}^K(s_{ft}^h)$  as the equilibrium value of variable  $X$  for usage of the technology  $K \in \{0, 1\}$  and for a certain labor market share  $s_{ft}^h$ . The equilibrium values for any endogenous variable  $X$  can be computed using the expressions in Section B.6. For instance,  $Q_{ft}^1(s_{ft}^h = 0.5)$  denotes the equilibrium output of firm  $f$  in year  $t$  when using cutting machines, and having a labor market share of 50%, and can be computed using Equation (16a).

In order to compute the equilibrium values of all endogenous variables  $X$ , I need to know the values of the output elasticity of skilled labor and the Hicks-neutral productivity level both when using cutting machines and when not doing so,  $\beta_{ft}(K_{ft})$  and  $\Omega_{ft}(K_{ft})$ . If the mine does not use cutting machines, I calculate the counterfactual output elasticity if it would use cutting machines as  $\beta_{ft}^h(K_{ft} = 1) = \beta_{ft}^h + \alpha_\beta$ , using Equation (7b). Similarly if the mine is already using cutting machines, the counterfactual output elasticity when not doing is  $\beta_{ft}^h(K_{ft} = 0) = \beta_{ft}^h - \alpha_\beta$ . The counterfactual Hicks-neutral productivity levels are computed in the same way:  $\omega_{ft}(K_{ft} = 0) = \omega_{ft} + \alpha_\omega$  is the counterfactual productivity of not using cutting machines, calculated if the firm is already using cutting machines, and  $\omega_{ft}(K_{ft} = 1) = \omega_{ft} - \alpha_\omega$  is the counterfactual productivity of using cutting machines, calculated if the firm is not currently using cutting machines.

The market-level demand shifter  $\zeta_{mt}$  is computed as the residual of the coal demand function. Similarly, the labor supply residual  $\xi_{nt}^h$  is the residual of the estimated labor supply function (9):

$$\exp(\xi_{nt}^h) = \frac{W_{nt}^h}{\left(\frac{H_{ft}}{s_{ft}^h}\right)^{\psi_{nt}^h - 1}}$$

### B Labor market competition and technology usage

Any equilibrium variable  $X_{ft}^K(s_{ft}^h)$  is given as a function of the labor market share  $s_{ft}^h$ , and can hence be evaluated for any labor market share, factual or counterfactual. In particular, I focus on how two key outcomes of interest change in function of labor market concentration: first, the *variable profit return* to machine usage,  $\frac{\Pi_{ft}^1(s_{ft}^h) - \Pi_{ft}^0(s_{ft}^h)}{\Pi_{ft}^0(s_{ft}^h)}$ . Second, equilibrium machine usage, which is calculated as



the share of firms for which machine adoption increases total profits, as measured by the indicator function for each firm  $\mathcal{I}[\Pi_{ft}^1(s_{ft}^h) - \Pi_{ft}^0(s_{ft}^h) - \Phi]$ .

A number of assumptions need to be explained at this point. First, the labor supply and coal demand residuals  $\xi_{nt}^h, \xi_{nt}^l, \zeta_{mt}$  are assumed to be invariant to both labor market structure and machine usage: both labor market structure and machine usage are assumed to affect worker and consumer preferences only through equilibrium wages and prices, not in any other way. Second, I assume that unskilled worker characteristics, which are equal to unskilled worker wages, are the same across firms in a given year  $\xi_{nt}^l = \xi_t^l$ . This assumption is motivated by the evidence in Figure 5c, which showed that there is very little cross-sectional variation in unskilled wages. The residual  $\xi_t^l$  is equal to the daily unskilled wage, which is unobserved. However, it can be backed out under the assumption of competitive unskilled labor markets. Writing out Equation (15) for both unskilled and skilled labor gives a system of equations (the variable input demand first order conditions) that can be solved for unskilled wages. The resulting unskilled wage expression is  $W_{ft}^l = \frac{\beta_{ft}^l P_{ft} Q_{ft}}{\beta_{ft}^h L_{ft}} (\psi_{nt}^h - 1) s_{ft}^h$ . I take the yearly average of this imputed wage to be the unskilled wage  $W_t^l$ , which is equal to the unskilled labor supply residual  $\xi_t^l$ . Third, when considering the effects of changing labor market structure on machine returns and machine usage, I do not let *coal* market structure vary simultaneously: the focus is to isolate the effects of labor market competition on technology returns and adoption, rather than the joint effect of labor and product market competition on these outcomes. Finally, fixed machine costs  $\Phi$  are assumed to be invariant to the level of labor and product market competition.

## C Counterfactual technologies

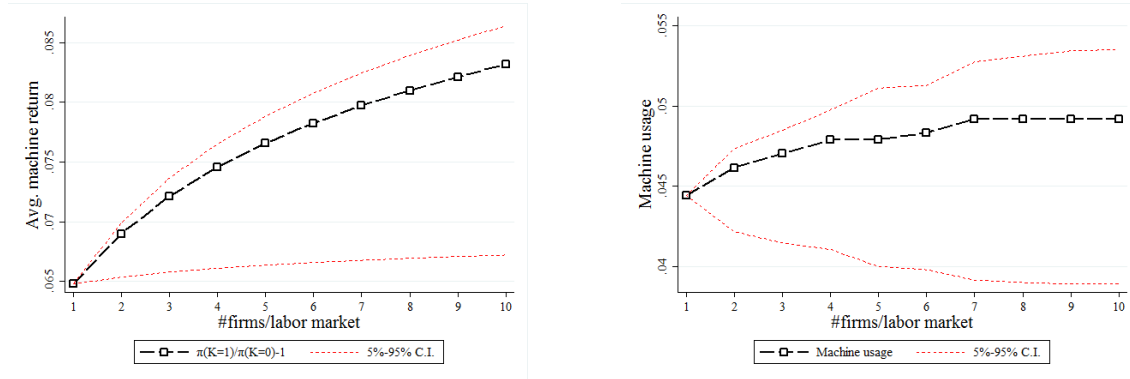
In order to understand how the directed and Hicks-neutral effects of technologies shape the relationship between labor market competition and technology adoption, I carry out the counterfactual exercise from the previous section under three different scenarios, which are summarized in Table 2. First, I consider the actual technology, the cutting machine, which was both unskill-biased and Hicks-neutral productivity-enhancing:  $\frac{\partial \beta^h}{\partial K} < 0$  and  $\frac{\partial \Omega}{\partial K} > 0$ . Second, I consider a skill-biased technology, such as hauling locomotives, for which  $\frac{\partial \beta^h}{\partial K} > 0$  and  $\frac{\partial \Omega}{\partial K} > 0$ . Third, I consider a Hicks-neutral technology, meaning that  $\frac{\partial \beta^h}{\partial K} = 0$  and  $\frac{\partial \Omega}{\partial K} > 0$ . I assume that fixed technology costs are invariant across the different counterfactual scenarios.

**Table 2: Counterfactuals: overview**

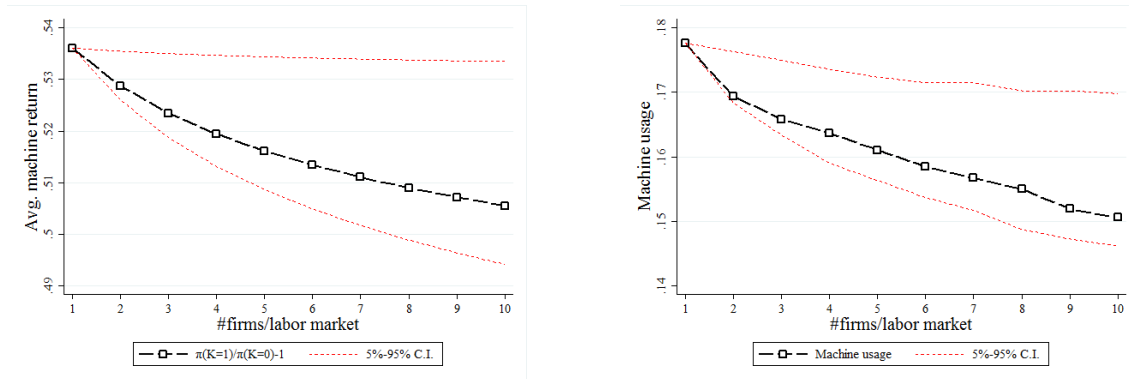
Technology	Direction	$\alpha^\beta$	$\alpha^\omega$
Actual	Unskill-biased	$< 0$	$> 0$
Counterfactual 1	Skill-biased	$> 0$	$> 0$
Counterfactual 2	Hicks-neutral	$= 0$	$> 0$

