Scale-Biased Technical Change and Inequality*

Hugo Reichardt†

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Abstract

Scale bias is the extent to which technical change increases the productivity of large relative to small firms. I show that this dimension of technical change is important for inequality. To illustrate the mechanism, I develop a tractable framework where people choose to work for wages or earn profits as entrepreneurs and where entrepreneurs choose from a set of available production technologies that differ in their fixed and marginal cost. Large-scale-biased technical change lowers entrepreneurship rates and increases top income inequality. Small-scale-biased technical change does the opposite. I show the empirical relevance of scale bias by identifying the causal effects of adoption of two general purpose technologies that vary in scale bias, but are otherwise similar: steam engines (large-scale-biased) and electric motors (small-scale-biased). Using newly collected data from the United States and the Netherlands and a range of identification strategies, I show that these two technologies had opposite effects on firm sizes and inequality. Steam engines increased firm sizes and inequality, while electric motors decreased both. Consistent with scale bias (rather than skill bias), I find that adopting entrepreneurs were the main drivers of inequality increases after steam engine adoption.

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†Department of Economics, London School of Economics. h.a.reichardt@lse.ac.uk

1 Introduction

Income and wealth inequality has significantly increased in many countries in recent decades. Between 1980 and 2014, top-decile incomes in the United States rose more than twice as fast as below-median incomes (Piketty et al., 2018). Skill-biased technical change is a common explanation for the increase in inequality: if new technologies more strongly complement high-skilled labor—or tend to automate low-skilled jobs—, this can increase wage inequality (Katz and Murphy, 1992; Krusell et al., 2000; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2022). But wages are not the only source of income. Business income is particularly important for the top of the income distribution. How does technical change affect the concentration of this income?

I propose *scale* bias in technical change—the extent to which technical change affects the relative productivity across firms of different sizes—as an important determinant of income inequality, especially because it affects the concentration of business income. Large-scale-biased technical change skews productive resources and profits towards larger firms. Because the ownership of any given firm tends to be concentrated, the redistribution of profits across firms implies a redistribution of income across households.

First, to formalize the theory of scale-biased technical change and inequality, I develop a simple and tractable model where households that are heterogeneous in productivity can choose to either work for wages or be an entrepreneur. Entrepreneurs have access to a set of available technologies—defined by a marginal and a fixed cost—and adopt the one that maximizes profits. I show that technical change is large-scale-biased if it increases fixed costs relative to previously adopted technologies. If technical change is large-scale-biased, it lowers entrepreneurship rates and leads to larger firms on average. With fewer and larger firms, top entrepreneurs are capturing a larger share of the profits which increases top income inequality. If technical change is small-scale-biased, it has the opposite effects.

Second, to empirically test the theory, I estimate and compare the causal effects of the adoption of steam engines and electric motors. These two GPTs provide an appropriate and useful comparison because i) their adoption was sufficiently widespread and transformative to have a meaningful impact on the overall economy ii) they were similar in their capability and purpose—converting energy into rotary motion in manufacturing—, and iii) their cost structure differed strongly so that they induced technical change with different scale bias. Steam engines became the dominant power source in manufacturing in the second half of the 19th century. Electric motors began to be widely used around 1900, but steam engines continued to play a significant role as a power source until approximately 1950.

Steam engines entailed much higher fixed costs of purchase and operation than electric motors. The annualized cost, exclusive of fuel, of a 50 horsepower (hp) steam engine was equal to the *yearly* wage of around 3 to 4 unskilled workers.[1] For an electric motor with the same capacity, these costs were only around 2 percent of a yearly wage, two hundred times lower than for steam engines.[2] Also, for reasons of technological efficiency, steam engines came in much larger sizes than electric motors.[3] As a result, the adoption rates of the two technologies across the firm size distribution were different. Large establishments were more likely to adopt steam engines than small establishments (see also Atack et al., 2008). I show that, in contrast, electric motors were adopted uniformly across the firm size distribution.

To measure the effect of scale-biased technical change, I construct a rich data set on steam engine and electric motor adoption, firm sizes, and inequality through digitization of various archival sources from the Netherlands and the United States. For the United States, I draw on the Census of Manufactures that provides information such as the number of establishments, employment, value added, and power adoption by state and industry. I digitize and compile these data for each decade year between 1850 and 1940 and 1947. The industry classification in the Census of Manufactures was highly granular, yielding over 50 thousand state-industry observations. Using these data, I investigate the role of steam engines and electric motors in shaping the firm size distribution in manufacturing in the United States.

The first main empirical result is that, consistent with the theory, steam engines increased establishment size, while electric motors decreased it. To identify these effects, I use variation in natural resources across the United States that affected the costs of adoption. Specifically, I use historical coal resources and hydropower potential as instruments for steam engine and electric motor adoption, respectively.[4] I estimate how this natural variation affected within-industry firm size differences over time. I find that high-coal access states experienced a growth in establishment sizes relative to 1850, when steam engines started to be adopted. In constrast, after the introduction of electric motors around 1900, high-hydropower states experienced a decrease in establishment sizes. I estimate the effect of a 1% increase in steam engine horsepower to be a 1.1% increase in firm size. For electric motors, I estimate this elasticity to be -0.4.

[1] Computations based on the United States in 1874. The total annualized cost was \$1404 (see Table E.3 in Appendix E) and the *yearly* wage of an unskilled worker was around \$400 Abbott (1905).

[2] Computations based on the United Kingdom, around 1925. Total annualized cost of an electric motor of 50 hp in 1925 was £2.46 (see Table E.3 in Appendix E) and the weekly wage was around £2.00 (Bank of England, 2017).

[3] In the United States in 1910, the average steam engine had a capacity of 93.4 horsepower, more than 10 times that of the average electric motor (8.5 hp).

[4] Data to construct the instruments are from the Coal Resources Data System (coal resources) and Young (1964) (hydropower potential).

I next study how the technologies affected income and wealth inequality. While the Census of Manufactures provides high-quality data on American manufacturing, granular data on income or wealth in the United States during steam engine and electric motor adoption is not available. To study the two technologies' effects on inequality, I therefore turn to the Netherlands, for which I collect unique data on income and wealth inequality over the course of industrialization. The dataset I build includes micro-level information on names, demographics, occupation, and, importantly, wealth of each decedent between 1878 and 1927 in five major provinces in the Netherlands, covering over a million decedents and more than half of the national population. It is, to the best of my knowledge, the largest dataset on inequality in any country during the period of steam engine and electric motor adoption.

Using the Dutch dataset, I verify the second main prediction of the theory: that large-scale-biased (small-scale-biased) technical change increases (decreases) inequality. Using municipality-by-industry level data from the Dutch Census of Companies in 1930, I compute the share of employees that work in establishments with steam engines, with electric motors, and without power for each municipality. I then show how wealth inequality evolved in municipalities that saw strong steam-engine adoption, controlling for municipality fixed effects. I find that municipalities that adopted engines became significantly more unequal over time, especially from around 1910 onward. In contrast, municipalities with high electric motor adoption saw a slight decrease in inequality after 1900. Furthermore, I use an industrial census from 1816—long before industrialization—to create an industry-based measure of "exposure" to steam engines and electric motors. Municipalities whose industrial composition in 1816 exposed them to steam engines showed a strong increase in inequality between 1880 and 1930, while those exposed to electric motors experienced a slight decrease in wealth inequality. The effects on inequality are primarily driven by the very top of the distribution, while the rest of the distribution was not much affected.

The third prediction of scale-biased technical change is that its effects on top inequality manifests themselves through entrepreneurs that adopt the technology. To test this prediction, I zoom into the major industrializing city of Enschede, in the east of the Netherlands. The pre-existing textile industry made this city particularly exposed to the introduction of the steam engine. Even though wealth inequality decreased in most areas, it increased sharply in Enschede. I find that the rise in top inequality was driven by the textile entrepreneurs that adopted the technology. I do not find any meaningful increase in inequality after excluding the textile entrepreneurs and their spouses from the sample. This finding shows that the rise in inequality was driven by entrepreneurial income—not wages—so that it can not be explained by skill-biased technical change. The proposed theory of *scale*-biased technical change does offer an explanation: the large-scale-biased technical change in textile manufacturing meant that firm concentration increased strongly, which in turn concentrated business income in the hands of a small set of entrepreneurs.

Related literature. First and foremost, this paper contributes to our understanding of the effect of technical change on income and wealth inequality. Scale-biased technical change offers a view on the distributional effects of technology that is complementary to the existing theories of skill bias (e.g., Katz and Murphy, 1992; Acemoglu and Autor, 2011). The case of the electric motor illustrates that the two theories can have opposite predictions. Goldin and Katz (1998) argue that the electric motor increased the relative demand for skilled workers, thereby exerting upward pressure on (wage) inequality.[5] I claim that electric motors reduced scale bias and pushed inequality between entrepreneurs and workers *down*. During the first half of the twentieth century, the time of electric motor adoption, almost every industrialized country witnessed a large decline in inequality (Lindert and Williamson, 2016, p. 194). The empirical findings in this paper suggest that electric motors contributed to this trend.

Another large literature relates increased firm concentration to technical change, especially a move toward high fixed cost technologies (e.g. Autor et al., 2020; Hsieh and Rossi-Hansberg, 2023; Kwon et al., 2023). Intangible inputs such as software have been posited as an example of this (Brynjolfsson et al., 2008; Lashkari et al., 2023; De Ridder, 2023). So far, it has been hard to establish credible causal evidence of the effect of technical change on the firm size distribution. Furthermore, because most modern technologies vary on many dimensions other than their cost structure, it is difficult to isolate the role of specific characteristics in driving their concentrating effect. A contribution of this paper is that it studies two technologies that were close to identical except for their cost structure, allowing to single out the role of fixed costs in shaping the firm size distribution. The theory of scale-biased technical change also provides an additional motive to study business patterns: their implications for economic inequality.[6]

This paper also relates to studies highlighting the role of entrepreneurship in income and wealth inequality (Quadrini, 2000; Cagetti and De Nardi, 2006; Buera and Shin, 2013). Accounting for entrepreneurship in models of wealth accumulation allows to match the high concentration of wealth observed in the data. In contrast to previous work, I focus on the role of the production technology in shaping inequality. For this purpose, I provide a simple and tractable framework in which entrepreneurs face a technology adoption decision. The tractability of the model allows to characterize in closed-form how entrepreneurship and the income distribution depend on the set of technologies available in the economy. Furthermore, I provide empirical evidence on the effect of

[5] Goldin and Katz (1998) argue, however, that an increase in the supply of high-school graduates kept the skill premium in check.

[6] See De Loecker et al. (2022) for other reasons to study the firm size distribution.

technology on inequality through entrepreneurship.

Lastly, this paper also speaks to the patterns of inequality during industrialization. Kuznets (1955) hypothesized that inequality rises in the early stage of industrialization and later decreases, because of a shift away from the agricultural sector to the more productive, but potentially more unequal, manufacturing sector. Interestingly, he explicitly related inequality to scale: "inequalities [in manufacturing] might be assumed to be far wider than those for the agricultural population which was organized in relatively small individual enterprise." This paper provides a theoretical foundation and empirical evidence for that argument.

The remainder of the paper is organized as follows. Section 2 lays out the theory of scale-biased technical change and inequality formally. Section 3 describes the historical background of, and differing scale bias between, steam engines and electric motors. In Section 4, I discuss how the data is constructed. The methodology and results on the effect of technology on scale and inequality are shown in Sections 5 and 6, respectively. Section 7 shows evidence that inequality between workers and entrepreneurs was the main channel through which steam engines increased inequality. Section 8 concludes.

2 Model

There is a continuum of households with unit measure that differ in their entrepreneurial productivity ψ. I assume that ψ has a probability density function $f(\cdot)$ with semi-infinite support on $\mathbb{R}^+$, i.e., $\{\psi \mid f(\psi) > 0\} = [\psi_m, \infty)$ for some $\psi_m \geq 0$.[7] In a first stage, before observing their entrepreneurial productivity ψ, each household decides whether to be a worker or to be an entrepreneur (Lucas, 1978). A household knows that by choosing entrepreneurship, it is foregoing the wage w.

Once this opportunity cost is sunk, in the second stage, entrepreneurs observe their productivity ψ and choose whether to enter business or not.

An entrant chooses, in a third stage, chooses from an exogenous set of available production technologies $T \equiv \{t_1, .., t_J\}$. Each technology $t_j \in T$ is a tuple $\{\alpha_j, \kappa_j\}$ where α_j is a parameter that affects marginal labor cost and $\kappa_j > 0$ is its fixed cost in terms of the final good.[8] I assume that T does not contain trivially dominated technologies. That is, if $t_j, t_k \in T$ and $\alpha_j < \alpha_k$, then $\kappa_j > \kappa_k$.[9] Technologies are arranged in order of increasing fixed costs ($\kappa_1 < .. < \kappa_J$).

Finally, in stage four, after adopting technology j, entrepreneurs maximize profits given their productivity ψ, yielding $\pi_j(\psi)$. Figure 1 visualizes the decision process and pay-offs. I characterize optimal behavior and derive equilibrium conditions by backward induction.

