Scale-Biased Technical Change and Inequality*

Hugo Reichardt[†]

[Most recent version here]

May 19, 2025

Abstract

Scale bias is the extent to which technical change increases the productivity of large relative to small firms. This paper shows that scale bias is an important driver of income and wealth inequality. To illustrate the mechanism, I develop a tractable framework where people choose to work for wages or earn profits as entrepreneurs and where entrepreneurs select from production technologies that differ in fixed and marginal costs. Large-scale-biased technological change reduces entrepreneurship and increases top income inequality primarily by concentrating business income, whereas small-scale-biased change has the opposite effect. To empirically validate the theory, I examine the causal impact of two general purpose technologies in manufacturing that vary in scale bias, but are otherwise similar: steam power (large-scale-biased) and electric power (small-scale-biased). To do so, I collect and digitize new data from the United States and the Netherlands on firm sizes, technology adoption, and inequality. Leveraging plausibly exogenous geographic variation in adoption, I show that these two technologies had opposite effects. Steam power increased firm sizes and inequality, while electric power decreased both. Finally, consistent with the theory, I find that the rise in inequality after steam power adoption was primarily driven by entrepreneurs at the top of the distribution.

*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, and Caterina Soto Vieira 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 Economica 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: if new technologies more strongly complement high-skilled labor—or tend to automate low-skilled jobs—, this can increase wage inequality (Katz and Murphy, 1992; Krusell et al., 2000; 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 and most of it accrues to entrepreneurs who own large shares of their own business (e.g. Smith et al., 2019; Kopczuk and Zwick, 2020).[1]

Can technical change affect the concentration of business income too and, if so, how and when? This paper shows that it can and that the direction of the effect on inequality depends on the *scale bias* in technical change. I define scale bias as the extent to which technical change differentially affects the productivity of large versus small firms. Large-scale-biased technical change skews productive resources and profits towards larger firms. Given that firm ownership tends to be very concentrated, this shift in profits across firms implies a redistribution of income across households. In sum, I argue that the firm size distribution constitutes a channel through which technical change can affect income inequality.

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

I then argue that the theory can be tested by comparing the causal effects of two of the most important general purpose technologies in history: steam and electric power. These two general purpose technologies provide an appropriate and useful comparison because i) their adoption was sufficiently widespread and transformative to have a mean-

[1] See also Atkeson and Irie (2022) that argue for the importance of undiversified business ownership in accounting for wealth mobility and changes in wealth inequality.

ingful impact on the overall economy ii) their adoption is well documented iii) they were similar in their capability and purpose, and iv) their cost structure induced technical change with strongly different scale bias.[2]

Using steam power involved significantly higher fixed costs than electric power. The annualized cost of a 50-horsepower (hp) steam engine—excluding fuel—was roughly equivalent to the yearly wages of three to four unskilled workers. In contrast, an electric motor driven by purchased electricity of the same capacity had operating costs nearly 200 times lower than those of a steam engine. Factories using electric motors had two options: they could purchase electricity from a power plant or generate it on-site, typically using steam engines. Because self-generated power entailed high fixed costs but lower marginal costs, firms faced a distinct fixed-to-marginal cost trade-off. As a result, adoption patterns differed across firm sizes: large establishments were more likely to use steam power (either to drive machines directly or to generate electricity), while electric motors powered by purchased electricity were adopted more by smaller establishments.

This paper estimates the causal effects of steam and electric power in manufacturing to verify the key theoretical predictions of the theory of scale-biased technical change and inequality. First, I show that large-scale-biased technical change, i.e., steam power, increases the average establishment size, while small-scale-biased technical change, i.e., electric power, decreases it. Second, I verify that the effects of technical change on the ratio between average profits and average wages depend on the scale bias, which I show to be an empirically relevant measure of inequality between entrepreneurs and workers. Third, I show that large-scale-biased technical change increases income and wealth inequality, while small-scale-biased technical change has the opposite effect. Lastly, I find evidence that these effects are driven by the concentration of business income at the top of the distribution.

I overcame the challenge of measuring adoption of the two technologies, firm sizes, and inequality in this historical period through an extensive effort to collect and digitize various historical sources from the United States and the Netherlands. For the United States, 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. To study the effects of scale-biased technical change on inequality directly, I collect unique micro-data on wealth from the Netherlands over the course of industrialization. To the best of my knowledge, it is the largest available dataset on the distribution of wealth in any country during the period of steam and electric power adoption. I dig-

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

itized these handwritten data using state-of-the-art computer vision technologies. The resulting dataset includes information on names, demographics, occupation, and, importantly, wealth of each decedent between 1878 and 1927 in five major provinces in the Netherlands, covering over a million decedents and more than half of the national population. I complement this database with newly digitized data on manufacturing in Dutch municipalities.

Using the US manufacturing data, I first confirm the theoretical prediction 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.[3] 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.

I then show that large-scale-biased technological change increases the ratio of average profits to average wages, whereas small-scale-biased change has the opposite effect. 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.[4] These effects are predicted by the theory because high fixed cost technologies push up the average firm size (and thus profits) relative to the wage. These effects capture both a selection effect, that the remaining entrepreneurs are on average more productive, and a causal effect, that their profits increase more than the average wage.

I then show that the profit distribution among firms matters for inequality among households. Hypothetically, if each individual holds a fully diversified portfolio of firms, the profit distribution is irrelevant for inequality between different households. In contrast, if each entrepreneur fully owns a single firm, the profit-wage ratio is a perfect measure of such inequality. More generally, how much the profit distribution matters for inequality depends on the concentration of firm ownership. In practice, entrepreneurs hold

[3] Various other 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).

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

significant shares of their own businesses (Hall and Woodward, 2010). In non-publicly traded firms, concentration tends to be near perfect (e.g., Smith et al., 2019). But even ownership of large publicly traded firms is concentrated. For instance, the founding family of Walmart, the largest company in the world by revenue, owns 45 percent of its shares.[5] Anderson and Reeb (2003) found that the average Fortune 500 firms was 18 percent owned by its founding family.[6] As a result of such ownership concentration, I find significantly larger wealth inequality between entrepreneurs and workers active in state-industry pairs where profit-wage ratios are higher, with correlations around 0.7. Since those at the top of the wealth distribution tend to be entrepreneurs, profit-wage ratios are similarly predictive of top wealth inequality.

The estimated effects of scale-biased technical change on profit-wage ratios, coupled with the strong correlation between profit-wage ratios and inequality, already offer suggestive evidence that scale-biased technical change affects inequality in the way predicted by the theory. To test the two technologies' effects on inequality directly, I turn to the newly compiled database on income and wealth during Dutch industrialization.

Using the Dutch dataset, I provide direct evidence that the effect of technical change on inequality depends on its scale bias. I find that, on the level of the municipality, steam power increased wealth inequality, while electric power decreased it. The effects on inequality are primarily driven by the very top of the distribution, while the rest of the distribution was not much affected. For identification in this context, I exploit a municipality's exposure to the technologies based on their industrial composition in 1816, long before industrialization.

Lastly, I show that scale-biased technical change affects top wealth inequality through entrepreneurs who adopt the technology. To test this, I focus on Enschede, a major industrializing city in the Netherlands, where the pre-existing textile industry made steam power especially attractive. Wealth inequality rose sharply, driven by textile entrepreneurs. Excluding the entrepreneurs and their spouses, I find no significant increase in inequality, indicating that entrepreneurial income—not wages—was the key driver. This supports the theory of scale-biased technical change: large-scale-biased technical change in textile manufacturing increased firm concentration, which, in turn, concentrated business income in the hands of a few entrepreneurs.

Related literature. First, this paper contributes to our understanding of the effect of technical change on income and wealth inequality. Scale-biased technical change offers a view on the distributional effects of technology that complements existing theories, such as skill bias (e.g., Katz and Murphy, 1992; Acemoglu and Autor, 2011). The case of elec-

[5] As estimated by Forbes as of January 2025.

[6] Similarly, Goldsmith et al. (1940) reports that in 1940, just 13 families held over 8 percent of equity in the largest 200 corporations, noting that each family "has shown a strong tendency to keep its holding concentrated in the enterprise in which the family fortune originated".

tricity illustrates the distinct implications of theories of skill- and scale-biased technical change. Goldin and Katz (1998) argue that electric motor adoption increased demand for skilled workers by facilitating a shift to continuous process and batch methods, primarily through more efficient "unit drive" systems.[7] For scale-biased technical change, a key feature of electricity is that it allows to "separate the place of generation from the place of use" (Helpman, 1998), reducing the fixed costs of power usage. To distinguish the role of scale from skill, I only use variation in the relative cost of using self-generated power (high fixed cost) and purchased electricity (low fixed cost), not in the relative cost of using electric motors per se. Importantly, the argument that electric motors favored skilled workers applies regardless of whether the electricity is purchased or self-generated.

The theory of scale-biased technical change also relates to the Schumpeterian model of top income inequality in (Jones and Kim, 2018). In such models, the growth rate of incumbent entrepreneurs' productivity is a key parameter in shaping top income inequality. This paper contributes to this literature in two ways. First, by incorporating the cost structure of technologies, it provides an endogenous technological driver for shifts in the returns to entrepreneurial talent or effort. Second, by pairing the theory with the historical comparison of steam and electric power, I provide empirical evidence that technological change that is biased to large-scale production can affect inequality through its effect on the returns to entrepreneurial talent.

I further contribute causal evidence to a large literature that relates increased firm 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). It has been hard to establish credible causal evidence of the effect of technical change on firm sizes. Furthermore, because most modern technologies vary on many dimensions other than their cost structure, it is difficult to isolate the role of specific technological characteristics. This paper studies two technologies that were similar except for their cost structure, allowing to single out the role of fixed costs in shaping the firm size distribution.

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

[7] Unit drive refers to a power distribution method where each machine is powered by its own electric motor.

et al. (2019); for electric power, see e.g., Fiszbein et al. (2020)).[8] To contribute to the above literature, this paper studies the causal effect of steam power and electricity in manufacturing on establishment sizes and inequality through the lens of the theory of scale-biased technical change.

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

2 Theoretical Framework

In this section, I introduce an occupational choice model that allows to study the effect of scale-biased technical change on entrepreneurship, firm concentration, and inequality in a unified general equilibrium framework. I provide testable implications of the theory to study in the empirical application.

2.1 Model

There is a continuum of households with unit measure that differ in their entrepreneurial productivity ψ. I assume that ψ has a probability density function $f(\cdot)$ with semi-infinite support on $\mathbb{R}^+$, i.e., $\{\psi \mid f(\psi) > 0\} = [\psi_m, \infty)$ for some $\psi_m \geq 0$.[9]

In a first stage, before observing their entrepreneurial productivity ψ, each household decides whether to be a worker or to be an entrepreneur (Lucas, 1978). A household knows that by choosing entrepreneurship, it is foregoing the wage w.

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

An entrant chooses, in a third stage, from an exogenous set of available production technologies $T \equiv \{t_1, .., t_J\}$. Each technology $t_j \in T$ is a tuple $\{\alpha_j, \kappa_j\}$ where α_j is a parameter that affects marginal labor cost and $\kappa_j > 0$ is its fixed cost in terms of the final good.[10] I assume that T does not contain trivially dominated technologies. That is, if

[8] Further, it contributes to a literature on the effects of electrification more generally (e.g., Vidart, 2024).