**Figure 6: Counterfactual technology returns and usage**

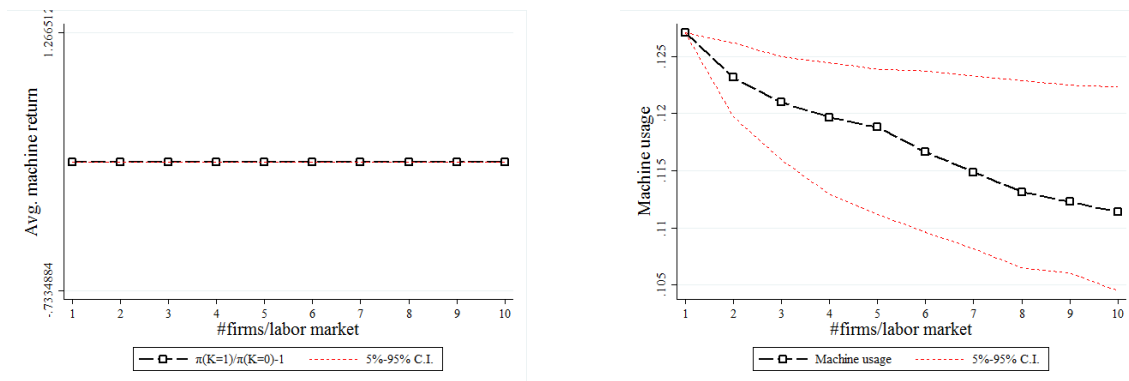
**(a) Unskill-biased technology**



**(b) Skill-biased technology**



**(c) Hicks-neutral technology**



## D Results

**Unskill-biased technology** The results of the counterfactual exercise for cutting machines, the skill-biased technology, is in Figure 6a. In line with theorem 1, the variable profit return of cutting machines  $\frac{\Pi(K=1) - \Pi(K=0)}{\Pi(K=0)}$  increases with the number of firms in the labor market. Whereas adopting a cutting machine increases variable profits by 6.5% on average under monopsonistic labor markets, this return is 6.9% under a symmetric duopsony, and 8.3% if there are 10 equally-sized firms on each labor

market. This increase in returns to mechanization is statistically significant. The confidence intervals around the change in mechanization returns are wide because the crucial coefficient, the factor-biased effect of cutting machines  $\alpha^\beta$ , is imprecisely estimated.

Machine usage is estimated to increase too with the number of firms per labor market: the usage rate increases from 4.4% of firms in monopsony to 4.9% if markets have 10 equally sized firms. This increase is, however, not significant. The reason for this is that both the Hicks-neutral and directed effects of cutting machines jointly determine whether their usage increases or falls with labor market concentration, following theorem 2, and both these coefficients are imprecisely estimated.

**Skill-biased technology** Second, consider a technology that is biased towards skilled labor, such as the mining locomotive. As is shown in Figure 6b, increasing skilled labor market competition would now decrease, rather than increase, the returns to such a technology. This is in line with theorem 1: increased competition for skilled labor decreases the markdown extracted from skilled workers, which decreases the incentive to adopt a technology that switches input usage towards these workers. The average return to the skill-biased technology drops from 53.6% to 50.6% on average when moving from a monopsonistic labor market to one with ten equally-sized employers per market, and this drop is statistically significant. The usage rate of a skill-biased technology would fall from 18% to 15% when moving from 1 to 10 firms per labor market, a relative decrease of nearly 17%. In monopsony, the usage rate of skill-biased machines, such as locomotives, is four times higher than the unskill-biased technology, the cutting machine, despite having an identical effect on Hicks-neutral productivity. Because coal firms have monopsony power over skilled labor but not over unskilled labor, they are more inclined to use technologies that shift input demand towards skilled workers. The fact that mining locomotives were introduced earlier than cutting machines, and were adopted four times faster than cutting machines, as shown in Appendix Figure A2, is consistent with this mechanism.

**Hicks-neutral technology** Finally, consider a Hicks-neutral technology, in Figure 6c. As was explained in Section 2, the markdown level does not affect the relative profit returns to such a technology. The usage rate of the Hicks-neutral technology does fall with an increasing number of firms per labor market, from 12.7% in monopsony to 11.1% with ten firms per labor market. A Hicks-neutral technology increases input demand for both inputs, so the higher the markdown, the higher the profit gain from adopting the technology. The usage rate for the Hicks-neutral technology is higher than the unskill-biased technology, but below the skill-biased technology, for the reasons mentioned earlier.

## 4.5 Discussion

### A Effect sizes

The counterfactual analysis above shows that changes in labor market structure had relatively small effects on cutting machine usage because the factor-biased and Hicks-neutral effects of these machines counteract each other. With an opposite direction of technical change, the effects of labor market structure on technology usage would be much larger. The innovation effect sizes are remarkable considering the modest degree of oligopsony power inferred from the model. The average firm sets wages at 3.5% below the marginal product of labor, and even under a pure monopsony, this markdown would be merely 14%. The current literature on oligopsony power usually finds much higher markdowns. For instance, Azar et al. (2017) find an average markdown of 17% using current U.S. data. With higher markdown levels, the effects of oligopsony power on technology usage would be even more pronounced.

### B Generalizing the results

**Adoption vs. invention** Throughout the paper, I took the invention of new technologies, and their directionality, as given, and investigated how the adoption of such technologies varied with the degree of oligopsony power. Given that invention is likely impacted by the demand for new technologies, it is conceivable that labor market power does not only affect the usage of new technologies, but also their invention. The direction of newly invented technologies could hence be endogenous to the (aggregate) degree of oligopsony power on the various input markets. This would complement the analysis in Acemoglu (2002) which assumed perfectly competitive input markets.

**Oligopsony vs. monopsonistic competition** In this paper, firms compete as oligopsonists on the labor market. The firm-level labor supply curves hence depend on their market shares. Other recent papers on labor market power, such as Lamadon et al. (2019), assume a model of monopsonistic competition. In such a world, the implications from the paper still go through: firms have an incentive to adopt a technology that increases the output elasticity of the input with the highest markdown.

### C Current-day implications

Although the application in this paper is historical, the results have several important current-day implications. The model shows that in order to understand the effects of oligopsony power on technological change today, one needs to know (i) the direction of technological change, and (ii) the relative degrees of monopsony/oligopsony power over different types of inputs. These two primitives will most likely differ between industries. Across the board, the consensus seems that automation has been mainly skill-biased throughout the last couple of decades. If firms mainly exert market power over unskilled workers, then such market power is reducing the returns to automation. Little

is known, however, about the relative degrees of oligopsony power across the skill and income distribution. Moreover, the model is not restricted to the study of labor markets and automation. Many technologies today are energy-saving. The model could potentially also be used to understand how oligopsony power on energy markets, which could exist locally by large energy-intensive industries, affects the incentives to adopt energy-saving technologies.

## 5 Conclusion

In this paper, I investigate how oligopsony power by firms affects the adoption of new production technologies. Using a theoretical model of log-linear labor supply and demand, I show that oligopsony power could either increase or decrease technological change, depending on the direction of technical change and its Hicks-neutral productivity effects. In an application, I implement an empirical version of this model to understand how oligopsony power over skilled coal miners affected the mechanization of the late 19th century Illinois coal mining industry. I find that the returns to unskill-biased technologies, such as cutting machines, increased with labor market competition, whereas the returns to skill-biased technologies, such as underground locomotives, decreased with labor market competition. In terms of technology usage, I find that oligopsony power on labor markets had a small negative effect on cutting machine adoption. If cutting machines would have been skill-biased or Hicks-neutral, rather than unskill-biased, oligopsony power would have considerably increased technology adoption. These findings show that in order to understand the consequences of oligopsony power on technological change and productivity growth, it is crucial to know the direction of technological change and the relative magnitude of oligopsony power on the various factor markets. Both of these are likely to differ between markets, industries, and even firms.

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*SSRN 4049993.*

# Appendices

## A Data

### A.1 Sources

**Mine Inspector Reports** The main data source is the biennial report of the Bureau of Labor Statistics of Illinois between 1884-1902 (Lord, 1884, 1886, 1888, 1890, 1892; Schilling, 1894, 1896; Ross, 1898, 1900, 1902).

Each report contains a list of all mines in each county, and reports the name of the mine owner, which I take to be the firm, the town nearest the mine, and a selection of variables that varies across the volumes. An overview of all 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 about 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** In 1888, I observe 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. I also obtain monthly coal price in the harbor of New York City from the Federal Reserve Economic Data: the *Wholesale Price of Bituminous Coal, George Creek, F.O.B. New York Harbor for New York, NY, Dollars per Short Ton*.<sup>29</sup>

### A.2 Data cleaning

**Employment** In every year, except for 1896, workers are divided into two categories, ‘miners’ and ‘other employees’. In 1896, the distinction is made between ‘underground workers’ and ‘above-ground workers’, which is not the same distinction: all miners were underground workers, but some underground workers were not miners (e.g. doorboys, mule drivers, etc.). The employment data are

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<sup>29</sup>Accessed through <https://fred.stlouisfed.org>

hence unobserved in 1896. 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 bar 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 reported at a yearly level, because wages were negotiated biennially after the large strikes of 1897-1898. 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** 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.

**Coal prices** 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 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.<sup>30</sup>

**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.

**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. For the individual mine operators, it is impossible to link mines over time when the operator changes. There will hence be a lot of false exits and entries. The dataset is hence not very suitable for panel-data analysis when used at the mine-level.