Stage 4: Profit maximization

Each entrepreneur produces a differentiated good. Given technology t_j and entrepreneurial productivity ψ, their production function is

$$y_j(\psi) = \frac{\psi l}{\alpha_j} \tag{1}$$

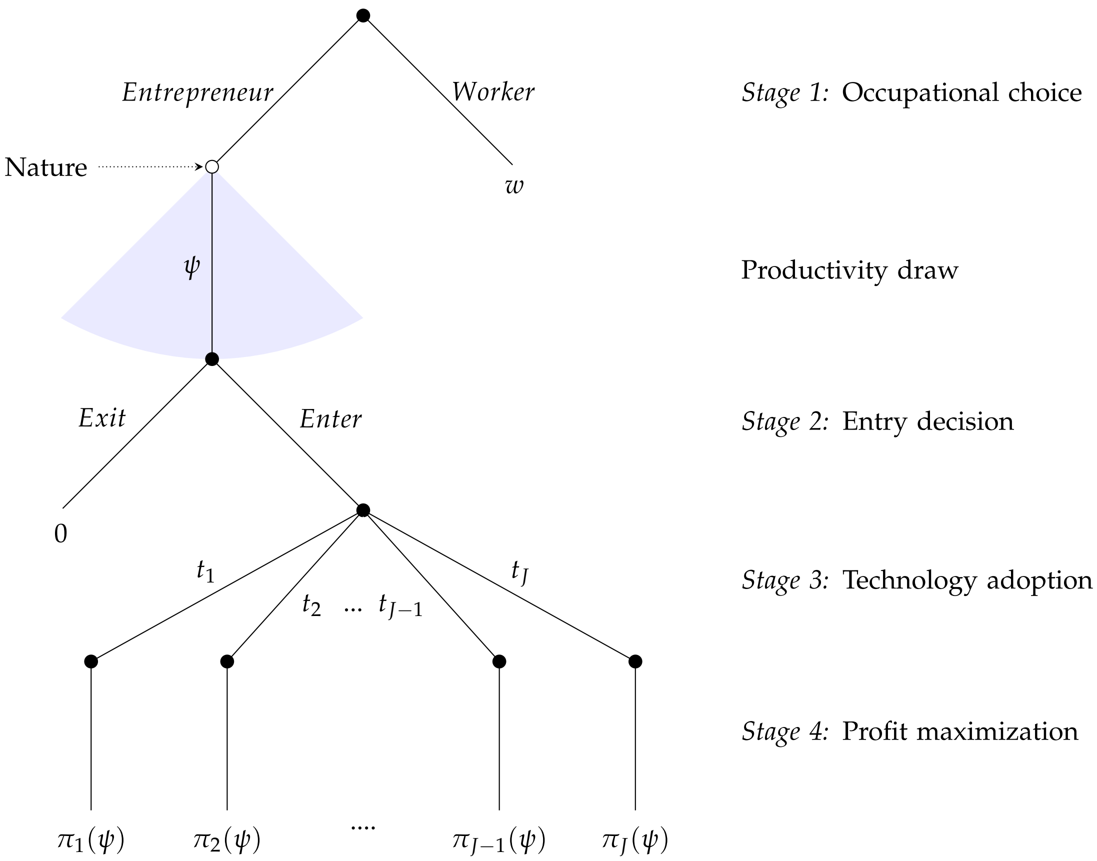
where l is labor and α_j is the marginal labor cost for technology t_j. The total cost to produce y given t_j and ψ is $C_j(y \mid \psi) = \frac{\alpha_j w}{\psi} y + \kappa_j$ where κ_j is the fixed cost in terms of the final good. Each household's utility is characterized by a constant elasticity of substitution σ over a continuum of these differentiated goods indexed by ω (Dixit and

[7]To derive a closed-form solution of the equilibrium, I will later assume that $\psi \sim \text{Pareto}(\psi_m, \xi)$.

[8]This can be seen as a generalization of the binary technology choice in (Yeaple, 2005; Bustos, 2011), who are concerned with the connection between trade and technology adoption.

[9]This assumption does not affect any equilibrium outcome as such trivially dominated technologies would not be adopted.

FIGURE 1: Pay-off tree



Stiglitz, 1977; Melitz, 2003):

$$U \equiv Y = \left[\int_{\omega \in \Omega} y(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

The demand for good ω is thus $y(\omega) = Y \left(\frac{p(\omega)}{P}\right)^{-\sigma}$ where $p(\omega)$ is the price of good ω and $P \equiv \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$. Hereafter, I use the normalization that $P = 1$. Profit maximization conditional on technology and productivity then yields the pricing rule

$$p_j(\psi) = \frac{\alpha_j w}{\rho \psi} \tag{3}$$

where $\rho \equiv \frac{\sigma-1}{\sigma}$. This pricing rule is standard (e.g., Melitz, 2003, eq. (3)), except that the production technology may vary across producers. In equilibrium, this yields (conditional) profits $\pi_j(\psi)$ equal to

$$\pi_j(\psi) = \frac{Y}{\sigma} \left(\frac{\rho \psi}{\alpha_j w} \right)^{\sigma-1} - \kappa_j. \tag{4}$$

Stage 3: Technology adoption

An entrepreneur that chooses to produce can use any of the J available technologies in the set T. She therefore adopts the technology j that yields largest profits, so the profits of an entrepreneur with productivity ψ are:

$$\pi(\psi) = \max_{j \in \{1,2,..,J\}} \{\pi_j(\psi)\}. \tag{5}$$

An important implication of this profit function is that more productive entrepreneurs choose higher fixed costs technologies. To see this, note that for an entrepreneur with productivity ψ, the difference in profits between technologies t_j and t_k are:

$$\Delta\pi_{jk}(\psi) \equiv \pi_j(\psi) - \pi_k(\psi) = \frac{Y}{\sigma}\left(\frac{\rho\psi}{w}\right)^{\sigma-1}\left(\alpha_j^{1-\sigma} - \alpha_k^{1-\sigma}\right) - (\kappa_j - \kappa_k). \tag{6}$$

Recall that since $j > k$, $\kappa_j > \kappa_k$ and $\alpha_j < \alpha_k$. It then follows from the expression that $\Delta\pi_{jk}(\psi)$ is strictly increasing in ψ. That is, the more productive an entrepreneur is, the larger their profits under technology j (higher fixed, lower marginal cost) relative to technology k (lower fixed, higher marginal cost). A corollary of this result is that prices are strictly decreasing in ψ (see equation (3)), such that entrepreneurs with higher productivity face more demand and, hence, produce more.

Stage 2: Entry decision

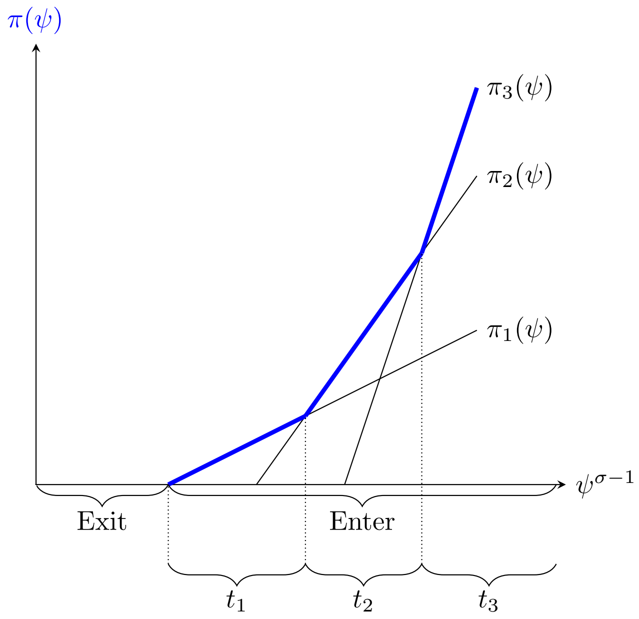
After observing their entrepreneurial productivity ψ, each entrepreneur decides whether or not to exit or enter. Since the opportunity cost is zero (as the opportunity cost of not working is already sunk), they decide to enter if and only if $\pi(\psi) \geq 0$.

There is a unique $\bar{\psi} > 0$ such that an entrepreneur enters if and only if $\psi \geq \bar{\psi}$. To see this, note that equation (4) implies that $\pi_j(\psi)$ is strictly increasing in ψ for each $j \in \{1, 2, .., J\}$. Therefore, $\pi(\psi)$ is the maximum of J strictly increasing functions and is thus also strictly increasing. Finally, $\pi(0) = -\kappa_1 < 0$ and $\pi(\psi) \to \infty$ as $\psi \to \infty$. It thus follows that there is a unique $\bar{\psi}$ implicitly defined by

$$\pi(\bar{\psi}) = 0. \tag{7}$$

To solve for this threshold, note that profits under each technology are strictly increasing in $\pi_j(\psi)$. Therefore, each technology j has itself a zero profit cut-off $\bar{\psi}_j$ above which

FIGURE 2: Profit $\pi(\psi)$ and productivity ψ in case of three adopted technologies



Notes: The braces indicate the optimal action in Stage 2 and 3 given productivity ψ. The elasticity of substitution σ is larger than one so that $\psi^{\sigma-1}$ is increasing in ψ.

profits are positive. From equation (4), this threshold is defined by

$$\bar{\psi}_j = \alpha_j \kappa_j^{\frac{1}{\sigma-1}} \left(\frac{\sigma}{Y}\right)^{\frac{1}{\sigma-1}} \frac{w}{\rho}.$$

Since an entrepreneur enters if and only if at least one technology yields positive profits, the entry decision is governed by the technology for which the entry threshold $\bar{\psi}_j$ is lowest. Combining equations (4), (5), (7) gives a solution for $\bar{\psi} > 0$:

$$\bar{\psi} = \min_{j \in 1,2,..,J} \bar{\psi}_j = \min_{j \in 1,2,..,J} \left\{\alpha_j \kappa_j^{\frac{1}{\sigma-1}}\right\} \left(\frac{\sigma}{Y}\right)^{\frac{1}{\sigma-1}} \frac{w}{\rho}. \tag{8}$$

Figure 2 shows the profit function $\pi(\psi)$ and the optimal decision in Stage 2 and 3. It illustrates that the entry cut-off $\bar{\psi}$ is the productivity level for which the technology with the lowest entry threshold gives positive profits.

Stage 1: Occupational choice

Free entry into entrepreneurship (and risk-neutrality) implies that in equilibrium the expected profits of entering must be equal to the wage. That is,

$$\int_{\bar{\psi}}^{\infty} \pi(\psi) dF(\psi) = w. \tag{9}$$

Defining average profits of producing entrepreneurs as $\bar{\pi} \equiv \frac{1}{1-F(\bar{\psi})} \int_{\bar{\psi}}^{\infty} \pi(\psi) dF(\psi)$, equation (9) can be written as

$$(1 - F(\bar{\psi}))\, \bar{\pi} = w.$$

The probability of entry times the average profits after entry should equate the wage. Were the wage lower (higher) than the expected profits, no one would decide to work (be an entrepreneur).

2.1 Which technologies are adopted?

Answering this question requires defining some notation. First, it follows from optimal behaviour in Stages 2 and 3 that a technology is adopted in equilibrium if there is a set of entrepreneurs that both i) decides to enter and ii) finds it profit-maximizing to produce with that technology. I define the *adopting set* for technology j as the set of productivity levels for which both conditions are satisfied:

$$\Psi_j \equiv \{\psi \mid \pi(\psi) \geq 0\} \cap \left\{\psi \mid \pi_j(\psi) = \max_{k \in \{1,2,..,J\}} \pi_k(\psi) \equiv \pi(\psi)\right\}. \tag{10}$$

A technology j is adopted if the probability measure of the adopting set Ψ_j is strictly positive. Let $T^* \subseteq T$ be *the set of adopted technologies*, so that

$$t_j \in T^* \iff \Pr\left(\psi \in \Psi_j\right) > 0 \text{ for any } j = 1, 2, ..J.$$

Proposition 1 shows which technologies are adopted in equilibrium.

Proposition 1 (Adopted technologies). *Let $t_j^* = \{\alpha_j^*, \kappa_j^*\}$ be the technology in T^* with the jth-lowest fixed cost κ_j^* and let $J^* \equiv |T^*|$. Then, the set of technologies adopted in equilibrium, $T^* = \left\{t_1^*, .., t_{J^*}^*\right\}$, is such that*

(a) the adopted technology with the highest marginal (lowest fixed) cost $t_1^* = (\alpha_1^*, \kappa_1^*)$ is such that

$$\alpha_1^* (\kappa_1^*)^{\frac{1}{\sigma-1}} = \min_{j \in 1,2,..,J} \left\{\alpha_j \kappa_j^{\frac{1}{\sigma-1}}\right\} \textit{ and;}$$
$$\alpha_1^* = \min_{j \in 1,2,..,J} \left\{\alpha_j \mid \alpha_j \kappa_j^{\frac{1}{\sigma-1}} = \min_{l \in 1,2,..,J} \left\{\alpha_l \kappa_l^{\frac{1}{\sigma-1}}\right\}\right\}$$

(b) the adopted technology with the lowest marginal (highest fixed) cost $t_{J^*}^* = (\alpha_{J^*}^*, \kappa_{J^*}^*)$ is such

that

$$\alpha^*_{J^*} = \min_{j \in 1,2,..,J} \{\alpha_j\} \textit{ and;}$$
$$\kappa^*_{J^*} = \min_{j \in 1,2,..,J} \left\{\kappa_j \mid \alpha_j = \min_{l \in 1,2,..,J} \{\alpha_l\}\right\}$$

(c) *any technology with fixed cost* $\kappa^*_1 < \kappa_j < \kappa^*_{J^*}$ *is adopted if and only if for any* $k \in \{1, .., j-1\}$ *and* $l \in \{j+1, .., J\}$

$$\frac{\alpha_l^{1-\sigma} - \alpha_j^{1-\sigma}}{\alpha_j^{1-\sigma} - \alpha_k^{1-\sigma}} < \frac{\kappa_l - \kappa_j}{\kappa_j - \kappa_k}.$$

Proof of Proposition 1. See Appendix C. □

Proposition 1(a) indicates which technology is the adopted technology with highest marginal cost (and thus lowest fixed cost). Since the profit gain of a marginal cost reduction is increasing in productivity ψ, this is the technology that is adopted by the marginal entrepreneur ($\psi = \bar{\psi}$). Also, the marginal entrepreneur must use the technology j with the lowest *entry threshold* $\bar{\psi}_j$ (in Figure 2, the technology with the leftmost intersection with the zero-profit axis). The first condition in Proposition 1(a) then follows from equation (8). The second condition in Proposition 1(a) states that—in knife-edge cases where there is more than one technology that minimizes the entry threshold—only the technology with the lowest marginal cost among those that minimize the entry threshold are adopted because all but the marginal entrepreneur would strictly prefer that technology.

Proposition 1(b) shows that the technology with the lowest marginal cost is always adopted, regardless of its fixed cost. The result follows from the unbounded support of the productivity distribution. Since the gains from lowering marginal cost are strictly increasing in productivity, the gains from lowering marginal cost are unbounded. Therefore, no matter how high the fixed cost, there is always a strictly positive measure of entrepreneurs willing to incur it to reduce marginal cost. Of course, if there are multiple technologies that minimize marginal cost, only the technology with lowest fixed cost among them is adopted. It follows from combining Propositions 1(a) and 1(b) that only one technology is adopted in equilibrium if and only if the technology in T with the lowest marginal cost also comes with the lowest entry threshold. Th

Lastly, Proposition 1(c) covers all remaining adopted technologies, if any. Intuitively, for a technology to be adopted by an entrepreneur, their productivity must be *high enough* to make the technology more profitable than any other technology with higher marginal cost (and lower fixed cost), but also *low enough* to make the technology more profitable than adopting any other technology with lower marginal cost (and higher fixed cost).

Proposition 1(c) sets out the conditions under which the set of productivities that satisfy these conditions has a strictly positive probability measure. To illustrate the condition, consider Figure 2: there is an intermediate set of productivity levels, for which technology t_2 yields higher profits than both t_1 and t_3. For such a set of productivity levels to exist, the lower bound above which t_2 higher profits than t_1 must be smaller than the upper bound below which it yields higher profits than t_3.