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

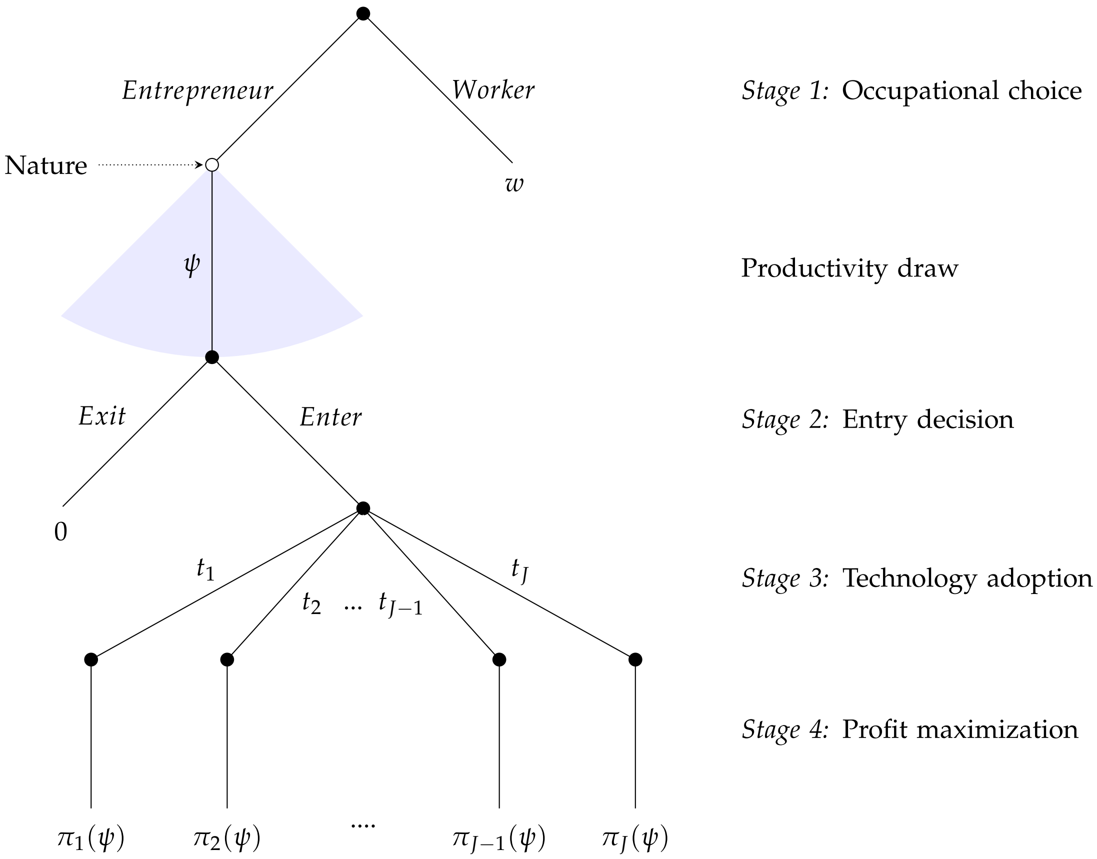
[10] This can be seen as a generalization of the binary technology choice in (Yeaple, 2005; Bustos, 2011), who are concerned with the connection between trade and technology adoption.

$t_j, t_k \in T$ and $\alpha_j < \alpha_k$, then $\kappa_j > \kappa_k$.[11] Technologies are arranged in order of increasing fixed costs ($\kappa_1 < .. < \kappa_J$).

Finally, in stage four, after adopting technology j, entrepreneurs maximize profits given their productivity ψ, yielding $\pi_j(\psi)$.

Figure 1 visualizes the decision process and pay-offs. I characterize optimal behavior and derive equilibrium conditions by backward induction.

FIGURE 1: Pay-off tree



***Stage 4:* Profit maximization.** Each household's utility is linearly increasing in the consumption of an aggregate good. The aggregate good is produced using a continuum of differentiated goods indexed by ω with constant elasticity of substitution σ (Dixit and Stiglitz, 1977; Melitz, 2003).

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

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

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

Each entrepreneur produces one of these differentiated goods. Given technology t_j and entrepreneurial productivity ψ, their production function is

$$y_j(\psi) = \frac{\psi l}{\alpha_j} \tag{2}$$

where l is labor and α_j is the marginal labor cost for technology t_j. The total cost to produce y given t_j and ψ is $C_j(y \mid \psi) = \frac{\alpha_j w}{\psi} y + \kappa_j$ where κ_j is the fixed cost in terms of the aggregate good.

Profit maximization conditional on technology and productivity then yields the pricing rule

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

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

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

***Stage 3:* Technology adoption.** An entrepreneur that chooses to produce can use any of the J available technologies in the set T. She therefore adopts the technology j that yields largest profits, so the profits of an entrepreneur with productivity ψ are:

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

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

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

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

***Stage 2:* Entry decision.** After observing their entrepreneurial productivity ψ, each entrepreneur decides whether or not to exit or enter. Since the opportunity cost is zero (as the opportunity cost of not working is already sunk), they decide to enter if and only if $\pi(\psi) \geq 0$.

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

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

To solve for this threshold, note that profits under each technology are strictly increasing in $\pi_j(\psi)$. Therefore, each technology j has itself a zero profit cut-off $\bar{\psi}_j$ above which profits are positive. From equation (4), this threshold is defined by

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

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

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

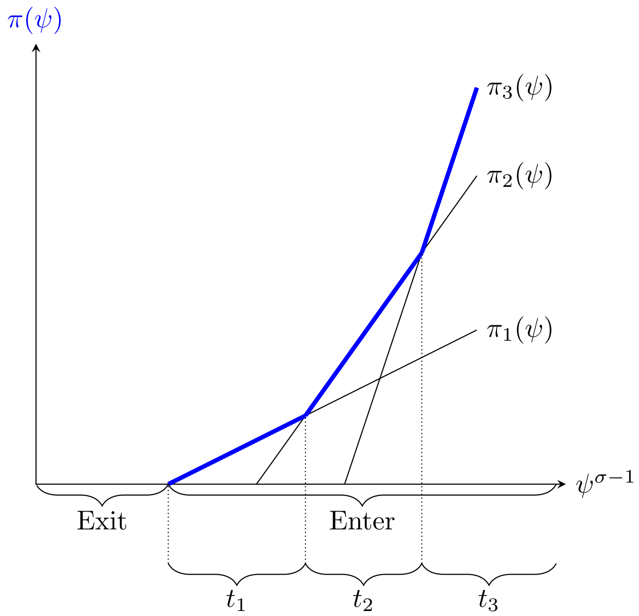
Figure 2 shows the profit function $\pi(\psi)$ and the optimal decision in Stage 2 and 3. It illustrates that the entry cut-off $\bar{\psi}$ is the productivity level for which the technology with the lowest entry threshold gives positive profits.

***Stage 1:* Occupational choice.** Free entry into entrepreneurship (and risk-neutrality) implies that the expected profits of entering must equal the wage. That is,

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

Defining average profits of producing entrepreneurs as $\bar{\pi} \equiv \frac{1}{1-F(\bar{\psi})} \int_{\bar{\psi}}^{\infty} \pi(\psi) dF(\psi)$, equation (9) can be alternatively written as $(1 - F(\bar{\psi}))\, \bar{\pi} = w$: the probability of entry times the average profits conditional on entry should equal the wage.

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



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

2.2 Which technologies are adopted?

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

$$\Psi_j \equiv \underbrace{\{\psi \mid \pi(\psi) \geq 0\}}_{\text{Enter}} \cap \underbrace{\left\{\psi \mid \pi_j(\psi) = \max_{k \in \{1,\ldots,J\}} \pi_k(\psi)\right\}}_{\text{Use technology } j} \tag{10}$$

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

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

Proposition 1 shows which technologies are adopted in equilibrium.

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

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

that

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

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

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

$$\alpha_{J^*}^* = \min_{j\in 1,2,..,J}\{\alpha_j\} \textit{ and;}$$

$$\kappa_{J^*}^* = \min_{j\in 1,2,..,J}\left\{\kappa_j \mid \alpha_j = \min_{l\in 1,2,..,J}\{\alpha_l\}\right\}$$

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

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

Proof of Proposition 1. See Appendix C. □

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

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

Lastly, Proposition 1(c) covers all remaining adopted technologies, if any. Intuitively, for a technology to be adopted by an entrepreneur, their productivity must be *high enough* to make using that technology more profitable than using any other technology with higher marginal cost (and lower fixed cost), but also *low enough* to make the technology more profitable than adopting any other technology with lower marginal cost (and higher fixed cost). Proposition 1(c) sets out the conditions under which the set of productivities that satisfy these conditions has a strictly positive probability measure. To illustrate the condition, consider Figure 2: there is an intermediate set of productivity levels, for which technology t_2 yields higher profits than both t_1 and t_3. For such a set of productivity levels to exist, the lower bound on productivity above which t_2 yields higher profits than t_1 must be smaller than the upper bound below which it yields higher profits than t_3.

2.3 Equilibrium

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

- profits $\pi(\psi)$ are as defined in (4) and (5);
- the adopting set of technology j, Ψ_j, is as defined in (10);
- the free entry condition in (9) holds;
- the labor and goods markets clear, so that

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

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

- consumption equals aggregate good production net of fixed cost

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

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

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

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

Proposition 2 (Closed-form equilibrium)**.** *Suppose that the distribution of productivity ψ is Pareto with shape parameter ξ and a minimum productivity level of $\psi_m > 0$ such that $\xi > 1$ and $\xi > \sigma - 1$. Then, the closed-form solutions to the competitive equilibrium for L, $\bar{\psi}$, Y, C, w, and $\bar{\pi}$ are given by equations (28), (29), (30), (31), (32), and (33) in Appendix C.*

Proof of Proposition 2. See Appendix C. □

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

2.4 Scale bias

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

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

where $\bar{\psi}\left(T\right)$ and $\alpha(\psi \mid T)$ are the entry threshold (derived in closed-form in Proposition 2) and the marginal cost parameter of the optimally adopted technology given technology set T. Total factor productivity is zero for entrepreneurs that do not produce, so that it reflects changes in the extensive margin (in and out of production).

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

Definition (Scale-biased technical change)**.** Technical change is *large-scale-biased* if and only if there exists some $k > \min\left\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\right\}$ such that it increases TFP for $\psi > k$

and does not increase it for $\psi < k$:

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

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

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

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

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

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

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

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

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

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

Proof. See Appendix C. □

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

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

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

The assumption that $\sigma > 2$ is supported by empirical evidence. First, it is consistent with estimates of σ around 6 for US manufacturing (Bernard et al., 2003) and with the calibration of $\sigma = 4$ by Melitz and Redding (2015). Second, $\sigma \leq 2$ implies a labor share of a half or lower, while the labor share has been consistently larger than a half in the US and other countries. Third, if $\sigma \leq 2$, the implied mark-up is larger than 2, while empirical estimates of mark-ups are considerably below 2 (e.g., De Loecker et al., 2020).

Proposition 3 covers all cases where the new technology is adopted without making existing technologies obsolete. Proposition 3A in Appendix C extends the analysis to cases where the new technology renders some previously adopted technologies obsolete.

2.5 Testable implications of the theory

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

Proposition 4 (Theoretical implications of scale-biased technical change)**.** *Suppose the assumptions in Proposition 3 hold. Then, large-scale-biased technical change* *(a) increases the average firm size as measured by employment;*

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

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

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

Proof of Proposition 4. See Appendix C. □

The remainder of the paper is devoted to testing the theoretical predictions above. I will use the case of steam and electric power. In the next section, I show that steam power adoption was large-scale-biased technical change, while the adoption of electric power constituted small-scale-biased technical change.