**Town identifiers and labor market definitions** The raw data report 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 350. The resulting labor markets lie at least 3 miles from the nearest labor 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

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<sup>30</sup><https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1800->

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 Theory

### B.1 Proof of theorem 1

**To prove:**  $\frac{\partial^2(\Pi_f)}{\partial \mu_f^h \partial \beta_f^h} \geq 0$

**Proof:** Omit subscripts  $f$  for simplicity. Denote  $\beta \equiv \beta^h$ . Assume  $\eta = 0$ , without loss of generality. I let the firm be a monopsonist on market  $L$ ,  $s^l = 1$  and consider the effect of changes in the market share  $s^h$ . The proof is analogous when keeping  $s^h = 1$  and considering variation in  $s^l$ . To simplify notation, denote  $y = 1 + s^h(\psi^h - 1)$ : I examine the sign of  $\frac{\partial^2(\Pi)}{\partial y \partial \beta^h}$ , which is the same as the sign of  $\frac{\partial^2(\Pi)}{\partial s^h \partial \beta^h}$ . Using Equations (5b)-(5a), variable profits are given by:

$$\Pi = \left[ \left( \frac{\beta}{y} \right)^{\frac{\beta}{\psi^h}} \left( \frac{\nu - \beta}{\psi^l} \right)^{\frac{\nu - \beta}{\psi^h}} \Omega \right]^{\frac{1}{1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l}}} \left( 1 - \frac{\beta}{y} - \frac{\nu - \beta}{\psi^l} \right)$$

with  $1 \leq y \leq \psi^h$ ;  $\psi^h \geq 1$ ;  $\psi^l \geq 1$ ;  $\nu \leq 1$ ;  $0 \leq \beta \leq \nu$ .

Define  $\pi \equiv \ln(\Pi)$ . I prove that  $\frac{\partial^2(\pi)}{\partial \psi^h \partial \beta^h} \geq 0$ . Variable profits are weakly positive due to the economic restrictions on the parameter values. Given that  $\Pi \geq 0$ , and that  $\pi(\cdot)$  is twice differentiable,  $\frac{\partial^2(\pi)}{\partial \beta^h \partial y} \geq 0 \Leftrightarrow \frac{\partial^2(\Pi)}{\partial y \partial \beta^h} \geq 0$ .

The effect of monopsony power on profits is equal to:

$$\frac{\partial \pi}{\partial y} = \frac{-\frac{\beta}{\psi^h y}}{1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l}} + \frac{\frac{\beta}{y^2}}{1 - \frac{\beta}{y} - \frac{\nu - \beta}{\psi^l}}$$

Taking second order derivatives w.r.t. the output elasticity of  $H$ ,  $\beta$ , gives:

$$\frac{\partial}{\partial \beta} \left( \frac{\partial \pi}{\partial y} \right) = \frac{\frac{(\nu - \psi^l)y}{\psi^h \psi^l (y)^2} \left( 1 - \frac{\beta}{y} - \frac{\nu - \beta}{\psi^l} \right)^2 + \frac{(\psi^l - \nu)\psi^h}{\psi^h \psi^l (y)^2} \left( 1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l} \right)^2}{\left( 1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l} \right)^2 \left( 1 - \frac{\beta}{y} - \frac{\nu - \beta}{\psi^l} \right)^2}$$

Working this out delivers the following expression, which is weakly positive given that  $\psi^l \geq 1$ ,  $\nu \leq 1$ , and  $y \leq \psi^h$ :

$$\frac{\partial}{\partial \beta} \left( \frac{\partial \pi}{\partial y} \right) = \frac{(\psi^l - \nu)(\psi^h - y^h) \left[ 1 - \left( \frac{\nu - \beta}{\psi^l} \right) \right]^2}{\left( 1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l} \right)^2 \left( 1 - \frac{\beta}{y} - \frac{\nu - \beta}{\psi^l} \right)^2} \geq 0 \quad \square$$

### B.2 Proof of theorem 2

Consider the effect of an input price markdown for input  $H$ ,  $\mu_f^h$ . Variable profits  $\Pi_f$  are assumed to be positive,  $\Pi_f > 0$ , otherwise the firm would not operate. Lemma 2 states that variable profits increase with markdowns, which is proven in section B.5.

**Lemma 2** *Variable profits increase with the markdown over any input:  $\frac{\Pi_f}{\mu_f^v} \geq 0 \forall v \in \{h, l\}$*

From Lemma 2, we know that the term  $B$  is positive,  $B > 0$ . The term  $C$  is assumed to be positive,  $C > 0$ : if adopting the technology would decrease variable profits, firms would never adopt it. From Theorem 1, we know that  $A > 0$  if the technology  $K$  is  $H$ -biased, and that  $A < 0$  if it is  $L$ -biased. Hence, if technology  $K$  is  $H$ -biased, then the input price markdown of  $H$  always increases its absolute effect on variable profits, because the entire right-hand side is positive. If, on the other hand, technology  $K$  is  $L$ -biased, the effect of markdowns on the absolute profit return from  $K$  is ambiguous, as term  $A$  is negative. Whether the markdown increases or decreases the absolute return to technology adoption then depends on the relative size of the term  $A$ , which is negative and the product of terms  $B$  and  $C$ , which is positive.

### B.3 Proof of theorem 3

**Proof:** Denote the variable profit margin as  $m_f \equiv \left(1 - \frac{\beta_f^h(1+\eta)}{\mu_f^h} - \frac{(\nu - \beta_f^h)(1+\eta)}{\mu_f^l}\right)$

$$\frac{\partial \Pi_f}{\partial \Omega_f} = \frac{\partial Q_f}{\partial \Omega_f} \frac{\partial \Omega_f}{\partial K_f} m_f + \frac{\partial Q_f}{\partial \beta_f} \frac{\partial \beta_f}{\partial K_f} m_f + \frac{\partial m_f}{\partial \beta_f} Q_f + \underbrace{\frac{\partial m_f}{\partial \Omega}}_{=0} Q_f$$

Under the assumptions made, the variable profit margin  $m_f$  is positive. It is easy to see that Hicks-neutral productivity increases output,  $\frac{\partial Q_f}{\partial \Omega_f} > 0$ . Hence, the higher the effect of the technology on Hicks-neutral productivity  $\frac{\partial \Omega_f}{\partial K_f}$ , the higher its effect on profits  $\frac{\partial \Pi_f}{\partial \Omega_f}$ . From Equation (6), it follows that a higher increase in profits due technology adoption also increases the effect of the markdown on this profit increase.

### B.4 Proof of lemma 1

**To prove:**  $\frac{\partial^2(\Pi_f)}{\partial \mu_f^h \partial \Omega_f} \geq 0$

**Proof:**

$$\frac{\partial \Pi}{\Omega} = \frac{Q}{\Omega} \left(1 - \frac{\beta}{\mu} - \frac{\nu - \beta}{\psi^l}\right)$$

$$\Rightarrow \frac{\partial}{\partial \mu^h} \left( \frac{\partial \Pi}{\partial \Omega} \right) = \frac{Q\beta}{\Omega \mu^2} + \frac{\partial Q}{\partial \mu} \frac{1}{\Omega} \left(1 - \frac{\beta}{x} - \frac{\nu - \beta}{\psi^l}\right)$$



Working this out gives:

$$\frac{\partial}{\partial \mu^h} \left( \frac{\partial \Pi}{\partial \Omega} \right) = \frac{Q\beta}{\Omega\mu} \left( \frac{(\psi^h - \mu)(1 - \frac{\nu - \beta}{\psi^l})}{\mu\psi^h(1 - \frac{\beta}{\psi^h} - \frac{\nu - \beta}{\psi^l})} \right) \geq 0 \quad \square$$

The numerator of this expression is weakly positive, because  $\mu \leq \psi^h$ ,  $\beta \leq \nu$ , and  $\psi^h \geq 1$ ,  $\psi^l \geq 1$ . The denominator is weakly positive (strictly positive if  $\nu < 1$  or  $\psi^h > 0$  or  $\psi^l > 0$ ), because of the same reason.