2.2 Equilibrium

Definition (Competitive equilibrium). Given an exogenous technology set $T = \{t_1, .., t_J\}$, a *competitive equilibrium* consists of a price w, profits $\{\pi(\psi)\}$, output Y, productivity threshold $\bar{\psi}$, adopting sets $\{\Psi_j\}_{j=1}^{J}$, and a share of entrants L such that

– profits $\pi(\psi)$ are as defined in (4) and (5);

– the adopting set of technology j, Ψ_j, is as defined in (10);

– the free entry condition in (9) holds;

– the labor and goods markets clear, so that

$$L = (1 - L)Y \left(\frac{\rho}{w}\right)^{\sigma} \sum_{j=1}^{J} \alpha_j^{1-\sigma} \int_{\psi \in \Psi_j} \psi^{\sigma-1} dF(\psi), \tag{11}$$

$$Y = Lw + (1 - L) \left(\sum_{j=1}^{J} \kappa_j \int_{\psi \in \Psi_j} dF(\psi) + \sum_{j=1}^{J} \int_{\psi \in \Psi_j} \pi(\psi) dF(\psi) \right); \tag{12}$$

– the pricing by entrepreneurs is consistent with a price index equal to 1, so that

$$1 = (1 - L) \left(\frac{w}{\rho}\right)^{1-\sigma} \sum_{j=1}^{J} \alpha_j^{1-\sigma} \int_{\psi \in \Psi_j} \psi^{\sigma-1} dF(\psi). \tag{13}$$

Having defined the equilibrium in general, in order to get more concrete results, form now on I assume that the distribution of productivity ψ is Pareto. With this assumption, the model has closed-form analytical solutions reported in Appendix C.

Proposition 2 (Closed-form equilibrium). *Suppose that the distribution of productivity ψ is Pareto with shape parameter ξ and a minimum productivity level of $\psi_m > 0$ such that $\xi > 1$ and $\xi > \sigma - 1$. Then, the closed-form solutions to the competitive equilibrium for L, $\bar{\psi}$, Y, w, and $\bar{\pi}$ are given by equations (29), (30), (31), (32), and (33) in Appendix C.*

Proof of Proposition 2. See Appendix C. □

Proposition 1 and 2 together fully characterize the equilibrium in closed form. In the next subsection, I use these results to study the effect of scale-biased technical change on entrepreneurship, firm concentration, wages, output, profits, and inequality.

2.3 Scale bias and testable implications

To formalize scale-biased technical change, I first define the *total factor productivity* of a firm as the idiosyncratic productivity of the entrepreneur ψ divided by the marginal cost parameter of the technology in T that it adopts:

$$TFP\left(\psi \mid T\right) = \begin{cases} \frac{\psi}{\alpha(\psi|T)} & \text{if } \psi \geq \bar{\psi}\left(T\right) \\ 0 & \text{otherwise} \end{cases}$$

where $\bar{\psi}\left(T\right)$ and $\alpha(\psi \mid T)$ are the entry threshold (derived in closed-form in Proposition 2) and the marginal cost parameter of the optimally adopted technology given technology set T. I set total factor productivity to zero for entrepreneurs that do not produce to ensure that changes on the extensive margin (in and out of production) are reflected in TFP changes.

Technical change is an addition of a new technology, say t_{new}, to the technology set T_{old} such that $T_{new} = T_{old} \cup \{t_{new}\}$. From there, I define scale-biased technical change formally.

Definition (Scale-biased technical change)**.** Technical change is *large-scale-biased* if and only if there exists some $k > \min\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\}$ such that it increases TFP for $\psi > k$ and does not increase it for $\psi < k$:

$$\begin{aligned} &TFP\left(\psi \mid T_{new}\right) > TFP\left(\psi \mid T_{old}\right) \quad \forall \psi > k \text{ and;} \\ &TFP\left(\psi \mid T_{new}\right) \leq TFP\left(\psi \mid T_{old}\right) \quad \forall \psi \in \left(\min\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\}, k\right). \end{aligned} \tag{14}$$

It is *small-scale-biased* if and only if

$$\begin{aligned} &TFP\left(\psi \mid T_{new}\right) \leq TFP\left(\psi \mid T_{old}\right) \quad \forall \psi > k \text{ and;} \\ &TFP\left(\psi \mid T_{new}\right) > TFP\left(\psi \mid T_{old}\right) \quad \forall \psi \in \left(\min\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\}, k\right). \end{aligned} \tag{15}$$

In other words, technical change is large-scale-biased if it increases the productivity of firms above some level of entrepreneurial productivity, while it does not increase the productivity of other firms. I do not consider cut-off levels k below $\min\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\}$ because for those levels of productivity people do not choose to be entrepreneurs under either technology set.

The definition is similar to that of *skill*-biased technical change as increasing skilled workers' productivity relative to unskilled labor (Katz and Murphy, 1992; Violante, 2008). Krusell et al. (2000) provide a micro-foundation for skill-biased technical change by considering that the relative productivity changes could be caused by capital-skill complementary. In the same vein, I provide an explicit mechanism for relative productivity increases of large firms in terms of the available technologies. That is, I derive the conditions on the technological parameters under which technical change is large-scale-biased in equilibrium. Proposition 3 lays out these conditions.

Proposition 3 (Scale-biased technical change)**.** *Suppose that the assumptions in Proposition 2 (Pareto distribution) hold, that $\sigma > 2$, and that $T^*_{new} = T^*_{old} \cup \{t_{new}\}$ (the new technology is adopted alongside the previously adopted technologies). Then,*

(a) the technical change is large-scale-biased if and only if

$$\kappa_{new} > \max_{\{\alpha_j, \kappa_j\} \in T^*_{old}} \kappa_j;$$

(b) and the technical change is small-scale-biased if and only if

$$\kappa_{new} < \min_{\{\alpha_j, \kappa_j\} \in T^*_{old}} \kappa_j.$$

Proof. See Appendix C. □

Proposition 3 shows that the addition of a technology constitutes large-scale-biased technical change if and only if the new technology comes with highest fixed cost. Conversely, it is small-scale-biased if the new technology has lowest fixed cost. Since no technology can strictly dominate another adopted technology, the result implies that technical change is large-scale-biased if and only if the new technology has lowest *marginal* cost.

The intuition behind the "if" is that a technology on the extreme end of the technology set would be adopted by the most productive or least productive entrepreneurs. Also, under the assumptions in Proposition 3, if a new technology is adopted, it *reduces* profitability of all other technologies. Therefore, entrepreneurs that do not adopt the new technology do not reduce marginal cost through a change to a third technology. If anything, some may find it optimal to use a technology with higher marginal and lower fixed costs than before in response to other entrepreneurs using the new technology. Thus, if a new technology has largest fixed cost, it increases the productivity of the top entrepreneurs, but not the rest. Vice versa, if it comes with lowest fixed cost, it increases the relative productivity of small entrepreneurs.

If a technology is adopted that has neither the highest or the lowest fixed cost, it will be used by a set of intermediate entrepreneurs. This means that both the largest and the smallest firms do not adopt this technology. Hence, by the same reasoning as above, this type of technical change does not increase the productivity of either small or large firms and is thus neither large- nor small-scale-biased.

The condition that $\sigma > 2$ is the empirically relevant case for at least three reasons. First, it is consistent with estimates of σ around 6 for US manufacturing data (Bernard et al., 2003) and with the calibration of $\sigma = 4$ by Melitz and Redding (2015). Second, $\sigma \leq 2$ implies a labor share of a half or lower, while the labor share has been consistently larger than a half in the US and other countries. Third, if $\sigma \leq 2$, the implied mark-up (i.e., the ratio of price to marginal cost) is larger than 2.

Using Propositions 2 and 3, I generate three main predictions of the theory. First, large-scale biased technical change increases average firm sizes, while small-scale-biased technical change decreases them. Second, large-scale biased technical change increases top income inequality. Small-scale-biased technical change decreases inequality. Third, scale bias affects inequality mostly through inequality between workers and entrepreneurs.

Proposition 4 (Theoretical implications of scale-biased technical change)**.** *Suppose the assumptions in Proposition 3 hold. Then, large-scale-biased technical change*

(a) increases the average firm size as measured by employment;

(b) increases income inequality between active entrepreneurs and workers;

(c) increases the income share of the top k% of income earners for any $k \in (0, 100)$.

Small-scale-biased technical change has the opposite effects.

Proof of Proposition 4. See Appendix C. □

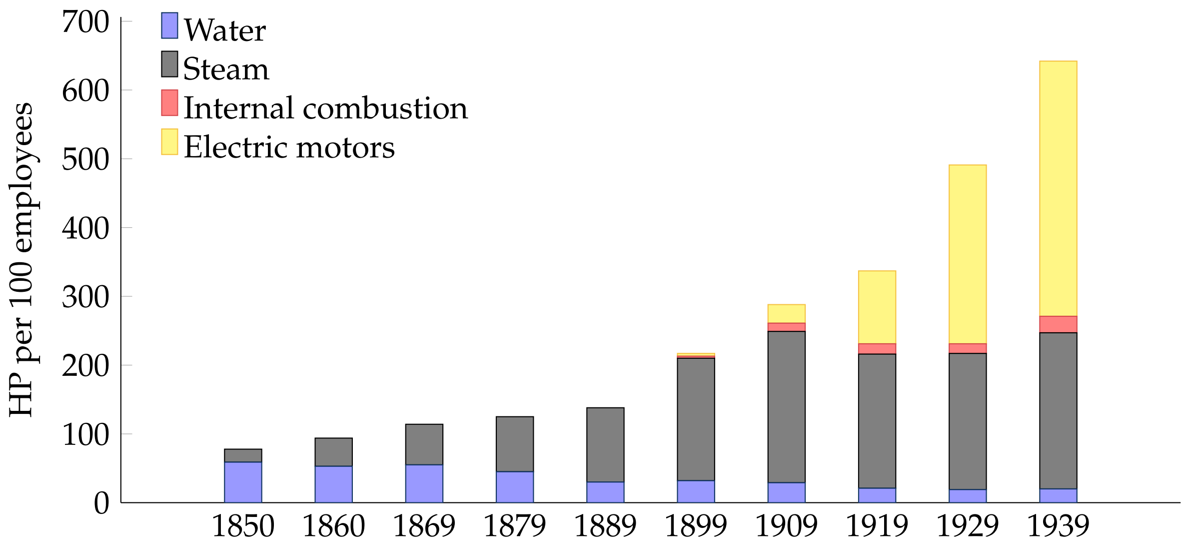
The remainder of the paper is devoted to testing the theoretical predictions above. I will use the case of steam engines and electric motors. In the next section, I show that steam engines are large-scale-biased and electric motors are small-scale-biased.

3 Scale bias in steam engines and electric motors

To test the theory of scale-biased technical change, I compare the effects of steam engine and electric motor adoption. I argue that the comparison of these two technologies is uniquely appropriate to test the theory for three main reasons. First, the steam engine and the electric motor are two of the most important general purpose technologies in human history. Second, they served a similar purpose: the conversion of energy into rotary motion in manufacturing. Third, as I will argue in this section, they varied crucially on scale bias: steam engine adoption constituted large-scale-biased technical change, while electric motor adoption constituted small-scale-biased technical change.

I first briefly describe the history of steam engine and electric motor adoption. Figure 3 illustrates the timing and degree of adoption of each type of primary power. Three main patterns jump out. First, the waterwheel was slowly replaced by the steam engine in the second half of the 19th century. Second, steam engines, and later the electric motor, were the dominant power source from around 1870 onward. Third, electric motors were adopted from around 1900 and their superiority meant that internal combustion engines were never adopted on a large scale (Du Boff, 1967). Fourth, electric motors driven by purchased electricity started to become dominant around the 1930s, but steam engines remained an important source of primary power until at least 1939. Figure A.1 shows the same patterns for the Netherlands.[10] Below, I lay out the features of the technologies that make steam engine adoption large-scale-biased and electric motor adoption small-scale-biased.

FIGURE 3: Capacity of primary power by type in horsepower per 100 employees in manufacturing in the United States



Notes: Electric motors refer to primary electric motors, i.e., electric motors driven by purchased electricity, only. Electric motors driven by energy generated in the plant are covered under steam engines. *Sources*: (Atack, 1979, Table 1) for the number of steam engines and waterwheels in 1850 and 1860; (Atack et al., 1980, p. 285) for their average size (21 and 15 hp, respectively); Census of Manufactures 1860 for the total number of employees in 1850 and 1860; Census of Manufactures 1939, Power equipment and energy consumption, Table 3 for all years after 1860.

[10] A distinction can be made between the primary source of power (from the perspective of the plant) and the system to deliver that power. Many electric motors in manufacturing were not driven by purchased electricity, but by electricity generated in the plant. Such "secondary movers" are excluded from Figure 3 to avoid double counting of capacity. The share of non-electric primary power, such as steam engines, that served to generate electricity for intra-plant use grew strongly over time: from 14.8% percent in 1909 to 65.8% in 1939 (Du Boff, 1979, Table 15). Hence, electricity as a system of power delivery was more dominant than suggested by considering only the primary source of power. For the remainder of this paper, I focus on the primary source of power as the key distinction between "steam engines" and "electric motors".

First, steam engines come with much higher fixed costs of purchase, renewal, and operation than electric motors. The price of a steam engine (including boiler) of average capacity was around $5331 in 1874, more than 13 times the yearly wage of an unskilled manufacturing worker (Emery, 1883; Abbott, 1905).[11] On top of that, it required an engineer and a firemen, supplies, oil, and repairs. In total, I estimate the annualized cost of purchase, renewal, maintenance, and operation of a 50 horsepower steam engine to be around $1378, about 3 to 4 times the yearly unskilled wage. In other words, for the cost of operating an average-sized steam engine excluding fuel, one could hire around 3 to 4 unskilled workers. In comparison, the equivalent annualized fixed costs of an electric motor of that size were negligible: the fixed cost amounted to only 2 percent of the yearly wage of an unskilled worker (Bolton, 1926). In Appendix E, I provide more details on computations and sources.

Second, larger steam engines were considerably more efficient in converting energy into motion than small ones (Atack, 1979; Devine, 1983). In contrast, electric motors' efficiency does not vary nearly as much with size. In the words of the contemporaneous engineer Bell (1891): "With the electric motor the case is very, very different [from steam engines]; an eight horse-power motor may be as completely worked out in detail as one of a hundred times its power, and may be only slightly less efficient." Figure A.2 illustrates the efficiency of steam engines and electric motors for different sizes (horse-power capacity) relative to a 100 hp equivalent based on estimates by Emery (1883) and Bolton (1926). A steam engine of 10 hp required more than twice as much coal per horse-power of energy output than a 100 hp steam engine. Coal-efficiency was an important consideration given that coal accounted for between a half and two-thirds of the total operating costs for the larger engines.

