Scale-Biased Technical Change and Inequality*

Hugo Reichardt†

August 27, 2025

Abstract

This paper studies the distributional effects of two general purpose technologies: steam and electric power. Using newly collected historical data from the US and the Netherlands and plausibly exogenous variation in adoption, I show that steam power increased firm sizes and top income and wealth inequality, while electric power had opposite effects. These effects reveal a key link between technology and inequality: scale bias—the extent to which technical change increases returns to scale. Steam entailed high fixed costs and was mainly adopted by large firms, whereas electricity was small-scale-biased. A model of occupational and technological choice illustrates how large-scale-biased technical change raises top income inequality by concentrating entrepreneurial income.

*I am grateful to my advisors Ethan Ilzetzki, Camille Landais, Ben Moll, and Ricardo Reis for their continued guidance and support. I also thank Lukas Althoff, Sina Ates, Marco Bellifemine, Leah Boustan, Jeremiah Dittmar, Matthias Doepke, Wouter den Haan, Jonathon Hazell, Stephen Machin, Robert Margo, Jane Olmstead-Rumsey, Maarten de Ridder, Richard Rogerson, Caterina Soto Vieira, and numerous seminar participants for insightful comments. I thank Jan Luiten van Zanden for kindly sharing data. I am furthermore indebted to many employees of archives in the Netherlands, in particular those at Brabants Historisch Informatie Centrum, Drents Archief, Gelders Archief, Historisch Centrum Overijssel, the National Archives, Noord-Hollands Archief, Statistics Netherlands and Zeeuws Archief. This work was financially supported by The Suntory and Toyota International Centres for Economics and Related Disciplines and the Centre for Macroeconomics at the London School of Economics.

†Centre de Recerca en Economia Internacional (CREI). hreichardt@crei.cat

1 Introduction

Income and wealth inequality have 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 frequently cited explanation for increases in wage inequality (Katz and Murphy, 1992; Krusell et al., 2000; Violante, 2008; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2022). But wages are not the only source of income. For those at the top of the distribution, business income is the dominant source of income, most of it accruing to entrepreneurs who own large shares of their own business (e.g., Smith et al., 2019; Kopczuk and Zwick, 2020; Atkeson and Irie, 2022).

This paper studies the causal effects of two of the most important general purpose technologies in history—steam and electric power—and lays out how scale-biased technical change affects inequality through entrepreneurial income. Scale bias is the extent to which technical change increases the returns to scale. Due to strong differences in fixed costs, steam was large-scale-biased, while purchased electric power was small-scale-biased. As a result, I find that steam and electric power had different effects. First, steam power increased establishment sizes and decreased entrepreneurship, while electric power spurred small-scale entrepreneurship. Second, as steam power increased the relative productivity of entrepreneurs with large-scale businesses, their profits rose relative to wages, while electric power disproportionately increased wages. Third, the concentration of business income induced by the adoption of steam power increased top income and wealth inequality. Electric power reduced inequality. I provide evidence that the distributional effects are driven by business income.

I develop a tractable general equilibrium framework that rationalizes these findings. In the model, households choose to be an entrepreneur or work for wages depending on their productivity. Entrepreneurs choose a technology—defined by their marginal and fixed costs—and hire workers. I use the model to study the effects of the introduction of different types of technologies, formally define scale bias, and provide the technological conditions that lead to large- and small-scale-biased technical change. I show that large-scale-biased technical change lowers entrepreneurship rates and thus leads to larger firms on average. With fewer and larger firms, top entrepreneurs are capturing a larger share of the profits, increasing top income inequality.

The case of steam and electric power provides a unique opportunity to study how scale affects inequality. First, their adoption was sufficiently widespread and transformative to have a meaningful impact on the overall economy. Second, their adoption is well documented. Third, they were similar in their capability and purpose. Fourth, their cost structure meant that they induced technical change with strongly different scale bias.[1] The annualized cost of a 50-horsepower (hp) steam engine was roughly equivalent to three to four yearly unskilled workers. In contrast, the fixed cost of running an electric motor by purchased electricity of comparable capacity was negligible. As a result, adoption patterns differed across firm sizes: large establishments were more likely to use steam power, while electric motors powered by purchased electricity were adopted more by smaller establishments.

The power source—self-generated or purchased—was the key technological feature underlying the marginal vs. fixed cost trade-off in steam and electric power. Factories using electricity had two options: purchase electricity from a power plant or generate it on-site, typically using steam engines. Self-generated energy entailed higher fixed but lower marginal costs. Importantly, the energy source can be conceptually and empirically distinguished from the tools used to convert this energy into motion such as electric motors. Goldin and Katz (1998) show that *electric motors* (not electric power) increased wage inequality by facilitating a shift to continuous process and batch methods. To distinguish the role of scale from skill, I only use variation in the relative cost of using self-generated and purchased electricity, not in the cost of using electric motors. Crucially, the argument that electric motors favored skilled workers applies regardless of whether it is driven by purchased or self-generated electricity.

A first empirical contribution of this paper is a large new database on adoption of the two technologies, firm sizes, and inequality collected and digitized from various archival sources from the United States and the Netherlands. To study the effects of scale-biased technical change on inequality, I collected unique microdata on wealth from the Netherlands over the course of industrialization. I digitized these handwritten data using state-of-the-art computer vision technologies. The resulting data include information on wealth of hundreds of thousands of decedents between 1878 and 1927 in five major provinces in

[1] Steam became the dominant power source in manufacturing in the second half of the 19th century. Electric power began to be widely used around 1900, and in the first half of the 20th century purchased electricity and steam power (used directly or to self-generate electricity) were substitutes for each other in providing power to the factory.

the Netherlands. To my knowledge, it is the largest such dataset in any country covering the Industrial Revolution (which happened later in the Netherlands) both in size and geographic scope. For the US, I draw on the Census of Manufactures that provides information such as the number of establishments, employment, value added, profits, wages, and power adoption by state and industry. I digitize and compile these data for each decade from 1850 to 1950.

The first main result is that steam power caused establishment sizes to increase, while electric power decreased them. To identify these effects, I use variation in natural resources across the United States that affected the costs of using the technologies. Specifically, I use access to historical coal resources and hydropower potential as instruments for steam power and electricity adoption, respectively.[2] I find that high-coal access states experienced a growth in establishment sizes relative to 1850, when steam started to be adopted in US manufacturing. In contrast, after the introduction of electric power around 1900, high-hydropower states experienced a decrease in establishment sizes (while no effect is estimated before 1900). Using this variation, I estimate the effect of a 1% increase in steam capacity in horsepower to be a 1.1% increase in firm size. For electric power, I estimate this elasticity to be -0.4. In support of the exclusion restriction, I find that the effects of hydropower and coal resources were limited to industries that used power. Lastly, I show that the estimated effects are almost identical when performing the analysis on the city-industry level (rather than state-industry).

Second, I find that large-scale-biased technological change like steam power increases the ratio of average profits to wages, whereas small-scale-biased change like electric power disproportionately increases wages. The effects are quantitatively similar to those on the firm size, as predicted by the theory. To estimate these effects on the profit-wage ratio, I use the same methodology as used for the effects on firm sizes.[3] Through the lens of the model, these effects capture both a selection effect, that the remaining entrepreneurs are on average more productive, and a causal effect, that profits of top entrepreneurs increase more than workers' wages.

I then provide evidence that the profit distribution among firms matters for

[2] Various authors have used hydropower potential as an instrument for electricity adoption (e.g., Leknes and Modalsli, 2020; Gaggl et al., 2021). Data to construct the instruments are from the Coal Resources Data System (coal resources) and Young (1964) (hydropower potential).

[3] I compute profits in the Census of Manufactures using data on output, raw material costs, labor costs, capital stock, and other expenses.

inequality among households. How much profits are reflected in the personal income distribution depends on the concentration of firm ownership. Even today, entrepreneurs hold significant shares of their own businesses (Peter, 2021). Concentration tends to be near perfect in private businesses (e.g., Smith et al., 2019) and even the average Fortune 500 firm is 18 percent owned by its founding family (Anderson and Reeb, 2003).[4] Correspondingly, I find that profits are highly predictive of inequality. In 1870, US states and industries with higher profit-wage ratios (and larger firm sizes) were also characterized by significantly more inequality between entrepreneurs and workers and higher top wealth shares, with correlations around 0.7.[5] The effects on profit-wage ratios, coupled with the correlation between profit-wage ratios and inequality, already offer evidence that scale-biased technical change affects inequality in the way predicted by the theory. To test the effects on inequality directly, I turn to the newly compiled database on wealth during Dutch industrialization.

Using the new Dutch wealth data, I establish the third and last main result: that steam and electric power had opposite effects on top wealth inequality. At the municipal level, steam power increased wealth inequality, while electric power decreased it. For identification in this context, I exploit a municipality's exposure to the technologies based on their industrial composition in 1816, long before industrialization.[6] The estimated effects on wealth inequality are sizable: a one standard deviation increase in steam power adoption increased the top 1% wealth share by around 4 p.p. (relative to an average of 21 percent).

Related literature. First, this paper contributes to our understanding of technologies' effect on income and wealth inequality by empirical evidence and theory on the role of scale-biased technical change. The theory is most directly connected to the Schumpeterian model of top income inequality (Jones and Kim, 2018). In this model, the Pareto tail of income is a function of entrepreneurs' return to effort. This paper pairs the theory of scale bias with a study of the causal effects of two general purpose technologies to show how technical change affects the returns to entrepreneurial talent, and hence, top income inequality.

I also contribute causal evidence to a literature that relates increased firm

[4]The founding family of Walmart, the largest company in the world by revenue, owns 45% of its shares (as estimated by Forbes). Goldsmith et al. (1940) covers the historical case.

[5]This result is obtained by combining state-industry data from the Census of Manufactures with microdata on wealth in the US 1870 Census, the last census that recorded wealth.

[6]Since the Netherlands had neither hydropower nor (much) coal, the same instrument can not be used there.

concentration to a move toward high fixed cost technologies (e.g., Poschke, 2018; Hsieh and Rossi-Hansberg, 2023; Kwon et al., 2024). Intangible inputs such as software have been posited as an example of this (Brynjolfsson et al., 2008; Lashkari et al., 2024; De Ridder, 2024). Since most modern technologies differ in many ways other than their cost structure, it is difficult to isolate the role of specific technological characteristics. This paper studies two technologies that were otherwise similar, allowing to distinguish the role of fixed costs.

This paper also relates to a large literature on the economic history of the adoption of steam and electric power. It specifically relates to a literature on the differential costs and adoption of the two technologies in manufacturing (for steam power, see, e.g., Atack (1979); Hunter (1979, 1985); Atack et al. (2008); for electric power, see, e.g., Du Boff (1967, 1979)). Hornbeck et al. (2024) show that the adoption of steam was hampered by lock-in effects of water-powered incumbents. This paper also relates to the literature on the economic effects of the two technologies (for steam power, see, e.g., Kim (2005); Atack et al. (2019); for electric power, see, e.g., Fiszbein et al. (2020)).[7] This paper focuses on the distributional effects of the adoption of steam and electric power in manufacturing through the lens of the theory of scale-biased technical change.

Lastly, this paper speaks to the patterns of inequality during industrialization. Kuznets (1955) argued that income inequality rises in the early stage of industrialization due to a shift from agricultural to the more unequal manufacturing sector. Kuznets (1955) 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 enterprises.” This paper provides a theoretical foundation and empirical evidence for that argument.

2 The Scale Bias of Steam and Electric Power

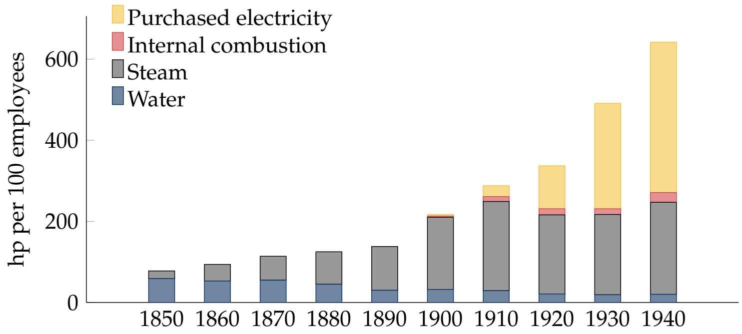
This section provides a brief history of power use and lays out the relevant technological and economic features of steam and electric power.

Figure 1 illustrates the history of power use in US manufacturing by type of “primary power”.[8] In the second half of the 19th century, steam power grad-

[7]Further, it contributes to a literature on the effects of electrification more generally such as Vidart (2024) on the rise of female labor force participation.

[8]The prime mover refers to the first machine in the power chain. For example, if electricity

FIGURE 1: The evolution of power in the United States



Notes: Purchased electricity refers to motors driven by purchased electricity. Those driven by self-generated energy are counted under steam. *Sources*: For steam engines and waterwheels up to 1860: (Atack, 1979) (number) and (Atack et al., 1980, p. 285) (average size); for employment up to 1860, Census of Manufactures 1860; for all other data: Census of Manufactures 1939.

ually replaced waterwheels. Electricity began to be adopted around 1900. By 1930, purchased electricity had become the dominant source of power. While steam remained an important source of power, it was increasingly used to generate electricity rather than to drive machinery directly: by 1940, two-thirds of non-electric power was driving generators (Du Boff, 1979).[9]

The evolution in power use was not scale-neutral because steam power generation exhibits steep economies of scale. Figure 2 shows the cost per kilowatt-hour (kWh) by total energy requirement.[10] The average cost per kWh of a 5 hp engine was more than four times that of a 100 hp engine. There are two main reasons for these economies of scale. First, the fixed labor costs of operating the engine increased much less than proportionally with capacity. Second, the energy efficiency of larger engines was significantly greater (see also Atack, 1979; Devine, 1983).

The costs of steam power were, besides scale-dependent, sizeable. For instance, the annualized cost of purchase, renewal, maintenance, operation, and fuel of a 50 hp steam engine was around \$2900 (in 1874\$) (Emery, 1883), more than seven times the yearly unskilled wage. In other words, from the cost of running an average-sized steam engine, one could hire seven workers.[11]

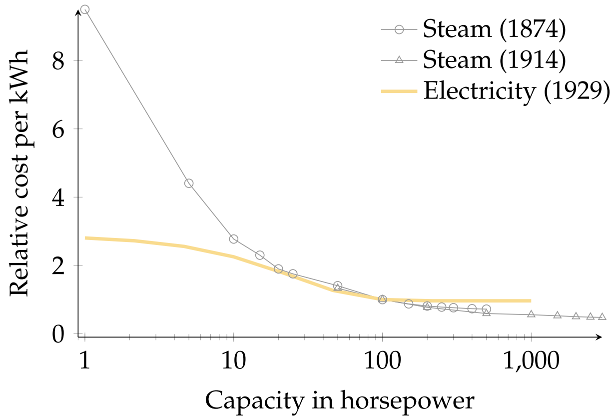
is purchased, the electric motor is the prime mover. If electricity is generated on-site by a steam engine, the engine is the prime mover and the electric motor is secondary.

[9]Adoption patterns in the Netherlands were similar, although steam power was adopted considerably later there than in the US (Blanken and Lintsen, 1981).

[10]The steam cost data are derived from Emery (1883) and Saitzew (1914). The electricity price schedule is estimated using microdata from the 1929 Census of Manufactures digitized by Vickers and Ziebarth (2018). In Appendix E, I detail the sources and computations.

[11]Based on the assumption that the worker and the steam engine operate 309 days per year,

FIGURE 2: Cost of steam and electric power by capacity (100hp = 1)



Notes: Steam cost data are derived from Emery (1883); Saitzew (1914) for 1874 and 1914, resp. Electricity prices at different levels of use are computed from micro-samples of the 1929 Census of Manufactures (Vickers and Ziebarth, 2018). Appendix E contains further details.

The cost of using purchased electricity was considerably less sensitive to scale. Figure 2 shows that the scale-gradient was considerably smaller than for steam.[12] As electricity became cheaper, the level of energy use at which purchased electricity could compete with self-generation increased. As the break-even point increased, the power cost advantage of large establishments decreased, earning small establishments "a new lease on life" (Du Boff, 1967). Based on the data underlying Figure 2 and the contemporaneous cost of coal, electricity, and labor, I estimate the break-even point to be between 50 and 100 hp in the Netherlands in 1930.

The adoption rates by plant size reflect the considerations above. Figure A.1a shows that large plants were more likely to adopt steam engines, as documented before by Atack et al. (2008). In contrast, Figure A.1b indicates that electric power was almost uniformly adopted across the establishment size distribution. However, small firms tended to rely solely on purchased electricity while large firms were more likely to use self-generated electricity.