## B.5 Proof of lemma 2

**To prove:**  $\frac{\partial \Pi}{\partial \mu_f^h} \geq 0$ .

**Proof:** Taking the first derivative of variable profits with respect to the markdown  $\mu^h$  (analogously for  $\mu^l$ ) gives:

$$\begin{aligned} \frac{\partial \Pi}{\partial \mu^h} &= \frac{\partial Q}{\partial \mu^h} \left( 1 - \frac{\beta^h}{\mu^h} - \frac{\beta^l}{\mu^l} \right) + Q \left( \frac{\beta^h}{(\mu^h)^2} \right) \\ &= \frac{Q\beta^h}{(\mu^h)^2 \psi^h} \left( \psi^h - \mu^h \frac{(1 - \frac{\beta^h}{\mu^h} - \frac{\beta^l}{\mu^l})}{(1 - \frac{\beta^h}{\psi^h} - \frac{\beta^l}{\psi^l})} \right) \end{aligned}$$

This last expression is weakly positive because  $\mu^h \leq \psi^h$ . □

## B.6 Equilibrium expressions for empirical model

The equilibrium output of a mine  $f$  at time  $t$  is denoted  $Q_{ft}^*$ . It can be solved for by computing the first order conditions of the profit maximization problem, (11), and using Equations (7a), (8), and (9), which are respectively the production, coal demand, and labor supply functions. The resulting equilibrium output expression is in Equation (16a), which is the empirical analogue of Equation (5a) with Cournot competition upstream and downstream. When assuming that the firm is a monopolist and monopsonist (all market shares become one, and  $f = m = n$ ), and there are no latent differences between coal and labor markets (no  $\xi_{nt}^l = \xi_{nt}^h = \zeta_{mt} = 1$ ), Equation (16a) simplifies to Equation (5a).

$$Q_{ft}^* = \left[ \left( \frac{\beta_{ft}^h (s_{ft}^h)^{\psi_{nt}^h - 1} (1 + s_{ft}^q \eta) (\frac{1}{s_{ft}^q})^\eta \exp(\zeta_{ft})}{((\psi_{nt}^h - 1) s_{ft}^h + 1) \exp(\xi_{nt}^h)} \right)^{\frac{\beta_{ft}^h}{\psi_{nt}^h}} \left( \frac{\beta_{ft}^l (s_{ft}^l)^{\psi_{nt}^l - 1} (1 + s_{ft}^q \eta) (\frac{1}{s_{ft}^q})^\eta \exp(\zeta_{ft})}{((\psi_{nt}^l - 1) s_{ft}^l + 1) \exp(\xi_{nt}^l)} \right)^{\frac{\beta_{ft}^l}{\psi_{nt}^l}} \Omega_{ft} \right]^{\frac{1}{1 - \frac{\beta_{ft}^h (\eta + 1)}{\psi_{nt}^h} - \frac{\beta_{ft}^l (\eta + 1)}{\psi_{nt}^l}}} \quad (16a)$$

The equilibrium coal price is  $P_{mt}^* = Q_{mt}^* \eta \zeta_{mt}$ . The equilibrium quantities of both labor types are then given by Equation (16b):

$$\begin{cases} H_{ft}^* &= \left( \frac{\beta_{ft}^h Q_{ft}^* P_{mt}^* (1+s_{ft}^q \eta) (\frac{1}{s_{ft}^q})^\eta}{((\psi_{mt}^h-1)s_{ft}^h+1)\xi_{mt}^h} \right)^{\frac{1}{\psi_{mt}^h}} (S_{ft}^h)^{\frac{\psi_{mt}^h-1}{\psi_{mt}^h}} \\ L_{ft}^* &= \left( \frac{\beta_{ft}^l Q_{ft}^* P_{mt}^* (1+s_{ft}^q \eta) (\frac{1}{s_{ft}^q})^\eta}{((\psi_{nt}^l-1)s_{ft}^l+1)\xi_{nt}^l} \right)^{\frac{1}{\psi_{nt}^l}} (S_{ft}^l)^{\frac{\psi_{nt}^l-1}{\psi_{nt}^l}} \end{cases} \quad (16b)$$

Substituting the equilibrium labor quantities from (16b) into the labor supply functions in (9) gives the expression for equilibrium wages, Equation (16c).

$$\begin{cases} W_{mt}^{h*} &= \left( \frac{\beta_{ft}^h P_{ft}^* Q_{ft}^* (1+\eta)}{((\psi_{mt}^h-1)s_{ft}^h+1)s_{ft}^h} \right)^{\frac{\psi_{mt}^h-1}{\psi_{mt}^h}} (\exp(\xi_{mt}^h))^{\frac{1}{\psi_{mt}^h}} \\ W_{nt}^{l*} &= \left( \frac{\beta_{ft}^l P_{ft}^* Q_{ft}^* (1+\eta)}{((\psi_{nt}^l-1)s_{ft}^l+1)s_{ft}^l} \right)^{\frac{\psi_{nt}^l-1}{\psi_{nt}^l}} (\exp(\xi_{nt}^l))^{\frac{1}{\psi_{nt}^l}} \end{cases} \quad (16c)$$

## B.7 Generalization to increasing returns to scale

Throughout the theory model, it was assumed that returns to scale are non-increasing. The findings can be generalized, however, when there are increasing returns to scale, meaning that  $\nu > 1$ . Theorem 1 applies as long as  $\nu < \psi^l$ . So even if there are increasing returns to scale, theorem 1 holds if  $1 < \nu < \psi^l$ . If  $\nu > \psi^l$ , the results invert, but this case is not interesting in practice, because it implies negative variable profits. To see this, consider the profit margin  $(1 - \frac{\beta}{x} - \frac{\nu-\beta}{\psi^l})$ . Suppose that  $\psi^l = \psi^h = \psi$ . As soon as  $\nu > \psi^l$ , the variable profit margin becomes negative because  $x < \psi$ , and the firm should not be producing.

## C Empirical analysis

### C.1 Alternative production model

In the main text, I assumed that the scale parameter  $\nu$  was equal to 0.9 and imposed a homogeneous goods Cournot model on the coal market to estimate markups. In this section, I use an alternative model in which I estimate the scale parameter and do not impose a demand model on the coal market, but which does not allow for unobserved heterogeneity in the output elasticities across firms and time.

**Production** In Equation (17), I impose a Cobb-Douglas production function in skilled and unskilled labor with each output elasticity shifting linearly with the usage of cutting machines, which is measured by the interaction effects  $\beta^{hk}$  and  $\beta^{lk}$ .

$$q_{ft} = \beta^h h_{ft} + \beta^l l_{ft} + \beta^{hk} h_{ft} K_{ft} + \beta^{lk} l_{ft} K_{ft} + \beta^k K_{ft} + \omega_{ft} \quad (17)$$

I assume that cutting machines do not change the degree of returns to scale in both labor inputs, which implies that  $\beta^{hk} = -\beta^{lk}$ . As usual, I rely on timing assumptions on the input demand problem of the firm to identify the production function coefficients (Olley & Pakes, 1996; Akerberg et al., 2015). As in Blundell and Bond (2000), I assume that total factor productivity evolves following an AR(1) process, with shock  $\varepsilon_{ft}$ :

$$\omega_{ft} = \rho \omega_{ft-1} + \varepsilon_{ft}$$

I keep the assumptions from the baseline model that both labor types are static, variable inputs, whereas cutting machines are a dynamic, fixed input. Hence, capital choices at time  $t$  and any past time period are orthogonal to the productivity shock  $\varepsilon_{ft}$  at time  $t$ , while labor choices at time  $t - 1$  are orthogonal to productivity shocks at time  $t$ :

$$\mathbb{E} \left[ \varepsilon_{ft} \left| \begin{matrix} h_{f\theta-1} \\ l_{f\theta-1} \\ K_{f\theta} \end{matrix} \right|_{\theta=1}^t \right] = 0$$

The markup  $\mu_{ft}^q$  can be expressed as the ratio of the output elasticity of miners over the product of its revenue share and markdown:<sup>31</sup>

$$\mu_{ft}^q = \frac{\beta^h + \beta^{hk} K_{ft}}{\frac{W_{ft}^l H_{ft}}{P_{ft} Q_{ft}} \psi_{ft}^h}$$

<sup>31</sup>Alternatively, the markup could be estimated using unskilled labor as well, but unskilled labor costs are latent.

**Estimation** As in the main text, I proceed by aggregating the data set to the town-year level, by summing output and labor and by defining the capital dummy at the town-year level. The estimable production function becomes Equation (18). I again denote towns as  $f$ , assuming that each town consists of either one firm or by multiple firms that are perfectly colluding:

$$q_{jt} = \beta^h h_{jt} + \beta^l l_{jt} + \beta^{hk} (h_{jt} - l_{jt}) K_{jt} + \beta^k K_{jt} + \omega_{jt} \quad (18)$$

Similarly to the main text, I estimate the integrated model using a block-bootstrapping procedure that resamples within towns, using 250 iterations.

**Results** The results of this alternative production model are in Table A5. Coal cutting machines are still unskill-biased: the output elasticity of miners is estimated to fall by 0.353 points when adopting a cutting machine, coming from 0.687. In the baseline model, this was a smaller drop of 0.143 points, down from 0.727. The scale parameter,  $\nu$  is equal to be 0.768, whereas it was assumed to be 0.9 in the main text. Thus, the assumption of decreasing returns to scale is confirmed. The average markup ratio  $\mu^q$  is estimated at 1.126, which implies that the coal price is 12.6% above marginal costs. This estimate does not impose any model of competition on the coal market. The homogeneous goods Cournot model in the baseline model delivered a very similar average markup ratio of 1.148.