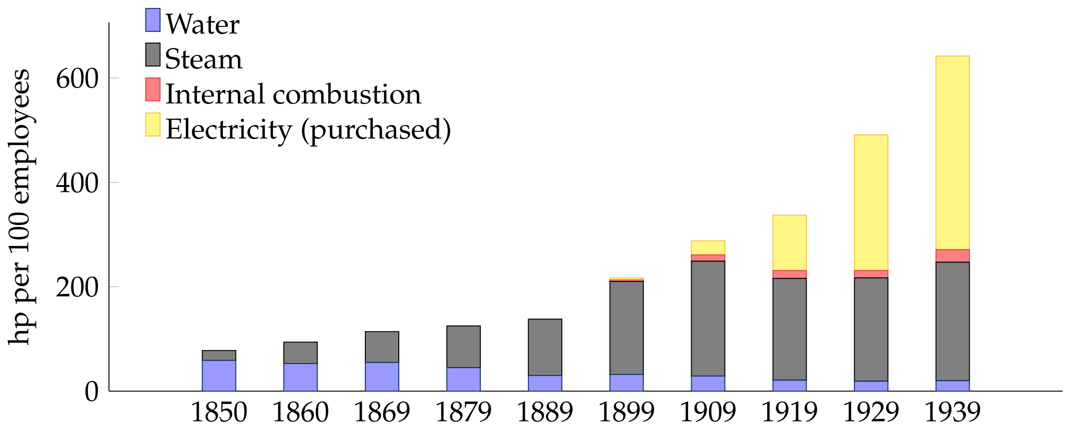
3 The Scale Bias in Steam and Electric Power

To test the theory of scale-biased technological change, I compare the effects of the adoption of steam power and electricity in manufacturing. This section establishes why these two technologies provide a suitable comparison for evaluating the theory. Specifically, I argue that while both served the same fundamental function—powering factories—they differed crucially in scale bias: steam power adoption represented large-scale-biased technological change, while electricity adoption was small-scale-biased.

Figure 3 illustrates the history of power use in US manufacturing. A few main patterns jump out. First, the waterwheel was slowly replaced by steam power in the second half of the 19th century (Hornbeck et al., 2024). Second, electricity was adopted from around 1900. Third, steam power and electricity combined accounted for most of power from around 1870 onward. Fourth, the superiority of electric motors meant that internal combustion engines were never adopted on a large scale (Du Boff, 1967). Fifth, electric motors driven by purchased electricity started to become dominant around the 1930s, but steam engines remained an important source of primary power until at least 1939. Figure A.1 shows the same patterns for the Netherlands.[12]

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

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



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

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

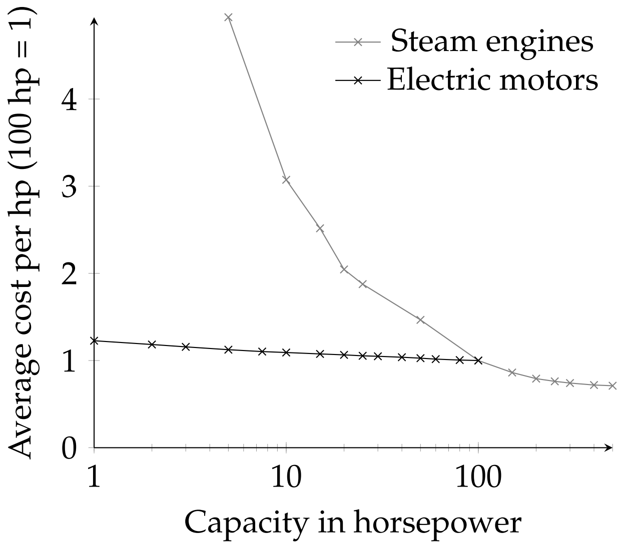
Larger steam engines are also considerably more efficient in converting energy into motion than small ones (Atack, 1979; Devine, 1983), while electric motors' efficiency does not vary nearly as much with size. In the words of the engineer Bell (1891): "With the electric motor the case is very, very different [from steam engines]; an eight horse-power motor may be as completely worked out in detail as one of a hundred times its power, and may be only slightly less efficient." Figure A.2 illustrates the efficiency of steam engines and electric motors for different sizes (horse-power capacity) relative to a 100 hp equivalent based on estimates by Emery (1883) and Bolton (1926). A steam engine

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

of 10 hp required more than twice as much coal per horse-power of energy output than a 100 hp steam engine. Coal-efficiency was an important consideration given that coal accounted for between a half and two-thirds of the total operating costs for the larger engines.

The marginal and fixed costs of steam engines and electric motors can be combined to estimate an average cost curve by rated capacity for the electric motor and the steam engine. Figure 4 shows the results.[14] Clearly, steam power was much more cost-efficient on a large scale. For electric motors, scale was close to irrelevant as almost all costs were marginal, coming from the purchase of electricity, and the efficiency loss of small motors was minor.

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



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

There were also some other, more indirect, reasons that steam power skewed to large establishments. First, a steam engine occupied a large amount of space. Second, steam engines had to be run at full capacity even if only small doses of power were required, a feature likely to be specifically uneconomical for small establishments where power needs vary more (Du Boff, 1967).

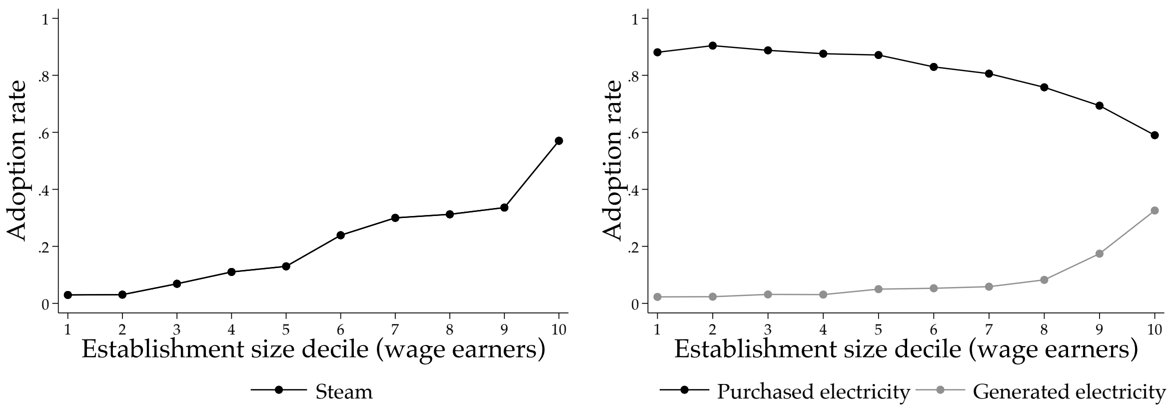
The adoption rates by plant size reflect the considerations above. Figure 5A shows that large plants were much more likely to adopt steam engines, as documented before by

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

Atack et al. (2008). In contrast, Figure 5B indicates that electric motors were 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. This further confirms that, for the purpose of studying scale bias, the relevant distinction is the primary source of power, not the system of delivery.

FIGURE 5: 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 micro-samples of the Census of Manufactures. *Sources*: for 1880, the national random sample of the Census of Manufactures (Atack and Bateman, 1999); for 1929, the Census of Manufactures for selected industries (Vickers and Ziebarth, 2018). I left out the concrete industry as data on electric motors driven by generated electricity is not available for that industry.

4 Data Construction

This paper uses newly collected and digitized data from the United States and the Netherlands. In this section, I discuss the sources and construction of the datasets for both countries. A key contribution is the collection and digitization of microdata on wealth of hundreds of thousnds of people in the Netherlands during the period of steam and electric power adoption. Additionally, I digitized and compiled manufacturing data for the same period for both the United States and the Netherlands.

4.1 Netherlands

4.1.1 Microdata on Wealth (1879-1927)

The data on wealth derive from the inheritance tax administration. The original source files are printed estate tax declarations that were filled in by hand indicating a decedent's name, place of residence and death, date of death, and importantly, the value of their estate. The documents are referred to in Dutch as "memories van successie".

I assemble a large micro-database that contains the names, residence, and wealth at death for all individuals who died in selected Dutch provinces between 1879 and 1927. The provinces cover slightly over half of the national population. I included all areas for which the universe of the source files were available online as scanned images, namely the provinces Noord-Holland, Noord-Brabant, Gelderland, Overijssel, and Zeeland.[15] 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. 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 ƒ1000 (a thousand Dutch guilders) were taxed, and some inheritances between ƒ300 and 1000, depending on the period and the relationship between the decedent and the heir. These thresholds meant that a considerably larger share of decedents were assessed for the tax than in other countries (see also Toussaint et al., 2022; Gelderblom et al., 2023), so that the data cover a relatively broad range of the wealth distribution: in the median region and period, I observe the wealth of about 20 percent of adult decedents. For further detail on the tax and its administration, I refer to De Vicq and Peeters (2020).

Main digitization procedure. 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). Deep learning is increasingly used in economics research for document scan digitization Dell et al. (2023); Dell (2025). However, handwritten text and numbers, especially from historical documents, is particularly challenging. I develop a framework that ensures accuracy even in the presence of large variation in image quality and handwriting using deep learning object detection and classification methods. While the framework is specifically designed for accuracy in extracting data from the source files of interest, I believe that the algorithm itself may nonetheless be useful for other researchers facing similar problems.

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. Figures D.1, D.2, and D.3 show examples of the type of

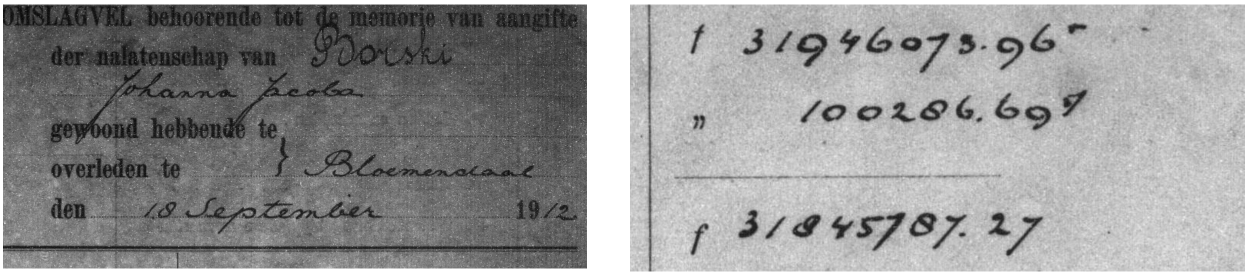
[15] The archival sources are: Noord Hollands Archief, record group 178 (for Noord-Holland); Brabants Historisch Informatie Centrum, various record groups (for Noord-Brabant); Gelders Archief, various record groups (for Gelderland); Collectie Overijssel, record group 136.4 (for Overijssel); Zeeuws Archief, record group 398 (for Zeeland).

documents in the inheritance tax files. The document in Figure D.1 is an example of a part of the form that contains the name and demographic information of the decedent. Figure D.2 shows the page that contained information on the decedent's assets, liabilities, and net worth at the time of death. Lastly, Figure D.3 shows an example of a miscellaneous document in the files that I do not use in the analysis. The object detection algorithm detected which images contained the relevant information and automatically cropped the relevant parts of the images shown in Figure 6. I apply this algorithm to 3,261,708 document scans. Of those scans, 837,620 scans were detected to contain the relevant information.