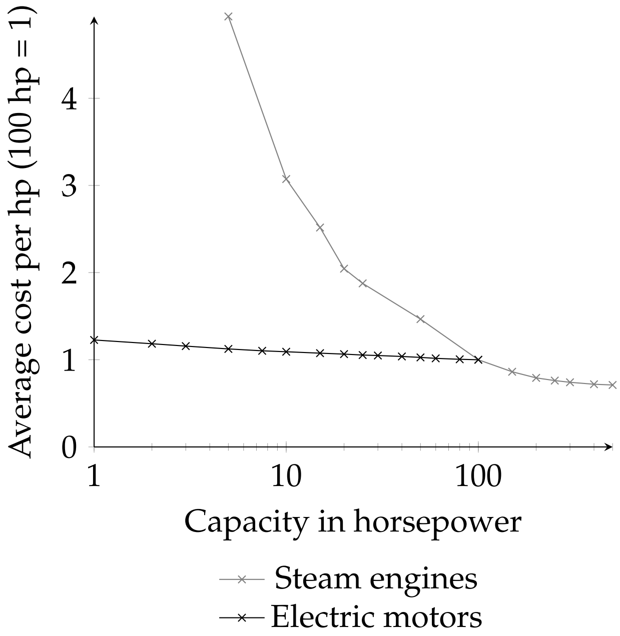
The marginal and fixed costs of steam engines and electric motors can be combined to estimate an average cost curve by rated capacity for the electric motor and the steam engine. Figure 4 shows the results.[12] Clearly, steam engines were much more cost-efficient on a large scale. For electric motors, scale was close to irrelevant as almost all costs were marginal, coming from the purchase of electricity, and the efficiency loss of small motors was minor.

Lastly, there were reasons for steam engine adoption to be skewed to large establishments that are less easily quantified, but no less important. A steam engine occupied a

[11] The average steam engine in the United States in 1889 had a capacity of 50.1 horsepower (Du Boff, 1979). The daily wage of an unskilled worker was $1.29 Abbott (1905), which I multiplied by 309 days as in (Emery, 1883).

[12] I have assumed an interest rate of 5 percent, depreciation rates as estimated by Emery (1883); Bolton (1926) and a price of electricity as reported by Hannah (1979) and of coal as Emery (1883). In Appendix E, I explain the assumptions and computations underlying Figure 4 in further detail. Consistent with my estimates based on Emery (1883), (Kapp, 1894, p. 234) reports that the cost per horsepower hour of a "small" steam engine was about four times the cost of that of a "large" engine.

FIGURE 4: Average cost per horsepower per year of steam engines and electric motors of different capacities relative to its 100-horse power equivalent



Notes: Author's computation based on contemporaneous price and efficiency data. *Sources*: (Emery, 1883) for steam engines and coal; (Bolton, 1926; Hannah, 1979) for electric motors and electricity. See Appendix E for further details.

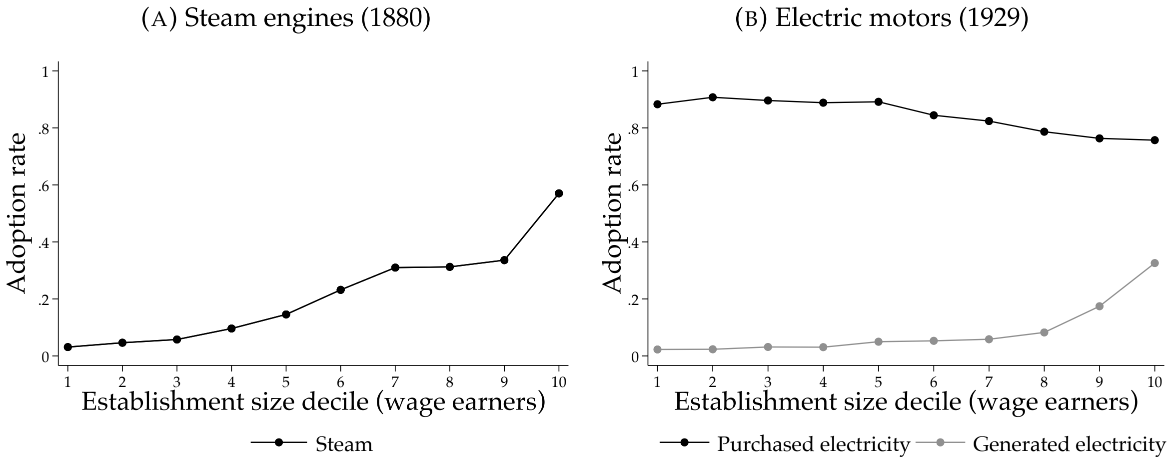
large amount of space and fuel storage, water supply, and mitigation of fire hazard further increased the fixed costs of operating steam engines (Hunter and Bryant, 1991, p. 56). Also, the "notoriously wasteful" steam engine had to be run at full capacity even if only small doses of power were required, a feature likely to be specifically uneconomical for small establishments (Du Boff, 1967).

The adoption rates by plant size reflect the considerations above. Figure 5(A) shows that large plants are much more likely to adopt steam engines, as documented before by Atack et al. (2008). In contrast, Figure 5(B) indicates that electric motors driven by purchased electricity were almost uniformly adopted across the establishment size distribution. In fact, larger firms were slightly less likely to use purchased electricity while they were much more likely to use self-generated electricity. This further confirms, that for the purpose of studying scale bias, the relevant distinction is the primary source of power, not the system of delivery.

4 Data construction

This paper uses newly collected and digitized data from the United States as well as the Netherlands. In this section, I discuss the sources and construction of the data for both countries.

FIGURE 5: Adoption rates by establishment size



Notes: This figure indicates the share of establishments using steam engines in 1880 (panel A) and electric motors in 1929 (panel B) by establishment size as computed from micro-samples of the Census of Manufactures. *Sources*: for 1880, the national random sample of the Census of Manufactures (Atack and Bateman, 1999); for 1929, the Census of Manufactures for selected industries (Vickers and Ziebarth, 2018). I left out the concrete industry as data on electric motors driven by generated electricity is not available for that industry.

4.1 United States

For the United States, I most heavily rely on the tabulations of the decennial Census of Manufactures by state and industry. I digitized and compiled these data for each decade year between 1850 and 1940 and 1947. The information in the Census of Manufactures varied somewhat from year to year, but key variables such as the number of establishments, employment, and value added are always available. Furthermore, from 1870 onward, the tabulations reported the adoption of power technologies such as water wheels, steam engines, and, later, electric motors. The industry classification is detailed; in the average year, there are around three to four hundred different manufacturing industries. In total, the data comprise of 51,263 state-industry-year observations.

Since industry classifications changed over time, I created two crosswalks that allow to compare industries over time. The first covers all industries between 1860 and 1900, the period of most rapid steam engine adoption, and consists of 182 industries. This crosswalk is an extension of the 1860 to 1880 crosswalk published by Hornbeck and Rotemberg (2021). The second crosswalks consists of 206 harmonized industries across the six censuses between 1890 and 1940. To create this second crosswalk, I used tabulations by industries over time published in the Census of Manufactures.[13] The final crosswalks can be found in Appendix D.2. I also coded each Census of Manufactures industry to the

[13]In particular, I mostly used "comparative summaries" and descriptions of industry classifications in the appendices in the Census of Manufactures.

1950 Census Bureau industrial classification system to allow matching with the IPUMS USA population censuses between 1850 and 1940.

To construct instrumental variables for technology adoption, I use data on coal resources and hydropower potential by state. Data on historical coal resources by county are taken from the National Coal Resources Data System from the United States Geological Survey (USGS).[14] The dataset contains information on the "rank" (i.e., type) of coal, the estimated tonnage available, the thickness of the field, and the "overburden" (i.e. the depth of the material that lies above the coalfield). Using this information, I compute the total coal resources in British thermal units (Btu) for each county.[15] Recognizing that coal was traded across counties, I compute a measure of "coal access" by county similar to the measure of market access used by Donaldson and Hornbeck (2016). That is, for destination county c in state s, coal access is given by

$$\text{COAL}_c^s = \sum_o \tau_{oc}^{-\theta} \text{BTU}_o \tag{16}$$

where $\tau_{oc} \geq 1$ is the "iceberg cost" of transporting coal between counties o and c in 1830, θ is the trade elasticity, and BTU_o is the total amount of coal resources in county o measured in Btu.[16] Intuitively, the coal resources in county o more strongly count towards county c's coal access if the transportation costs between these counties is low. Importantly, I use transportation costs before the introduction of the railroads to avoid capturing infrastructure investments. I similarly use estimates of coal resources prior to mining to avoid contamination by selective mining. Figure A.3 shows the spatial distribution of coal access on the county-level.

Hydropower potential is defined as the total horsepower of energy that can be feasibly generated by waterpower given the topographic characteristics of the area. Importantly, it covers both developed and undeveloped sites. Estimates of hydropower potential of each state were published by USGS at various points in time. I use the estimates of hydropower potential published in (Young, 1964, Table 10).[17] Figure A.4 shows a map of hydropower potential across the United States.

[14]The source file can be downloaded from `https://www.usgs.gov/media/files/uscoal`.

[15]Following Averitt (1975), I convert the tonnage of coal of different ranks to Btu using the following ratios: Anthracite, 12,700 Btu per pound; bituminous coal, 13,100 Btu per pound; subbituminous coal, 9,500 Btu per pound; lignite, 6,700 Btu per pound. I include the coal resource only if the overburden is less than 3,000 feet and the thickness is more than 14 inches for anthracite and (sub)bituminous coal or more than 28 inches for lignite (Averitt, 1975).

[16]Specifically, as in (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2021), $\tau_{oc} = 1 + t_{oc}/\bar{P}_{coal}$. I set $\bar{P}_{coal} = 6.08$ to the average dollar per ton anthracite coal price in 1830, Philadelphia (Chandler, 1972, Table 2). t_{oc} is the transportation cost per ton-mile between counties o and c in 1830 as estimated by Donaldson and Hornbeck (2016). The trade elasticity θ is set to 8.22 as estimated by (Donaldson and Hornbeck, 2016).

[17]Since water flow can vary seasonally, hydropower potential may not be constant within a year. I use estimates of hydropower potential available 50 percent or more of the time.

4.2 Netherlands

For the Netherlands, I measure income and wealth inequality using two new datasets. The first dataset contains the names, occupation, residence, birth place, and wealth at death for all individual s who died in selected provinces between 1879 and 1927. The provinces cover around a half to two-thirds of the national population. The second dataset contains digitized tabulations of income and wealth distributions for each municipality and for around every five years between 1946 and 1975. Furthermore, I collected data on manufacturing on the local level for selected years. In all data, each municipality is coded to their "Amsterdamse code", an identifier for each historical Dutch municipality.[18]

4.2.1 Inheritance tax data (1879-1927)

The data on wealth at death derive from the inheritance tax administration. The tax was levied nationally since 1818. All source data up to 1927 is publicly available in regional archives in the Netherlands. Before 1878, the inheritances were only subject to tax if not all recipients were descendants in the direct line. After 1878, all inheritances above f1000 (a thousand Dutch guilders) were taxed. However, the value of many estates worth less than f1000 were assessed and recorded. The source files are printed tables that were filled in by hand indicating decedent's name, occupation, place of residence, marital status, date of death, and importantly, the value of their estate. The tables were referred to contemporaneously as "Tafels V-bis". Figure D.1 is an example of a source image. It also contains decedents whose inheritance were not subject to taxation. De Vicq and Peeters (2020) have digitized the Tafels V-bis for decedents who were subject to taxation in 1921. For more information on the source, I refer to their paper.

I cover the entire period between 1879 and 1927. I included all areas for which the source files were available online as scanned images, namely the provinces Noord-Holland, Zuid-Holland, Noord-Brabant, Gelderland, and Overijssel.[19] In 1900, these five provinces contained 70 percent of the population.[20] For Zuid-Holland, scanned images were only available up to around 1900. The source files are printed tables that were filled in by hand indicating decedent's name, occupation, place of residence, marital status, date of death, and importantly, the value of their estate. Figure D.1 is an example of a source image. The tables were digitized using Transkribus, an AI-powered platform specialized

[18]See Huijsmans (2020) for a database of all historical municipalities.

[19]The archival sources are: Noord Hollands Archief, record group 178 (for Noord-Holland); Nationaal Archief, record group (i.e. "inventarisnummer") 3.06.05 (for Zuid-Holland); Brabants Historisch Informatie Centrum, record group 82 (for Noord-Brabant); Gelders Archief, various record groups (for Gelderland); Collectie Overijssel, record group 136.4 (for Overijssel).

[20]See http://www.volkstelling.nl for data on population by province. The four provinces for which the entire period is covered contained 47 percent of the population in 1900.

in digitization of historical records.[21] In total, I digitized more than 130 thousand images.

I mitigate noise coming from automatic digitization of the data in two ways. First, the wealth of all observations with wealth recognized to be larger than ƒ100,000 (19,178 observations) were checked by hand. Second, I link the digitized dataset to existing high-quality hand-collected information from the civil death registry by (fuzzy) matching based on name, place and date of death, and age.[22] Around 80 percent of the observations can be linked to a record in the civil death registry.

Using the data, I create a panel data on the local wealth distribution. I use the smallest geographical unit, the municipality, as the unit of analysis. To ensure a sufficient amount of observations per time period, I compute the distributional statistics by decade.[23] As reported above, all estates worth more than the taxable threshold of ƒ1000 were assessed and taxed, but many estates were assessed to be below the threshold. Which estates were assessed may have varied somewhat across tax offices and over time: the exact criteria under which an estate was assessed are to my knowledge unknown. The need to avoid that variations in assessments affect the measures of inequality, would suggest to only include decedents with an assessed wealth above ƒ1000 (as they should always have been assessed). However, including as many people as possible reduces variance in the measures of inequality. I balance these interests by including every decedent with an assessed wealth above ƒ300 in the sample on which measures of the wealth distribution are computed.