## C.2 Cost dynamics

There are multiple sources of cost dynamics that would invalidate the productivity transition equation. If it becomes increasingly costly to operate deeper mines, for instance, productivity would depend on past *cumulative* output, as Aguirregabiria and Luengo (2017) find for copper mining. Such dependence could also exist due to learning by doing, as in Benkard (2000), but productivity would then increase with cumulative output, rather than fall. I test this by regressing the logarithms of the productivity residual  $\omega_{ft}$  on log cumulative output. The estimated coefficients are in Table A2. If not including mine fixed effects, lagged cumulative output is associated with higher total factor productivity. This could, however, be due to selection: more productive mines are more likely to have extracted and sold more coal. Once I include mine fixed effects to track how productivity co-varies with cumulative output within each mine over time, the coefficient on lagged cumulative output becomes small and insignificant.

## C.3 Inverse miner supply elasticity: correlations

Appendix Table A3 regresses the log town-level inverse miner supply elasticity  $\psi_{mt}^h$  on a number of town and county characteristics. The town-level inverse supply elasticity is equal to the profit-maximizing wage markdown of a monopolist. Labor supply is more inelastic (implying higher wage markdowns) if the share of total coal employment over the town population is higher: in towns

that are coal mining towns with few outside work opportunities, miner supply is more inelastic. A second regressor is the log of the ratio of the total farmed area in a county divided by the county's surface. Miner supply is more inelastic in areas with less farming (for instance, because of rugged geography), presumably because there are fewer outside work opportunities to switch to. Third, the population share of African Americans in the county does not correlate significantly with the miner supply elasticity. Fourth, towns with a higher share of firms connected to the railroad network have slightly more inelastic miner supply. This is in line with historical evidence that railroads were not used to transport workers, and confirms the assumption of isolated mining towns.<sup>32</sup> Finally, the average wage in manufacturing industries in the same county does not correlate significantly with the miner supply elasticity, which suggests that the outside option was mainly to work in agriculture, rather than in manufacturing industries, which were in any case scarce in rural Illinois.

## **C.4 Robustness checks**

### **A Alternative values for the scale returns parameter**

In the baseline analysis, I calibrated the degree of returns to scale  $\nu$  to be 0.9, and motivated why decreasing returns to scale is an appropriate assumption in the historical coal mining industry setting. In this robustness check, I re-calibrate the returns parameter to be, alternatively, 0.85 and 0.95. The results are in Figure A6 and Figure A6 for  $\nu = 0.85$  and  $\nu = 0.95$ , respectively. The direction of all counterfactual effects is the same as in the baseline analysis with  $\nu = 0.90$ .

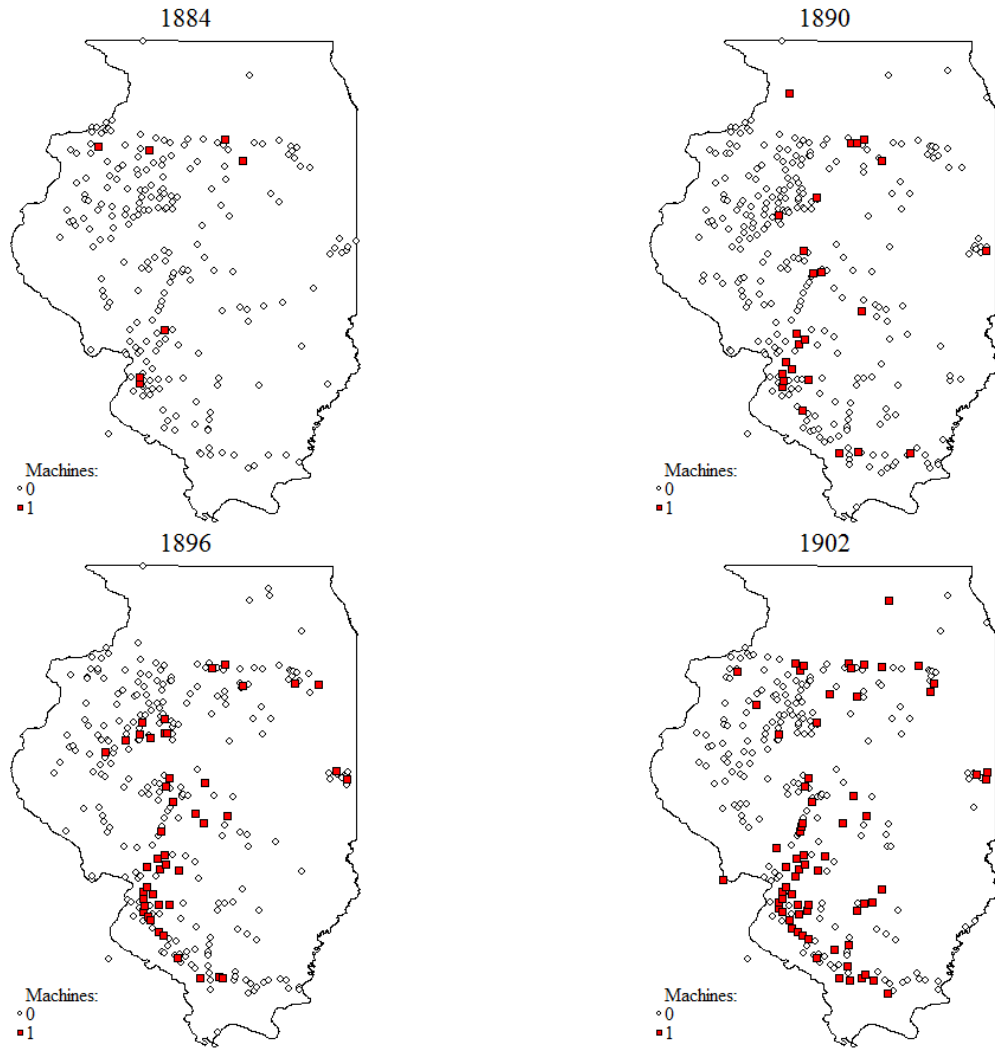
### **B Wage screens**

The usage of wage screens cause measurement error in the data, because miners were not remunerated on the total (reported) output at the mine, but based on a lower coal output that consisted only of larger pieces of coal. In 1898, I observe which firms paid screened wages and which did not. As a robustness check, I re-run the analysis while excluding counties for which at least one firm paid a screened wage in 1898, which was the case for 13.9% of observations. The estimated counterfactuals for this selected sample of firms are in Figure A8, and again look very similar to those in the baseline analysis containing both firms that pay screened wages and those that do not.

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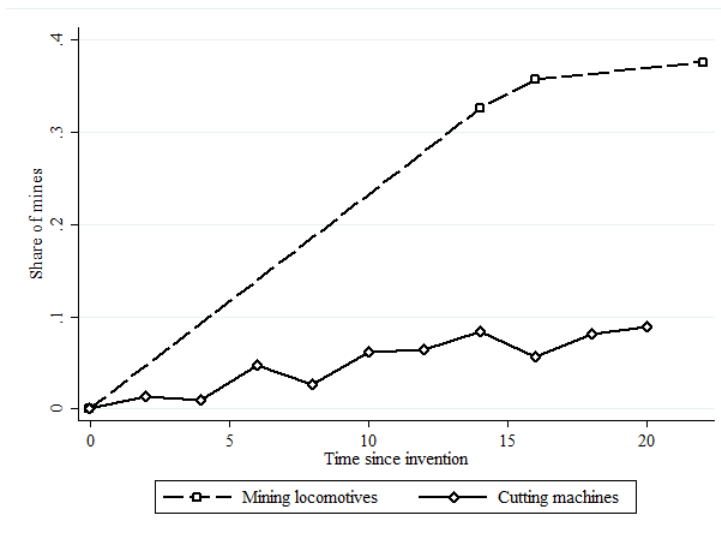
<sup>32</sup>If mining towns would not be isolated due to workers commuting by train, being connected to the railroad network should result in more elastic labor supply.

**Figure A1: Geographical spread of cutting machines**

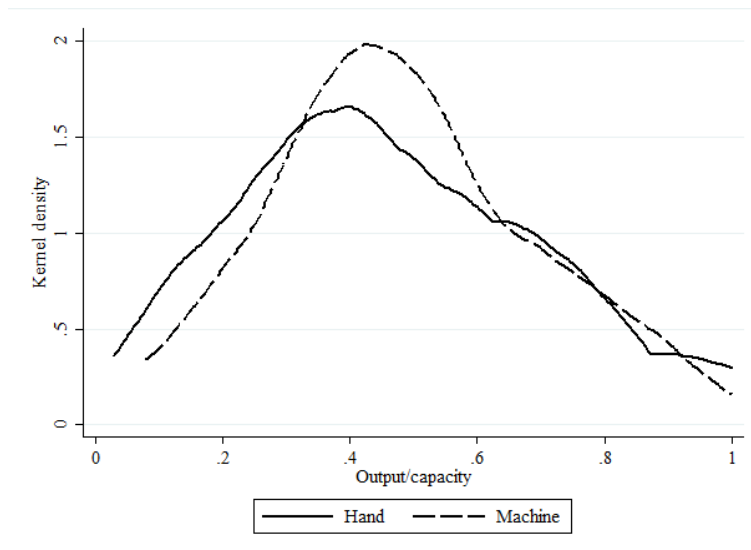


**Notes:**The dots represent mining towns, each of which can contain multiple mines. Villages with squares contain at least one machine mine.