FIGURE 6: Example of relevant source information

(A) Decedent's name, location, and date of death

(B) Decedent's wealth


OMSLAGVEL behoorende tot de memorie van aangifte
der nalatenschap van Borski
Johanna Jacoba
gewoond hebbende te
overleden te } Bloemendaal
den 18 September 1912

f 31946073.96
" 100286.69
f 31845787.27

Notes: the images above show an example of the relevant source information for the richest person in the database, Johanna Jacoba Borski, who died in Bloemendaal, North Holland, on September 18$^{\text{th}}$, 1912 with an estate worth 31.8 million guilders. These images are cropped automatically using a YOLOv5 object detection algorithm. Panel A shows the part of the form that contains personal information of the decedent and Panel B shows the part that contains information on the value of their assets, liabilities, and net worth.

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 found the exact location of the relevant information in the cropped image. 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. Lastly, by combining the detected numbers with the information on the detected location of assets, liabilities, and net worth data, I construct the estimated wealth 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 input the images into

OpenAI's GPT-4o and request it to output assets, liabilities, and net worth. 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.

To mitigate any remaining noise, I manually checked all observations that do not add up exactly and where net worth is recognized to be larger than ƒ50,000—which would place someone roughly in the top 10% of wealth nationally—, since those observations are particularly important in shaping overall wealth inequality.

Name, date, and place of death I use OpenAI's GPT-4o to transcribe the names, places of residence, and places and dates of death. That is, I input the automatically cropped images similar to Figure 6A into the GPT-4o API and request that it provides the first name, prefix, surname, place of death, place of residence, and date of death reported in the image.

Matching with existing civil registry data. I link the digitized dataset to existing high-quality hand-collected information from the civil death registry. The civil death registry cover the near-universe of deaths in the relevant provinces.[16] The only exception is the city of Amsterdam, for which the civil death registry is not digitized. I match the newly digitized inheritance tax by (fuzzy) matching based on name, date of death, and inheritance tax district.[17] See Appendix D.3 for further details on this procedure.

Description of micro-level database. Table 1 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 to narrow down the place of death to the level of the municipality. Furthermore, the civil registry data often contain the age at death.[18] I assign all observations from the tax office in Amsterdam to the Amsterdam municipality.

[16]The civil registry data can be downloaded in bulk at https://www.openarch.nl/exports/csv/.

[17]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.

[18]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 1: 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, such that the bottom row reflects the number of individuals for whom we observe their wealth, municipality, civil registry data, and age.

The resulting dataset on wealth during industrialization is unique in its size and geographic scope. The existing literature has focused on documenting national trends in the wealth distribution. For instance, Lindert (1986) (UK) samples 12,581 estates across four regions and five dates between 1670 and 1875, Piketty et al. (2006) (France) cover a random sample of Parisian estates in selected years in the 19$^{\text{th}}$ century, and Bengtsson et al. (2018) (Sweden) collect information on samples of around 5000 probate inventories between 1750 and 1900. This dataset is an illustration of the value of using newly available technologies for scalable digitization of handwritten historical records. Furthermore, and importantly for the purpose of this paper, it covers many regions in a period in which first steam engines and then electric motors were adopted in the Netherlands.

4.1.2 Constructing 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 time period, I compute the distributional statistics by decade.[19] As described above, tax thresholds varied between ƒ300 and ƒ1000, but some estates were assessed to have values below the threshold. Which estates were assessed may have varied somewhat across tax offices and over time: the exact criteria under which an estate was assessed are to my knowledge unknown. The need to avoid that variations in assessments affect the measures of local inequality, would suggest to only include decedents with an assessed wealth above ƒ1000 (as they should always have been assessed). However, including as many people as possible reduces variance and makes wealth statistics more representative of the overall population. I balance these interests by including every decedent with assessed wealth above ƒ300, the lowest tax threshold, in the sample on which measures of the wealth distribution are computed.

We do not directly observe decedents who were not assessed for the tax. In principle, it

[19]Since the dataset starts in 1879, I assign that year to the 1880s too.

is possible to observe the total number of decedents and infer the number of individuals below the threshold from there. However, this relies on the estate files to be complete and the algorithm to recognize all the relevant files. Experimentation showed that the coverage is close to complete for most regions and periods but is likely low for a subset of them. Therefore, I focus on measures of inequality among those who were taxed, roughly the top 20 percent of the wealth distribution among decedents.

The distribution of wealth among decedents is likely different from that of the living. To control for "selection into death", one can weight each tax return by the inverse probability of death given their age (e.g., Kopczuk and Saez, 2004). However, weighting comes with a few disadvantages. First, while it reduces bias, it can substantially increase variance because it places a high weight on a small set of young decedents. This issue is particularly pressing when estimating inequality in smaller local units. Second, more practically, age is not observed for about a third of the observations. I therefore use unweighted estimates as the baseline measures of wealth inequality. However, as a test of the sensitivity to weighting, I impute the age when missing, and compute wealth statistics based on those.[20] I find that weighted and unweighted measures of wealth inequality are strongly correlated across space and time (e.g., for the top 1% share, the correlation is 0.90). In the main analysis, I show robustness to using the weighted estimates.

4.1.3 Complementary Data on Local Income Distributions

I uncovered and digitized sources on local income distributions. First, I uncovered a parliamentary document that recorded a detailed distribution of income for 79 municipalities in 1883, including many large cities.[21] Specifically, it indicates the number of inhabitants within 41 income brackets for each municipality. These data were derived from local income tax administrations. I also collected data 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.[22]

I find that local income inequality is strongly correlated with measures of wealth inequality from the inheritance tax data. Since the income brackets are extremely narrow (and in many cases only included one or a few people), I compute income inequality under the assumption that each individual earned the midpoint of their bracket. Figure A.3 plots income and wealth inequality at the municipal level for those municipalities for which both are observed. The correlations vary between 0.88 and 0.93 across inequality

[20]Specifically, for individuals for whom the age is unknown, I set their weight equal to the average weight of a return in the relevant local wealth decile, province, and decade.

[21]Tweede Kamer (*House of Representatives*) 1883-1884 kamerstuknummer (*document number*) 172.13. The source file can be found here.

[22]The cities are: Breda (1880), Vlissingen (1883), Enschede (1880), Utrecht (1888), Delft (1893), Eindhoven (1885), Hilversum (1880), Nijmegen (1880). The sources for these cities are documented in Appendix D.2.

measures, providing strong evidence that the constructed wealth (and income) data are reliable. Second, it shows that, practically speaking, whether one uses data on income or wealth inequality on the local level is not likely to affect conclusions qualitatively.

4.1.4 Manufacturing

I further newly digitize data on manufacturing by Dutch municipality for the years 1816-1819 and 1930. The first official Census of Companies ("Bedrijfstelling") in the Netherlands was performed in 1930. It offers a high-quality snapshot of manufacturing by industry by municipality.[23] This source provides information on the number of establishments and workers by size class by industry by municipality and the adoption of motive power (in horsepower).[24] Importantly, it breaks down motive power by electric motors driven by purchased energy and other motive power (i.e., steam engines or electric motors driven by steam engines in the plant). Figure D.4 provides an example of a source page. In total, the data consists of 33,134 municipality-by-industry observations.

The data for the years 1816 and 1819 derive from two government surveys of which results are compiled and published in print by (Brugmans, 1956; Damsma et al., 1979).[25] The survey data contain, by municipality, information on the number of establishments and workers for each type of establishment (e.g. tannery or cotton factory). 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 neighbouring municipalities—which were excluded by (Brugmans, 1956; Damsma et al., 1979)—from (Korteweg, 1926). Brugmans (1956); Damsma et al. (1979) were not able to retrieve the survey results of all municipalities in three out of eleven provinces (Zuid-Holland, Overijssel, and Groningen). The final data contain 3,658 municipality-by-industry observations in 539 distinct municipalities and cover nearly all large cities and other places with a strong manufacturing presence.[26]

For comparability across years, I coded each industry or establishment type to its relevant 2-digit ISIC industry code.

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

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

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

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

4.2 United States

4.2.1 Manufacturing

For the United States, I rely onthe tabulations of the decennial Census of Manufactures by state and industry. I digitized and compiled these data for each decade year between 1850 and 1940 and for 1947. The information in the Census of Manufactures varies somewhat from year to year, but key variables such as the number of establishments, employment, and value added are available for each year. Furthermore, for 1870 and onward, the tabulations report the adoption of power technologies such as water wheels, steam engines, and, later, electric motors and electricity use. The industry classification is detailed: the number of distinct industries averages 386 across years. In total, the data comprise of 51,263 state-industry-year observations.

Since industry classifications changed over time, I created two crosswalks that allow to compare industries over time. The first covers all industries between 1860 and 1900, the period of most rapid steam engine adoption, and consists of 182 industries. This crosswalk is an extension of the 1860 to 1880 crosswalk published by Hornbeck and Rotemberg (2021). The second crosswalks consists of 206 harmonized industries across the six censuses between 1890 and 1940. To create this second crosswalk, I used tabulations by industries over time published in the Census of Manufactures.[27] I also coded each Census of Manufactures industry to the 1950 Census Bureau industrial classification system to allow matching with the IPUMS USA population censuses between 1850 and 1940. To further improve consistency, I drop "hand trades" such as blacksmithing, carpentering, and masonry from the data as these industries were no longer included in the Census of Manufactures from 1909 onward.

4.2.2 Coal Resources and Hydropower Potential

To construct instrumental variables for steam and electric power adoption, I use data on coal resources and hydropower potential by state. Data on historical coal resources by county are taken from the National Coal Resources Data System from the United States Geological Survey (USGS).[28] The dataset contains information on the "rank" (i.e., type) of coal, the estimated tonnage available, the thickness of the field, and the "overburden" (i.e. the depth of the material that lies above the coalfield).

Hydropower potential is defined as the total horsepower of energy that can be feasibly generated by waterpower given the topographic characteristics of the area. The USGS

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

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

published estimates of hydropower potential of each state at various points in time. I use the estimates of hydropower potential published in (Young, 1964, Table 10).[29]

Hydropower potential is defined as the total horsepower of energy that can be feasibly generated by waterpower given the topographic characteristics of the area. Importantly, it covers both developed and undeveloped sites. Estimates of hydropower potential of each state were published by USGS at various points in time. I use the estimates of hydropower potential published in (Young, 1964, Table 10).[30] Figure A.5 shows a map of hydropower potential across the United States.

5 Scale-Biased Technical Change and Firm Size

This section documents the impact of the adoption of steam power—large-scale-biased technical change—and electric power—small-scale-biased technical change—on establishment sizes. The theory predicts that steam power adoption increases the average establishment size, while electric power adoption decreases it. I verify this prediction using exogenous geographical variation in the costs of the two technologies.

Instruments. I use a state's coal access as an instrument for steam power adoption. To construct the instrument, I first compute the total coal resources in British thermal units (Btu) for each county from the USGS coal resources data.[31] Recognizing that coal was traded across counties, I then compute a measure of "coal access" by county similar to the measure of market access used by Donaldson and Hornbeck (2016). That is, for destination county c in state s, coal access is given by

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

where $\tau_{oc} \geq 1$ is the "iceberg cost" of transporting coal between counties o and c in 1830, θ is the trade elasticity, and BTU_o is the total amount of coal resources in county o measured in Btu.[32] Intuitively, the coal resources in county o more strongly count towards county

[29] 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.

[30] 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.

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

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

c's coal access if the transportation costs between these counties is low. Importantly, I use transportation costs before the introduction of the railroads to avoid that the instrument reflects potentially endogenous infrastructure investments. Similarly, I use estimates of coal resources *prior to mining* to avoid endogeneity arising from selective mining. Figure A.4 shows the spatial distribution of coal access on the county-level.