3 A Model of Scale-Biased Technical Change

In this section, I introduce a tractable general equilibrium model of occupational and technological choice. Households choose between working for wages

10 hours per day. The daily wage of an unskilled worker in 1874 was $1.29 (Abbott, 1905).

[12]The reason it was not completely independent of scale is that utilities tended to offer some discount to large consumers (see Appendix E for details).

or being an entrepreneur. Entrepreneurs choose which production technology, defined by their marginal and fixed costs, to use. The model is simple and its main innovation lies in the introduction of occupational and technological choice and the analysis of the impact of technological changes on these choices. The framework is otherwise similar to Melitz (2003). I define scale-biased technical change formally. The model predicts that large-scale-biased technical change such as steam power increases firm sizes, inequality between workers and entrepreneurs, and overall top income inequality. Small-scale-biased technical change like electric power has the opposite effects.

3.1 Setup

There is a continuum of households with unit measure who differ in their entrepreneurial productivity ψ. I assume that ψ has a density function $f(\cdot)$ with semi-infinite support on $\mathbb{R}^+$, i.e., $\{\psi \mid f(\psi) > 0\} = [\psi_m, \infty)$ for some $\psi_m \geq 0$.[13]

In a first stage, each household decides whether to be a worker or an entrepreneur (Lucas, 1978). As an entrepreneur their profits $\pi(\psi)$ depend on their entrepreneurial productivity. As a worker, they earn the equilibrium wage w.

An entrepreneur chooses, in a second stage, from an exogenous set of available production technologies $T \equiv \{t_1, \ldots, t_J\}$. 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 labor cost.[14] Given technology t_j and entrepreneurial productivity ψ, the production function is $y_j(l \mid \psi) = \frac{\psi \max\{l-\kappa_j, 0\}}{\alpha_j}$ where l is total labor input. T does not contain trivially dominated technologies: if $t_j, t_k \in T$ and $\alpha_j < \alpha_k$, then $\kappa_j > \kappa_k$.[15] Technologies are ordered by their fixed costs: $\kappa_1 < \cdots < \kappa_J$.

Finally, in stage three, after adopting technology j, entrepreneurs compete monopolistically and maximize profits given their productivity ψ, yielding $\pi_j(\psi)$. Households substitute the goods produced by the entrepreneurs with constant elasticity of substitution σ (Dixit and Stiglitz, 1977; Melitz, 2003). That is, household utility is increasing in $Y^{\frac{\sigma-1}{\sigma}} \equiv \int_{\psi \in \Psi} y(\psi)^{\frac{\sigma-1}{\sigma}} d\psi$. The demand for good ψ is thus $y(\psi) = YP^{\sigma} p(\psi)^{-\sigma}$ where $p(\psi)$ is the price of good ψ and $P^{1-\sigma} \equiv$

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

[14] 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 and do not consider occupational choice.

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

$\int_{\psi \in \Psi} p(\psi)^{1-\sigma} d\psi$. Hereafter, I use the normalization that $P = 1$.

In section 3.2, I characterize optimal behavior by backward induction.

3.2 The household's problem

***Stage 3:* Profit maximization.** Profit maximization conditional on technology j and productivity ψ yields the standard constant-markup pricing rule $p_j(\psi) = \frac{\alpha_j w}{\rho \psi}$ where $\rho \equiv \frac{\sigma-1}{\sigma}$ which yields (conditional) profits $\pi_j(\psi)$ equal to

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

***Stage 2:* Technology adoption.** An entrepreneur can choose from any of the J technologies in T. She adopts the technology j that yields highest profits so the profits of an entrepreneur with productivity ψ are $\pi(\psi) = \max_{j \in \{1,\ldots,J\}} \{\pi_j(\psi)\}$. An important implication of the conditional profit function in (1) is that more productive entrepreneurs choose technologies with higher fixed costs. To see this, note that for an entrepreneur with productivity ψ, the difference in profits between technologies t_j and t_k are:

$$\Delta \pi_{jk}(\psi) \equiv \pi_j(\psi) - \pi_k(\psi) = \frac{Y}{\sigma} \left(\frac{\rho \psi}{w} \right)^{\sigma-1} \left(\alpha_j^{1-\sigma} - \alpha_k^{1-\sigma} \right) - (\kappa_j - \kappa_k) w. \tag{2}$$

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).

***Stage 1:* Occupational choice.** After observing their entrepreneurial productivity ψ, each household decides on their occupation. Naturally, they decide on entrepreneurship if and only if the profits exceed wages: $\pi(\psi) \geq w$. Since $\pi(\psi)$ is strictly increasing and continuous in ψ, there is a unique $\bar{\psi} > \psi_m$ such that a household chooses entrepreneurship iff $\psi \geq \bar{\psi}$. Further, each technology j has itself a cut-off $\bar{\psi}_j$ above which profits are higher than the wage, defined by $\pi\left(\bar{\psi}_j\right) = w$. Since a household becomes an entrepreneur iff at least one technology yields profits exceeding wages, the occupational choice decision is governed by the technology with the lowest threshold. Therefore,

$$\bar{\psi} = \min_{j \in 1,\ldots,J} \bar{\psi}_j = \min_{j \in 1,\ldots,J} \left\{ \alpha_j (1+\kappa_j)^{\frac{1}{\sigma-1}} \right\} \left(\frac{\sigma}{Y} \right)^{\frac{1}{\sigma-1}} \frac{w^{\frac{\sigma}{\sigma-1}}}{\rho} \tag{3}$$

and the marginal entrepreneur uses the technology for which the marginal and fixed costs are such that $\alpha_j(1+\kappa_j)^{\frac{1}{\sigma-1}}$ is lowest.

Figure A.2 visualizes the profit function $\pi(\psi)$ and the optimal occupational and technological choice.

3.3 Competitive equilibrium

The competitive equilibrium is defined by three conditions. First, occupational and technological choice must be income maximizing. Second, labor demand equals labor supply. Third, goods prices must be consistent with wages. I provide a formal definition of the competitive equilibrium in Appendix C.1.

I first characterize which technologies are adopted by a strictly positive measure of entrepreneurs in equilibrium. A given technology is adopted if there is a set of households for which i) it is profit-maximizing to produce with that technology and 2) optimal profits exceed wages. Proposition A.1 (Appendix C.2) states the technological conditions under which this is true. It first shows that the technology with the lowest threshold $\bar{\psi}_j$ is adopted (by the marginal entrepreneur). Second, the technology with the lowest marginal cost is also adopted, regardless of its fixed cost.[16] Only one technology is adopted iff it has both the lowest entry threshold and lowest marginal cost. The proposition also covers conditions under which more than two technologies are adopted.

Having defined the equilibrium in general, in order to get more concrete results, I assume from now on that the distribution of productivity ψ is Pareto. With this assumption, the equilibrium of the model has closed-form analytical solutions that I lay out in Proposition A.2 (Appendix C.3). Proposition A.1 and A.2 together fully characterize the competitive equilibrium. In Proposition A.3, I show that the competitive equilibrium is socially optimal.

[16] Since the gains from lowering marginal cost are strictly increasing in productivity and the productivity distribution is unbounded, the gains from lowering marginal cost are unbounded.

3.4 Scale-biased technical change and its implications

Having characterized the equilibrium, I now consider the effect of *technical change*. I define technical change as an addition of a new technology, say t_{new}, to the existing technology set T_{old} such that $T_{new} = T_{old} \cup \{t_{new}\}$ and assume that it is adopted, i.e., $t_{new} \in T^*_{new}$.

From there, I call technical change *large-scale-biased* if it only increases productivity on a sufficiently large scale. I provide a formal definition below.

Definition (Scale-biased technical change)**.** The adoption of a new technology t_{new} constitutes *large-scale-biased* technical change relative to an existing adopted technology set T^*_{old} for firm ψ iff $\exists \bar{l} > 0$ such that $y_{t_{new}}(l \mid \psi) > \max_{j \in T^*_{old}} y_j(l \mid \psi)$ for all $l > \bar{l}$ and $y_{t_{new}}(l \mid \psi) \leq \max_{j \in T^*_{old}} y_j(l \mid \psi)$ for all $l \leq \bar{l}$. It is *small-scale-biased* iff $\exists \bar{l} > 0$ such that $y_{t_{new}}(l \mid \psi) \leq \max_{j \in T^*_{old}} y_j(l \mid \psi)$ for all $l \geq \bar{l}$ and $y_{t_{new}}(l \mid \psi) > \max_{j \in T^*_{old}} y_j(l \mid \psi)$ for all $l < \bar{l}$ for which $\max_{j \in T^*_{old}} y_j(l \mid \psi) > 0$.

This definition is related to the notion of returns to scale. If technical change is large-scale-biased, there exists $l > 0, \lambda > 1$ such that scaling the inputs from l to λl increases output more with the new technology than without it. Similarly, if it is small-scale-biased, decreasing inputs decreases output less than before for some l and $\lambda \in (0, 1)$.

Also note that the definition allows for technical change to be large-scale-biased for some entrepreneur ψ, but not for others. However, when ψ reflects a multiplicative productivity term like in the model above—i.e., $y_j(l \mid \psi) = \psi \tilde{y}_j(l)$ for some $\tilde{y}_j(\cdot)$—technical change is large- or small-scale-biased either for all ψ or for no ψ.

Under the production function in the model above, it is straightforward to characterize the type of technical change that leads to scale bias. Large-scale-biased technical change occurs if and only if the new technology has lower marginal costs than those of any previously adopted technology but does not have the lowest fixed costs.[17] On the other hand, the adoption of a new technology is small-scale-biased iff it has lowest fixed costs, but not lowest marginal costs.[18]

[17]Proof: to increase productivity at large scales, it must have lower marginal costs. To not increase productivity at smaller scales, it cannot have the lowest fixed costs.

[18]Proof: to increase productivity at all of the lower scales, it must have lowest fixed cost. To not increase productivity at higher scales, it must not have lowest marginal cost.

Using Propositions A.2 and the definition of scale-biased technical change, I generate three main predictions from the theory.

Proposition 1 (Theoretical implications of scale-biased technical change)**.** *Suppose that the productivity distribution is Pareto, $f(\psi) = \xi \psi_m^{\xi} \psi^{-\xi-1}$ with $\xi > \sigma - 1$, that $\sigma > 2$, and that $T^*_{new} = T^*_{old} \cup \{t_{new}\}$ (the new technology is adopted alongside the previously adopted technologies). Then, large-scale-biased technical change*

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

(b) increases income inequality between entrepreneurs and workers;

(c) increases the income share of the top k% for any k below some $\bar{k} \in (0, 100)$.

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

Proof of Proposition 1. See Appendix C.5. □

The remainder of the paper is devoted to testing the theoretical predictions above for the case of steam and electric power.

4 Data Construction

In this section, I discuss the sources, digitization, and construction of the data used in the empirical analysis. A key contribution is the collection and digitization of microdata on wealth of hundreds of thousands of people in the Netherlands during the period of steam and electric power adoption ($\approx 1850 - 1950$). In addition, I digitized and compiled manufacturing data for the same period for both the United States and the Netherlands.

4.1 Netherlands

Microdata on wealth: 1879-1927. The data on wealth derive from the inheritance tax administration. The original source files are printed estate tax forms that were filled by hand indicating a decedent's name, place of residence and death, date of death, and importantly, the value of their estate. I collected and digitized these data for individuals who died in selected Dutch provinces between 1879 and 1927 and were subject to inheritance taxation. I included all provinces for which the source files were available online as scanned images:

Noord-Holland, Noord-Brabant, Gelderland, Overijssel, and Zeeland. In 1900, these five provinces contained 52 percent of the population (Ekamper et al., 2003, p. 29) and include the capital city, Amsterdam.

The inheritance tax was introduced in 1818 and all the tax returns up to 1927 are 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 1000 Dutch guilders (*ƒ*) were taxed, and some inheritances between *ƒ*300 and *ƒ*1000. This meant that a considerably larger share of decedents was assessed than in other countries (see also Toussaint et al., 2022; Gelderblom et al., 2023). The tax data thus cover a relatively broad range of the wealth distribution: in the median region and period, about 20 percent of adult decedents. For further detail on the tax and its administration, I refer to De Vicq and Peeters (2020).

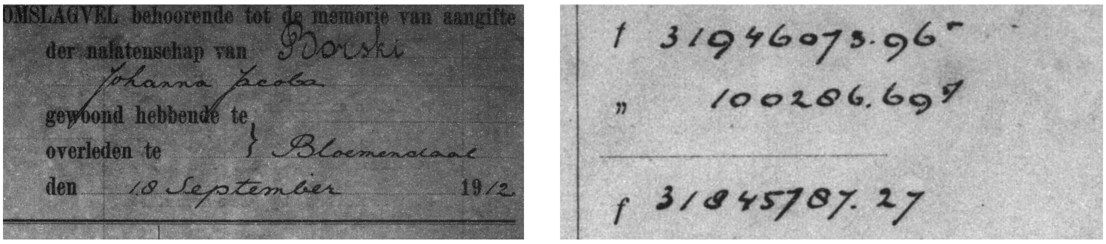
I extracted the data from 3,261,708 scanned documents by training various state-of-the-art object detection and classification algorithms. Detection and recognition of handwritten data, especially of non-integer numbers, is a problem at the frontier of deep learning research (e.g., Kusetogullari et al., 2021). While deep learning is increasingly used in economics research for document scan digitization, handwritten text and numbers, especially from historical documents, pose particular challenges (Dell et al., 2023; Dell, 2025). I develop a framework that ensures accuracy even in the presence of such challenges.

The procedure is summarized as follows. First, I trained an object detection algorithm called YOLOv5 to recognize the location in the image that contains the relevant information and automatically crop the relevant parts of the images. Figure 3 shows an example of the cropped data for the richest person in the database. I then trained another such algorithm to detect the image locations of the assets, liabilities, dates, etc., and subsequently, of individual numbers. Third, I trained a classification algorithm (also YOLOv5) to assign each detected number an integer from 0 to 9 and constructed the data on assets, liabilities, and net worth from there. Fourth, I inputted the automatically cropped images similar to Figure 3a into the GPT-4o API and requested to provide the name, place of death and residence, and date of death reported in the image. Fifth, I matched the records to existing high-quality hand-collected demographic information from the civil death registry. Appendix D.1 provides further detail on sources and the digitization procedure.

I ensure the quality of the wealth data in two ways. First, Figure 3b shows

FIGURE 3: Example of relevant source information

(A) Name, location, and date of death (B) Wealth



Notes: the images above show the source data for the richest person in the database, Johanna Jacoba Borski, who died in Bloemendaal on September 18, 1912 with an estate worth ƒ31.8 million. The images are cropped automatically using an object detection algorithm. Panel A (raw source here) shows the part of the form that contains her personal information and Panel B (raw source here) indicates the value of her assets, liabilities, and net worth.

that the source files provide an internal test: recognized assets minus liabilities should equal net worth. The discrepancy in the output of the algorithm is zero up to the last digit in 92% of cases and below 20% for 97% of cases. Second, to mitigate noise from the remaining observations, I manually checked all observations that do not add up exactly and for which net worth is recognized to be larger than ƒ50,000, roughly the 90$^{\text{th}}$ percentile of national wealth.

The resulting dataset on wealth during industrialization is unique in its size and geographic scope, which is necessary for the empirical analysis. In total, the database consists of 380,131 wealth observations of which 97 percent can be confidently assigned to a municipality (of which there were over a thousand nationally). The existing literature has focused on documenting national trends in wealth distribution using much smaller and geographically concentrated samples. 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 19$^{\text{th}}$ century, and Bengtsson et al. (2018) (Sweden) collect information on samples of around 5000 probate inventories between 1750 and 1900.

Local wealth distributions. Using the micro-level data, I create a panel dataset 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 period, I compute statistics by decade from the 1880s to the 1920s. I include every decedent with assessed wealth above ƒ300, the lowest tax threshold, in the sample on which measures of the wealth distribution are computed.

A limitation of tax data is that non-assessed individuals are not observed. In principle, it is possible to infer the number of individuals below the threshold from the total number of decedents. However, this relies on the estate files to be complete. Experimentation showed that the coverage is close to complete for most regions and periods but is low for a small subset of them. I therefore focus on measures of inequality among those who were assessed.

A second challenge is that the decedent's wealth distribution is different from that of the living. While weighting observations by the inverse probability of death can reduce bias (e.g., Kopczuk and Saez, 2004), it substantially increases the variance by placing a high weight on a small set of young decedents. Limiting variance is particularly pressing when estimating inequality within small units. For the baseline analysis, I thus do not weight. To gauge sensitivity to weighting, I also compute age-weighted wealth statistics. I find that weighted and unweighted measures of inequality are strongly correlated (e.g., for the top 1% share, the correlation is 0.90) and, in the main analysis, I also show robustness to using the weighted estimates.