**Figure A2: Cutting machine vs. locomotive adoption**



**Figure A3: Capacity utilization**



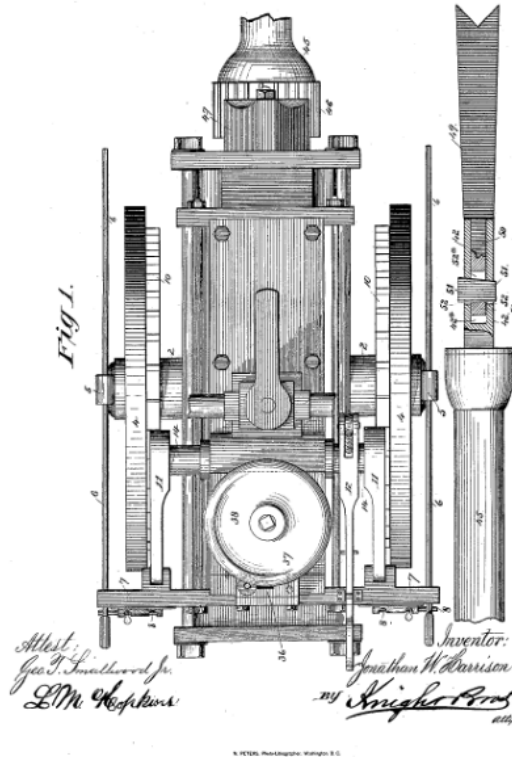
**Notes:** This graph plots the distribution of capacity utilization, defined as annual mine output over annual mine capacity, across mines in 1898. A distinction is made between hand mines, which did not use cutting machines, and machine mines, which did.



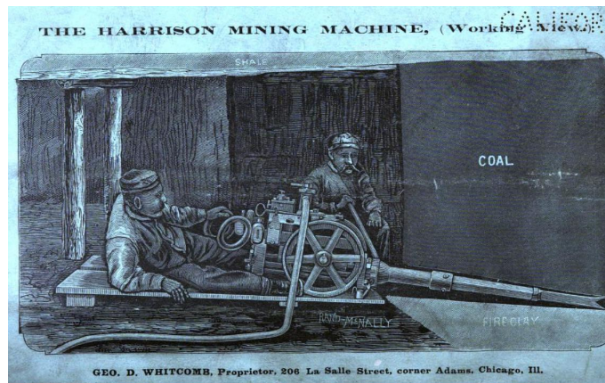
# Figure A4: Harrison Cutting Machine

## (a) Patent

(No Model.) 4 Sheets—Sheet 1.  
J. W. HARRISON.  
COAL MINING MACHINE.  
No. 262,225. Patented Aug. 8, 1882.



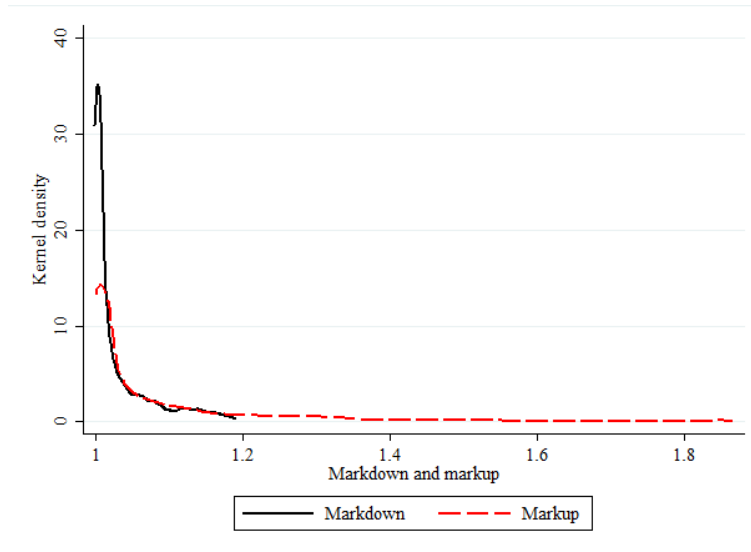
## (b) Illustration



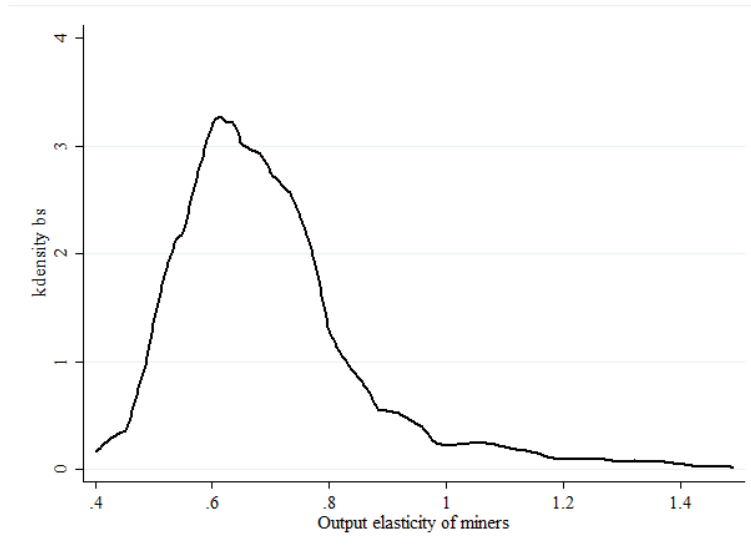
**Notes:** U.S.A. patent of the 1882 Improved Harrison Coal Cutting Machine (Whitcomb, 1882). This was the most frequently used coal cutting machine in the data set.

**Figure A5: Distributions of latent variables**

**(a) Markdowns and markups**



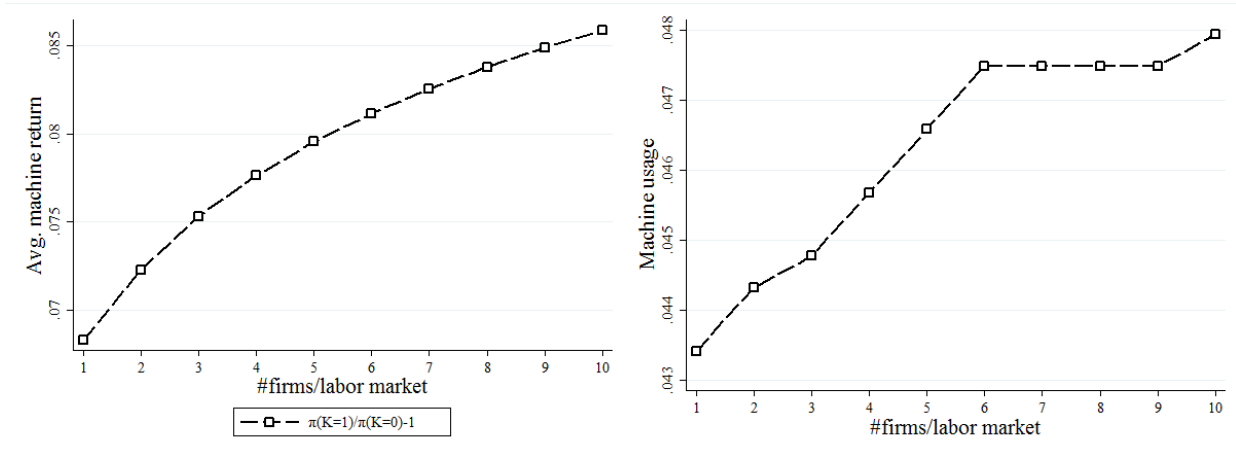
**(b) Skilled labor output elasticity**



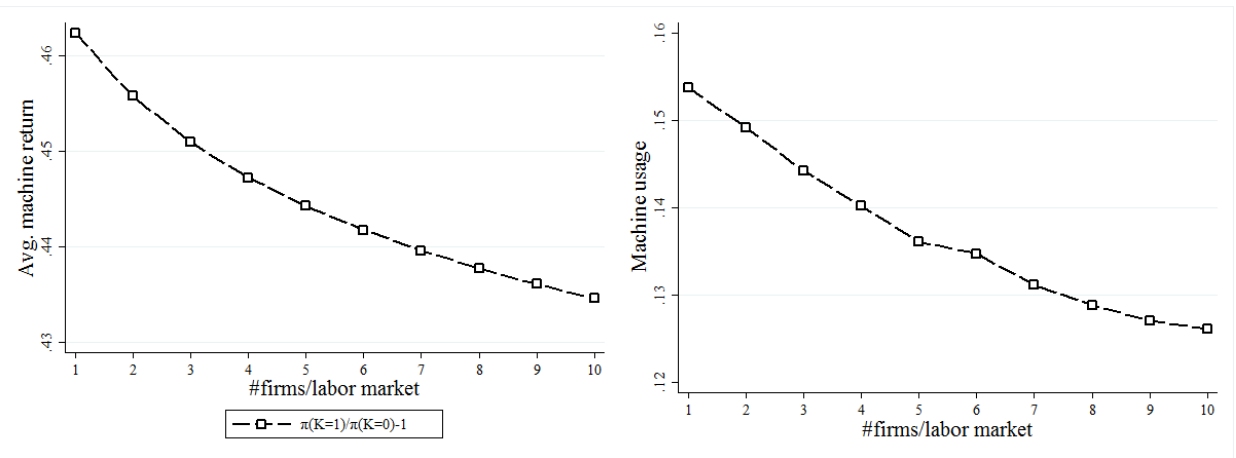
**Notes:** Distribution of the inverse miner supply elasticity across mines between 1884-1894. Each distribution censored at its 5th and 95th percentile.