The resulting dataset on wealth over the period of industrialization is unique in its size and geographic scope. The existing literature has focused on documenting national trends in the wealth distribution. For instance, Lindert (1986) (UK) samples 12,581 estates across four regions and five dates between 1670 and 1875, Piketty et al. (2006) (France) cover a random sample of Parisian estates in selected years in the 19th century, and Bengtsson et al. (2018) (Sweden) collect information on samples of around 5000 probate inventories between 1750 and 1900. This dataset is an illustration of the value of using newly available technologies for scalable digitization of handwritten historical records. With more than 1.5 million decedents—of which 550,966 had their wealth assessed and recorded—and coverage across the country, it allows for a detailed look on the wealth distribution. Furthermore, and importantly for the purpose of this paper, it provides complete coverage between 1879 and 1927, the period where first steam engines and then electric motors were adopted in the Netherlands.

I assess the reliability of the data by comparing the measures of inequality with data from two other sources that I have digitized. First, I uncovered a parliamentary docu-

[21]For more information, see `https://readcoop.eu/transkribus/`.
[22]The civil registry data can be downloaded in bulk at `https://www.openarch.nl/exports/csv/`.
[23]Since the dataset starts in 1879, I assign that year to the 1880s too.

TABLE 1: Correlations between top decile shares based on inheritance data and alternative data sources

	Wealth, inheritance data				
	1880	1890	1900	1910	1920
Income, 1883	**0.86**	0.77	0.73	0.62	0.54
Income, 1926	0.38	0.33	0.54	0.60	**0.71**
Wealth, 1926	0.48	0.56	0.66	0.72	**0.76**

Notes: This table shows the correlations between the measures of municipality-level top wealth inequality for each decade derived from the inheritance data and measures of income and wealth inequality from other sources. Observations are weighted by the number of individuals on which the inheritance wealth inequality measure is based. *Sources*: local income tax data for income inequality in 1883; national income (wealth) tax data for income (wealth) inequality in 1926.

ment that recorded in large detail the distribution of income by municipality in 1883 for 79 municipalities.[24] These data were derived from local income tax administrations. I also collected data on income distributions of 8 additional cities with a local income tax whose distribution was not included in the parliamentary study.[25] The second source of the data are income and wealth distributions derived from national taxation for the largest 45 municipalities for 1926 in (Centraal Bureau voor de Statistiek, 1928). Table 1 shows that the correlations are strong, and importantly, they are strongest for the relevant time period. For instance, the top decile share of income in 1883 correlates strongly with the top decile wealth share in 1880, but much less strongly with that in 1920. These correlations provide evidence that the data is accurate both in the cross-section and over time. Furthermore, Table 1 shows that wealth inequality among decedents (as measured by the inheritance data) correlates strongly with wealth (and income) inequality among the living population.

4.2.2 Income and wealth distributions by muncipality (1946-1975)

From 1946 onward, Statistics Netherlands published detailed income and wealth distributions for each municipality. The tabulations indicated the number of inhabitants in specific income (wealth) brackets as well as total bracket income (wealth).[26] Figure D.2 shows an example of the source data for one municipality. The data originate from the national income and wealth tax administration. Since 1941, the national income tax cov-

[24]Tweede Kamer (*House of Representatives*) 1883-1884 kamerstuknummer (*document number*) 172.13. The source file can be found on `https://zoek.officielebekendmakingen.nl/0000397139`.

[25]The cities are: Breda (1880), Vlissingen (1883), Enschede (1880), Utrecht (1888), Delft (1893), Eindhoven (1885), Hilversum (1880), Nijmegen (1880). The sources for these extra cities are documented in Appendix D.3.

[26]The relevant publications are (Statistics Netherlands, 1953, 1954b, 1959b, 1965, 1967b, 1976b, 1979b) for wealth and (Statistics Netherlands, 1952, 1954a, 1959a, 1962, 1964, 1967a, 1970, 1976a, 1979a) for income.

ered almost the entire active population.[27] In line with Hartog and Veenbergen (1978), I therefore treat the units subject to income tax in a municipality as the target population for which I estimate the distribution of income and wealth.

To estimate the income and wealth distribution by municipality from the tabulations, I use the generalized Pareto interpolation method (Blanchet et al., 2022).[28] For income, since the target population is the taxed population, I perform this method directly on the source data. For wealth, the tax exemption limit was such that only around the wealthiest 10 percent of households subject to income tax were covered. I therefore first estimate the average wealth of a household below the threshold, using log-normal extrapolation. After this imputation, I estimate the overall wealth distribution using the generalized Pareto interpolation method.

4.2.3 Manufacturing

I use newly digitized data on manufacturing by municipality for the years 1816-1819 and 1930. The first official Census of Companies ("Bedrijfstelling") in the Netherlands was performed in 1930. It offers a high-quality snapshot of manufacturing by industry by municipality.[29] This source provides information on the number of establishments and workers by size class by industry by municipality and the adoption of motive power (in horsepower).[30] Importantly, it breaks down motive power by electric motors driven by purchased energy and other motive power (i.e., steam engines or electric motors driven by steam engines in the plant). Figure D.3 provides an example of a source page. In total, the data consists of 33,134 municipality-by-industry observations.

The data for the years 1816-1819 derive from two government surveys from which the results are compiled and published in print by (Brugmans, 1956; Damsma et al., 1979).[31] I digitized the data from that source and coded the establishment types to a 2-digit ISIC industry code.[32] Where data is available for both 1816 and 1819, I use the data for 1819. Furthermore, I added the results for the municipality of Rotterdam and neighbouring municipalities—which were excluded by (Brugmans, 1956; Damsma et al., 1979)—from (Korteweg, 1926). The inquiry contains, by municipality, information on the number of establishments for each type of establishment (e.g. tannery or cotton factory) and the

[27]The coverage rose over time from around 85 to 99 percent (Schultz, 1968).

[28]The R-package `gpinter` implements the method.

[29]While it also provides information on non-manufacturing firms, I have digitized the data only for manufacturing firms. Source images can be downloaded from https://doi.org/10.17026/dans-xqs-5q6e.

[30]The establishments are broken down by those employing none or one person, 2 to 5 persons, 6 to 10 persons, or 11 or more persons.

[31]The source images can be downloaded from https://resources.huygens.knaw.nl/nijverheid.

[32]Specifically, I coded the establishment types to the International Standard Industrial Classification of All Economic Activities, Rev. 4.

number of workers. Brugmans (1956); Damsma et al. (1979) were not able to retrieve the survey results of all municipalities in three out of eleven provinces (Zuid-Holland, Overijssel, and Groningen). The final data contain 3,658 municipality-by-industry observations in 539 distinct municipalities.[33] The data includes nearly all large cities and other places with a strong manufacturing presence.

Lastly, to estimate firm sizes in manufacturing in 1889, I use the Census of Occupations, which enumerated by municipality-by-industry the number of business owners and employees for the largest 285 municipalities. The data was digitized and made available by Mourits et al. (2016). I approximate the firm size in a municipality by dividing the number of employees by the number of business owners in manufacturing.

For comparability across years, I coded each industry or establishment type to its relevant 2-digit ISIC industry code for all the Dutch manufacturing data.

5 The effect of scale-biased technical change on firm size

This section documents the impact of the adoption of steam engines—large-scale-biased technical change—and the adoption of electric motors—small-scale-biased technical change—on establishment sizes. The first prediction of the theory is that steam engine adoption causes an increase in the average establishment size, while electric motor adoption decreases it. I verify the prediction using exogenous geographical variation within the United States in the relative costs of the technologies.

The theory combined with the evidence in Section 3 suggests that large firms have an advantage over small firms in the adoption of steam power. Such selective adoption means that a correlation between firm sizes and technology adoption does not necessarily imply a causal effect of the technology. We therefore require exogenous variation in the adoption of both technologies to distinguish the causal effects from reverse causality and potential other confounders. I argue that differences in access to natural coal reserves and hydropower potential across the United States provide such variation.

First stage. Manufacturing plants in states with more access to coal tended to use more steam engines. As the most important input to steam engines, the availability of affordable coal affected the adoption of steam engines. Figure A.5 shows a strong negative correlation between coal prices and "coal access" ($\rho = -0.58$). I test the hypothesis that coal access affected the adoption of steam engines. In 1890, the Census of Manufactures reported steam engine and other power use for each state-industry combination. For that

[33] Around 1200 municipalities existed at the time. For eight out of eleven provinces, (Brugmans, 1956; Damsma et al., 1979) retrieved the complete returns of the surveys so that any "missing" municipalities are likely to not have had any significant manufacturing presence. For the remaining three provinces, some municipalities may be missing despite some manufacturing industry.

TABLE 2: The effect of coal access on steam engine adoption (1890)

	Steam hp per worker (asinh)			Steam as share of total hp		
Coal access (logs)	0.022***	0.022***	0.021***	0.031***	0.031***	0.029***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Hydro-potential		X	X		X	X
Firm size			X			X
Observations	4237	4237	4237	3395	3395	3395

Notes: This table shows the estimated effect of coal access (in logs) on horsepower of adopted steam engines per employee and as fraction of total horsepower. Standard errors in parentheses are clustered at the state-level. Industry fixed-effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

year, I estimate

$$\text{STEAM}_{ist} = \delta_i + \theta \ln(\text{COAL}_s) + \epsilon_{ist} \tag{17}$$

where the subscripts i, s, and t refer to industry, state, and year, respectively. STEAM_{ist} refers to measures of steam engine adoption, i.e., steam engines' horsepower per employee and the share of steam engines in total horsepower. COAL_s is the measure of state s's coal access, computed as the average coal access of the counties in state s as given by equation (16). Standard errors are clustered at the state-level and the regression is weighted by the total number of establishments in industry i, state s, and year t. Table 2 shows that coal resources strongly predicted steam engine adoption, both relative to employment and relative to other power sources (mostly water wheels), even within narrow industries. This relationship is robust to—and if anything strengthened by—controlling for hydropower potential of state s and the average firm size in industry i and state s. Table B.1 shows that coal access did not strongly affect overall power use in 1890 on the state-level. Instead, it mostly induced substitution away from water wheels to steam engines.

In contrast, plants in states with high hydropower potential relied relatively more on electric motors driven by purchased electricity. The price of electricity depended strongly on the "hydropower potential" that a state had to offer. Figure A.6 shows the correlation between hydropower potential and electricity prices in 1929 ($\rho = -0.56$). Coal access and hydropower potential are not correlated (Figure A.7, $\rho = 0.03$). I estimate the effect of the instrument (hydropower potential) on the use of purchased electric energy, first reported in 1939. That is, I estimate for the year 1939:

$$\text{ELECTRICITY}_{ist} = \delta_i + \theta \ln(\text{HYDRO}_s) + \boldsymbol{\lambda}'\boldsymbol{X}_{ist} + \epsilon_{ist}.^{34} \tag{18}$$

[34] For simplicity, I chose notation identical to (17). Of course, the parameters in (17) and (18) are different.

TABLE 3: The effect of hydropower potential on purchased electric energy use (1939)

	MWh per worker (asinh)			Electricity as share of fuel		
Hydro-potential	0.110***	0.116***	0.113***	0.020***	0.018***	0.017***
	(0.029)	(0.024)	(0.024)	(0.004)	(0.003)	(0.003)
Coal access		X	X		X	X
Firm size			X			X
Observations	5031	5031	5031	5010	5010	5010

Notes: This table shows the estimated effect of hydropower potential (in logs) on megawatt hour of purchased electricty per employee of adopted steam engines per employee and as fraction of total horsepower. Standard errors in parentheses are clustered at the state-level. Industry fixed-effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ELECTRICITY$_{ist}$ refers to two measures of electric motor adoption: the total megawatt hour of purchased electric energy per employee and the cost of purchased electric energy as a share of total fuel costs.[35] $\ln(\text{HYDRO}_s)$ refers to the logarithm of the hydropower potential of state s. Table 3 shows the results. Hydropower potential caused firms to use more electric energy, relative to employment as well as relative to other fuels.

Results. I estimate the reduced form effects of coal access and hydropower potential on the firm size using the following regression equation:

$$\ln(y_{ist}) = \alpha_s + \eta_{it} + \sum_{k \in T} \left[\beta_k \ln(\text{COAL}_s) D_{tk} + \gamma_k \ln(\text{HYDRO}_s) D_{tk}\right] + \boldsymbol{\lambda}' \boldsymbol{X}_{st} + \varepsilon_{ist} \quad (19)$$

where the subscripts i, s, and t refer to industry, state, and year, respectively. D_{tk} is a dummy that is 1 if $t = k$ and 0 otherwise and T contains all but one reference census year. y_{ist} is the average firm size (in terms of employment). Standard errors are clustered at the state-level and the regression is weighted by the total number of establishments in industry i, state s, and year t. $\boldsymbol{X}_{st}$ is a vector of controls on the state-year level: it contains the density of the population in state s at time t and interactions between time and "market access" in state s.[36] Controlling for market access ensures that the estimated effect of access to coal does not reflect low-cost access to consumer markets.

Figure 6 shows the estimates and 95% confidence intervals for the effects of coal access and hydropower potential across years. I find that firm sizes in states with high coal

[35] The megawatt hour of purchased electric energy per employee is obtained by dividing the cost of purchased electricity by the average price of electricity per MWh for manufacturers in the state in 1939. The average price was, in turn, computed by dividing the total cost of purchased electric energy in the state (Census of Manufactures 1939, Volume 1, Ch. VII, Table 3) by the quantity purchased in MWh. (Census of Manufactures 1939, Volume 1, Ch. VI, Table 6).

[36] I compute market access by county for the year 1830 (before railroads) as in (Donaldson and Hornbeck, 2016) and average it to the state-level.

access—adopting more steam engines—grew from 1850 onward relative to other states. In contrast, states with high hydropower potential—adopting more electric motors—experienced relative reductions in average firm sizes. Importantly, as depicted in Figure 6(B), there were no differential trends in firm size based on hydropower potential prior to the electric motor's introduction between 1890 and 1900, providing evidence for the validity of the instrument.

Consistent with the exclusion restriction that coal access affects firm sizes only through steam engine adoption, I show that firm sizes in industries that used little power nationally in 1890 were affected less strongly by coal (see Figure A.8). Specifically, I estimate equation (19) for the years between 1860 and 1900, now including state $\times$ industry fixed effects using the 1860 to 1900 industry crosswalk in Appendix D.2.1. I estimate this equation separately for a set of "placebo" industries—industries in the bottom quartile of power usage in 1890—and the remaining "treated" industries.[37]

Similarly, hydropower potential only affected firm sizes in industries that used electric motors (see Figure A.9). To test this, I run the same procedure for the years between 1890 and 1939 using the crosswalks in Appendix D.2.2. For electric motors, I define placebo industries as those in the bottom quartile of the share of purchased electricity in overall fuel costs.