Local income distributions. I also uncovered and digitized local income distribution data for 87 municipalities, including most large cities (see Appendix D.2 for details).[19] These data show that local income inequality is strongly correlated with wealth inequality, measured from the new wealth data. Figure A.3 plots income and wealth inequality for those municipalities for which both are observed. The correlations are around 0.9, providing strong evidence that the constructed wealth and income data are reliable. It also suggests that whether one uses income or wealth inequality as an outcome is not likely to affect conclusions qualitatively.

Local manufacturing. I additionally digitize data on manufacturing by Dutch municipality for the years 1816-1819 and 1930. The first official Dutch firm census was performed in 1930 and offers high-quality data on firms by industry and municipality.[20] The source contains the number of establishments and workers by establishment size class and the adoption of motive power. It separates electric motors driven by purchased energy from self-generated power. In total, the data consist of 33,134 municipality-by-industry observations.

[19] I thank Jan Luiten van Zanden for kindly sharing data for some cities.

[20] I have digitized the data only for manufacturing firms. Source images can be found here.

For the years 1816 and 1819, I digitized data from two manufacturing surveys of which results were compiled and published by (Brugmans, 1956; Damsma et al., 1979).[21] These data contain, by municipality, information on the number of establishments and workers for each type of establishment (e.g., tannery or grain mill). Where data is available for both 1816 and 1819, I use the data for 1819. I added the results for the municipality of Rotterdam and neighboring municipalities from Korteweg (1926). The final data contain 3,658 municipality-by-industry observations in 539 distinct municipalities and cover nearly all large cities and other places with a strong manufacturing presence.[22] For comparability across years, I coded each industry to a 2-digit ISIC code.

4.2 United States

For the United States, I rely on the tabulations of the decennial Census of Manufactures by state and industry. I digitized and compiled these data for each decade between 1850 and 1940 and for 1947.[23] For 1860, I use the county-industry level information digitized by Hornbeck and Rotemberg (2024). The information in this census varies from year to year, but key variables such as the number of establishments, employment, and value added are available for each year. From 1870 onward, the tabulations report the adoption of power technologies such as water wheels, steam power, and, later, electric power use. In total, the data comprise 51,263 state-industry-year observations.

Since industry classifications changed over time, I created two crosswalks that allow us to compare industries over time. The first covers all industries between 1860 and 1900, the period of most rapid steam power adoption, and consists of 182 industries. This crosswalk is an extension of the 1860 to 1880 crosswalk published by Hornbeck and Rotemberg (2024). The second crosswalk 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. I also coded each industry its 1950 Census Bureau industry codes. To further improve consistency across censuses, I drop "hand trades" such as blacksmithing and masonry as these industries were not included after 1900.

[21] The source images can be found here.

[22] For eight out of eleven provinces, the returns are complete. For the remaining three, returns were only found for a subset of municipalities.

[23] While some authors have used a subset of the data contained in this source (e.g., Kim, 1995), I am not aware of any publicly available and machine-readable database.

5 Scale-Biased Technical Change and Firm Size

This section documents the impact of steam and electric power adoption on establishment sizes. Using exogenous variation in the technologies' costs across US states, I find that steam power adoption increased establishment sizes, while electric power decreased them. The results are similar on the city-level.

Instruments. I use a state's access to historical coal resources as an instrument for steam power adoption. The data is sourced from the National Coal Resources Data System. I convert historical coal resources to energy in British thermal units (Btu).[24] I then compute "coal access" similar to the usual measure of market access Donaldson and Hornbeck (2016). That is, for destination county c, coal access is $Coal_c = \sum_o \tau_{oc}^{-\theta} BTU_o$ where $\tau_{oc} \geq 1$ is the "iceberg" cost of transporting coal between o and c in 1830, θ is the trade elasticity, and BTU_o is county o's coal resources in Btu.[25] I use transportation cost estimates for 1830, before the (potentially endogenous) introduction of railroads. Similarly, I use estimates of coal available prior to (potentially selective) mining. For the state-level analysis, I use the average coal access across counties in the state.

Hydropower potential serves as the instrument for electric power adoption.[26] Importantly for exogeneity, the measures reflect the *potential* to generate energy with water power and also counts sites with unrealized potential. I use the estimates of hydropower potential published in (Young, 1964, Table 10).[27]

Figure A.4 shows the spatial distribution of coal access and hydropower potential. Importantly, coal access and hydropower potential are almost uncorrelated at the state-level ($\rho = -0.07$) so that the instruments have strong power in distinguishing the effects of steam and electric power.

First stage. Coal access and coal prices are strongly negatively correlated on the state level ($\rho = -0.55$, Figure A.5a). Because coal was an important input to

[24] I follow (Averitt, 1975, Figure 4) in converting coal to Btu and (Averitt, 1975, Table 2) in including only coal resources with an appropriate overburden and thickness.

[25] Specifically, as in (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024), $\tau_{oc} = 1 + t_{oc}/\bar{P}_{coal}$. I set $\bar{P}_{coal} = 6.08$ to the average dollar price of a ton of anthracite coal in 1830, Philadelphia (Chandler, 1972, Table 2). t_{oc}, the transportation cost per ton-mile in 1830, and the trade elasticity $\theta = 8.22$ are taken from (Donaldson and Hornbeck, 2016).

[26] See, e.g., Gaggl et al. (2021); Severnini (2022) for other applications of this instrument.

[27] 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.

steam power production, coal access affected the adoption of steam power. In 1890, the Census of Manufactures reported steam engine and other power use for each state-industry combination. For that year, I regress measures of steam power use in industry i in state s on that state's coal access and industry-fixed effects. The results in Table B.1 show that coal access strongly affected steam power use, both measured as steam horsepower per employee and as the share of steam in total horsepower.

Hydropower potential had a similarly strong effect on electricity prices and electric power use. Figure A.5b shows that hydropotential lowered electricity prices by state in 1929 ($\rho = -0.70$). A within-industry regression shows that hydropower affected purchased electric power as measured in megawatt-hour (MWh) per employee, as well as share of total fuel cost (Table B.3).[28]

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

$$\log\left(y_{ist}\right) = \alpha_s + \eta_{it} + \sum_{k \in T} \left[\beta_k \ln\left(Coal_s\right) + \gamma_k \ln\left(Hydro_s\right)\right] D_{tk} + \lambda' X_{st} + \varepsilon_{ist} \quad (4)$$

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 number of employees per establishment. $\boldsymbol{X}_{st}$ is a vector of controls on the state-year level: it contains population density and "market access" interacted with time to ensures that the estimated effect of coal access does not reflect low-cost access to consumer markets.[29]

The results show that steam power adoption increased establishment sizes. Figure 4 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 access—adopting more steam power—grew from 1850 onward relative to other states (Figure 4a).

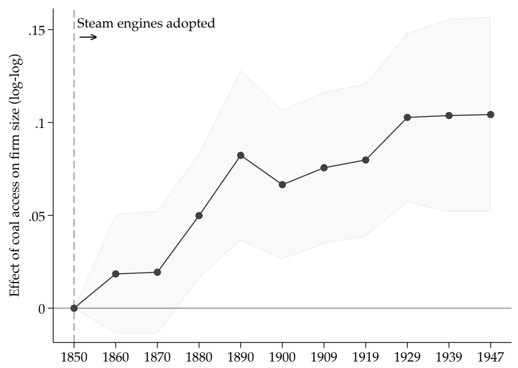
In contrast, states with high hydropower potential—adopting more electric power—experienced relative reductions in average firm sizes (Figure 4b). Im-

[28]The megawatt-hour of purchased electric energy 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 computed by dividing the total state-wide cost of purchased electric energy by the quantity purchased. (Census of Manufactures 1939, Volume 1, Ch. VII, Table 3 and Ch. VI, Table 6).

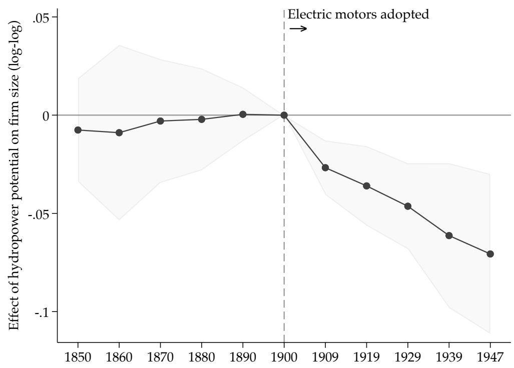
[29]I compute market access by county for the year 1830 (before railroads) as in (Donaldson and Hornbeck, 2016) and average it to the state-level.

FIGURE 4: Effects of coal access and hydropower potential on firm sizes

(A) Coal access



(B) Hydropower potential



Notes: Panels 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 panels A and B are jointly estimated in one specification (equation (4)), the only difference being the base year relative to which the coefficients are estimated. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the state-level.

portantly, 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.

I find evidence for the exclusion restriction that the instruments only affect the outcomes through power adoption. First, firm sizes in industries that used little power nationally in 1890 were not affected by coal access (see Figure A.6). Specifically, I estimate equation (4) for the years between 1860 and 1900, now including state $\times$ industry fixed effects using the 1860 to 1900 industry crosswalk. 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.[30] Similarly, hydropower potential only affected firm sizes in industries above the 25th percentile of purchased electric power use (see Figure A.7).

To quantify the effect of steam and electric power adoption on the firm size, I estimate an instrumental variable regression for two distinct periods: 1860 to 1890 for steam power and 1900 to 1939 for electric power. Specifically, I regress state-by-industry establishment size growth on technology adoption,

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

instrumented by hydropower potential and coal access. That is, I estimate

$$\log(y_{is,1890}) - \log(y_{is,1860}) = \alpha_1 + \beta_1 \text{Steam}_{is,1890} + \boldsymbol{\lambda}_1' \boldsymbol{X}_{is} + \varepsilon_{is} \tag{5}$$

$$\log(y_{is,1939}) - \log(y_{is,1900}) = \alpha_2 + \beta_2 \text{Electric}_{is,1939} + \boldsymbol{\lambda}_2' \boldsymbol{X}_{is} + \eta_{is} \tag{6}$$

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

Table B.4 shows the results of the IV regressions in equations (5) and (6). The estimate in the first column suggests 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 changes in the set of controls. Column four to six show that electric power adoption decreased firm sizes with an elasticity of around -0.4.

Further evidence using city-level data. I show that the state-level estimated effects of power on establishment sizes are qualitatively and quantitatively similar when estimated on the city-level. From 1880, the Census of Manufactures also tabulated data by city and industry, for some cities and industries.[31] I use the data from these tabulations digitized by Lafortune et al. (2019). Figure A.8 shows that the effects estimated using city-level data line up qualitatively and quantitatively with the state-level findings: cities with more coal access see a steady increase of establishment sizes over time, while cities with more hydropower potential see a sharp decline in establishment sizes after 1900.

A specific advantage of the city-level data is that they allow us to separate any effect hydropower may have had through its effect on water wheel adoption from its effect through electric power adoption.[32] Water wheels required hydropower potential at the site of the plant itself. In contrast, electric energy can be transmitted over long distances. Electricity was for a large part regulated and priced at the state-level (Stigler and Friedland, 1962).[33] This means that hydropower potential outside the city (but within the state) could affect

[31] The trade-off between the city- and state-level data is that, while the city-level provides more geographic granularity, the state-level data is more detailed, especially on power use.

[32] Table B.2 showed that hydro-potential had some effect on water power use.

[33] Almost no electricity was purchased from other states. Only 5.7 percent of electricity crossed state-borders in 1932 (Morin, 2015).

local electricity prices. However, such hydropower potential could not have affected the establishment sizes through water wheel adoption. Using estimates of hydropower potential on the county-level provided by (Gaggl et al., 2021), I find that the effects of hydropower potential are driven by hydropower potential out of the city, suggesting that water power adoption did not contaminate the estimated effects of electric power much (see Figure A.9).

6 Scale-Biased Technical Change and Inequality

In this section, I study the distributional effects of scale-biased technical change. I first show using US data that steam power adoption increased the profit-wage ratio, a measure of income inequality between workers and entrepreneurs, while electric power decreased it. Furthermore, by using wealth data from the 1860 and 1870 US Census, I find that profit-wage ratios are indeed strongly correlated with inequality between households.

I then test directly how steam and electric power had affected inequality using the Dutch panel data on local wealth inequality. I find that wealth inequality rose in municipalities with high steam power adoption, while it declined in those with high electric power adoption. For identification purposes, 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 The Effect on Profit-Wage Ratios

In the model in Section 3—where each entrepreneur owns one firm—the ratio between the average profits, $\bar{\pi}$, and the wage, w, equates income inequality between workers and entrepreneurs.

The profit-wage ratio is structurally related to the average firm size. In the model, $\frac{\bar{\pi}}{w} = A + (A-1) \times \textit{Average firm size}$ where $A \equiv \frac{\xi\sigma}{\xi\sigma - \sigma + 1} > 1$.[34] That is, the more employees per firm, the larger the average profits of entrepreneurs relative to the wage. Figure A.10 shows that this relationship holds empirically across states and industries. For the years between 1890 and 1920, the census data allow us to compute profits as output minus costs of wages, raw materials,

[34]Proof: $(1 - F(\bar{\psi}))\,\bar{\pi} + F(\bar{\psi})\,w = Y$. In equilibrium $Y = Aw$ (Proposition A.2), so that $\frac{\bar{\pi}}{w} = 1 + \frac{A-1}{1-F(\bar{\psi})}$. The result then follows from $1 + \textit{Average firm size} = \frac{1}{1-F(\bar{\psi})}$.

capital, and other expenses (Atack and Bateman, 2008).[35] I set the wage to the wage bill divided by the number of workers. I also repeat this exercise using establishment-level data from the 1880 census digitized by Atack and Bateman (1999) where hourly wages are directly observed and find an almost identical relation between firm sizes and profit-wage ratios (Panel B of Figure A.10)

Consistent with this structural relationship, I find that the effects of steam and electric power on profit-wage ratio are similar to the effects on firm size. Steam power adoption increased the average profits of an establishment relative to the average wage (Figure 5a), while electric power adoption decreased it (Figure 5b). The theory predicts this because high fixed cost technologies push up the average firm size and thus profits relative to the wage. The methodology to estimate these effects is identical to those used in Section 5, except that the outcome variable is now the profit-wage ratio in industry i, state s, and year t. Because data on the capital stock and "miscellaneous expenses" are not available for all years, I approximate average profits as value added minus labor costs per establishment.[36] Table B.5 shows the IV estimates of the elasticity of the profit-wage ratio to steam and electric power adoption.

I also find that profit-wage ratios are strongly associated with inequality among households. Using US microdata on wealth from 1870, the last year for which such data is available, I show that firm sizes and profit-wage ratios are strongly correlated with measures of wealth inequality. To do so, I compute wealth inequality between entrepreneurs and workers in a given state and industry in the 1870 Census of Population and merge these measures with data from the 1870 Census of Manufactures.[37] Figure 6a shows that this wealth gap was larger in state-industry pairs with larger profit-wage ratio: a one percent increase in the profit-wage ratio is associated with a 0.99 percent increase in the entrepreneur-worker wealth gap. Since entrepreneurs dominate the very top of the distribution, top 1% wealth shares are similarly correlated with firm sizes

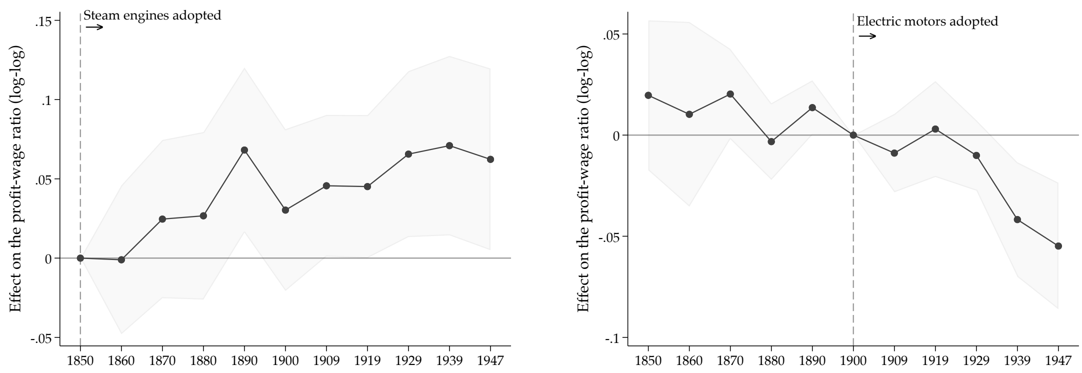
[35] I approximate capital costs as 4.33 percent of the capital stock. Atack and Bateman (2008) assumed different capital costs for plants (2%) than for equipment (6.67%). Since I cannot distinguish between different types of capital, I use the average of these two rates.