**Figure A6: Counterfactuals with  $\nu = 0.85$**

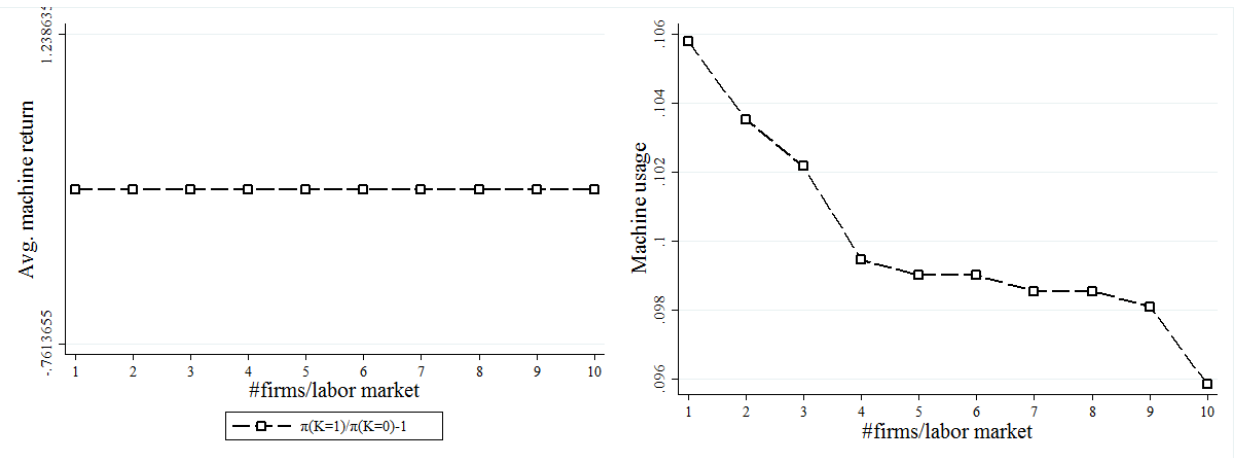
**(a) Unskill-biased technology**



**(b) Skill-biased technology**

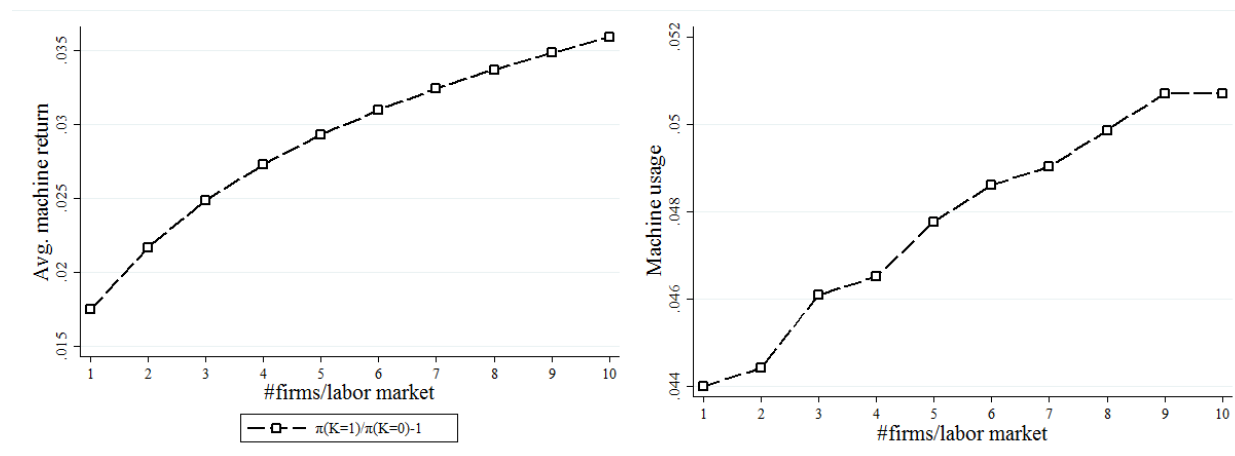


**(c) Hicks-neutral technology**

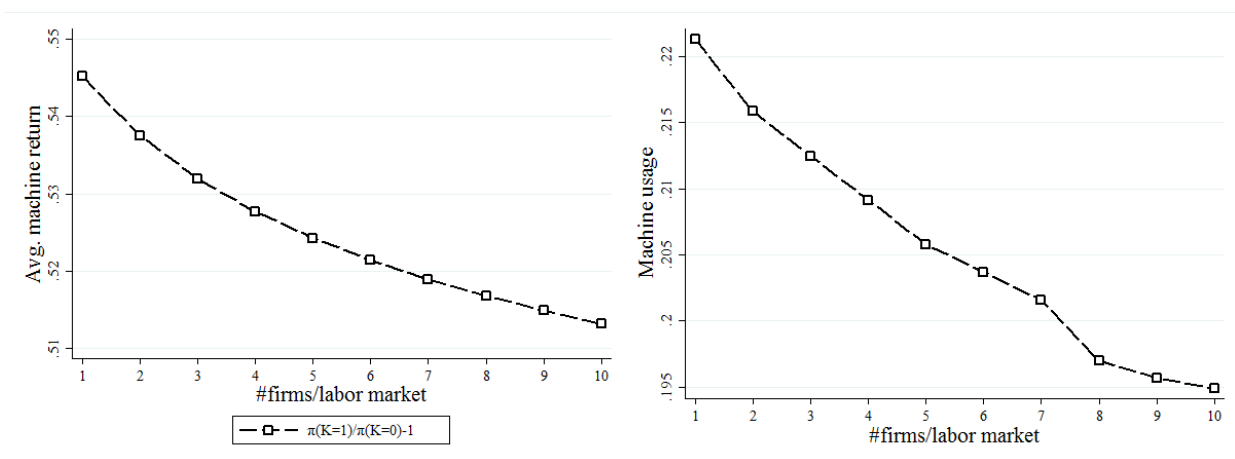


**Figure A7: Counterfactuals with  $\nu = 0.95$**

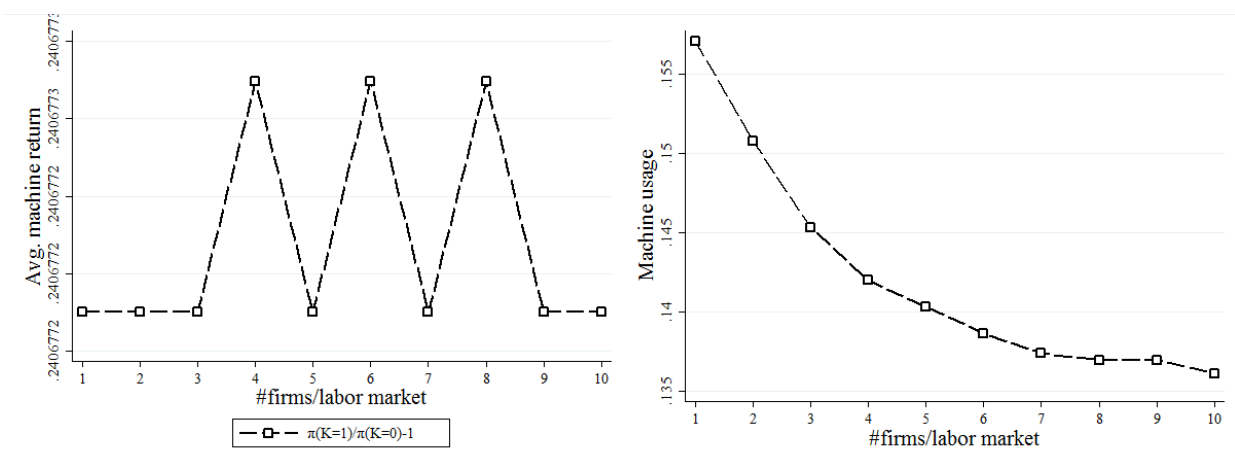
**(a) Unskill-biased technology**



**(b) Skill-biased technology**

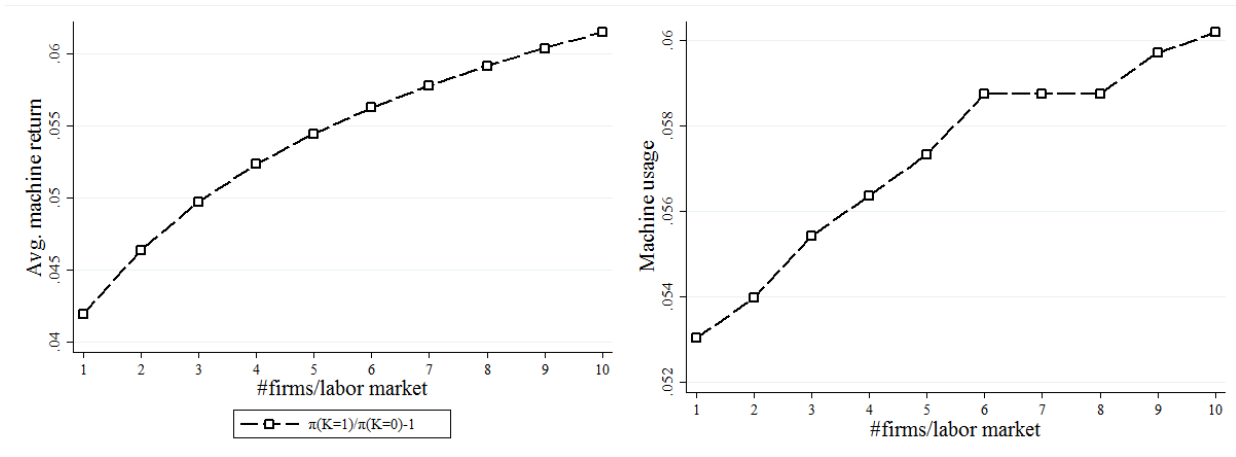


**(c) Hicks-neutral technology**

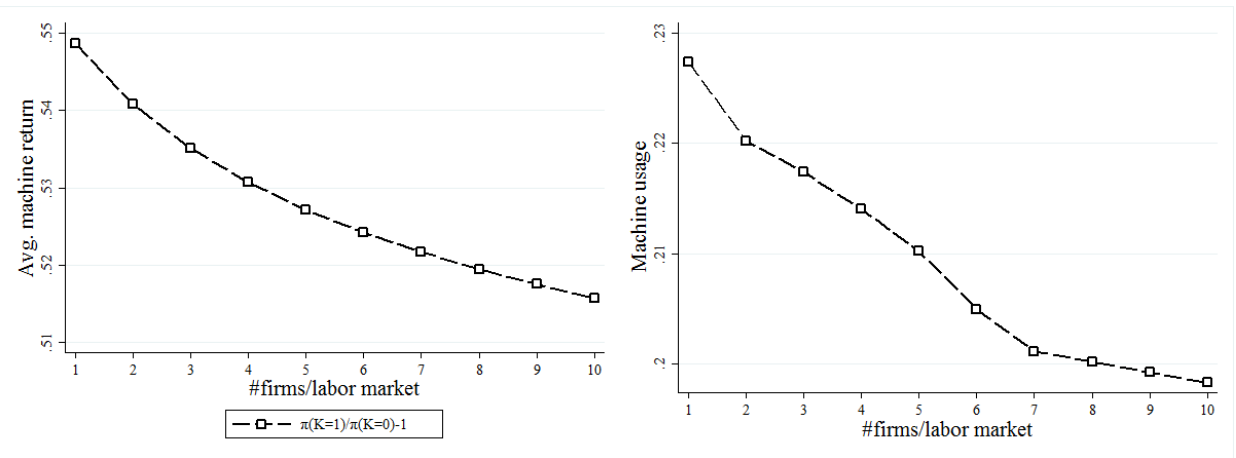


**Figure A8: Counterfactuals accounting for wage screens**

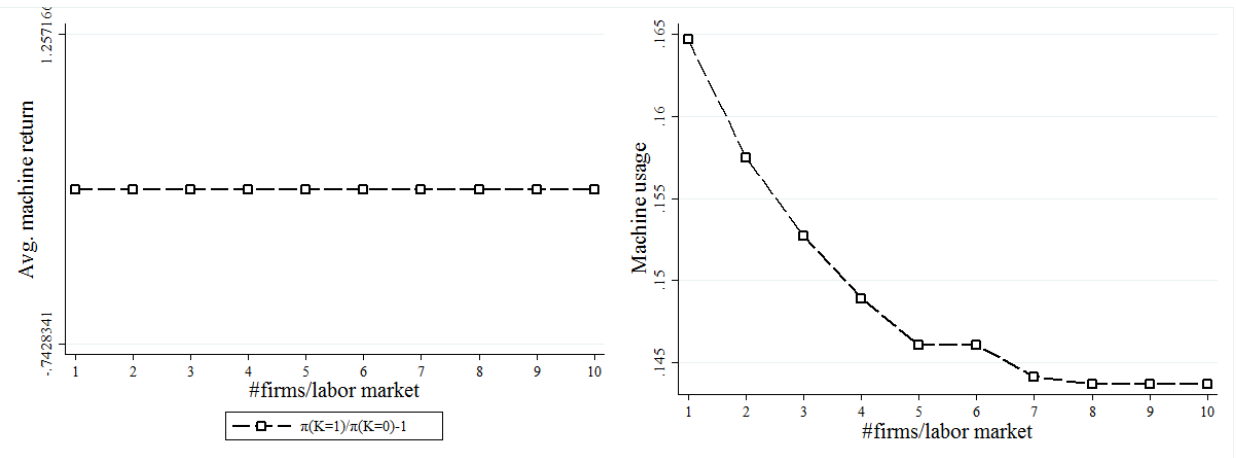
**(a) Unskill-biased technology**



**(b) Skill-biased technology**



**(c) Hicks-neutral technology**



**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))			
	Estimate	SE	Estimate	SE
log(Cum. output)	0.124	0.003	-0.011	0.017
Mine FE	No		Yes	
Observations	3766		3766	
R-squared	.326		.810	

**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: Markdown correlations**

	log(Markdown)	
	Estimate	SE
log(Coal employment share)	0.022	0.004
log(Farmland/Total Area)	-0.136	0.066
log(African Americans / Population)	-0.001	0.004
Share of firms connected to railroad	0.029	0.010
log(Manufacturing wage)	0.021	0.022
Observations	876	
R-squared	0.342	

**Notes:** Regression of log miner wage markdown on mine and county characteristics. Standard errors clustered at the county level.



**Table A4: Coal demand and production estimates: all coefficients**

<i>(a) Coal demand (county-level)</i>			
	Est.	log(Coal price) CI05	CI95
log(Quantity)	-0.465	-0.671	-0.362
1(Railroad connection)	0.353	0.242	0.641
1(Railroad crossing)	0.689	0.462	1.141
log(Dist. to St. Louis)	-0.069	-0.194	0.039
log(Dist. to Chicago)	-0.044	-0.167	0.042
Observations		453	
F-stat 1st stage		51.3	
R-squared		.191	
<i>(b) Output elasticity transition</i>			