I then estimate the effect of steam engine and electric motor adoption on the firm size by using an instrumental variable approach. Specifically, I regress state-by-industry firm size growth on adoption, instrumented by hydropower potential and coal access. That is, I estimate

$$\ln\left(y_{is,1890}\right) - \ln\left(y_{is,1860}\right) = \alpha_1 + \beta_1 \text{STEAM}_{is,1890} + \boldsymbol{\lambda}_1' \mathbf{X}_{is} + \varepsilon_{is} \tag{20}$$

$$\ln\left(y_{is,1939}\right) - \ln\left(y_{is,1890}\right) = \alpha_2 + \beta_2 \text{ELECTRICITY}_{is,1939} + \boldsymbol{\lambda}_2' \mathbf{X}_{is} + \eta_{is} \tag{21}$$

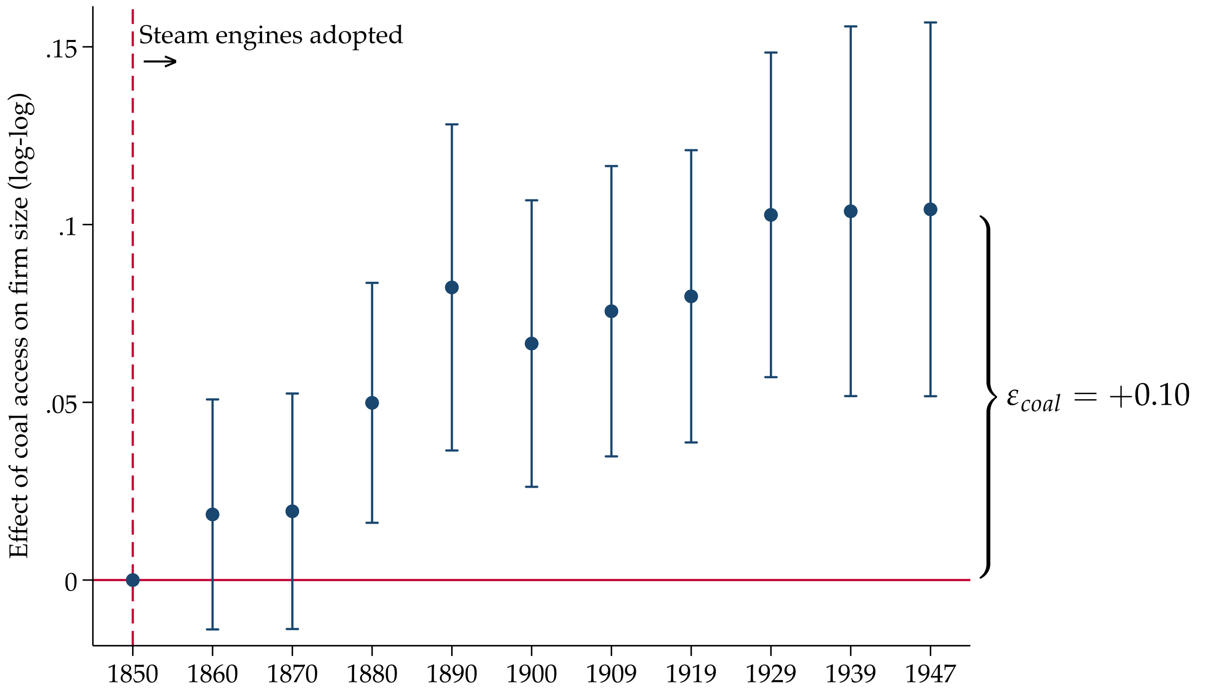
where $\text{STEAM}_{is,1890}$ and $\text{ELECTRICITY}_{is,1939}$ are steam engine horsepower in 1890 and megawatt hour of purchased electricity per worker in 1939. Both are transformed using the inverse hyperbolic sine function.

Table 4 shows the results of the instrumental variable regressions in equations (20) and (21). The estimate in the first column suggest that a 1% percent increase in steam engine use led to an increase in average firm size of about 1.1%. The second and third columns explore the sensitivity of the estimates to a change in the set of instruments. The coefficients remain remarkably stable even if only hydropower potential is used as an instrument for steam. While steam engines increased firm size, column four and five show that electric motor adoption decreased it with an elasticity of about -0.4.

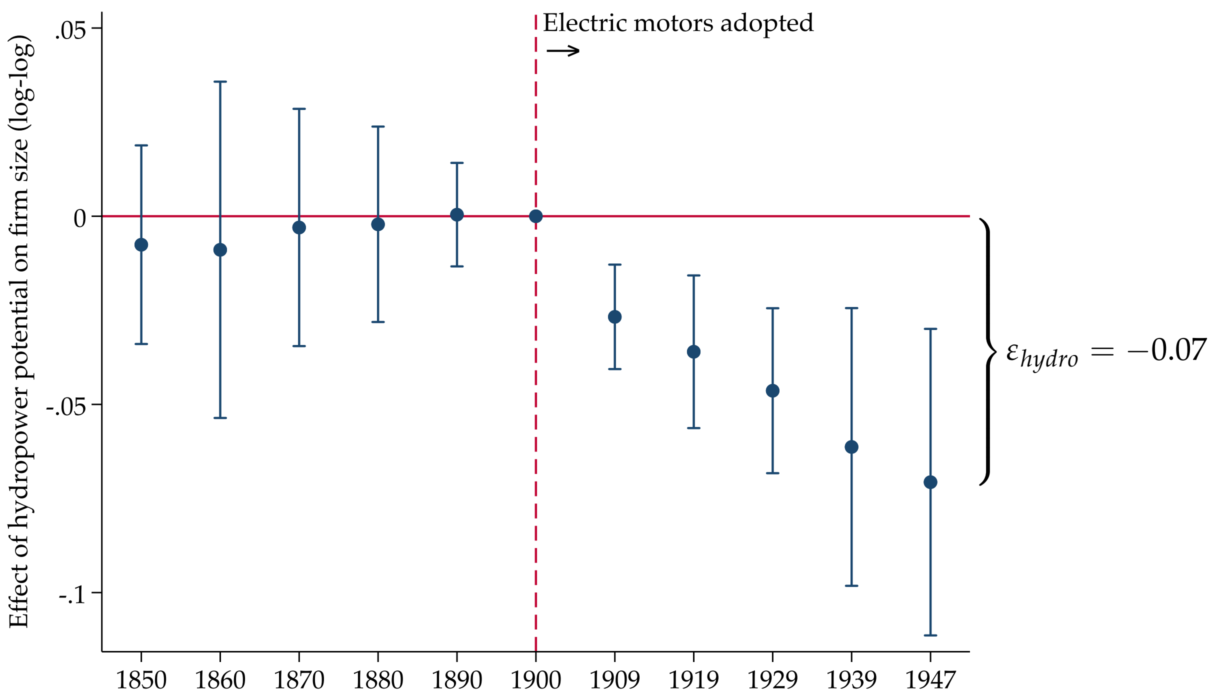
[37] Power usage is defined as the share of establishments reporting any power use.

FIGURE 6: Effects of coal access and hydropower potential on firm sizes

(A) Coal access



(B) Hydropower potential



Notes: Panel (A) and (B) of this figure show estimates of the reduced form effects of coal access and hydropower potential on firm sizes relative to the base year, accounting for industry and state fixed effects. Estimates in Panel (A) and (B) are jointly estimated in one specification (see equation (19) for the econometric specification), the only difference being the base year relative to which the estimates are estimated. Bars represent 95% confidence intervals. Standard errors are clustered at the state-level.

TABLE 4: The effect of steam engine and electric motor adoption on firm sizes

	$\Delta \ln(\text{firm size}_{is})$				
	1860-1890			1890-1940	
$\text{STEAM}_{is,1890}$	1.067***	1.058**	1.144**		
	(0.375)	(0.450)	(0.475)		
$\text{ELECTRICITY}_{is,1939}$				-0.392***	-0.415***
				(0.135)	(0.129)
Included instruments					
Coal access	X	X		X	
Hydropower potential	X		X	X	X
Observations	1900	1900	1900	1888	1888
Kleibergen-Paap F-stat.	26.3	42.9	15.3	18.7	31.7

Notes: This table shows the estimated effects of steam engine and electric motor adoption on the change in log firm size in a given state and industry. The explanatory variables are the inverse hyperbolic sine of steam engine horse power in 1890 and megawatt-hour of purchased electricity per worker in 1939. The adoption variables are instrumented with coal access and hydropower potential. Observations are weighted by the number of establishments in the base year. Standard errors in parentheses are clustered at the state-level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 The effect of scale-biased technical change on inequality

The previous section's results demonstrated that large-scale-biased technical change increases establishment sizes, while small-scale-biased technical change does the opposite. In this section, I study the second and third prediction of the theory.

The second prediction is that large-scale biased technical change increases the profit-to-wage ratio. I use data from the Census of Manufactures in the United States—and the same geographic variation as in the previous section—to show that steam engines increased the profit-wage ratio, while electric motors decreased it. Furthermore, I find that profit-wage ratios are, as suggested by the theory, a good proxy for economic inequality. Using data from the 1860 and 1870 US Census of Population, I find a remarkably strong correlation between profit-wage ratios and top wealth inequality ($\rho = 0.67$).

The third prediction of the theory is that steam engines and electric motors had opposite effects on income inequality. I use the Dutch panel data on local wealth inequality for this purpose. Local wealth inequality, besides being a measure of economic inequality in its own right, was strongly correlated with local income inequality (see Section 4). I show that wealth inequality rose in municipalities with high steam engine adoption, while it did not in those with high electric motor adoption. For identification of causal effects, I exploit that some municipalities were more exposed to the use of these technologies given their industry composition within manufacturing in 1816, long before the widespread adoption of either technology.

6.1 Profit-wage ratio

In the model in Section 2 people can either work or operate a firm alone. Under that assumption, the ratio between the average profits and the wage is a perfect measure of income inequality between workers and entrepreneurs. The free entry condition in equation (9) suggests that this ratio is proportional to the average firm size. Specifically, it implies

$$\ln\left(\frac{\bar{\pi}_{is}}{w_{is}}\right) = \text{constant} + \ln\left(\text{firm size}_{is}\right).$$

That is, the larger is the average firm size, the larger is the average profit of an establishment relative to the wage.

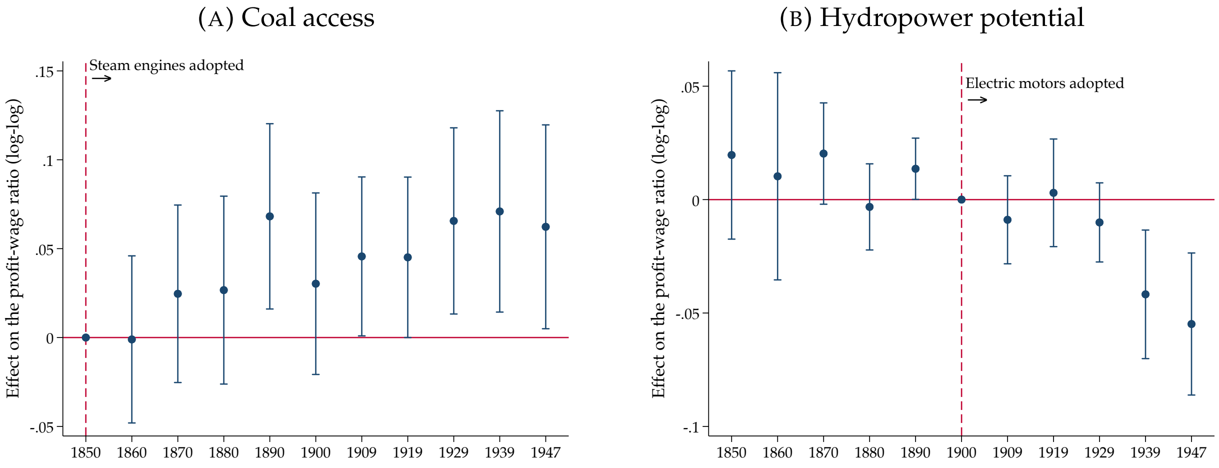
To test whether the free entry condition holds empirically, I estimate average profits and wages from the Census of Manufactures. Atack and Bateman (2008) estimate profits in the 1890 Census of Manufactures using information on output, wage costs, raw materials, the capital stock, and other expenses. Unfortunately, such detailed information is not available for all years. In particular, estimates of the capital stock were only reported up to 1919 and "miscellaneous expenses" only between 1890 and 1909. I therefore approximate average profits as output minus cost of raw materials and labor costs per establishment, which can be computed for all years. The correlation between this measure of average profits and the measure used by Atack and Bateman (2008) high: 0.75 in levels and 0.96 in logs.[38] I estimate the wage as the total wage bill divided by the total number of workers. For 1940, this measure of wage income corresponds closely with the average reported wage income by state and industry in the population census, with a correlation of 0.93 in levels and 0.94 in logs.

Figure A.10 shows that the relation between firm sizes and profit-wage ratios implied by the free entry condition holds strongly in the data ($\rho = 0.87$). Because the previous section showed that firm sizes were affected by steam engine and electric motor adoption, it is natural to test whether profit-wage ratios were too. I do this by re-estimating the reduced-form effect of coal access and hydropower potential on the profit-wage ratio. Specifically, I estimate equation (19) where the outcome variable y_{ist} is now the profit-wage ratio in industry i, state s, and year t.

I find that the reduced form effects of coal access and hydropower potential on profit-

[38]Specifically, for manufacturing censuses between 1890 and 1909, I compute profits as output minus cost of raw materials, labor costs, capital expenses, and miscellaneous expenses per establishment. I compute capital costs as 4.33 percent of the capital stock. Atack and Bateman (2008) assumed a different capital cost rates for plants (2%) than for equipment (6.67%); I choose 4.33 percent as the average of these two rates.