[36] The correlation between this measure of average profits and the measure used by Atack and Bateman (2008) is high: 0.75 in levels and 0.96 in logs.

[37] I harmonize industry groups between the Census of Manufactures and the Census of Population by aggregating industries in the manufacturing data to the 1950 industry classification. To identify entrepreneurs, I use that the occupational code "manufacturer" in the 1870 census was reserved for owners of establishments. I therefore assume individuals with occupational code 198 "manufacturer" to be entrepreneurs and those with any other manufacturing occupations (codes between 130 to 265, excluding 198) to be workers.

FIGURE 5: Effects of coal access and hydropower potential on the profit-wage ratio

(A) Coal access (B) Hydropower potential



Notes: Panels 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 panels A and B are jointly estimated in one specification (see equation (4) for the econometric specification), the only difference being the base year relative to which the estimates are estimated. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the state-level.

and profit-wage ratios (Figure 6b).

Figure A.11 shows that average wages were not affected by coal access or hydropower potential, implying that the effects of profit-wage ratios are mostly due to increases in average profits. This result also provides empirical evidence that the technologies did not significantly affect the skill composition of the workforce, and that we can thus distinguish the effects of scale from skill.

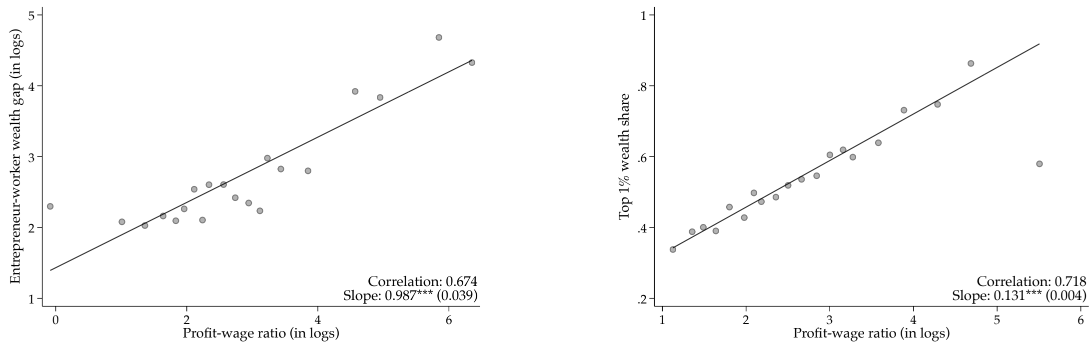
6.2 The Effect on Wealth Inequality

The finding that steam power increased the profit-wage ratio and electric power decreased it, coupled with the strong correlation between profit-wage ratios and inequality, already suggests that steam increased inequality, while electricity decreased it. In this subsection, I use the newly digitized wealth data from the Netherlands to provide direct evidence on the distributional effects of scale-biased technical change.

I use the digitized Dutch inheritance tax data described in Section 4.1 to create various measures of local (municipality-level) wealth inequality for the period between 1879 and 1927. In the analysis, I only use municipality-time measures of wealth inequality that are based on at least a hundred observations.

FIGURE 6: Profit-wage ratios $\left(\frac{\bar{\pi}}{w}\right)$ correlate strongly with wealth inequality

(A) $\frac{\bar{\pi}}{w}$ and $\frac{\text{entrepreneurial wealth}}{\text{worker wealth}}$ (B) $\frac{\bar{\pi}}{w}$ and top 1% wealth share



Notes: These figures show the correlation between a state-industry's profit-wage ratios and wealth inequality between households active in it. Wealth inequality is computed from microdata from the 1870 population census. Profit-wage ratios are computed from the Census of Manufacturing. The manufacturing industries are converted to 1950 industry for consistency with the population census. State-industry pairs are weighted by the number of individuals for which wealth is observed.

This yields 819 municipality-decade observations from 210 municipalities.

I measure power adoption in each Dutch municipality using the newly digitized 1930 firm census. These data divide establishments into 1) those using prime movers run by energy generated in the plant, 2) those only using prime movers run by purchased electricity, and 3) those not using any power. The measure of local steam power adoption in municipality m, $Steam_{1930,m}$, is the share of workers in the first type of establishments. Similarly, $Electric_{1930,m}$, is the share of workers in the second group of establishments.

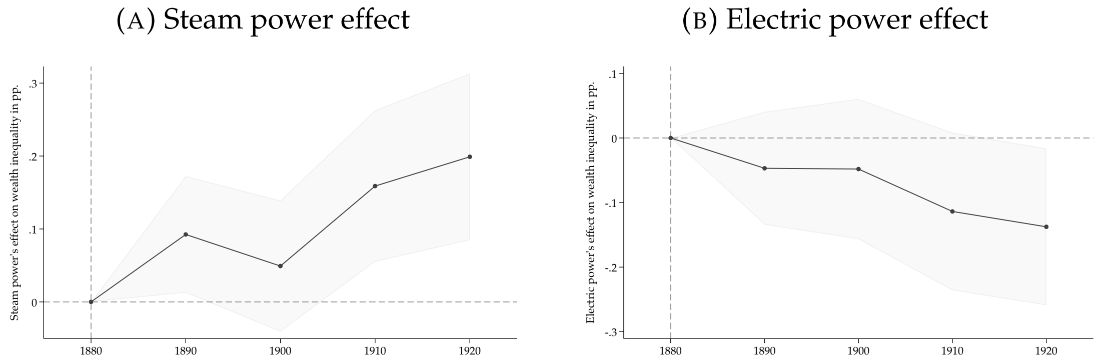
For steam use, the specification is as follows:

$$y_{mt} = \alpha_m + \eta_t + \sum_{k \in T \setminus \{1880\}} \beta_k Steam_{1930,m} D_{tk} + \varepsilon_{1,mt} \tag{7}$$

where the subscript $t \in T$ refers to the decade between 1880 and 1920, m to the municipality and D_{tk} is 1 if $t = k$ and 0 otherwise. The specification for electric power use is analogous. The dependent variable y_{mt} is a moment of the wealth distribution, e.g., the top 1 percent wealth share. The coefficient β_k captures the association between steam power and electric power adoption and the change in wealth inequality from 1880 to year k.

Figure 7 shows that places adopting steam power saw a relative increase in wealth inequality, while electric power adoption is associated with decreases

FIGURE 7: Steam power increased inequality, electric power decreased it



Notes: This figure shows the estimated effects in percentage points of steam power (in panel A) and purchased electric power adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The econometric specification is shown in equation (7). Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

in inequality. The coefficients in Figure 7a mean that a 1 p.p. increase in the share of employment exposed to steam power leads to an increase in the top 1% wealth share of about 0.2 p.p. This effect is statistically and economically significant. Local steam power adoption varied strongly: a one standard deviation increase in steam power adoption (0.2) increases the top 1% wealth share by around 4 p.p. in 1920, while the average top 1% wealth share across municipalities was 21 percent. In contrast, Figure 7b shows that the adoption of purchased electric power is associated with a *decrease* in top 1% wealth shares. Figure A.12 shows that results are almost identical when using weighted estimates of wealth inequality as the dependent variable. I find similar effects on income inequality for the subset of municipalities for which data is available (results available upon request).

To directly compare the effect of steam power adoption and electric power adoption, I also estimate equation (7) while controlling for the share of employment in establishments that did not use any power.[38] The coefficient of interest then reflects the increase in wealth inequality associated with a 1 p.p. increase in steam power use and a 1 p.p. *decrease* in purchased electric power use. The results are shown in Figure A.13. Holding total power usage constant, wealth inequality increased in places with steam relative to electric power.

[38] That is, I estimate:

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

Lastly, Figure A.14 shows how different parts of the wealth distribution are affected. Power use is most strongly correlated with rising wealth shares of the very top. The more one zooms into the top—from the top 25% to the top 1%—the more strongly is steam power (relative to electric power) correlated with an increasing share of the top relative to its complement. This too, is consistent with the theory: since most entrepreneurs are at the very top of the distribution, large-scale-biased technical change mostly implies an increase in inequality within the higher end of the distribution.

Instrumental variable analysis. The municipality-fixed effects specification in equations (7) controls for any time-invariant unobserved heterogeneity across municipalities. Time-varying heterogeneity is a potential remaining threat to a causal interpretation of the coefficients in Figure 7. For instance, it is a priori conceivable that changes in local inequality between 1880 and 1920 also affected technology adoption, leading to reverse causality. I use an instrumental variable strategy to assess the quantitative importance of such mechanisms.

The identification strategy uses that the local industry composition in manufacturing in 1816—long before Dutch industrialization—is predictive of later local steam and electric power adoption.[39] To construct the instrument, I first use the Dutch manufacturing data from 1930 to compute each 2-digit industry i's adoption of steam and electric power.[40] Then, I calculate the employment share of each industry within total manufacturing in 1816 in each municipality. I combine these into a measure of exposure to steam and electric power in municipality m in 1816 as:

$$SteamExposure_{1816,m} = \sum_{i \in I} \frac{\text{Emp. in ind. } i \text{ in } m \text{ in 1816}}{\text{Total emp. in } m \text{ in 1816}} \times Steam_{1930,i} \qquad (8)$$

where the adoption rates on the industry-level $Steam_{1930,i}$ is computed analogously to its equivalent on the municipality-level, $Steam_{1930,m}$. $ElectricExposure_{1816,m}$ is defined analogously. The exposure measures are strong predictors of actual adoption in 1930 (the raw correlations are 0.50 and 0.39 for steam and electric power, respectively). I then estimate the "reduced form" of the instrumental

[39] The geographic instruments used in the US context can not be reliably applied to the Dutch case because there is no hydropower potential nor any coal deposits except for the southern tip.

[40] For example, the textiles and beverage industries were the largest adopter of steam power, with half of employment in establishments using steam. On the other hand, the leather, apparel, tobacco, and printing industries barely used any steam at all.

variable analysis equivalently to equations (7) except that the actual adoption rates are changed for the predicted rates.

Figure A.15 shows that places more exposed to steam power became more unequal between 1880 and 1927, while those exposed to electric power became more equal, providing further evidence that steam and electric power affected inequality in opposite ways.

7 Conclusion

In this paper, I study the distributional effects of steam and electric power, two revolutionary general purpose technologies. These two technologies shed light on a new channel through which technical change affects inequality: scale bias. When technical change is large-scale-biased, profits concentrate into a smaller set of firms. With fewer and larger firms, top entrepreneurs gain disproportionately, driving up top income inequality.

The theory of scale-biased technical change and inequality provides a unified framework to explain three macroeconomic trends of the last decades. First, firm concentration is increasing (Autor et al., 2017, 2020; Kwon et al., 2024) and entrepreneurship is declining (Salgado, 2020; Jiang and Sohail, 2023), mostly driven by increased entry costs (Deb, 2024; Kozeniauskas, 2024). A large literature relates these patterns to increasing returns to scale coming from information technology and intangible capital (Brynjolfsson et al., 2008; Unger, 2022; Aghion et al., 2023; Hsieh and Rossi-Hansberg, 2023; De Ridder, 2024; Lashkari et al., 2024; Kwon et al., 2024). Second, top income and wealth inequality has increased sharply. 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).

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 empirical case studied in this paper, a concentrated firm size distribution may further incentivize large-scale-biased technical change, similar to how innovation is directed to the more abundant skill (Acemoglu, 2002). Further, in the presence of liquidity constraints, entrepreneurship naturally skews towards high wealth individuals (Quadrini, 2000; Cagetti and De Nardi, 2006; Buera et al., 2011; Buera and Shin, 2013). In such an environment, large-scale-biased technical change may aggravate selection on wealth and even worsen aggregate productivity. Lastly, the rapid adoption of AI technologies raises questions on its distributional effects. Research shows that large firms tend to be the early adopters of the technology (McElheran et al., 2023). More research is necessary to understand whether this will remain the case as these technologies mature.

References

ABBOTT, E. (1905): "The wages of unskilled labor in the United States 1850-1900," *Journal of Political Economy*, 13, 321–367.

ACEMOGLU, D. (2002): "Directed technical change," *The review of economic studies*, 69, 781–809.

ACEMOGLU, D. AND D. AUTOR (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Handbook of labor economics*, Elsevier, vol. 4, 1043–1171.

ACEMOGLU, D. AND P. RESTREPO (2018): "The race between man and machine: Implications of technology for growth, factor shares, and employment," *American Economic Review*, 108, 1488–1542.

——— (2022): "Tasks, automation, and the rise in US wage inequality," *Econometrica*, 90, 1973–2016.

AGHION, P., A. BERGEAUD, T. BOPPART, P. J. KLENOW, AND H. LI (2023): "A theory of falling growth and rising rents," *Review of Economic Studies*, 90, 2675–2702.

ANDERSON, R. C. AND D. M. REEB (2003): "Founding-family ownership and firm performance: evidence from the S&P 500," *The journal of finance*, 58, 1301–1328.

ATACK, J. (1979): "Fact in fiction? The relative costs of steam and water power: a simulation approach," *Explorations in Economic History*, 16, 409–437.

Atack, J. and F. Bateman (1999): "Nineteenth-century US industrial development through the eyes of the census of manufactures a new resource for historical research," *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 32, 177–188.

——— (2008): "Profitability, firm size, and business organization in nineteenth-century US manufacturing," in *Quantitative Economic History*, Routledge, 72–95.

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

Atack, J., F. Bateman, and T. Weiss (1980): "The regional diffusion and adoption of the steam engine in American manufacturing," *The Journal of Economic History*, 40, 281–308.

Atack, J., R. A. Margo, and P. W. Rhode (2019): ""Automation" of manufacturing in the late nineteenth century: The hand and machine labor study," *Journal of Economic Perspectives*, 33, 51–70.

Atkeson, A. G. and M. Irie (2022): "Rapid dynamics of top wealth shares and self-made fortunes: What is the role of family firms?" *American Economic Review: Insights*, 4, 409–424.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. V. Reenen (2017): "Concentrating on the Fall of the Labor Share," *American Economic Review*, 107, 180–185.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020): "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 135, 645–709.

Averitt, P. (1975): *Coal Resources of the United States, January 1, 1974*, 1410-1412, US Government Printing Office.

Bengtsson, E., A. Missiaia, M. Olsson, and P. Svensson (2018): "Wealth inequality in Sweden, 1750–1900," *The Economic History Review*, 71, 772–794.

Blanken, I. and H. Lintsen (1981): "Mechanische kracht in de industrialisatie van Nederland (1850-1950)," .

BRUGMANS, I. J. (1956): *Statistieken van de Nederlandse nijverheid uit de eerste helft der 19e eeuw*, vol. 98, M. Nijhoff.

BRYNJOLFSSON, E., A. MCAFEE, M. SORELL, AND F. ZHU (2008): "Scale without mass: business process replication and industry dynamics," *Harvard Business School Technology & Operations Mgt. Unit Research Paper*.

BUERA, F. J., J. P. KABOSKI, AND Y. SHIN (2011): "Finance and development: A tale of two sectors," *American economic review*, 101, 1964–2002.

BUERA, F. J. AND Y. SHIN (2013): "Financial frictions and the persistence of history: A quantitative exploration," *Journal of Political Economy*, 121, 221–272.

BUSTOS, P. (2011): "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms," *American economic review*, 101, 304–340.

CAGETTI, M. AND M. DE NARDI (2006): "Entrepreneurship, frictions, and wealth," *Journal of political Economy*, 114, 835–870.

CHANDLER, A. D. (1972): "Anthracite coal and the beginnings of the industrial revolution in the United States," *Business History Review*, 46, 141–181.

DAMSMA, D., J. DE MEERE, AND L. NOORDEGRAAF (1979): *Statistieken van de Nederlandse nijverheid uit de eerste helft der 19e eeuw: supplement*, vol. 3, Nijhoff.

DE RIDDER, M. (2024): "Market power and innovation in the intangible economy," *American Economic Review*, 114, 199–251.

DE VICQ, A. AND R. PEETERS (2020): "Introduction to the Tafel v-bis Dataset: Death Duty Summary Information for The Netherlands, 1921: Social and Economic History," *Research Data Journal for the Humanities and Social Sciences*, 5, 1–19.

DEB, S. (2024): "How Market Structure Shapes Entrepreneurship and Inequality," *Unpublished Working Paper*.

DELL, M. (2025): "Deep learning for economists," *Journal of Economic Literature*, 63, 5–58.

DELL, M., J. CARLSON, T. BRYAN, E. SILCOCK, A. ARORA, Z. SHEN, L. D'AMICO-WONG, Q. LE, P. QUERUBIN, AND L. HELDRING (2023): "American stories: A large-scale structured text dataset of historical us newspapers," *Advances in Neural Information Processing Systems*, 36, 80744–80772.