Hydropower potential serves as the instrument for electric power adoption. Importantly for exogeneity, the measures reflect the *potential* to generate energy with water power, and thus capture both developed and undeveloped power sites. Figure A.5 shows a map of hydropower potential across the United States.

Coal access and hydropower potential are not correlated at the state-level (Figure A.8, $\rho = 0.03$), such that the instruments have strong power in distuinguishing the effects of steam and electric power.

First stage: coal access. Coal access strongly affected coal prices and, as a result, steam power use (see Table B.1). The correlation between coal access and prices is -0.58 on the state-level (see Figure A.6). Because coal was an important input to steam power production, coal access also affected the adoption of steam. In 1890, the Census of Manufactures reported steam engine and other power use for each state-industry combination. For that year, I estimate

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

where the subscripts i, s, and t refer to industry, state, and year, respectively. STEAM_{ist} refers to measures of steam power adoption, i.e., steam engines' horsepower per employee and the share of steam engines in total horsepower. COAL_s is the measure of state s's coal access, computed as the average coal access of the counties in state s as given by equation (16).

First stage: hydropower potential. Hydropower potential had a strong effect on electricity prices and electric power use (Table B.3). Figure A.7 shows hydropower potential and electricity prices in each state in 1929, with a correlation of -0.56. I estimate the effect of the instrument (hydropower potential) on the use of purchased electric energy, first reported in 1939. That is, I estimate for the year 1939:

$$\text{ELECTRICITY}_{ist} = \delta_i + \theta \log\left(\text{HYDRO}_s\right) + \epsilon_{ist}.\text{[33]} \tag{18}$$

ELECTRICITY_{ist} refers to two measures of electric power use: the total megawatt hour of purchased electric energy per employee and the cost of purchased electric energy as a share of total fuel costs.[34] $\log\left(\text{HYDRO}_s\right)$ is the logarithm of state s's hydropower poten-

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

[34] The megawatt hour of purchased electric energy per employee is obtained by dividing the cost of purchased electricity by the average price of electricity per MWh for manufacturers in the state in 1939.

tial.

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

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

where the subscripts i, s, and t refer to industry, state, and year, respectively, D_{tk} is a dummy that is 1 if $t = k$ and 0 otherwise and T contains all but one reference census year. y_{ist} is the average firm size (in terms of employment). $\boldsymbol{X}_{st}$ is a vector of controls on the state-year level: it contains the density of the population in state s at time t and interactions between time and "market access" in state s.[35] Controlling for market access interacted with time ensures that the estimated effect of access to coal does not reflect low-cost access to consumer markets.

The results are in line with the predictions of the theory that steam power increased establishment sizes while electric power decreased it. Figure 7 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. In contrast, states with high hydropower potential—adopting more electric power—experienced relative reductions in average firm sizes. Importantly, as depicted in Figure 7B, 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 their effect on power use. First, I find that firm sizes in industries that used little power nationally in 1890 were not affected by coal access (see Figure A.9). Specifically, I estimate equation (19) for the years between 1860 and 1900, now including state $\times$ industry fixed effects using the 1860 to 1900 industry crosswalk. 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.[36] Similarly, hydropower potential only affected firm sizes in industries that used electric motors (see Figure A.10). To test this, I run the same procedure for the years between 1890 and 1939. For electric power, I define placebo industries as those in the bottom quartile of the share of purchased electricity in overall fuel costs.

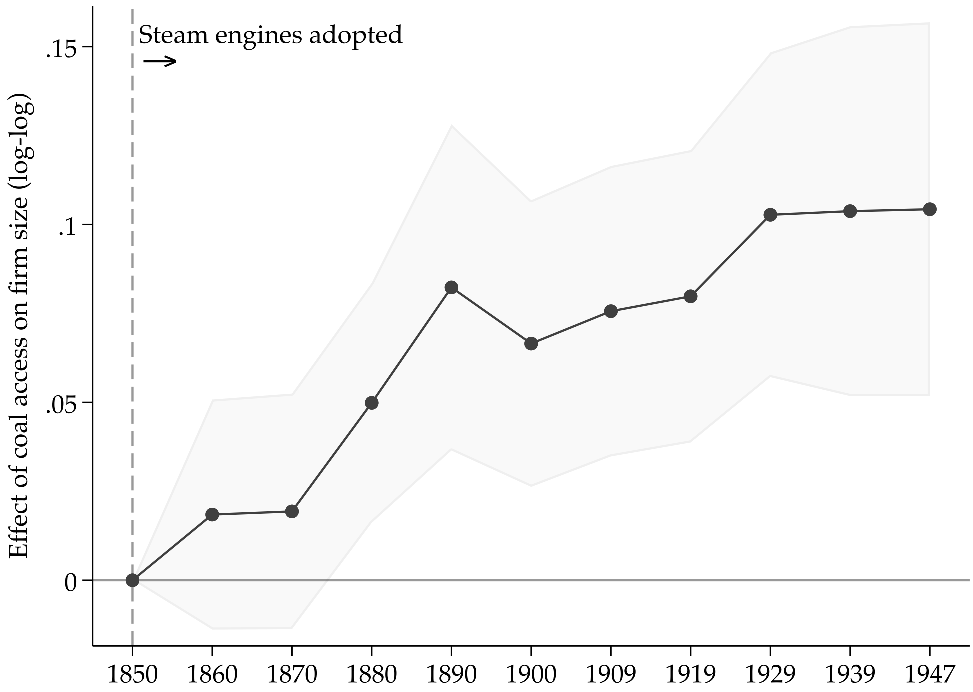
The average price was, in turn, computed by dividing the total cost of purchased electric energy in the state (Census of Manufactures 1939, Volume 1, Ch. VII, Table 3) by the quantity purchased in MWh. (Census of Manufactures 1939, Volume 1, Ch. VI, Table 6).

[35] 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.

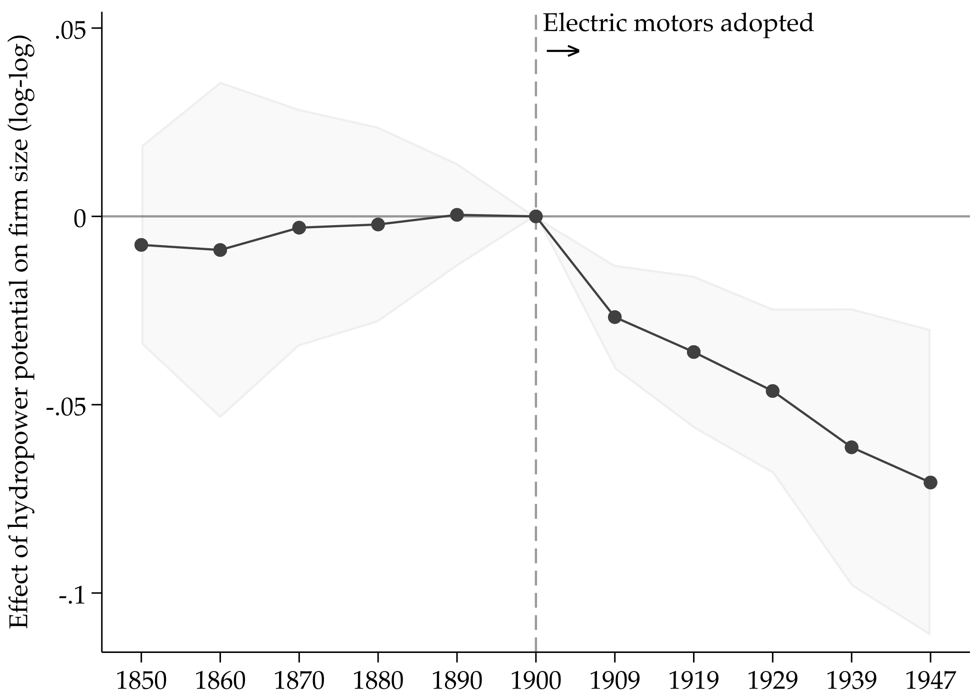
[36] Power usage is defined as the share of establishments reporting any power use.

FIGURE 7: Effects of coal access and hydropower potential on firm sizes

(A) Coal access



(B) Hydropower potential



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

Instrumental variable regression. I quantify the effect of steam and electric power adoption on the firm size using an instrumental variable regression for two distinct periods: 1860 to 1890 for steam engines and 1900 to 1939 for electric motors. Specifically, I regress state-by-industry firm size growth on technology adoption, instrumented by hydropower potential and coal access. That is, I estimate

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

$$\log\left(y_{is,1939}\right) - \log\left(y_{is,1900}\right) = \alpha_2 + \beta_2 \text{ELECTRICITY}_{is,1939} + \boldsymbol{\lambda}_2' \boldsymbol{X}_{is} + \eta_{is} \tag{21}$$

where $\text{STEAM}_{is,1890}$ and $\text{ELECTRICITY}_{is,1939}$ 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 instrumental variable regressions in equations (20) and (21). The estimate in the first column suggest that a 1% percent increase in steam engine use led to an increase in average firm size of about 1.1%. The second and third columns explore the sensitivity of the estimates to changes in the set of controls. While steam power increased firm size, column four to six show that electric power adoption decreased it 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. I use the data from these tabulations digitized by Lafortune et al. (2019). Figure A.11 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.

An advantage of the city-level data is that they allow to separate any effect hydropower may have had through its effect on water wheel adoption from its effect through electric power adoption.[37] 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).[38] This meant that out-of-city-within-state hydropower potential affected 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

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

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

did not contaminate the estimated effects of electric power much (see Figure A.12).

6 Scale-Biased Technical Change and Inequality

In this section, I study the predictions the theory related to the distributional effects of scale-biased technical change. I first show using data from the Census of Manufactures that steam power 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 whether steam and electric power had opposite effects on inequality. I use the Dutch panel data on local wealth inequality. Local wealth inequality, in addition to being a measure of economic inequality in its own right, was strongly correlated with local income inequality (see Section 4). 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 (Why) Does the Firm Size Distribution Matter For Inequality?

In the model in Section 2—where each entrepreneur owns one firm—the ratio between the average profits and the wage is a perfect measure of income inequality between workers and entrepreneurs. The free entry condition in equation (9) suggests that this ratio is proportional to the average firm size. Specifically, it implies

$$\log\left(\frac{\bar{\pi}_{is}}{w_{is}}\right) = \text{constant} + \log\left(\text{firm size}_{is}\right). \tag{22}$$

That is, the larger is the average firm size (measured in employment per worker), the larger is the average profit of an establishment relative to the wage.

Figure A.13 confirms that a strong relationship exists between average profits and firm size in the Census of Manufactures data. For the years between 1890 and 1920, the data allows to follow Atack and Bateman (2008) by computing profits as output minus wage costs, raw materials, capital costs, and miscellaneous expenses.[39] The average wage is approximated by the total wage bill divided by the number of workers. A potential issue

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

with this measuring wages by dividing the wage bill by the number of workers is that the hours worked per worker may vary with firm size, biasing the result. However, when using establishment-level data for 1880 where the average wages are directly observed—digitized by Atack and Bateman (1999)—, I find an almost identical relation between firm sizes and profit-wage ratios (Panel B of Figure A.13).

Consistent with the theoretical prediction, I find that the effects of steam and electric power on profit-wage ratio are quantitatively similar to the effects on firm size (Figure A.14). That is, steam power increased the average profits of an establishment relative to the average wage of a worker. From the perspective of the theory, this is expected 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.[40] Table B.5 shows the IV estimates of the elasticity of the profit-wage ratio to steam and electric power adoption.