FIGURE 7: Effects of coal access and hydropower potential on the profit-wage ratio



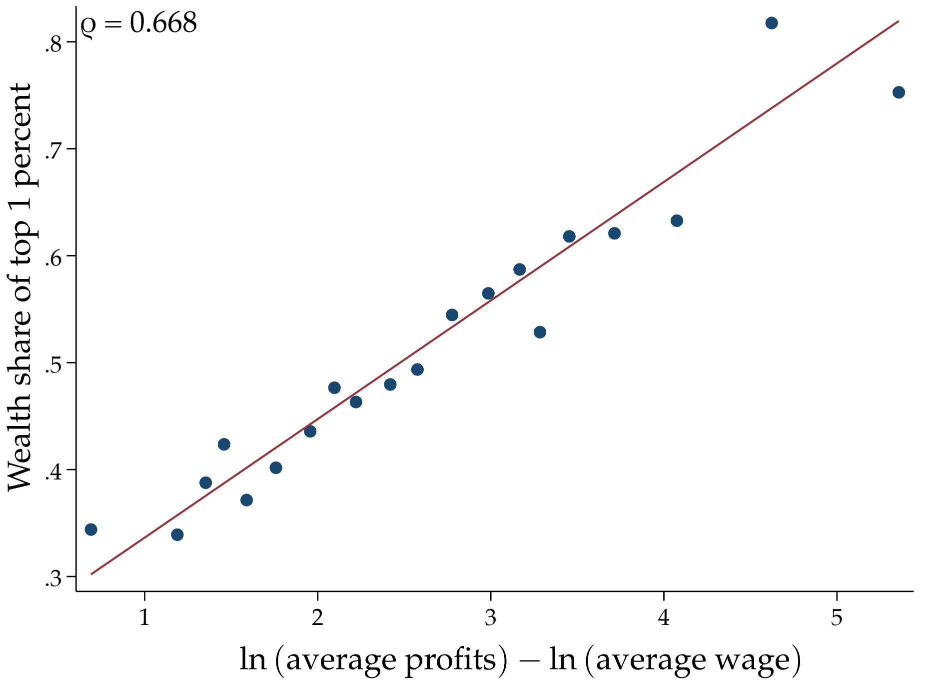
Notes: Panel (A) and (B) of this figure show estimates of the reduced form effects of coal access and hydropower potential on the ratio between average profits and average wages relative to the base year, accounting for industry and state fixed effects. Estimates in Panel (A) and (B) are jointly estimated in one specification (see equation (19) for the econometric specification), the only difference being the base year relative to which the estimates are estimated. Bars represent 95% confidence intervals. Standard errors are clustered at the state-level.

wage ratio are qualitatively and quantitatively similar to the effects on firm size (Figure 7). Therefore, steam engines increased the profit-wage ratio, while electric motors decreased it.

Under the model's assumptions, this finding is sufficient to conclude that large-scale-biased technical change—in the form of steam engines—increases income inequality between workers and entrepreneurs. When technical change is large-scale-biased, fewer entrepreneurs operate in equilibrium, and the surviving entrepreneurs capture a larger share of profits than they did before. Of course, in practice, firm ownership is less concentrated than it is in the model. People may own shares in one or multiple firms, reducing the relation between the firm size distribution and inequality between households quantitatively.

Using data on wealth from the Census of Population in 1860 and 1870, I show that profit-wage ratios strongly correlate with measures of wealth inequality. That is, I compute top wealth inequality by year, state and 1950 industry in the Census of Population. I compute profit-wage ratios in the Census of Manufactures by the same industry classification using newly created crosswalks. Figure 8 illustrates the strong relationship between wealth inequality (as measured by the share of wealth held by the top 1 percent) and the profit-wage ratio. This suggests that the profit-wage ratio is a good proxy for inequality.

FIGURE 8: The profit-wage ratio correlates strongly with wealth inequality



Notes: This figure shows a bin scatter visualizing the correlation of wealth inequality and the profit-wage ratio by state and industry. Each dot is an industry-state-year combination in 1860 and 1870. Wealth inequality is computed from the Census of Population. Average profits are approximated by dividing total output minus cost of raw materials and labor costs by the number of establishments. The wage rate is approximated by dividing total wage costs by employment.

The finding that steam engines increased profit-wage ratios and electric motors decreased them, coupled with the strong correlation between profit-wage ratios and inequality, suggests that steam engines increased inequality, while electric motors decreased it. To verify this using direct evidence, I use data from the Netherlands for which detailed information on wealth and income over a longer horizon is available.

6.2 Wealth and income inequality

I use the digitized Dutch inheritance tax data to create various measures of local inequality for the period between 1879 and 1927. With this dataset, I first study how wealth inequality evolved across municipalities with varying rates of adoption of steam engines and electric motors. I use wealth inequality, not income inequality as suggested by the theory, for reasons of data availability. Table 1 shows, however, that income and wealth inequality are strongly correlated. Furthermore, I also show the effects on income inequality for a subset of municipalities for which data is available.

As a measure adoption, I use the share of local manufacturing employment that works in establishments using these technologies. I measure this using the newly digitized 1930 Census of Dutch Companies. Particularly, I divide establishments in three groups: 1) those using prime movers run by energy generated in the plant (steam engines), 2) those only using prime movers run by purchased electricity (electric motors), and 3) those not using any prime movers at all. The measure of local steam engine adoption is the share of workers in the first type of establishments. Similarly, electric motor adoption is measured as the share of workers in the second group of establishments, so that:

$$\text{STEAM}_{1930,m} = \frac{\text{Employment in plants using prime movers run by generated energy in } m}{\text{Total employment in } m} \tag{22}$$

$$\text{ELECTR}_{1930,m} = \frac{\text{Employment in plants using prime movers run by purchased electricity in } m}{\text{Total employment in } m}. \tag{23}$$

The main specifications are as follows:

$$\text{INEQUALITY}_{mt} = \alpha_{1m} + \eta_{1t} + \sum_{k \in T \setminus \{1880\}} \beta_{1k} \left(\text{STEAM}_{1930,m} \times D_{tk}\right) + \varepsilon_{1,mt} \tag{24}$$

$$\text{INEQUALITY}_{mt} = \alpha_{2m} + \eta_{1t} + \sum_{k \in T \setminus \{1880\}} \beta_{2k} \left(\text{ELECTR}_{1930,m} \times D_{tk}\right) + \varepsilon_{2,mt} \tag{25}$$

where the subscript $t \in T = \{1880, 1890, 1900, 1910, 1920\}$ refers to the decade, m to the municipality and D_{tk} is a dummy that 1 if $t = k$ and 0 otherwise. INEQUALITY_{mt} is the share of wealth held by the top 1% of decedents with wealth. The coefficients β_{1k} and β_{2k} capture the association between steam engine and electric motor adoption and the change in wealth inequality from 1880, the reference year, to year k.

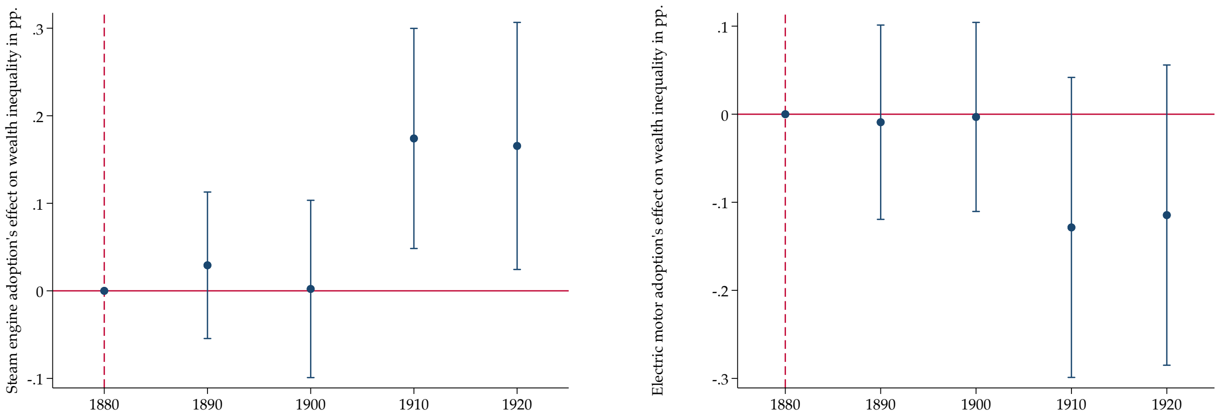
Figure 9(a) plots the coefficients of β_t for each decade relative to 1880. The coefficient suggest that a 1 percentage point increase in the share of employment exposed to steam engines leads to an increase in the top 1% wealth share of about 0.2 percentage points. This effect is statistically and economically significant. Local steam engine adoption varied strongly: around 10 percent of municipalities adopted no steam engines at all, while in some municipalities more than 90 percent of manufacturing employment was in steam-powered establishments. A one standard deviation increase in steam engine adoption (0.19) increases the top 1% wealth share by around 4 percentage points in 1920. The average top 1% wealth share across municipalities was 21 percent.

The estimated effects of electric motor adoption on wealth inequality are shown in Figure 9(b). The figure shows that electric motor adoption did not increase wealth inequality. If anything, it decreased it. However, the size of the estimated effect is smaller than for steam engines and not statistically significant on the 95% confidence level.

The coefficients in Figure 9 reflect the different evolution of wealth inequality in municipalities along one dimension of power usage (steam engine adoption or electric motor adoption). But when electric motor adoption is low, this could be because steam engine adoption was high or because there was little use of power of any sort. To directly

FIGURE 9: Steam engine adoption increased wealth inequality, electric motors did not

(A) Effect of steam engines (B) Effect of electric motors



Notes: This figure shows the estimated effects in percentage points of steam engine (in panel A) and electric motor adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The econometric specifications are detailed in equations (24) and (25). Observations are weighted by the number of individuals on which the inequality measure is based. Bars represent 95% confidence intervals.

compare the effect of steam engine adoption and electric motor adoption, I also estimate equation (24) while controlling for the share of employment in establishments that do not use any power in 1930 (similarly interacted with time dummies).[39] Since $\text{STEAM}_{1930,m}$, $\text{ELEC}_{1930,m}$, and $\text{NOPOWER}_{1930,m}$ sum to one by construction, the coefficient of interest in this regression reflects the increase in wealth inequality associated with a 1 percentage point increase in steam engine adoption and a 1 percentage point *decrease* in electric motor adoption. The results are shown in Figure A.11. It shows that holding total power usage constant, when more steam engines were used—and thus less electric motors—wealth inequality increased relative to 1880.

Instrumental variable analysis. The municipality-fixed effects specifications in equations (24) and (25) control for any time-invariant unobserved heterogeneity across municipalities. Time-varying heterogeneity is a potential remaining threat to causal interpretation of the coefficients in Figure 9. For instance, it is a priori conceivable that changes in local inequality between 1880 and 1920 also affected technology adoption, leading to reverse causality. To assess the quantitative importance of such threats to identification, I employ an instrumental variable strategy.

The identification strategy uses that the local industry composition in manufacturing in 1816 (see Section 4.2.3 for details on the data) is predictive of the local adoption rates

[39]That is, I estimate:

$$\text{INEQUALITY}_{mt} = \alpha_{3m} + \eta_{3t} + \sum_{k \in T \setminus \{1880\}} \left[\beta_{3k} \left(\text{STEAM}_{1930,m} \times D_{tk}\right) + \gamma_{3k} \left(\text{NOPOWER}_{1930,m} \times D_{tk}\right)\right] + \varepsilon_{3,mt}.$$

of steam engines and electric motors. I assign 2-digit ISIC industry codes to each industry in the manufacturing data in 1930 and 1816. Then, using the 1930 data, I compute industry i's adoption of steam engines and electric motor adoption. The adoption rates are computed analogously to $\text{STEAM}_{1930,m}$ and $\text{ELECTR}_{1930,m}$ in equations (22) and (23), only changing the unit of analysis from municipality m to industry i.

Table B.2 shows the adoption rates for each manufacturing industry. The textile industry, together with the much smaller beverage industry, was the largest adopter of steam engines, with half of employment in establishments using steam. On the other hand, the leather, apparel, tobacco, and printing industries almost did not use any steam engines at all. Using these adoption rates in 1930, I then compute the exposure to steam engines and electric motors in municipality m in 1816 as:

$$\text{STEAM\_EXP}_{1816,m} = \sum_{i \in I} \frac{\text{Employment in industry } i \text{ in } m \text{ in } 1816}{\text{Total employment in } m \text{ in } 1816} \times \text{STEAM}_{1930,i} \tag{26}$$

$$\text{ELECTR\_EXP}_{1816,m} = \sum_{i \in I} \frac{\text{Employment in industry } i \text{ in } m \text{ in } 1816}{\text{Total employment in } m \text{ in } 1816} \times \text{ELECTR}_{1930,i}. \tag{27}$$

The exposure measure is a strong predictor of actual adoption in 1930 (see Table B.3 for the correlation).

I estimate the "reduced form" of the instrumental variable analysis equivalently to equations (24) and (25) except that the actual adoption rates are changed for the predicted rates in equations (26) and (27). That is, I estimate how wealth inequality evolved between 1880 and 1927 across municipalities that were more or less exposed to the two technologies.

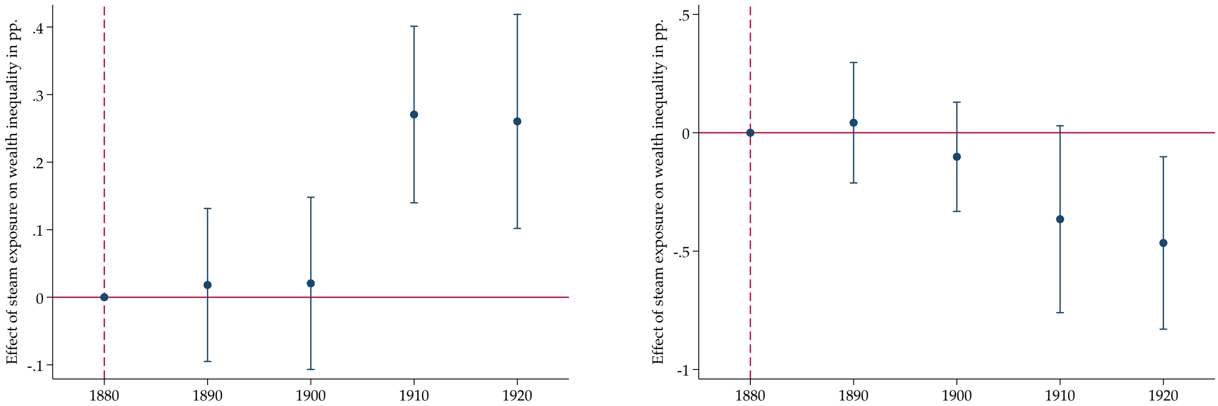
Figure 10 shows that places more exposed to steam engines became more unequal, while places more exposed to electric motors became more equal, providing further evidence that steam engines and electric motors had a causal effect on inequality as predicted by the theory.

Further evidence using income data. The model of scale-biased technical change proposed in this paper relates technical change to income inequality. Since wealth inequality is strongly correlated with income inequality (see Table 1) and consistent time-series data is only available for local wealth inequality, I used wealth inequality for the main analysis. Here, I assess the robustness of the results to studying income inequality instead with the more limited data on the income distribution that is available.