DEVINE, W. D. (1983): "From shafts to wires: Historical perspective on electrification," *The Journal of Economic History*, 43, 347–372.

DIXIT, A. K. AND J. E. STIGLITZ (1977): "Monopolistic competition and optimum product diversity," *American Economic Review*, 67, 297–308.

DONALDSON, D. AND R. HORNBECK (2016): "Railroads and American economic growth: A "market access" approach," *The Quarterly Journal of Economics*, 131, 799–858.

DU BOFF, R. B. (1967): "The introduction of electric power in American manufacturing," *The Economic History Review*, 20, 509–518.

——— (1979): *Electric Power in American Manufacturing, 1889-1958*, New York, NY: Arno Press.

EKAMPER, P., R. VAN DER ERF, N. VAN DER GAAG, K. HENKENS, E. VAN IMHOFF, AND F. VAN POPPEL (2003): "Bevolkingsatlas van Nederland: Demografische ontwikkelingen van 1850 tot heden [Population atlas of the Netherlands: Demographic trends from 1850 to the present]," *The Hague: Netherlands Interdisciplinary Demographic Institute*.

EMERY, C. E. (1883): "The Cost of Steam Power," *Transactions of the American Society of Civil Engineers*, 12, 425–431.

FISZBEIN, M., J. LAFORTUNE, E. G. LEWIS, AND J. TESSADA (2020): "Powering Up Productivity: The Effects of Electrification on US Manufacturing," *NBER Working Paper*.

GAGGL, P., R. GRAY, I. MARINESCU, AND M. MORIN (2021): "Does electricity drive structural transformation? Evidence from the United States," *Labour Economics*, 68, 101944.

GELDERBLOM, O., J. JONKER, R. PEETERS, AND A. DE VICQ (2023): "Exploring modern bank penetration: Evidence from early twentieth-century Netherlands," *The Economic History Review*, 76, 892–916.

GOLDIN, C. AND L. F. KATZ (1998): "The origins of technology-skill complementarity," *The Quarterly journal of economics*, 113, 693–732.

GOLDSMITH, R. W. ET AL. (1940): "The distribution of ownership in the 200 largest nonfinancial corporations," *Washington DC: Securities and Exchange Commission.*

HORNBECK, R., S. H.-M. HSU, A. HUMLUM, AND M. ROTEMBERG (2024): "Gaining Steam: Incumbent Lock-in and Entrant Leapfrogging," .

HORNBECK, R. AND M. ROTEMBERG (2024): "Growth off the rails: Aggregate productivity growth in distorted economies," *Journal of Political Economy*, 132, 3547–3602.

HSIEH, C.-T. AND E. ROSSI-HANSBERG (2023): "The industrial revolution in services," *Journal of Political Economy Macroeconomics*, 1, 000–000.

HUNTER, L. C. (1979): *A History of Industrial Power in the United States, 1780–1930, Volume 1: Waterpower in the Century of the Steam Engine*, Charlottesville, VA: University Press of Virginia.

——— (1985): *A History of Industrial Power in the United States, 1780–1930, Volume 2: Steam Power*, Charlottesville, VA: University Press of Virginia.

JIANG, H. AND F. SOHAIL (2023): "Skill-biased entrepreneurial decline," *Review of Economic Dynamics*, 48, 18–44.

JONES, C. I. AND J. KIM (2018): "A Schumpeterian model of top income inequality," *Journal of political Economy*, 126, 1785–1826.

KATZ, L. F. AND K. M. MURPHY (1992): "Changes in relative wages, 1963–1987: supply and demand factors," *The quarterly journal of economics*, 107, 35–78.

KIM, S. (1995): "Expansion of markets and the geographic distribution of economic activities: the trends in US regional manufacturing structure, 1860–1987," *The Quarterly Journal of Economics*, 110, 881–908.

——— (2005): "Industrialization and urbanization: Did the steam engine contribute to the growth of cities in the United States?" *Explorations in Economic History*, 42, 586–598.

KOPCZUK, W. AND E. SAEZ (2004): "Top wealth shares in the United States, 1916–2000: Evidence from estate tax returns," *National Tax Journal*, 57, 445–487.

KOPCZUK, W. AND E. ZWICK (2020): "Business incomes at the top," *Journal of Economic Perspectives*, 34, 27–51.

KORTEWEG, S. (1926): *Rotterdams welvaartsbronnen in 1816*, Brusse.

KOZENIAUSKAS, N. (2024): "What's driving the decline in entrepreneurship?" *Unpublished paper. New York University, New York, NY*.

KRUSELL, P., L. E. OHANIAN, J.-V. RÍOS-RULL, AND G. L. VIOLANTE (2000): "Capital-skill complementarity and inequality: A macroeconomic analysis," *Econometrica*, 68, 1029–1053.

KUSETOGULLARI, H., A. YAVARIABDI, J. HALL, AND N. LAVESSON (2021): "Digitnet: a deep handwritten digit detection and recognition method using a new historical handwritten digit dataset," *Big Data Research*, 23, 100182.

KUZNETS, S. (1955): "Economic growth and income inequality," *The American economic review*, 45, 1–28.

KWON, S. Y., Y. MA, AND K. ZIMMERMANN (2024): "100 years of rising corporate concentration," *American Economic Review*, 114, 2111–2140.

LAFORTUNE, J., E. LEWIS, AND J. TESSADA (2019): "People and machines: A look at the evolving relationship between capital and skill in manufacturing, 1860–1930, using immigration shocks," *Review of Economics and Statistics*, 101, 30–43.

LASHKARI, D., A. BAUER, AND J. BOUSSARD (2024): "Information technology and returns to scale," *American Economic Review*, 114, 1769–1815.

LEKNES, S. AND J. MODALSLI (2020): "Who Benefited from Industrialization? The Local Effects of Hydropower Technology Adoption in Norway," *The Journal of Economic History*, 80, 207–245.

LINDERT, P. H. (1986): "Unequal English wealth since 1670," *Journal of Political Economy*, 94, 1127–1162.

LUCAS, R. E. J. (1978): "On the size distribution of business firms," *The Bell Journal of Economics*, 508–523.

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Krof, E. Dinlersoz, L. Foster, and N. Zolas (2023): "AI Adoption in America: Who, What, and Where," *NBER Working Paper*.

Melitz, M. J. (2003): "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica*, 71, 1695–1725.

Morin, M. (2015): "The labor market consequences of technology adoption: concrete evidence from the Great Depression," *University of Cambridge*.

Peter, A. (2021): "Equity Frictions and Firm Ownership," .

Piketty, T., G. Postel-Vinay, and J.-L. Rosenthal (2006): "Wealth concentration in a developing economy: Paris and France, 1807-1994," *American economic review*, 96, 236–256.

Piketty, T., E. Saez, and G. Zucman (2018): "Distributional national accounts: methods and estimates for the United States," *The Quarterly Journal of Economics*, 133, 553–609.

Poschke, M. (2018): "The firm size distribution across countries and skill-biased change in entrepreneurial technology," *American Economic Journal: Macroeconomics*, 10, 1–41.

Quadrini, V. (2000): "Entrepreneurship, saving, and social mobility," *Review of economic dynamics*, 3, 1–40.

Saitzew, M. (1914): *Steinkohlenpreise und Dampfkraftkosten: Untersuchungen über Preisbildung. AbteilungB: Preisbildung für gewerbliche Erzeugnisse. Zweiter Teil*, vol. 143-II of *Schriften des Vereins für Sozial-politik*, Berlin: Duncker Humblot.

Salgado, S. (2020): "Technical change and entrepreneurship," *Available at SSRN 3616568*.

Severnini, E. (2022): "The Power of Hydroelectric Dams: Historical Evidence from the United States over the Twentieth Century," *The Economic Journal*, 133, 420–459.

Smith, M., D. Yagan, O. Zidar, and E. Zwick (2019): "Capitalists in the Twenty-first Century," *The Quarterly Journal of Economics*, 134, 1675–1745.

STIGLER, G. J. AND C. FRIEDLAND (1962): "What can regulators regulate? The case of electricity," *The Journal of Law and Economics*, 5, 1–16.

TOUSSAINT, S., A. DE VICQ DE CUMPTICH, M. MOATSOS, AND T. VAN DER VALK (2022): "Household Wealth and its Distribution in the Netherlands, 1854-2019," *World Inequality Lab Working Paper*, 19.

UNGER, G. (2022): "Scale-Biased Technological Change," .

VICKERS, C. AND N. L. ZIEBARTH (2018): "United States Census of Manufactures, 1929-1935," .

VIDART, D. (2024): "Human capital, female employment, and electricity: Evidence from the early 20th-century United States," *Review of Economic Studies*, 91, 560–594.

VIOLANTE, G. L. (2008): "Skill-biased technical change," *The new Palgrave dictionary of economics*, 2, 1–6.

YEAPLE, S. R. (2005): "A simple model of firm heterogeneity, international trade, and wages," *Journal of international Economics*, 65, 1–20.

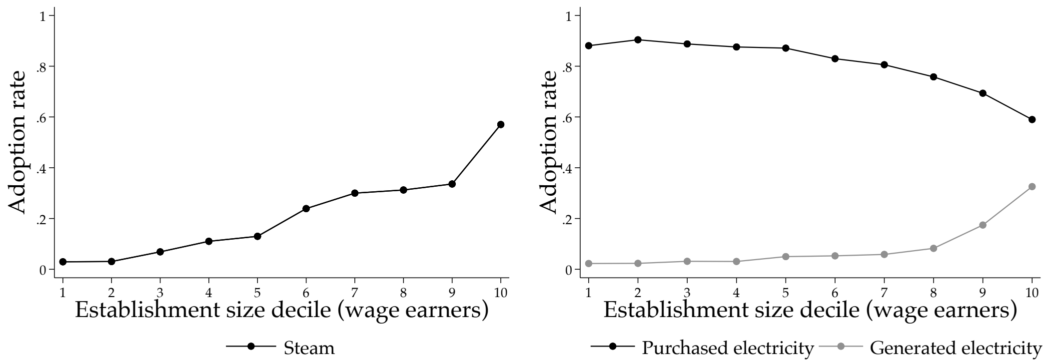
YOUNG, L. L. (1964): *Summary of Developed and Potential Waterpower of the United States and Other Countries of the World, 1955-62*, vol. 483, US Government Printing Office.

Appendix

A Figures

FIGURE A.1: Adoption rates by establishment size

(A) Steam engines (1880) (B) Electric motors (1929)



Notes: This figure indicates the share of establishments using steam engines in 1880 (panel A) and electric motors driven only by purchased electricity vs. generated electricity in 1929 (panel B) by establishment size as computed from samples of the Census of Manufactures. *Sources*: for 1880: (Atack and Bateman, 1999) (national sample); for 1929: (Vickers and Ziebarth, 2018).

FIGURE A.2: Illustration of pay-offs and optimal decisions

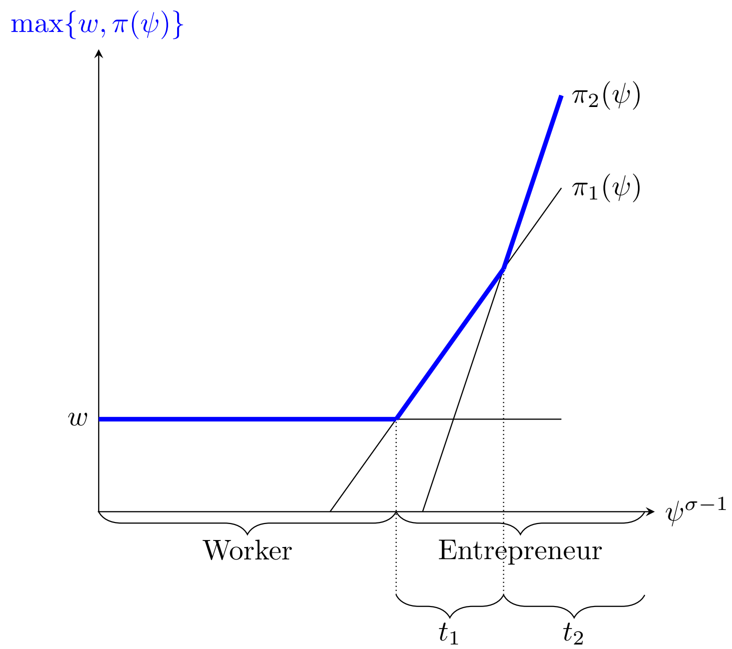
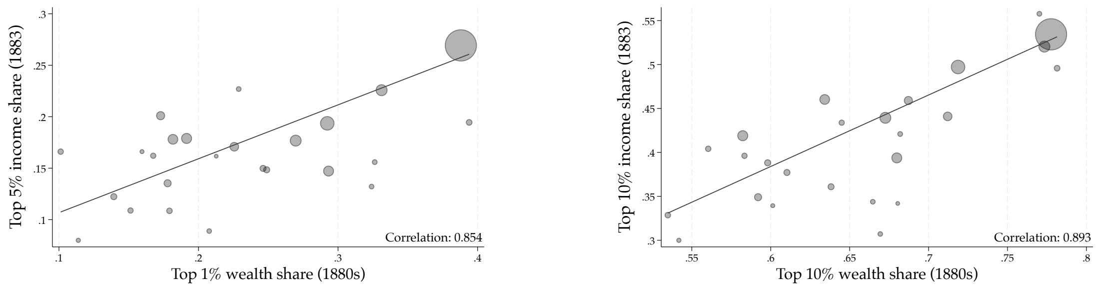


FIGURE A.3: Correlation between income and wealth inequality

(A) Top 1% share

(B) Top 10% share

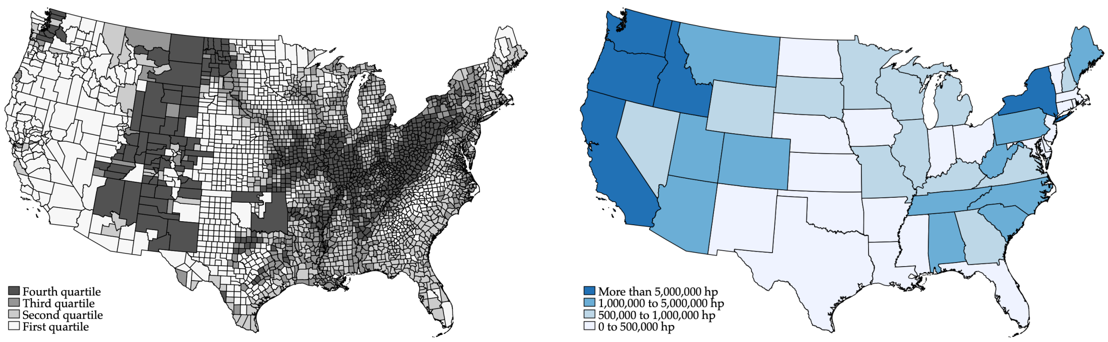


Notes: This figure shows the correlation between income inequality and wealth inequality in the 1880s. Each dot is a municipality and its size represents the number of wealth observations.

FIGURE A.4: Map of coal access and hydropower potential

(A) Coal access

(B) Hydropower potential

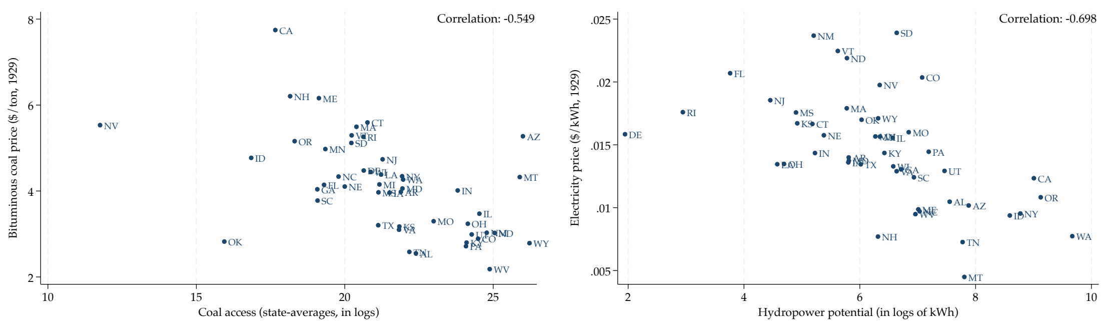


Sources: USGS for coal; (Young, 1964, Table 10) for hydropower potential.