I find that the profit distribution among firms matters for the income distribution among people. Using US micro-level data on wealth from 1870, the last year for which such data is available, I show that firm sizes and profit-wage ratios strongly correlate with measures of wealth inequality. To do so, I compute wealth inequality between people in a given state and industry in the 1870 Census of Population and merge these measures with data from the 1870 Census of Manufactures.[41] To identify entrepreneurs, I use that the occupational code "manufacturer" in the 1870 census was reserved for owners of establishments.[42] The unconditional average wealth of an entrepreneur was 16 times larger than that of a worker. Panels A and B of Figure 8 show that this wealth gap was larger in state-industry pairs with larger average establishment size and larger profit-wage ratios. The elasticity is close to unitary, as predicted by the model: 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 and profit-wage ratios (Panels C and D of Figure 8). These results show that the profit-wage distribution is a highly informative measure of inequality.

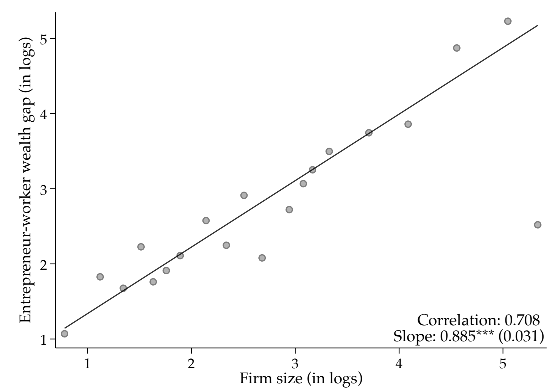
[40] The correlation between this measure of average profits and the measure used by Atack and Bateman (2008) is high: 0.75 in levels and 0.96 in logs.

[41] 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

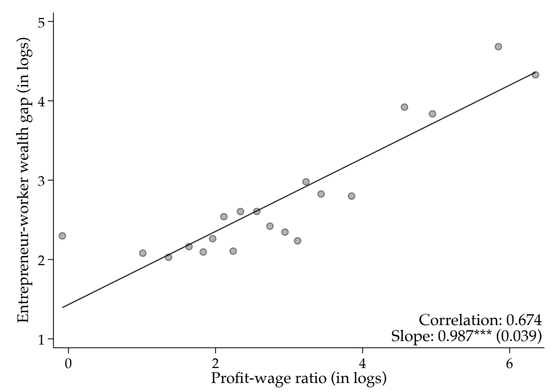
[42] The instructions to census enumerators included: "Do not call a paper-bonnet maker a bonnet manufacturer [..]. Reserve the term Manufacturer for proprietors of establishments: always give the branch of manufacture." I therefore assume individuals with occupational code 198 "manufacturer" to be entrepreneurs and those with any other manufacturing occupations (codes between 130 to 265, including 198) to be workers.

FIGURE 8: Wealth inequality correlates strongly with firm size and profit-wage ratios

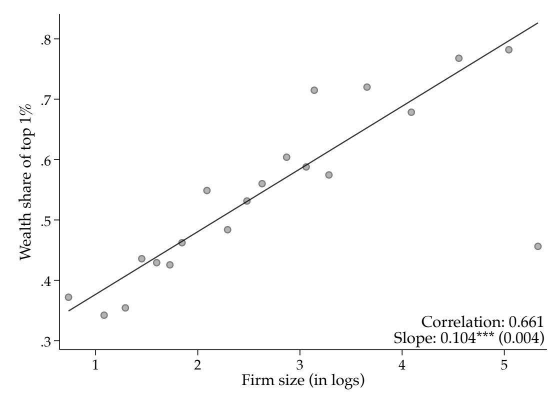
(A) Firm size and $\frac{\text{entrepreneurial wealth}}{\text{worker wealth}}$



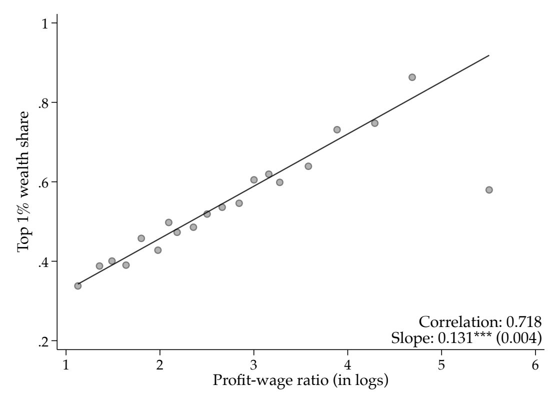
(B) Profit-wage ratio and $\frac{\text{entrepreneurial wealth}}{\text{worker wealth}}$



(C) Firm size and top 1% wealth share



(D) Profit-wage ratio and top 1% wealth share



Notes: These figures show the relationship between state-industry level data on firm sizes and profit-wage ratios and measures of wealth inequality between households that are active in those state-industry pairs in the United States. Wealth inequality is computed from micro-level wealth data from the 1870 Census of Population. Firm sizes and profit-wage ratios are computed from the Census of Manufacturing. The Census of Manufacturing industries are converted to 1950 industry for consistency with the Census of Population. State-industry pairs are weighted by the number of individuals for which wealth is observed.

6.2 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, suggests that steam increased inequality, while electricity decreased it. In this subsection, I use the newly digitized wealth data from the Netherlands to provide further evidence on the effect of scale-biased technical change on inequality.

I use the digitized Dutch inheritance tax data described in section 4 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. This yields 819 municipality-decade observations from 210 distinct municipalities. With this dataset, I first study how wealth inequality evolved across municipalities with varying rates of adoption of steam and electric power adoption in manufacturing.

I measure power adoption in each Dutch municipality using the newly digitized 1930 Census of Dutch Companies. These data divide establishments in three groups: 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 prime movers at all. The measure of local steam power adoption in municipality m, $\text{STEAM}_{1930,m}$, is the share of workers in the first type of establishments. Similarly, electric power adoption, $\text{ELECTR}_{1930,m}$, is the share of workers in the second group of establishments.

The main specification is as follows:

$$y_{mt} = \alpha_{1m} + \eta_{1t} + \sum_{k \in T \setminus \{1880\}} \beta_{1k} \left(\text{STEAM}_{1930,m} \times D_{tk}\right) + \varepsilon_{1,mt} \tag{23}$$

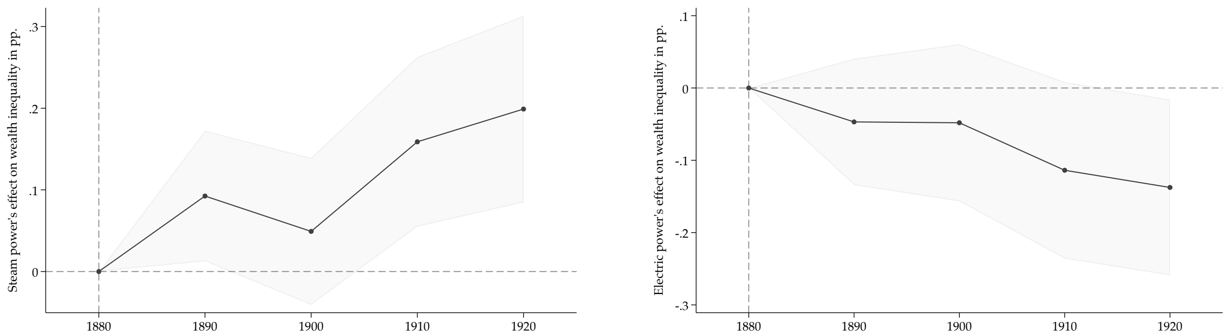
$$y_{mt} = \alpha_{2m} + \eta_{2t} + \sum_{k \in T \setminus \{1880\}} \beta_{2k} \left(\text{ELECTR}_{1930,m} \times D_{tk}\right) + \varepsilon_{2,mt} \tag{24}$$

where the subscript $t \in T = \{1880, 1890, 1900, 1910, 1920\}$ refers to the decade, m to the municipality and D_{tk} is a dummy that 1 if $t = k$ and 0 otherwise. The dependent variable y_{mt} is a moment of the wealth distribution, e.g., the top 1 percent wealth share. The coefficients β_{1k} and β_{2k} capture the association between steam power and electric power adoption and the change in wealth inequality from 1880, the reference year, to year k. I run this analysis on each of the 169 municipalities for which enough wealth observations are available in each decade to compute top 1% wealth shares.

Figure 9 shows that places experiencing large-scale-biased technical change saw a relative increase in wealth inequality, while small-scale-biased technical change is associated with decreases in inequality. Figure 9A shows that places with more steam power adoption saw a relative increase in the share of wealth owned by the top 1 percent. The coefficients suggest that a 1 percentage point increase in the share of employment exposed to steam power leads to an increase in the top 1% wealth share of about 0.2 percentage points. This effect is statistically and economically significant. Local steam power adoption varied strongly: around 10 percent of municipalities adopted no steam power at all, while in some municipalities more than 90 percent of manufacturing employment was in steam-powered establishments. A one standard deviation increase in steam power adoption (0.2) increases the top 1% wealth share by around 4 percentage points in 1920. The average top 1% wealth share across municipalities was 21 percent. In contrast, Figure 9B shows that the adoption of electric power correlates with a *decrease* in top 1 percent wealth shares. Figure A.15 shows that results are almost identical when using weighted estimates of wealth inequality as the dependent variable.

FIGURE 9: Steam power increased wealth inequality, electric power decreased it

(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 econometric specifications are detailed in equations (23) and (24). Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

The results so far show the evolution of wealth inequality in municipalities along one dimension of power use (steam power or purchased electric power). When purchasing electric power adoption is low, this could be because mainly steam power was used or because there was little power use of any kind. To directly compare the effect of steam power adoption and electric power adoption, I also estimate equation (23) while controlling for the share of employment in establishments that did not use any power in 1930, $\text{NOPOWER}_{1930,m}$.[43] Since $\text{STEAM}_{1930,m}$, $\text{ELEC}_{1930,m}$, and $\text{NOPOWER}_{1930,m}$ sum to one by construction, the coefficient of interest in this regression reflects the increase in wealth inequality associated with a 1 percentage point increase in steam power use and a 1 percentage point *decrease* in purchased electric power use. The results are shown in Figure A.16. It shows that holding total power usage constant, wealth inequality increased in places where more steam power was used relative to places that relied more on electric power.

Lastly, Figure A.17 shows how different parts of the wealth distribution are affected. It shows that power use is most strongly correlated with the very top wealth inequality measures. 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

[43]That is, I estimate:

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

mostly implies an increase in inequality *within* the higher end of the distribution.

Instrumental variable analysis. The municipality-fixed effects specifications in equations (23) and (24) control for any time-invariant unobserved heterogeneity across municipalities. Time-varying heterogeneity is a potential remaining threat to causal interpretation of the coefficients in Figure 9. For instance, it is a priori conceivable that changes in local inequality between 1880 and 1920 also affected technology adoption, leading to reverse causality. To assess the quantitative importance of such threats to identification, I employ an instrumental variable strategy.

The identification strategy uses that the local industry composition in manufacturing in 1816 (see Section 4.1.4 for details on the data) is predictive of the local adoption rates of steam and electric power. 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.[44] 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:

$$\text{STEAM\_EXP}_{1816,m} = \sum_{i \in I} \frac{\text{Employment in industry } i \text{ in } m \text{ in } 1816}{\text{Total employment in } m \text{ in } 1816} \times \text{STEAM}_{1930,i} \qquad (25)$$

$$\text{ELECTR\_EXP}_{1816,m} = \sum_{i \in I} \frac{\text{Employment in industry } i \text{ in } m \text{ in } 1816}{\text{Total employment in } m \text{ in } 1816} \times \text{ELECTR}_{1930,i}. \qquad (26)$$

where the adoption rates on the industry-level $\text{STEAM}_{1930,i}$ and $\text{ELECTR}_{1930,i}$, are computed analogously to those on the municipality-level, $\text{STEAM}_{1930,m}$ and $\text{ELECTR}_{1930,m}$. The exposure measure is a strong predictor of actual adoption in 1930 (see Table B.7 for the correlation).