	Est.	log(Output elasticity of skilled miners) CI05	CI95
1(Cutting machine)	-0.143	-0.186	0.005
log(Materials)	0.016	-0.020	0.006
Year	-0.013	-11.052	39.121
Constant	25.084	-0.036	0.030
Observations		1133	
R-squared		.007	
<i>(c) Hicks-neutral productivity transition</i>			
	Est.	log(Hicks-neutral productivity) CI05	CI95
1(Cutting machine)	0.242	-0.112	0.396
log(Materials)	0.135	-0.114	0.151
Year	-0.013		
Constant	-44.104	-0.008	0.135
Year		-0.142	0.082
Observations		1050	
R-squared		.204	

**Notes:**

**Table A5: Alternative production model**

<i>(a) Production function</i>			
log(Skilled labor)	0.687	0.557	1.239
log(Skilled labor/Unskilled labor)*1(Cutting machine)	-0.353	-0.684	-0.244
log(Unskilled labor)	0.081	-0.134	0.430
1(Cutting machine)	0.551	0.424	0.989
Constant	1.950	-3.187	7.283
Observations			
R-squared			
<i>(b) Markup and returns to scale</i>			
Returns to scale	0.768	0.551	1.438
Markup	1.126	0.921	2.052

**Notes:** Alternative production function that estimates markup and degrees to scale, as specified in Appendix C.1.  
Standard errors are block-bootstrapped with 250 iterations.

**Table A6: All variables per year**

Year	1884	'86	'88	'90	'92	'94	'96	'98	'00	'02
<b>Output quantities</b>										
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
<b>Input quantities</b>										
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
<b>Output price</b>										
Price/ton at mine	X	X	X	X	X			X	X	X
Price/ton at mine, lump						X	X	X		
<b>Input prices</b>										
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			
<b>Technicals</b>										
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 seam 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		
<b>Cutting machine usage</b>										
Cutting machine dummy					X	X	X	X		
# Cutting machines	X	X	X	X						
# Tons cut by machines									X	X
# Cutting machines, by type			X							