FIGURE A.5: Correlation between instruments and coal and electricity prices

(A) Coal access and coal prices

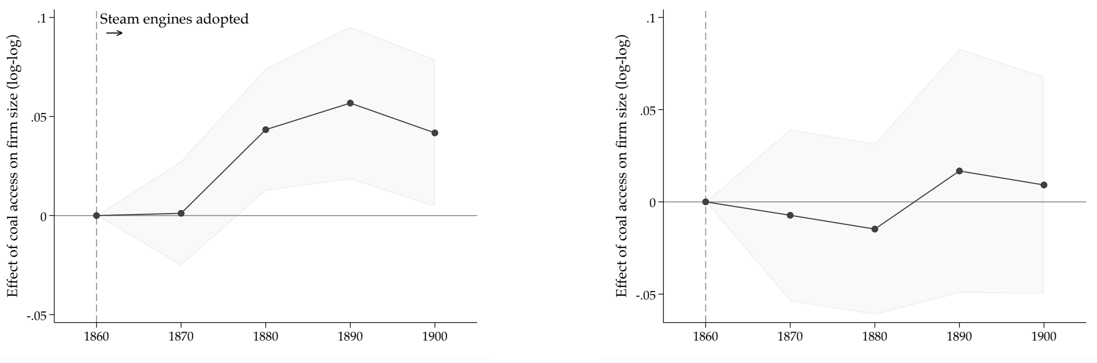
(B) Hydropotential and electricity prices



Sources: For prices, Census of Manufactures 1929; other sources are the same as for Figure A.4.

FIGURE A.6: Heterogeneous effects of coal access across industries

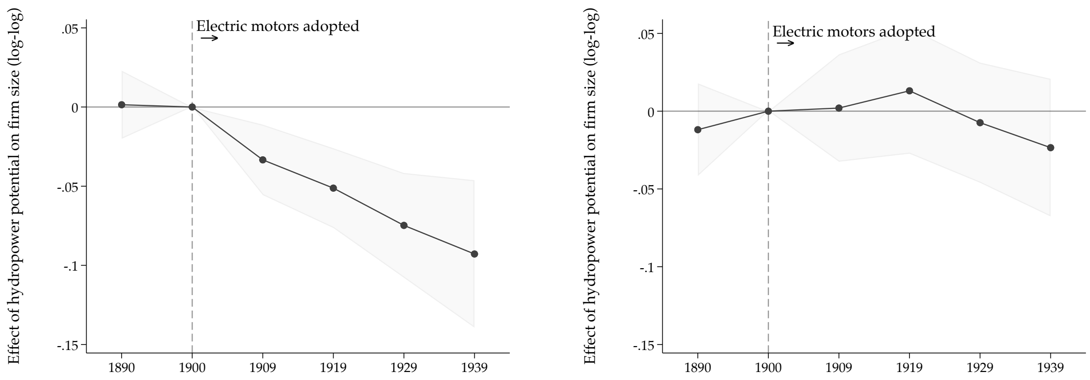
(A) Adopting industries (B) Placebo industries



Notes: This figure shows estimated reduced form effects of coal access. Panel A shows the effect estimated on a subset of industries that adopt any power nationally in 1890 (above the 25th percentile in share of establishments using power). Panel B shows the effect estimated on "placebo" industries, below the 25th percentile. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the state-level.

FIGURE A.7: Heterogeneous effects of hydropower potential across industries

(A) Adopting industries (B) Placebo industries



Notes: This figure shows estimated reduced form effects of hydropower potential on establishment sizes. Panel A shows the effect for industries that adopt electric motors nationally in 1939 (above the 25th percentile in share of fuel costs that is electric in 1939). Panel B shows the effect estimated on "placebo" industries, below the 25th percentile. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the state-level.

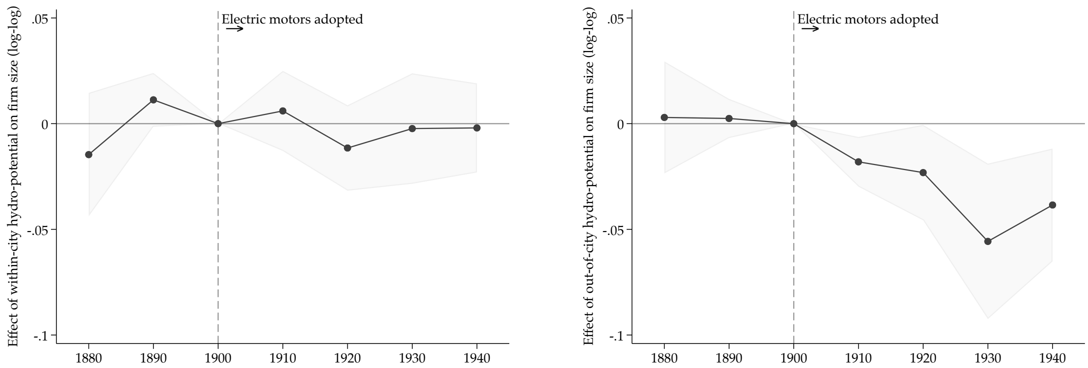
FIGURE A.8: Effects of coal access and hydropower potential on the city-industry level

(A) Coal access   (B) Hydropower potential

Notes: Panels A and B of this figure show estimates of the reduced form effects of coal access and hydropower potential on establishment sizes on the city-industry level. Estimates in panels A and B are jointly estimated in one specification (see equation (4) for the econometric specification), the only difference being the base year relative to which the estimates are estimated. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the city-level.

FIGURE A.9: Effects of hydropower potential on the city-industry is mostly through state-level hydropower

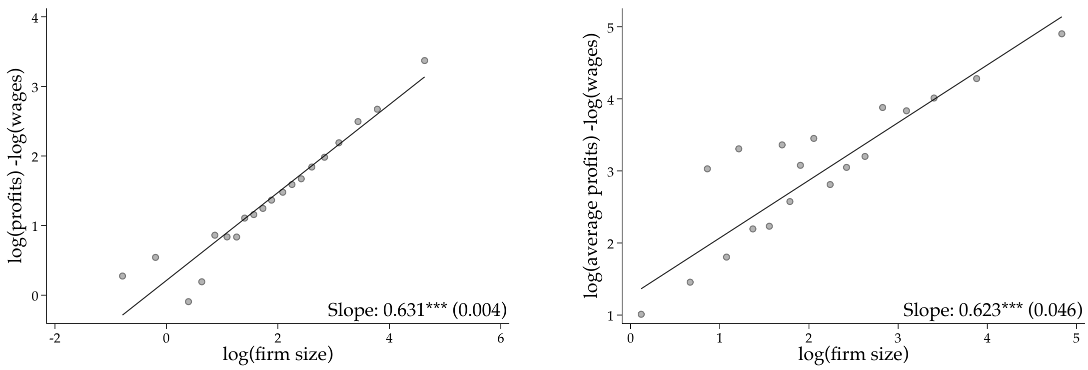
(A) Hydropower potential in the city   (B) Hydropower potential outside the city



Notes: Panels A and B of this figure show estimates of the reduced form effects of hydropower potential on establishment sizes on the city-industry level. Estimates in panels A and B are jointly estimated in one specification where the regression includes both hydropower potential within a 50 mile radius of the city and hydropower potential within the state outside of a 50 mile radius. Data on hydropower potential by county is from (Gaggl et al., 2021). Shaded areas represent 95% confidence intervals. Standard errors are clustered at the city-level.

FIGURE A.10: Correlation between profit-wage ratio and firm size

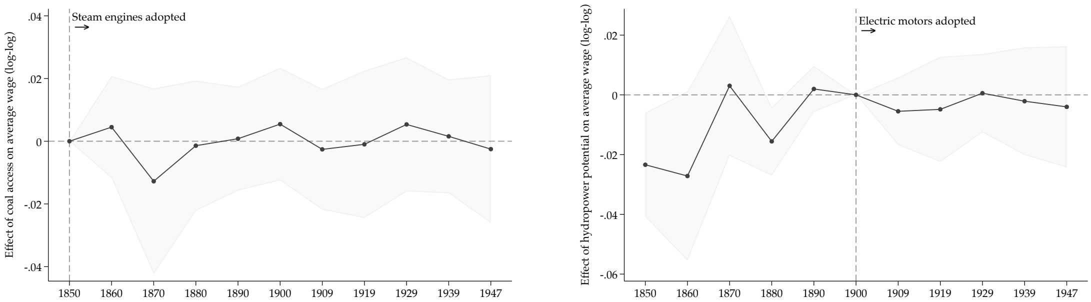
(A) State-industry level data | (B) Establishment level-data



Notes: Panels A and B show binscatters of firm sizes and the ratio between average profits and wages by industry (each in logs). Each observation is an industry-state-year combination. Average profits are approximated by dividing total output minus cost of raw materials, labor costs, capital costs, and other expenses by the number of establishments. Panel A is computed from the newly digitized state-industry data. There, the wage rate is approximated by dividing total wage costs by total employment. Panel B is computed from establishment-level data digitized by (Atack and Bateman, 1999), similarly aggregated to the state-industry level. In these data, the daily wage is directly observed. In both panels, state-industry pairs are weighted by the number of establishments.

FIGURE A.11: No detectable wage effects of either technology

(A) Coal's effect on wages | (B) Hydropower's effect on wages

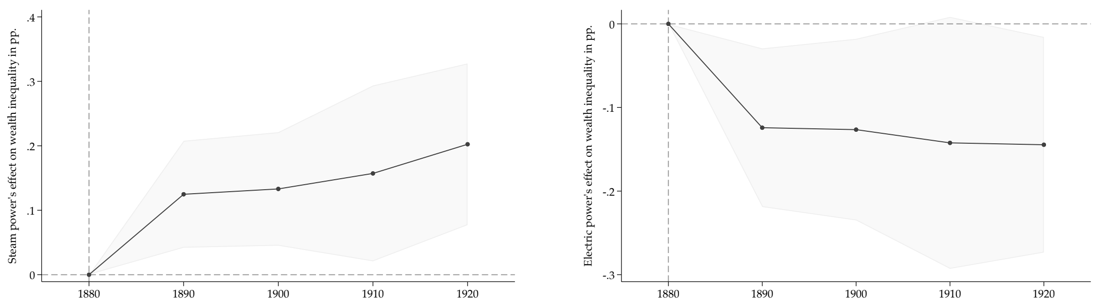


Notes: Panels A and B of this figure show estimates of the reduced form effects of coal access and hydropower potential on the average wage in logs relative to the base year, accounting for industry and state fixed effects. Estimates in panels A and B are jointly estimated in one specification (see equation (4) for the econometric specification where the outcome variable is the log of the average wage), the only difference being the base year relative to which the estimates are estimated. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the state-level.

FIGURE A.12: Robustness to using weighted wealth inequality measures

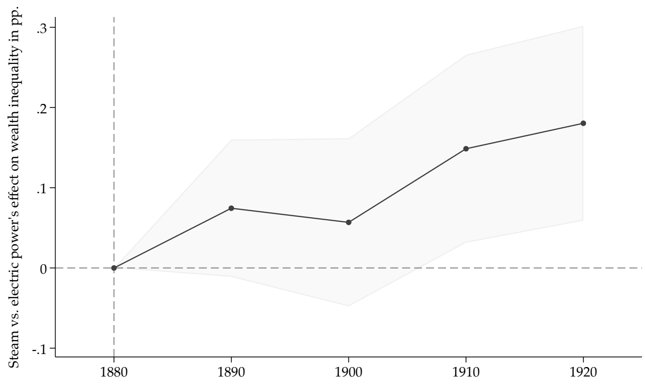
(A) Steam power effect

(B) Electric power effect



Notes: This figure shows the estimated effects in percentage points of steam power (in panel A) and electric power adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The only difference with 7 is that wealth inequality is computed by weighting individuals by the inverse probability of death as estimated by their age. The econometric specifications is detailed in equations (7). Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

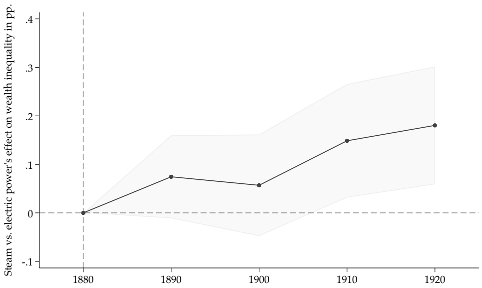
FIGURE A.13: Steam power adoption relative to electric power adoption increased wealth inequality.



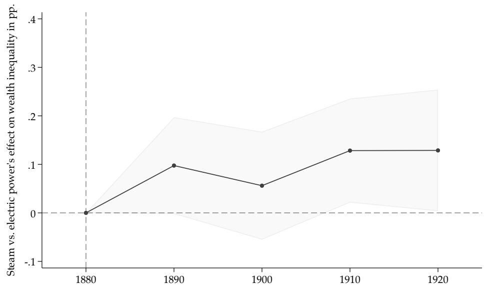
Notes: This figure shows the estimated effects in percentage points of steam power adoption on within-municipality top wealth inequality for each decade relative to 1880 relative to electric power adoption. Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

FIGURE A.14: Steam vs. electric power is most correlated with increased wealth inequality at the very top

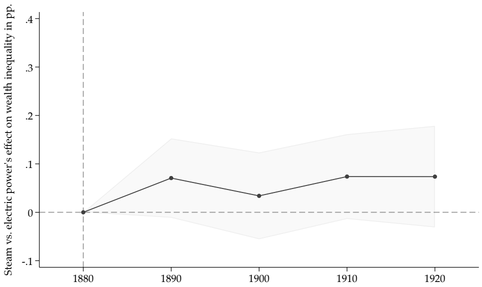
(A) Top 1% share



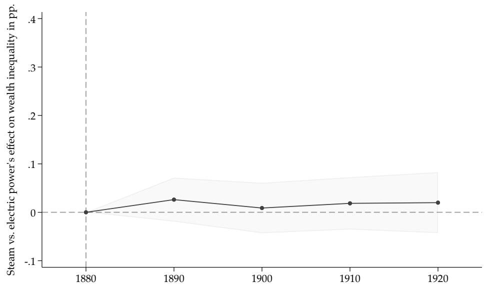
(B) Top 5% share



(C) Top 10% share



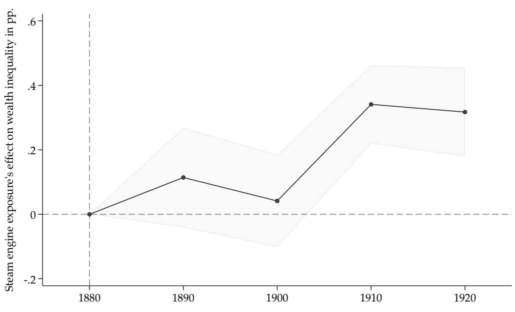
(D) Top 25% share



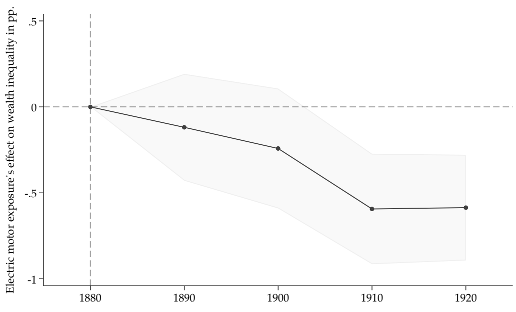
Notes: This figure shows the estimated effects in percentage points of steam power (panel A) and electric (panel B) power on within-municipality on wealth shares of different groups of top wealth owners. Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

FIGURE A.15: Steam power increased wealth inequality, electric power decreased it (IV)

(A) Steam power effect



(B) Electric power effect



Notes: This figure shows the estimated effects in p.p. of pre-industrial exposure to steam (in panel A) and electric power (in panel B) on within-municipality top wealth inequality (top 1% share) for each decade relative to 1880. The instrumental variable is exposure to the respective technology based on 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. Shaded areas represent 95% confidence intervals.