I estimate the "reduced form" of the instrumental variable analysis equivalently to equations (23) and (24) except that the actual adoption rates are changed for the predicted rates in equations (25) and (26). That is, I estimate how wealth inequality evolved between 1880 and 1927 across municipalities that were more or less exposed to the two types of power.

Figure A.18 shows that places more exposed to steam power became more unequal, while places more exposed to electric power became more equal, providing further evidence that steam and electric power causally affected inequality in opposite ways, as predicted by the theory.

[44]Table B.6 shows the adoption rates for each manufacturing industry. The textile industry, together with the much smaller beverage industry, was 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.

7 Who Gains from Large-Scale-Biased Technical Change?

Section 6 showed that steam power increased inequality, while electric power did not. The last question I ask is: who were the main beneficiaries of steam power? In this section, I zoom in to Enschede, the major Dutch textile city, to understand *who* was capturing the rents from large-scale-biased technical change. I find that the rise in wealth inequality was almost entirely due to the textile factory owners who amassed wealth at a much higher rate than other households. This finding confirms the prediction of the theory of scale-biased technical change that the concentration of business income, not of wages, was the key driver of increased inequality.

I selected Enschede for this case study because, being a major textile producer, it heavily relied on steam power and witnessed a strong increase in wealth inequality. Figure A.19 charts the wealth share of the top 1% over time. Another advantage of studying Enschede is that the history of its textile industry is well documented and the identities of the factory owners are known.

The foundations of the textile industry in Twente, the region around Enschede, had already been laid in the 16th century. At that time, many Flemish entrepreneurs had their linen woven in Twente, due to its attractive position between Amsterdam and northern Germany (Schot et al., 2003). By 1750, 40% of the local labor force worked in the textile industry, predominantly at home. Since textile manufacturing was the industry most exposed to steam power (see Table B.6), Enschede's rate of adoption of steam power was among the highest in the country.

The theory predicts that large-scale-biased technical change impacts inequality through the profits accrued by entrepreneurs. Therefore, one should expect to see that wealth inequality is driven mostly by them. To test this prediction, I compute the evolution of average wealth in different parts of the wealth distribution on samples including and excluding textile factory owners. Specifically, I exclude people from the sample if they belong to one of the 22 families that are considered within the "core" and "inner circle" of textile factory owners by Willink (2015). I use the last name as a proxy for family membership.[45]

To make the data for Enschede as accurate and representative as possible, all the wealth data for the tax office in Enschede, which covered the city of Enschede and surrounding towns, were manually entered from tables containing all decedents (not just those assessed for taxes) and linked to the civil registry. The source of the wealth data in

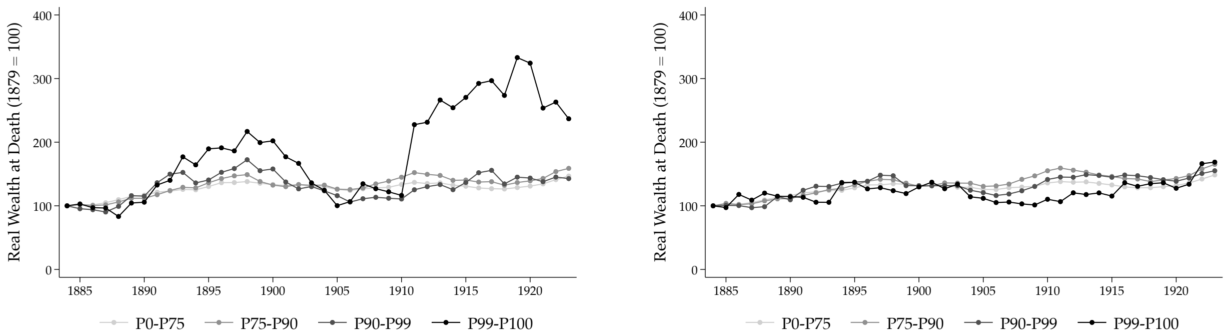
[45] The 7 families belonging to the "core" (Willink, 2015, Ch. 12) are: Blijdenstein, Ten Cate, Van Heek, Jannink, Ter Kuile, Scholten, and Stork. The 15 families in the "inner circle" (Willink, 2015, Ch. 13) are: Van Delden, Elderink, Van Gelderen, Gelderman, Hofkes, Ter Horst, Jordaan, Ledeboer, Menko, De Monchy, Palthe, Salomonson, Spanjaard, Stroink, Willink

the tables were the inheritance tax records that I digitized more generally, and I find that the agreement between the two sources is almost perfect for decedents that are taxed. The benefit of the tables is that they also include decedents that were not assessed for the tax (while the cost is that they are much harder to reliably digitize than the inheritance tax files I use on a large scale).[46] The database contains 50,019 decedents, of which 27,753 were older than 20 years at the time of death. Of those 27,753, wealth is directly observed for 12,780 individuals, and assumed to be zero for the others. 2.6 percent of the population is classified to be part of a textile family.

Figure 10 shows that entrepreneurial wealth in textile manufacturing is driving the large increase in wealth inequality in Enschede. Figure 10A shows the mean wealth at death for different percentile groups. It illustrates that wealth inequality increased through a divergence of the top 1 percent from the rest of the distribution. Most importantly, panel B shows that wealth inequality among everyone except the textile families Figure 10B did not go up. These patterns indicate the importance of studying inequality in the overall population, not only among wage earners. Scale-biased technical change primarily affects the concentration of business income. Therefore, it most strongly affects the income of top business owners relative to the rest of the distribution.

FIGURE 10: Wealth inequality is driven by entrepreneurs adopting steam power

(A) Full sample (B) Excluding textile owners



Notes: This figure shows the evolution of mean wealth by percentile group in Enschede, a major textile producing city in the Netherlands. Panel A shows the evolution when estimated on the full population, while Panel B excluding individuals belong to the 22 most important textile factory owning families as defined by Willink (2015). For each year, the average wealth is computed from the sample of decedents in a 10-year window around it.

8 Conclusion

In this paper, I highlight a new channel through which technical change affects inequality: scale bias, the degree to which technical change increases the relative productivity of

[46] Figure D.5 shows an example of a source image.

large firms. I show that technical change is large-scale-biased if it increases fixed costs. When fixed costs of a new technology are sufficiently high, only the largest firms opt to incur the fixed cost to reduce marginal cost, while smaller firms keep using the existing technology or even go out of business. As a result, profits concentrate into a smaller set of firms. With fewer and larger firms, top entrepreneurs are capturing a larger share of the profits, pushing top income inequality up.

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

While this research shows that entrepreneurs and their incomes are key for shaping and understanding inequality, existing work primarily focuses on the impact of technical change on wage inequality, not overall income inequality.[47] The effect of technical change on the distribution of business income and inequality between workers and entrepreneurs has, to the best of my knowledge, so far not been studied empirically. This is an important omission, because business income is a large source of income, especially at the top of the distribution. In the US, more than half of total income for the top 0.1 percentile is business income (Smith et al., 2019). Similarly, 81 percent of individuals in the top 1 percent of the wealth distribution was a business owner or self-employed (Cagetti and De Nardi, 2006).

Even today, the concentration of firm ownership is high, so that the distribution of profits across firms matters for the distribution of income across people. In the US, "pass-through" businesses account for 51 percent of all business income in 2013 (Nelson, 2016).[48] The typical such business is owned by one to three people (Smith et al., 2019) and 69% of its income accrues to the top 1% (Cooper et al., 2016). The great bulk of the remaining income is earned by a small share of publicly traded firms (Clarke and Kopczuk, 2017). While ownership of publicly traded firms is less concentrated, it is not as diffuse as commonly thought. For instance, among a random sample of US publicly traded firms, 96 percent had shareholders that own at least 5% of the stock, and in 53 percent of firms, the largest shareholder is a family (Holderness, 2009).

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

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

The theory of scale-biased technical change and inequality provides a unified framework to understand three major macroeconomic trends in the last three decades. First, firm size concentration is increasing (Autor et al., 2017, 2020; Kwon et al., 2024) and there is decline inentrepreneurship (Salgado, 2020; Jiang and Sohail, 2023), mostly driven by entry costs Kozeniauskas (2024). A large and growing literature relates these patterns to technical change, specifically the growing importance of scale advantages arising from intangible capital and information technology (Brynjolfsson et al., 2008; Hsieh and Rossi-Hansberg, 2023; De Ridder, 2024; Lashkari et al., 2024; Kwon et al., 2024). Unger (2022) shows that specifically customized software (large fixed cost) is highly skewed to large firms, while pre-packaged software (low fixed cost) is used by small and large firms alike. Second, top income and wealth inequality has increased sharply. For example, between 1980 and 2014, the United States experienced 21% growth in the incomes of the bottom half of the distribution, while the top 10 percent saw their incomes more than double during the same period (Piketty et al., 2018). Third, since the 1990s, business income—not wage income—accounts for the largest part of the rise of top incomes in the United States (Smith et al., 2019, Figure IX).

This paper leaves several important questions for future research. First, in the stylized model presented, technical change and its direction is exogenous. While this assumption is reasonable in the case of steam and electric power adoption in the US and the Netherlands, modelling technical change as the outcome of a directed research effort could provide further useful insights. A concentrated firm size distribution may further incentivize large-scale-biased technical change, similar to how the skill distribution may induce innovation in technologies that complement the more abundant factor (Acemoglu, 2002). Another important simplification of the model is that while technology adoption matters for inequality, inequality does not matter for technology adoption. In more quantitative model, with risk aversion or liquidity constraints, entrepreneurship skews towards high wealth individuals because they are more equipped to take risk or afford larger up-front investments (Quadrini, 2000; Cagetti and De Nardi, 2006; Buera et al., 2011; Buera and Shin, 2013). In such a model, large-scale-biased technical change may further reduce entry of low-wealth individuals and worsen aggregate productivity. Lastly, the on-going development of artificial intelligence technologies raises important questions on its distributional effects. Research shows that large firms tended to be the early adopters of the technology (McElheran et al., 2023). More research 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.

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.

BELL, L. (1891): "Electricity as the rival steam," *Journal of the Franklin Institute*, 131, 212–227.

BENGTSSON, E., A. MISSIAIA, M. OLSSON, AND P. SVENSSON (2018): "Wealth inequality in Sweden, 1750–1900," *The Economic History Review*, 71, 772–794.

BERNARD, A. B., J. EATON, J. B. JENSEN, AND S. KORTUM (2003): "Plants and productivity in international trade," *American economic review*, 93, 1268–1290.

BOLTON, D. (1926): "The variation of efficiency with size, and the economic choice of electrical machinery," *Journal of the Institution of Electrical Engineers*, 64, 337–348.

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.

CLARKE, C. AND W. KOPCZUK (2017): "Business income and business taxation in the United States since the 1950s," *Tax Policy and the Economy*, 31, 121–159.

COOPER, M., J. MCCLELLAND, J. PEARCE, R. PRISINZANO, J. SULLIVAN, D. YAGAN, O. ZIDAR, AND E. ZWICK (2016): "Business in the United States: Who Owns It, and How Much Tax Do They Pay?" *Tax Policy and the Economy*, 30, 91–128.