As described in Section 4.2.1, I uncovered and digitized data on the income distribution in 1883 for 87 (mostly large) municipalities. Also, for 1946 income distributions are available for each municipality (see Section 4.2.2 for details). From there, I compute the percentage point change in income inequality (as measured by the income share of the

FIGURE 10: Steam engine adoption increased wealth inequality, electric motors did not

(A) Effect of steam engines (B) Effect of electric motors



Notes: This figure shows the estimated effects in percentage points of pre-industrial exposure to steam engine (in panel A) and electric motor adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The instrumental variable is exposure to the respective technology which is computed on the basis of the local industry composition in 1816 and adoption rates by industry in 1930. Observations are weighted by the number of individuals on which the inequality measure is based. Bars represent 95% confidence intervals.

top percentile) between 1946 and 1883 as

$$\Delta\text{INC\_INEQUALITY}_{1946,1883} = \text{INC\_INEQUALITY}_{1946} - \text{INC\_INEQUALITY}_{1883}$$

I then regress the growth in income inequality on $\text{STEAM}_{1930,m}$ and $\text{ELECTR}_{1930,m}$ defined in equations (22) and (23). I do this using ordinary least squares as well as using the respective instrumental variables.

Table 5 shows the results. It verifies the results obtained using wealth inequality as the dependent variable: steam engine adoption increased inequality and electric motors had a marginal negative effect.

7 Who gains from large-scale-biased technical change?

Section 6 showed that steam engine adoption led to increased inequality, while electric motor adoption did not. The last question is then: how did steam engines increase inequality? In this section, I zoom in to Enschede—the major Dutch textile city—to understand *who* was capturing the rents from large-scale-biased technical change. I find that the increased inequality was predominantly due to the textile factory owners amassing wealth at a much higher rate than other households. This finding confirms the prediction of the theory of scale-biased technical change that the concentration of business income, not of wages, was the key driver of inequality.

TABLE 5: The effect of steam engine and electric motor adoption on the change in income inequality (1946 - 1883)

	ΔINC_INEQUALITY$_{1946,1883}$			
	OLS		IV	
STEAM$_{1930,m}$	0.118**		0.353***	
	(0.052)		(0.120)	
ELECTRICITY$_{1930,m}$		-0.072		-0.876*
		(0.062)		(0.458)
Observations	82	82	78	78
C-D Wald F-stat			24.549	4.895

Notes: Standard errors in parentheses. * p< 0.10, ** p< 0.05, *** p< 0.01. This table shows the estimated effects of steam engine and electric motor adoption on the change of within-municipality top income inequality between 1946 and 1883. Exposure is computed on the basis of the local industry composition in 1816 and adoption rates by industry in 1930. Observations are weighted by the number of individuals on which the inequality measure in 1946 is based.

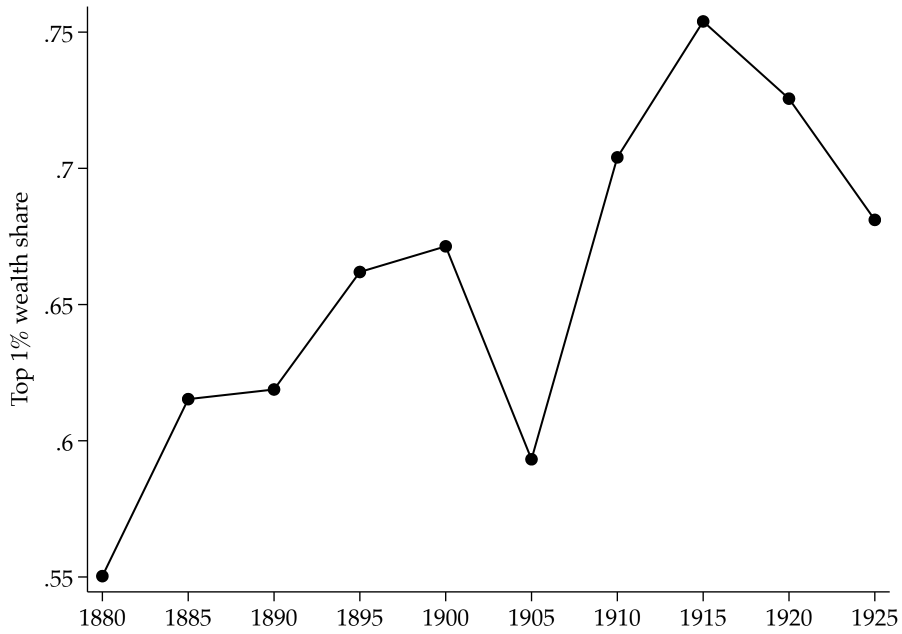
I selected Enschede for this case study because, being a major textile producer, it heavily depended on steam engines and witnessed a strong increase in wealth inequality. Figure 11 charts the wealth share of the top 1% over time. Another advantage of studying Enschede is that the history of its textile industry is well documented and the identities of the factory owners are known.

The foundations of the textile industry in Twente, the region around Enschede, already had been laid in the 16th century. At the time, many Flemish entrepreneurs had their linen woven in Twente, due to its attractive position between Amsterdam and North Germany (Schot et al., 2003). In 1728, Enschede had acquired the right to produce *bombazijn*, a textile woven from a combination of linen and cotton threads, and it became the largest producer of this textile halfway into the 18th century (Stroink, 1962). By 1750, 40% of the labor force was occupied in the textile industry. Since textile manufacturing was the industry most exposed to steam engines (see Table B.2), Enschede's rate of steam engine adoption was among the highest in the country.

The theory predicts that large-scale-biased technical change impacts inequality through the profits accrued by entrepreneurs. Therefore, one should expect the see that wealth inequality is driven mostly by them too. To test this prediction, I compute the average wealth at different parts of the wealth distribution separately on a sample including and excluding textile owners. Specifically, I exclude people from the sample if they belong to one of 22 families that are considered the "core" and "inner circle" of textile owners by Willink (2015). I use the last name as a proxy for being part of one of the families.[40]

[40]The last names are: Blijdenstein, Ten Cate, Van Heek, Jannink, Ter Kuile, Scholten, Stork, Van Delden, Elderink, Van Gelderen, Gelderman, Hofkes, Ter Horst, Jordaan, Ledeboer, Menko, De Monchy, Palthe,

FIGURE 11: Top 1% wealth share in Enschede, Netherlands

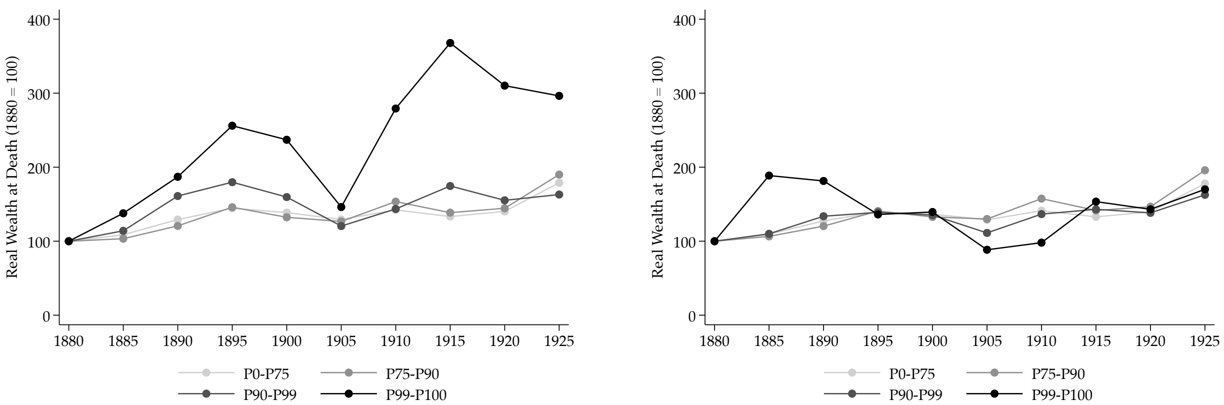


Notes: This figure shows the share of wealth held by the top 1% of decedents aged 20 and over in Enschede between 1879 and 1919. For each year, wealth inequality is computed from the sample of decedents in a 10-year window around it.

FIGURE 12: Wealth inequality is driven by entrepreneurs adopting steam engines

(A) Including textile owners

(B) Excluding textile owners



Notes: This figure shows the evolution of the top 1 percent wealth share in Enschede when this measure is estimated on the full population (in panel A) and when measured on the sample excluding textile owners (in panel B). For each year, wealth inequality is computed from the sample of decedents in a 10-year window around it.

Figure 12(A) shows the mean wealth at death for different percentile groups. It illustrates that wealth inequality increased through a divergence of the top 1 percent from the rest of the distribution. However, panel (B) indicates that wealth inequality among everyone except the textile families Figure 12(B) did not go up. These pattern indicate the importance of studying inequality in the overall population, not only among wage earners. If technical change is scale-biased, it will most strongly affect the income of top business owners relative to the rest of the distribution.

8 Conclusion

In this paper, I highlight a new channel through which technical change can affect inequality: scale bias. I large-scale-biased technical change as technical change that it increases the relative productivity of large firms. I show that technical change can be large-scale-biased if it increases fixed costs sufficiently. Only large firms would opt to incur the fixed cost to reduce marginal cost, while smaller firms keep using the existing technology or even go out of business. As a result, profits accrue to a smaller set of firms. With fewer and larger firms, top entrepreneurs are capturing a larger share of the profits, pushing top income inequality up.

I showed that the adoption of steam engines and electric motors offer a unique opportunity to test the theory: the fixed cost of the technologies varied strongly, while the technologies are otherwise similar, the fixed costs of steam engines were an order of magnitude larger. I then tested the theoretical predictions on the effects of steam engine adoption (large-scale-biased) and electric motor adoption (small-scale-biased). I found that the effects of these technologies were in line with the theory's prediction: steam engines increased firm sizes and inequality while electric motors reduced it.

While this research shows that entrepreneurs and their incomes are key for shaping and understanding inequality, existing work primarily focuses on the impact of technical change on wage inequality, not overall income inequality.[41] The effect of technical change on the distribution of business income and inequality between workers and entrepreneurs has, to the best of my knowledge, so far not been studied. This is an important omission, because business income is a large source of income, especially at the top of the distribution. In the US, more than half of total income for the top 0.1 percentile is business income (Smith et al., 2019). Similarly, 81 percent of individuals in the top 1 percent of the wealth distribution was a business owner or self-employed (Cagetti and

Salomonson, Spanjaard, Stroink, Willink Cromhoff, Jannink, Gelderman, Heek, Ledeboer, Kuile, and Scholten.

[41] As a notable exception, Moll et al. (2022) recently expanded the scope beyond wage inequality by studying automation's effect on income (and wealth) derived from both wages and capital: by raising the returns to capital, automation increases income and wealth inequality.

De Nardi, 2006). Changes in the distribution of business income can therefore strongly affect top income and wealth inequality.

The quantitative importance of scale bias for inequality depends on the concentration of business ownership. If households hold a perfectly diversified portfolio of firms, the distribution of profits across firms does not determine the distribution of income. The model assumes the other extreme: that a household can only own one firm. In practice, business ownership tends to be strongly concentrated even today. In the US, "pass-through" businesses account for 51 percent of all business income in 2013 (Nelson, 2016).[42] The typical such business is owned by one to three people (Smith et al., 2019) and 69% of its income accrues to the top 1% (Cooper et al., 2016). The great bulk of the remaining income earned by "C-corporations", businesses who are taxed at the entity level, is earned by a small share of publicly traded firms (Clarke and Kopczuk, 2017). While ownership of publicly traded firms is less concentrated, it is not as diffuse as commonly thought.[43] Even for firms in the Fortune 500, the 500 largest US firms by revenue, founding families alone accounted for 18 percent of outstanding equity between 1992 and 1999 (Anderson and Reeb, 2003).[44] This empirical reality means that scale bias—through its effect on the firm size distribution—still has important implications for inequality.

Trends in the last three decades are consistent with the presence of on-going scale-biased technical change. All three theoretical implications of large-scale-biased technical change are observed in the data. First, firm sizes and concentration are increasing and entrepreneurship is in decline (Autor et al., 2017, 2020; Salgado, 2020; Jiang and Sohail, 2023; Kwon et al., 2023). A large and growing theoretical literature relates these patterns to technical change, specifically the growing importance of scale advantages arising from intangible capital and information technology (Brynjolfsson et al., 2008; De Ridder, 2023; Hsieh and Rossi-Hansberg, 2023; Kwon et al., 2023; Lashkari et al., 2023). Unger (2022) shows that specifically customized software (large fixed adoption cost) is highly skewed to large firms, while pre-packaged software (low fixed adoption cost) is used by small and large firms alike. Second, top income and wealth inequality has increased sharply. For example, between 1980 and 2014, the United States experienced 21% growth in the incomes of the bottom half of the distribution, while the top 10 percent saw their incomes more than double during the same period (Piketty et al., 2018). Third, since the 1990s, business income—not wage income—accounts for the largest part of the rise of top incomes in the United States (Smith et al., 2019, Figure IX). This paper provides a unified

[42] Pass-through businesses are businesses that are not subject to corporate tax and whose income instead "pass through" to their owners to be taxed under individual income tax. Specifically, they comprise S-corporations, sole proprietorships, and partnerships.

[43] For instance, among a random sample of US publicly traded firms, 96 percent had shareholders that own at least 5% of the stock, and in 53 percent of firms, the largest shareholder is a family (Holderness, 2009).

[44] Peter (2021) shows evidence on concentrated ownership of European firms.

framework to understand all these trends.

This paper leaves several important questions for future research. First, in the stylized model presented, technical change and its direction is *exogenous*. While I think this assumption is reasonable in the case of steam engine and electric motor adoption in the US and the Netherlands, modelling technical change as the outcome of a directed research effort could be very useful. A concentrated firm size distribution may further incentivize scale-biased technical change, similar to a model where the distribution of skill across workers can induce innovation in technologies that complement the abundant factor (Acemoglu, 2002). Another important simplification of the model is that while technology adoption matters for inequality, inequality does not matter for technology adoption. A useful, more quantitative, model could include risk aversion or liquidity constraints. In such models, entrepreneurship is intuitively skewed towards high wealth individuals because they are more equipped to take risk (in case of risk aversion) and can afford larger up-front investments (in case of liquidity constraints) (Quadrini, 2000; Cagetti and De Nardi, 2006; Buera and Shin, 2013). High fixed cost technologies may further reduce entry of low-wealth individuals and can thus worsen aggregate productivity. Lastly, the on-going development of artificial intelligence technologies raises important questions on its distributional effects. Research shows that large firms tended to be the early adopters of the technology (McElheran et al., 2023). More research into the cost structure of these technologies is necessary to understand whether this will remain the case as the technologies mature.

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