B Tables

TABLE B.1: Positive effects 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***	0.023***	0.031***	0.031***	0.035***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Hydro-potential (logs)		-0.006**	-0.006*		-0.007	-0.006
		(0.003)	(0.003)		(0.007)	(0.005)
Market access (logs)			X			X
Observations	4237	4237	4237	3395	3395	3395

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

TABLE B.2: Little effect of coal access on overall power use (1890)

	Water hp per worker (asinh)			Total hp per worker (asinh)		
Coal access (logs)	-0.030**	-0.028**	-0.037***	-0.001	-0.001	-0.005
	(0.013)	(0.013)	(0.012)	(0.006)	(0.006)	(0.006)
Hydro-potential (logs)		0.017	0.016**		0.002	0.002
		(0.010)	(0.008)		(0.006)	(0.004)
Market access (logs)			X			X
Observations	4237	4237	4237	4237	4237	4237

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

TABLE B.3: Positive effects of hydropower potential on purchased electric energy use (1939)

	MWh per worker (asinh)			Electricity as share of fuel		
Hydro-potential (logs)	0.110***	0.116***	0.120***	0.020***	0.018***	0.017***
	(0.029)	(0.024)	(0.021)	(0.004)	(0.003)	(0.003)
Coal access (logs)		0.022	0.015		-0.007**	-0.005*
		(0.017)	(0.017)		(0.003)	(0.002)
Market access (logs)			X			X
Observations	5031	5031	5031	5010	5010	5010

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

TABLE B.4: Opposite effects of steam and electric power adoption on firm sizes

	$\Delta \ln(\text{firm size}_{is})$			
	1860-1890		1900-1939	
$\frac{\text{Steam power in hp}}{\text{Employees}}$	1.058	1.089		
	(0.450)	(0.483)		
$\frac{\text{Electricity in MWh}}{\text{Employees}}$			-0.338	-0.266
			(0.123)	(0.157)
Controls		X		X
Observations	1900	1900	2117	2117
Kleibergen-Paap F-stat.	42.9	24.7	40.9	37.9

Notes: This table shows the estimated effects of steam and electric power adoption per employee on the change in log firm size by state and industry. The explanatory variables are the inverse hyperbolic sine of steam engine horsepower in 1890 and megawatt-hour of purchased electricity per worker in 1939. The adoption variables are instrumented with coal access (for steam) and hydropower potential (for electricity). Industry fixed effects are included in all regressions. Where controls are indicated, the regression is controlled for the state's income (1900-1940) and wealth (1860-1890) growth per capita. Market access is used as a control in all specifications. Observations are weighted by the number of establishments in the base year. Standard errors in parentheses are clustered at the state-level.

TABLE B.5: Opposite effects of steam and electric power on profit-wage ratios

	$\Delta \ln(\text{profit-wage ratio}_{is})$			
	1860-1890		1900-1939	
$\frac{\text{Steam power in hp}}{\text{Employees}}$	1.134	1.020		
	(0.529)	(0.512)		
$\frac{\text{Electricity in MWh}}{\text{Employees}}$			-0.440	-0.322
			(0.268)	(0.315)
Controls		X		X
Observations	1869	1869	1935	1935
Kleibergen-Paap F-stat.	42.8	24.8	11.6	9.9

Notes: This table shows the estimated effects of steam power and electric power adoption on the change in the log profit-wage ratio in a given state and industry. The explanatory variables are the inverse hyperbolic sine of steam engine horsepower in 1890 and megawatt-hour of purchased electricity per worker in 1939. The adoption variables are instrumented with coal access (for steam) and hydropower potential (for electricity). Where controls are indicated, the regression is controlled for the state's income (1900-1940) and wealth (1860-1890) growth per capita. Market access is used as a control in all specifications. Observations are weighted by the number of establishments in the base year. Standard errors in parentheses are clustered at the state-level.

C Model appendix

C.1 Definition of competitive equilibrium

Definition (Competitive equilibrium).
Given an exogenous technology set $T = \{t_1, .., t_J\}$, a *competitive equilibrium* consists of a price w, output Y, a set of adopted technologies T^*, and adopting sets Ψ_j, such that

– the set of households choosing entrepreneurship with technology j is

$$\Psi_j \equiv \{\psi \mid \pi_j(\psi) \geq w\} \cap \left\{\psi \mid \pi_j(\psi) = \max_k \pi_k(\psi)\right\}. \tag{9}$$

where $\pi_j(\psi)$ is as defined in equation (1);

– the labor market clears, so that

$$\underbrace{F(\bar{\psi})}_{\text{Labor supply}} = \underbrace{Y\left(\frac{\rho}{w}\right)^{\sigma}\sum_{j=1}^{J}\alpha_j^{1-\sigma}\int_{\psi\in\Psi_j}\psi^{\sigma-1}dF(\psi) + \sum_{j=1}^{J}\int_{\psi\in\Psi_j}\kappa_j dF(\psi);}_{\text{Labor demand}} \tag{10}$$

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

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

C.2 Proposition A.1

Proposition A.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, $T^* = \left\{t_1^*, \ldots, t_{J^*}^*\right\}$, is such that*

(a) the adopted technology with the highest marginal (lowest fixed) cost $t_1^* = (\alpha_1^*, \kappa_1^*)$ is such that $(\alpha_1^*)^{\sigma-1}(1+\kappa_1^*) = \min_{j\in\{1,\ldots,J\}} \alpha_j^{\sigma-1}(1+\kappa_j)$. In case more than one technology satisfies this criterion, only the technology with lower marginal cost is adopted;

(b) the adopted technology with the lowest marginal (highest fixed) cost $t_{J^*}^* = (\alpha_{J^*}^*, \kappa_{J^*}^*)$ is such that $\alpha_{J^*}^* = \min_{j\in\{1,\ldots,J\}} \{\alpha_j\}$;

(c) *any technology with fixed cost $\kappa_1^* < \kappa_j < \kappa_{J^*}^*$ is adopted if and only if for any $k \in \{1, \ldots, j-1\}$ and $l \in \{j+1, \ldots, J\}$*

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

Proof of Proposition A.1. I prove Proposition A.1 by proving its elements (a) to (c) sequentially.

Proposition A.1(a): Since $\Delta\pi_{jk}(\psi)$ (defined in equation (2)) is strictly increasing in ψ if $\kappa_j > \kappa_k$ and $\alpha_j < \alpha_k$, the least productive entrepreneur uses the adopted technology with the highest marginal and lowest fixed cost. Also, the least productive entrepreneur has productivity ψ equal to the lowest threshold $\bar{\psi}_j$ of all available technologies, $\min_{j \in 1,\ldots,J} \bar{\psi}_j$. From equation (3), technology t_j has the lowest entry threshold if and only if $\alpha_j (1+\kappa_j)^{\frac{1}{\sigma-1}} = \min_{k \in \{1,\ldots,J\}} \left\{ \alpha_k (1+\kappa_k)^{\frac{1}{\sigma-1}} \right\}$. If more than one technology that satisfies this, then among those only the technology with lowest marginal cost is adopted by a strictly positive measure of entrepreneurs (since $\Delta\pi_{jk}(\psi)$ is strictly increasing, any entrepreneur with $\psi > \bar{\psi}$ would strictly prefer the technology with lower marginal cost).

Proposition A.1(b): Note that $\Delta\pi_{jk}(\psi) \to \infty$ in (2) as $\psi \to \infty$ if and only if $\alpha_j < \alpha_k$. Hence, there exists a productivity level high enough such that it is profitable to adopt the lower marginal cost technology. The assumptions on the productivity distribution imply that for any $C > 0$, $\Pr(\psi > C) > 0$ so that the technology with lowest marginal cost is always adopted.

Proposition A.1(c): A technology t_j with fixed cost κ_j such that $\kappa_1^* < \kappa_j < \kappa_{J^*}^*$ is adopted if and only if there exists a $\psi > \psi_m$ for which it 1) dominates all technologies with lower fixed costs, 2) dominates all technologies with higher fixed cost, and 3) yields positive profits. Condition 3) is redundant since it can only dominate technology t_1^* if $\psi > \bar{\psi}$ and t_1^* yields positive profits for all $\psi > \bar{\psi}$. An intermediate technology t_j is thus adopted iff there exists a $\psi > \psi_m$ such that $\Delta\pi_{jk}(\psi) > 0$ for all $k \in \{1, \ldots, j-1\}$ and $\Delta\pi_{jl}(\psi) > 0$ for all $l \in \{j+1, \ldots, J\}$. Using equation (2), this yields the following two restrictions:

$$\frac{Y}{\sigma} (\rho\psi)^{\sigma-1} w^{-\sigma} > \frac{\kappa_j - \kappa_k}{\alpha_j^{1-\sigma} - \alpha_k^{1-\sigma}} \text{ for all } k \in \{1, \ldots, j-1\} \text{ and;} \tag{12a}$$

$$\frac{Y}{\sigma} (\rho\psi)^{\sigma-1} w^{-\sigma} < \frac{\kappa_l - \kappa_j}{\alpha_l^{1-\sigma} - \alpha_j^{1-\sigma}} \text{ for all } l \in \{j+1, \ldots, J\} \tag{12b}$$

For (12a) and (12b) to hold for some $\psi > \bar{\psi}$, it is necessary and sufficient that the lower bound in (12a) is lower than the upper bound in (12b). This yields the inequality in part (c) of the proposition. □

C.3 Proposition A.2

Proposition A.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, given the set of technologies adopted in equilibrium T^*, the solution to the competitive equilibrium is*

$$\bar{\psi} = \psi_m \left(1 + \frac{\xi(\sigma-1)}{\xi-\sigma+1}\right)^{\frac{1}{\xi}} (1+\bar{\kappa})^{\frac{1}{\xi}} \tag{13}$$

$$\bar{\psi}_{j,j+1} = \bar{\psi} \left(\frac{\kappa^*_{j+1} - \kappa^*_j}{(\alpha^*_{j+1})^{1-\sigma} - (\alpha^*_j)^{1-\sigma}}\right)^{\frac{1}{\sigma-1}} \left(\alpha^*_1 (1+\kappa^*_1)^{\frac{1}{\sigma-1}}\right)^{-1} \quad \forall j = 1, \ldots, J^* \tag{14}$$

$$Y = \psi_m(\sigma-1) \left(\frac{\xi}{\xi-\sigma+1}\right)^{\frac{\sigma}{\sigma-1}} \left(1+\frac{\xi(\sigma-1)}{\xi-\sigma+1}\right)^{\frac{\sigma-\xi\sigma-1}{\xi(\sigma-1)}} \frac{(1+\bar{\kappa})^{\frac{1}{\xi}}}{\alpha^*_1(1+\kappa^*_1)^{\frac{1}{\sigma-1}}} \tag{15}$$

$$w = \left(1 - \frac{\sigma-1}{\xi\sigma}\right) Y \tag{16}$$

where $\bar{\kappa}$ is the average fixed cost among entrepreneurs:

$$\bar{\kappa} = \begin{cases} \kappa^*_1 & \text{if } J^* = 1 \\ \kappa^*_1 + \left(\alpha^*_1\,(1+\kappa^*_1)^{\frac{1}{\sigma-1}}\right)^{\xi} \sum_{j=2}^{J^*} \left(\frac{\left((\alpha^*_j)^{1-\sigma} - (\alpha^*_{j-1})^{1-\sigma}\right)^{\xi}}{\left(\kappa^*_j - \kappa^*_{j-1}\right)^{\xi-\sigma+1}}\right)^{\frac{1}{\sigma-1}} & \text{if } J^* > 1. \end{cases}$$

The set of households choosing entrepreneurship with technology $j^* = 1, \ldots, J^*$ is

$$\Psi^*_j = \begin{cases} [\bar{\psi}_{j-1,j}, \bar{\psi}_{j,j+1}] & \text{if } j^* < J^* \\ [\bar{\psi}_{j-1,j}, \infty) & \text{if } j^* = J^* \end{cases} \tag{17}$$

where $\bar{\psi}_{0,1} \equiv \bar{\psi}$. The remaining households choose to work.

Proof of Proposition A.2. Setting the profit difference $\Delta\pi_{j,j+1}(\psi)$ in (2) to zero yields that an entrepreneur is indifferent between adopting t^*_j and t^*_{j+1} if their productivity is

$$\bar{\psi}_{j,j+1} = \left(\frac{\kappa^*_{j+1} - \kappa^*_j}{(\alpha^*_{j+1})^{1-\sigma} - (\alpha^*_j)^{1-\sigma}} \right)^{\frac{1}{\sigma-1}} \left(\frac{\sigma}{Y} \right)^{\frac{1}{\sigma-1}} \frac{w^{\frac{\sigma}{\sigma-1}}}{\rho}$$

so that a comparison with $\bar{\psi}$ in equation (3) yields (14). The adopting sets Ψ^*_j in equation (17) then follow from the fact that the profit gain from lower marginal cost technologies is increasing in ψ.

Equation (13) follows by combining equations (3), (10), (14), and (17), and imposing the Pareto distribution: $f(\psi) = \xi \psi_m^\xi \psi^{-\xi-1}$ and $F(\psi) = 1 - \psi_m^\xi \psi^{-\xi}$. Equations (15) and (16) then follow from combining equations (11) and (13), and the definition of $\bar{\kappa}$. □

C.4 Proposition A.3

Proposition A.3 (The competitive equilibrium is socially optimal)**.** *Suppose the assumption in Proposition A.2 (Pareto distribution) holds. Then, the competitive equilibrium is socially optimal. That is, it maximizes output subject to the resource constraint.*

Proof of Proposition A.3. We maximize (a monotonic transformation of) output Y

$$\max_{\{\Psi_j, l_j(\psi)\}_{j=1}^J} \left[\sum_{j=1}^J \int_{\Psi_j} \left(\frac{\psi l_j(\psi)}{\alpha_j} \right)^{\frac{\sigma-1}{\sigma}} dF(\psi) \right]^{\frac{\sigma}{\sigma-1}}$$

subject to the resource constraint

$$\sum_{j=1}^J \int_{\Psi_j} l_j(\psi) dF(\psi) + \sum_{j=1}^J \kappa_j \int_{\Psi_j} dF(\psi) = 1 - \sum_{j=1}^J \int_{\Psi_j} dF(\psi).$$

First, conditional on occupational and technological choice, it is straightforward to derive that the optimal allocation of labor to an entrepreneur with productivity ψ and technology j is

$$l_j^{SP}(\psi) = \left(\frac{\sigma - 1}{\sigma} \frac{1}{\lambda} \right)^{\sigma} \left(\frac{\psi}{\alpha_j} \right)^{\sigma-1}$$

where λ is the Lagrange multiplier on the resource constraint (i.e., the marginal product of labor). Thus, the relative allocation of labor across entrepreneurs with given ψ and technology j is equal to the competitive equilibrium.

Given the optimal allocation of labor to entrepreneur-technology pairs, the social surplus of being an entrepreneur with technology j and productivity ψ relative to being a worker is

$$\frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\frac{1}{\lambda}\right)^{\sigma-1}\left(\frac{\psi}{\alpha_j}\right)^{\sigma-1}-(1+\kappa_j)\lambda$$

where the first term reflects output minus variable labor costs and the second term reflects the fixed labor costs (which includes the opportunity cost of the entrepreneur's own labor). Since this surplus is increasing in ψ, there is a threshold $\bar{\psi}_j^{SP}$ above which being an entrepreneur with technology j yields higher surplus than being a laborer:

$$\bar{\psi}_j^{SP}=\alpha_j(1+\kappa_j)^{\frac{1}{\sigma-1}}\sigma^{\frac{1}{\sigma-1}}\frac{\sigma}{\sigma-1}\lambda^{\frac{\sigma}{\sigma-1}}.$$

The productivity threshold above which a household becomes an entrepreneur is $\bar{\psi}^{SP}=\min_{j\in 1,\ldots,J}\bar{\psi}_j^{SP}$. Note that the above equation implies that the marginal entrepreneur in the social planner allocation uses the same technology as the marginal entrepreneur in the competitive equilibrium (the one that minimizes $\alpha_j(1+\kappa_j)^{\frac{1}{\sigma-1}}$).

The social surplus when using technology j relative to technology k is

$$\frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\frac{1}{\lambda}\right)^{\sigma-1}\psi^{\sigma-1}(\alpha_j^{1-\sigma}-\alpha_k^{1-\sigma})-(\kappa_j-\kappa_k)\lambda.$$

As in the competitive equilibrium, when $\alpha_j<\alpha_k$ (and $\kappa_j>\kappa_k$), this surplus is increasing in ψ. Hence, there is a productivity threshold above which the social planner prefers the entrepreneur to use the higher fixed (and lower marginal) cost technology. Further, it follows from the above equation and the reasoning in Proposition A.1 that the social planner adopts the exact same set of technologies as those adopted in the competitive equilibrium. Setting the above equation to zero, yields the threshold above which the entrepreneur optimally adopts technology $j+1$ instead of j:

$$\bar{\psi}_{j,j+1}^{SP} = \left(\frac{\kappa_{j+1}^* - \kappa_j^*}{(\alpha_{j+1}^*)^{1-\sigma} - (\alpha_j^*)^{1-\sigma}} \right)^{\frac{1}{\sigma-1}} \sigma^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} \lambda^{\frac{\sigma}{\sigma-1}} = \bar{\psi}^{SP} \frac{\left(\frac{\kappa_{j+1}^* - \kappa_j^*}{(\alpha_{j+1}^*)^{1-\sigma} - (\alpha_j^*)^{1-\sigma}} \right)^{\frac{1}{\sigma-1}}}{\alpha_j^* (1+\kappa_j^*)^{\frac{1}{\sigma-1}}}.$$

The above equation proves that the productivity cut-offs for occupational and technological choice in the competitive and socially optimal allocation are the same up to a constant. It remains to prove that they are identical.

One can solve for $\bar{\psi}$ in an exactly analogous way to solving for the threshold in the competitive equilibrium: combine the resource constraint with the definition of the entrepreneurial threshold and the relation between the entrepreneurial threshold and the technological choice thresholds. The terms depending on λ cancel out and the following expression for the socially optimal entrepreneurial threshold remains:

$$\bar{\psi}^{SP} = \psi_m \left(1 + \frac{\xi(\sigma-1)}{\xi - \sigma + 1} \right)^{\frac{1}{\xi}} (1+\bar{\kappa})^{\frac{1}{\xi}}$$

where the average fixed cost among entrepreneurs, $\bar{\kappa}$, is identical to the competitive equilibrium and thus $\bar{\psi}^{SP} = \bar{\psi}^{CE}$. Thus, all cutoffs are identical and the competitive equilibrium allocates each household to the socially optimal occupation and technology.

Because both the relative labor demand across entrepreneurs and the total labor supply are socially optimal, the amount of labor assigned to each entrepreneur is socially optimal. This means that output in the competitive equilibrium is equal to the socially optimal output. □

C.5 Proposition 1

Proposition 1 (Theoretical implications of scale-biased technical change).
Suppose that the productivity distribution is Pareto, $f(\psi) = \xi \psi_m^{\xi} \psi^{-\xi-1}$ with $\xi > \sigma - 1$ and that $\sigma > 2$. Then, large-scale-biased technical change increases

(a) the average number of employees per firm;

(b) income inequality between entrepreneurs and workers;

(c) the income share that accrues to the top k% for any k below some $\bar{k} \in (0, 100)$.

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

Proof of Proposition 1. I prove Proposition 1 by proving its elements (a), (b), and (c) sequentially.

Proposition 1(a): Since the average number of employees per entrepreneur or firm, $F(\bar{\psi})/(1 - F(\bar{\psi}))$, is increasing in $\bar{\psi}$ it suffices to show that $\bar{\psi}$ increases (decreases) with large-scale-biased (small-scale-biased) technical change.

If technical change is large-scale-biased, the new technology has highest fixed costs. If it is the only adopted technology in the new equilibrium, it must increase the average fixed cost $\bar{\kappa}$, and thus $\bar{\psi}$ (equation (13)). If it is instead adopted alongside existing technologies, it cannot be used by the marginal entrepreneur (as that must have lowest fixed cost among adopted technologies). As the equilibrium is socially efficient (Proposition A.3), output Y and thus wages w must rise with a new adopted technology. The profit function in (1) combined with equilibrium output and wages in (15) and (16) shows that profits for any given technology is decreasing in w if $\sigma > 2$. Thus, $\bar{\psi}_j$ must increase for any pre-existing technology j, so that $\bar{\psi}$ increases.

If technical change is small-scale-biased, the new technology has lowest fixed cost. Thus, any entrepreneur with $\psi \geq \bar{\psi}_{old}$ that adopts the technology would lower their fixed cost. Also, any existing entrepreneur that changes technology will lower their fixed costs (since the wage cannot decrease with technical change and equation (2) is decreasing in wage/output). In sum, no entrepreneur with $\psi \geq \bar{\psi}_{old}$ increases their fixed costs and average fixed cost can only rise if there is a set of entrepreneurs with $\psi < \bar{\psi}_{old}$ that adopts a technology j with $\kappa_j > \bar{\kappa}_{old}$, but this requires that $\bar{\psi}$ and $\bar{\kappa}$ declined. Hence, $\bar{\psi}$ declines.

Proposition 1(b): Combining the resource constraint $\bar{\pi}(1 - F(\bar{\psi})) + wF(\bar{\psi}) = Y$ with $Aw = Y$ for some $A > 1$ (equation (16)), yields that $\frac{\bar{\pi}}{w} = \frac{A - F(\bar{\psi})}{1 - F(\bar{\psi})}$. This is increasing in $\bar{\psi}$ so that the result follows from the Proposition 1(a).

Proposition 1(c): To show that top k% income shares increase for a small enough k, it is sufficient to show that $\lim_{\psi \to \infty} \frac{\pi(\psi|T_{new})}{\pi(\psi|T_{old})} > \frac{Y_{new}}{Y_{old}}$ (since this implies that there is a strictly positive measure of entrepreneurs at the top of the income distribution whose income increases by more than average income Y). Similarly, to show that this measure of top income inequality decreases, it is sufficient to show that $\lim_{\psi \to \infty} \frac{\pi(\psi|T_{new})}{\pi(\psi|T_{old})} < \frac{Y_{new}}{Y_{old}}$.

When technical change is small-scale-biased, the most productive entrepreneurs do not adopt the technology. Therefore, in the limit of $\psi \to \infty$, profits decrease in absolute terms (since wages increase and $\sigma > 2$). Since output goes up, this proves the statement.

Now consider the case when technical change is large-scale-biased. The profit function in equation (1), implies

$$\lim_{\psi \to \infty} \frac{\pi(\psi|T_{new})}{\pi(\psi|T_{old})} = \frac{Y_{new}}{Y_{old}} \left(\frac{\tilde{\alpha}_{old} Y_{old}}{\tilde{\alpha}_{new} Y_{new}} \right)^{\sigma-1}.$$

where $\tilde{\alpha}_{old}$ and $\tilde{\alpha}_{new}$ are the lowest marginal cost technology before and after the introduction of the new technology, respectively. Hence, it is sufficient to prove that the proportional output increase is smaller than the decrease in the lowest marginal cost, i.e., $\frac{\tilde{\alpha}_{old} Y_{old}}{\tilde{\alpha}_{new} Y_{new}} > 1$.

To prove this, consider a scenario where the marginal cost of all technologies reduces proportionally without affecting fixed costs. From Proposition A.1, it can be seen that such scenario leaves the set of adopted technologies unchanged. From Proposition A.2, $\bar{\kappa}$ and κ_1^* are also unchanged. Equations (15) and (16) then imply that the output gain of such a uniform marginal cost decrease would be $\frac{\tilde{\alpha}_{old}}{\tilde{\alpha}_{new}}$. By efficiency of the equilibrium, the output gain from a new technology with lower marginal but higher fixed costs must be strictly lower. Therefore, $\frac{\tilde{\alpha}_{old} Y_{old}}{\tilde{\alpha}_{new} Y_{new}} > 1$ when technical change is large-scale-biased. $\square$

D Data appendix

D.1 Details on Dutch wealth data

Sources. The estate tax returns are referred to in Dutch as *memories van successie*. Table D.1 reports the sources for each of the five provinces included in the sample:

TABLE D.1: Sources of Dutch wealth data by provincial archive

Province	Archive	Record group(s)
Gelderland	Gelders Archief	Various record groups
Noord-Brabant	BHIC	Various record groups
Noord-Holland	Noord-Hollands Archief	Record group 178
Overijssel	Collectie Overijssel	Record group 136.4
Zeeland	Zeeuws Archief	Record group 398

Notes: BHIC stands for "Brabants Historisch Informatie Centrum".

Details on digitization procedure. I first trained a state-of-the-art object detection algorithm called YOLOv5 to filter out and crop relevant parts of millions of scans of inheritance tax files. Thankfully, the form used in the inheritance tax was consistent nationally and over time between 1879 and 1927. I trained the object detection algorithm to recognize the location of the form that contains the relevant information and automatically cropped the relevant parts of the images shown in Figure 3. I apply this algorithm to 3,261,708 document scans. Of those scans, 837,620 scans were detected to contain the relevant information.

After detecting and cropping the relevant parts of the source images, I then trained another computer vision algorithm to extract information on the date of death and the value of assets, liabilities, and net worth. This algorithm consists of several steps. First, I trained an object detection algorithm to find the location of the relevant information (e.g., date or wealth) in the cropped images. Then, to extract the date of death, I trained three object classification algorithms that respectively classify the date of death to be, e.g., the 18th day of the month, the month of September, and the year 1912. Third, I trained an object detection algorithm to detect each number that appears in the wealth data. Finally, I construct the wealth data, by combining the detected numbers with the information on the detected location of assets, liabilities, and net worth data.

An inherent advantage of the source files is that the wealth data present a direct test of the accuracy of the digitization. That is, I test whether assets minus liabilities equals net worth. The recognized numbers add up to the last digit in 82 percent of the cases. In 90 percent of the cases, the discrepancy is smaller than 20 percent. For those images for which the recognized numbers do not add up exactly or for which either assets, liabilities, or net worth are not recognized, I digitize the data using OpenAI's GPT-4o. Since the GPT-4o method is prone to errors, I only use this information if it can be validated with the numbers obtained from the YOLO algorithm. That is, if net worth is consistent between YOLO and GPT-4o or if both assets and liabilities are consistent. This procedure increases the number of cases for which net worth can be validated up to the last digit to 91.5 percent and those for which the discrepancy is below 20 percent to 96.8 percent.

Matching with existing civil registry data. The civil death registry covers the near-universe of deaths in the relevant provinces.[41] The only exception is the city of Amsterdam, for which the civil death registry is not digitized. While the type of information that was digitized varies somewhat by archive, each archive has digitized the name(s) of the decedent and their parents, the date of death, the sex, and the place of death. In all cases except Noord-Brabant, the age at death was also collected. To maximize the amount of information available for each person that appears in the death records, I also link the civil death records to the civil marriage and birth records.

I match the newly digitized inheritance tax by (fuzzy) matching based on name, date of death, and inheritance tax district.[42] In record linking terminology, I use the relevant image set as defined by the place and date of death as *blocking variables* for the linking between the inheritance tax records and the civil registry data. This generates for each individual in the inheritance tax records, a set of possible matches from the civil registry. From the set of available matches, I choose the most appropriate match (if any) by using a heuristic multi-stage matching algorithm. The algorithm takes into account information on the name and date of death.

[41] The civil registry data can be downloaded in bulk at here.

[42] A tax district consisted of a set of municipalities. Since the inheritance tax files are arranged by tax district, the tax district can be inferred without any transcription.

Description of micro-level database. Table D.2 summarizes the availability of key variables and the total number of observations for which these variables are observed. Around 79 percent of the observations can be linked to a record in the civil death registry. Outside of Amsterdam, for which the registry is not available, the match rate is over 90 percent. The civil registry data allow us to narrow down the place of death to the level of the municipality. Furthermore, the civil registry data often contain the age at death.[43] I assign all observations from the tax office in Amsterdam to the Amsterdam municipality.

TABLE D.2: Number of observations

Subset	Observations
Individuals with wealth data	380,131
of whom municipality is known	370,311
of whom a civil registry link is available	301,920
of whom age at death is known	256,093

Notes: This table shows the number of observations for which key information is observed. Besides rare exceptions, each is a subset of the other, so that the bottom row reflects the number of individuals for whom their wealth, location, civil registry data, and age are recorded.

D.2 Details on Dutch income data

The main source of the Dutch local income distribution data is a parliamentary document that recorded a detailed distribution of income for 79 municipalities in 1883, including many large cities. These data were derived from local income tax administrations and indicate the number of inhabitants within 41 income brackets for each municipality.

I supplemented these data with data collected from local archives on the income distributions of 8 additional cities with a local income tax whose distribution was not included in the parliamentary study. I thank Jan Luiten van Zanden for kindly sharing the data for Hilversum. Table D.3 provides an overview of all the sources used.

[43]The age at death was always record in the source data, but in some cases this information was not included by the archive in the digitized version of the registry.

TABLE D.3: Sources of income distribution data for 8 additional cities

City	Year	Archive	Source
Main sample	1883	House of Representatives	1883-1884, document no. 172.13
Breda	1881	Stadsarchief Breda	Municipal year report 1880
Delft	1893	Stadsarchief Delft	Municipal year report 1893
Eindhoven	1885	RHC Eindhoven	Assessment lists, archive no. 10246.925
Enschede	1880	Stadsarchief Enschede	Assessment lists, archive no. 1.1226
Hilversum	1880	Archive Prof. Van Zanden	Assessment lists
Nijmegen	1880	Regionaal Archief Nijmegen	Income by class, archive no. 2.14167
Utrecht	1888	Utrechts Archief	Municipal year report 1900
Vlissingen	1883	Zeeuws Archief	Assessment lists, available here.

E Details on steam engines and electric motors' costs

In this section, I explain in detail the sources, assumptions and computations underlying the average cost curves of steam and electric power shown in Figure 2. The underlying data for steam engines are taken from (Emery, 1883) (in 1874 US) and (Saitzew, 1914) (in 1914 Germany).

Table E.1 gives an overview of the data provided by Emery (1883). Saitzew (1914) provided similar information. Saitzew (1914) provided cost estimates depending on the intensity of use: 1500, 3000, 8640 hours per year (generally, the higher the usage, the lower the cost per kWh). For consistency with Emery (1883), I use the estimates for 3000 hours per year.

From the data provided by Emery (1883), I compute the annualized cost of purchase and renewal as $(r + \delta) \times$ Price where δ is estimated as the inverse of the expected lifetime. I set the interest rate r equal to 0.05. For example, the annualized cost of renewal of a 5 hp steam engine (worth \$645) is \$53.75. The total costs per kWh are calculated as the sum of the annualized purchase costs and the yearly operating costs divided by the yearly horsepower hours (or kWh).

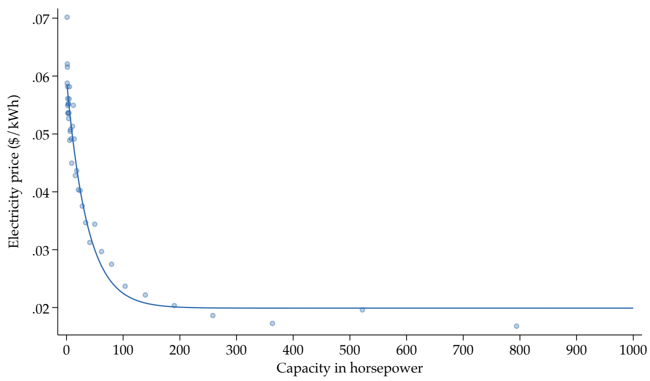
TABLE E.1: Costs (in \$, 1874) of steam engines of different capacities

	Purchase costs		Yearly operating costs (\$)				
hp	Price (\$)	Life (yrs)	Engineer	Firemen	Oil, etc.	Repairs	Coal
5	645	30	540.75		61.80	40.17	226.64
10	988	30	540.75		77.25	49.44	412.44
25	2441	30	695.25		101.90	83.43	752.41
50	5331	30	618.00	432.60	111.24	135.96	1202.82
100	9207	30	695.25	463.50	123.60	237.93	1898.28
250	20426	30	849.75	463.50	200.85	454.23	4504.68
500	36220	30	927.00	927.00	355.35	886.83	9009.94

Source: (Emery, 1883, p. 430).

For purchased electricity, the costs were only dependent on the rate schedule offered by the utility. In principle, the utility could offer a flat rate to any user. In practice, however, they gave discounts to large users. This probably to some degree reflected the fact that the large users had more bargaining power since their outside option was to use self-generated power in a relatively cost effective way. I estimate this cost schedule by using data from the 1929 Census of Manufactures microsamples. I estimate how an individual manufacturer's electricity rate was a function of the quantity of electricity purchased. Figure E.1 shows the results. The fitted line in this graph is used in Figure 2.

FIGURE E.1: Electricity prices by quantity purchased (1929 US)



This figure shows the electricity price in \$ per kWh relative to the quantity of electricity purchased for US manufacturing establishments in 1929. The line is the best fit of the non-linear regression $y = \alpha + \beta \exp(-\gamma x)$. All data is from the 1929 Census of Manufactures microsamples (Vickers and Ziebarth, 2018).

References

ATACK, J. AND F. BATEMAN (1999): "Nineteenth-century US industrial development through the eyes of the census of manufactures a new resource for historical research," *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 32, 177–188.

EMERY, C. E. (1883): "The Cost of Steam Power," *Transactions of the American Society of Civil Engineers*, 12, 425–431.

GAGGL, P., R. GRAY, I. MARINESCU, AND M. MORIN (2021): "Does electricity drive structural transformation? Evidence from the United States," *Labour Economics*, 68, 101944.

SAITZEW, M. (1914): *Steinkohlenpreise und Dampfkraftkosten: Untersuchungen über Preisbildung. AbteilungB: Preisbildung für gewerbliche Erzeugnisse. Zweiter Teil*, vol. 143-II of *Schriften des Vereins für Sozial-politik*, Berlin: Duncker Humblot.

VICKERS, C. AND N. L. ZIEBARTH (2018): "United States Census of Manufactures, 1929-1935," .

YOUNG, L. L. (1964): *Summary of Developed and Potential Waterpower of the United States and Other Countries of the World, 1955-62*, vol. 483, US Government Printing Office.