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 LOECKER, J., J. EECKHOUT, AND G. UNGER (2020): "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 135, 561–644.

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.

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 non-financial corporations," *Washington DC: Securities and Exchange Commission*.

HALL, R. E. AND S. E. WOODWARD (2010): "The burden of the nondiversifiable risk of entrepreneurship," *American Economic Review*, 100, 1163–1194.

HANNAH, L. (1979): *Electricity before nationalisation*, Springer.

HELPMAN, E. (1998): *General purpose technologies and economic growth*, MIT press.

HOLDERNESS, C. G. (2009): "The myth of diffuse ownership in the United States," *The Review of Financial Studies*, 22, 1377–1408.

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 (2021): "Growth Off the Rails: Aggregate Productivity Growth in Distorted Economies," .

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.

KAPP, G. (1894): *Electric Transmission of Energy and Its Transformation, Subdivision, and Distribution: A Practical Handbook*, Whittaker & Company.

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. (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.

MELITZ, M. J. AND S. J. REDDING (2015): "New trade models, new welfare implications," *American Economic Review*, 105, 1105–1146.

MOLL, B., L. RACHEL, AND P. RESTREPO (2022): "Uneven growth: automation's impact on income and wealth inequality," *Econometrica*, 90, 2645–2683.

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

NELSON, S. C. (2016): *Paying Themselves: S Corporation Owners and Trends in S Corporation Income, 1980-2013*, Department of the Treasury.

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.

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

SCHOT, J. W., H. W. LINTSEN, A. RIP, AND A. A. DE LA BRUHÈZE (2003): *Techniek in Nederland in de twintigste eeuw*, Walburg Pers.

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.

WILLINK, B. (2015): *De textielbaronnen: Twents-Gelders familisme en de eerste grootindustrie van Nederland 1800-1980*, Walburg Pers.

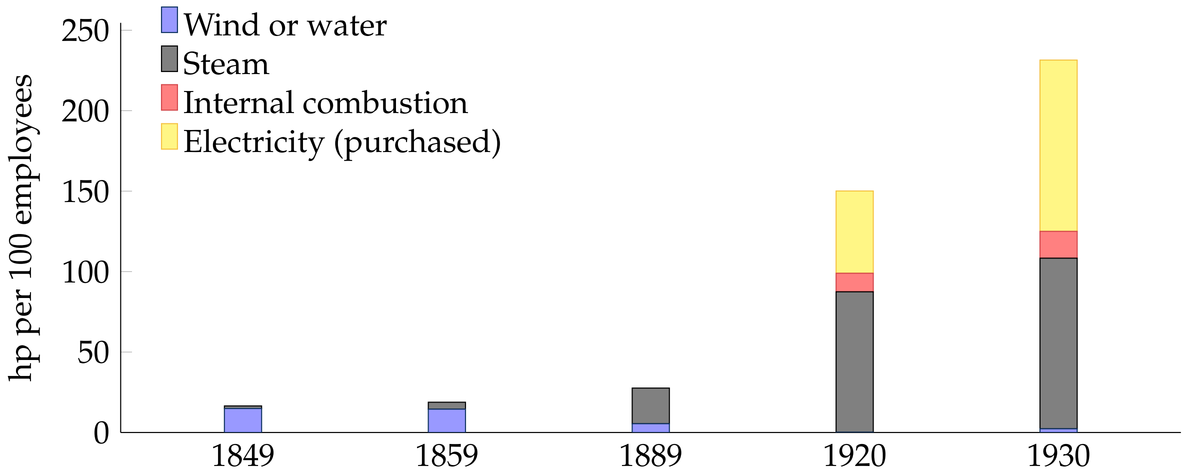
YEAPLE, S. R. (2005): "A simple model of firm heterogeneity, international trade, and wages," *Journal of international Economics*, 65, 1–20.

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

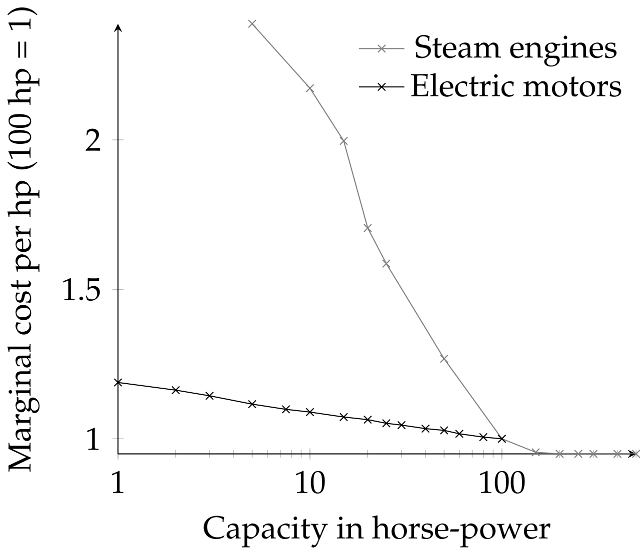
A Figures

FIGURE A.1: Capacity of primary power by type in horsepower per 100 employees in manufacturing in the Netherlands



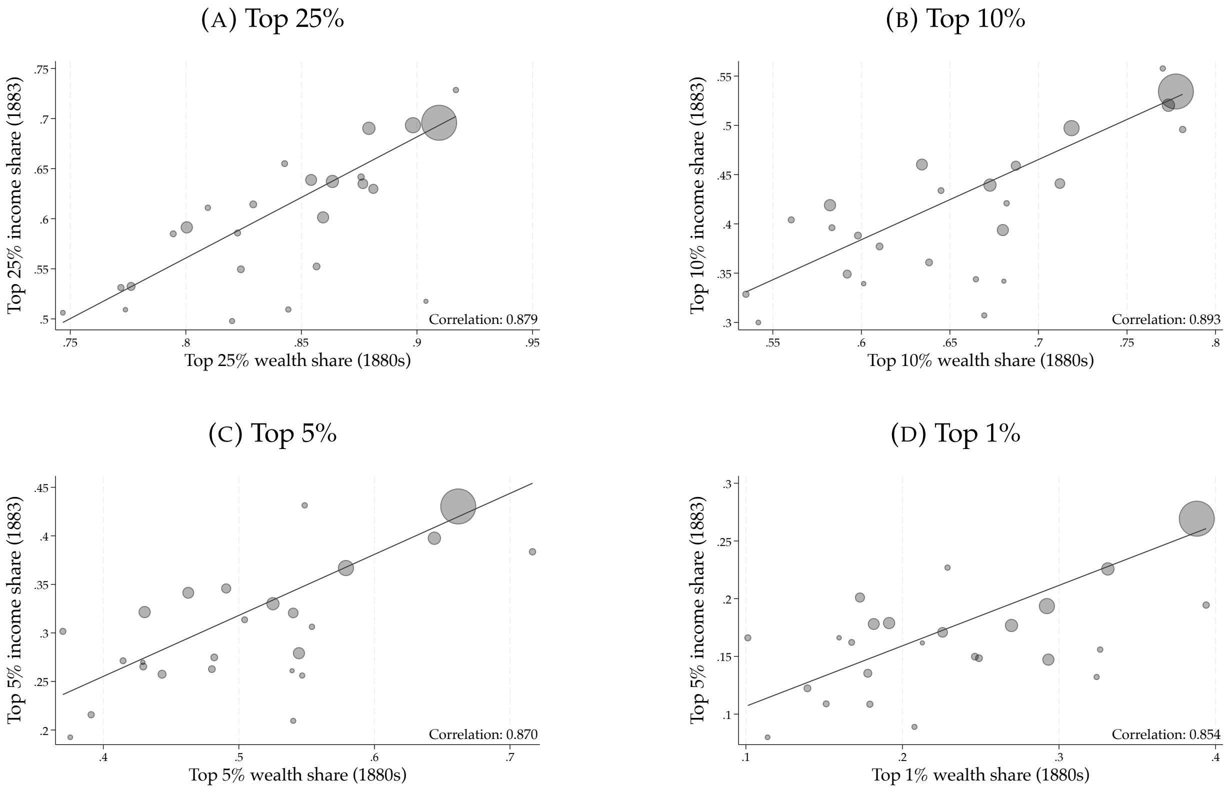
Notes: Electricity (purchased) refer to electric motors driven by purchased electricity, only. *Sources*: (Blanken and Lintsen, 1981, Table 8) for primary power by type, (Statistics Netherlands, 2001) for employment in manufacturing.

FIGURE A.2: Marginal cost of steam engines and electric motors of different capacities relative to its 100-horse power equivalent



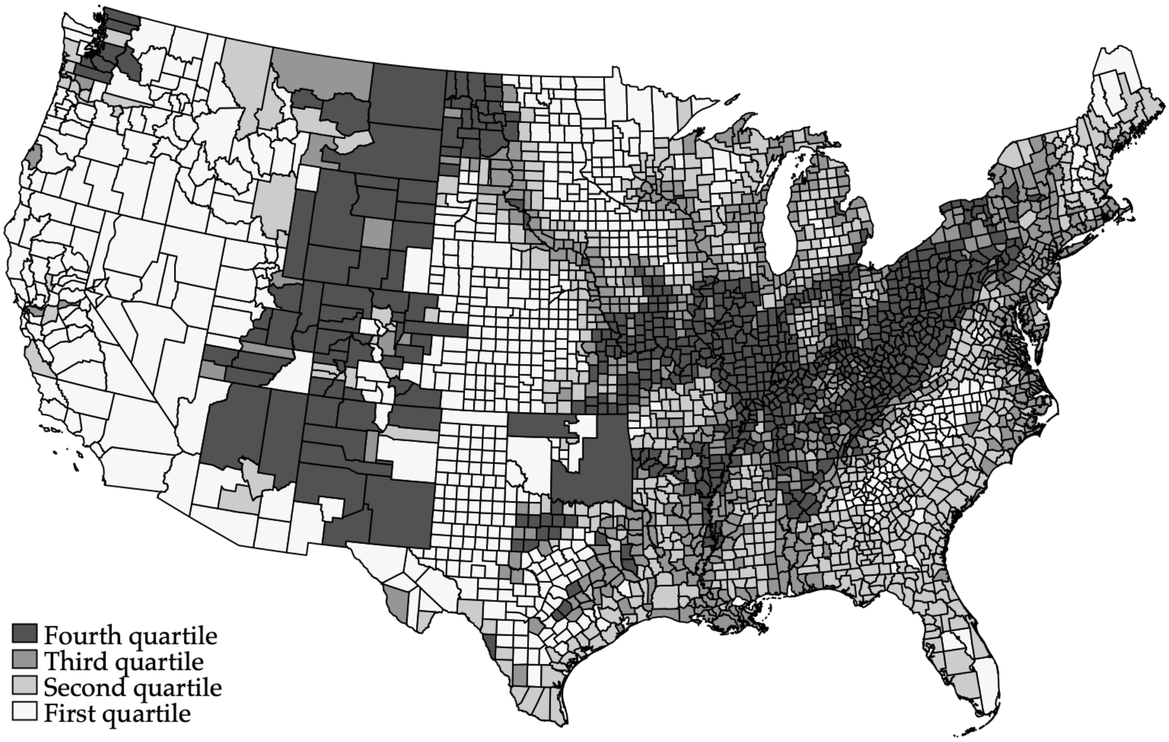
Sources: (Emery, 1883) for coal per horse-power in steam engines; (Bolton, 1926) for full load efficiency of squirrel-cage induction motor.

FIGURE A.3: Correlation between income and wealth inequality



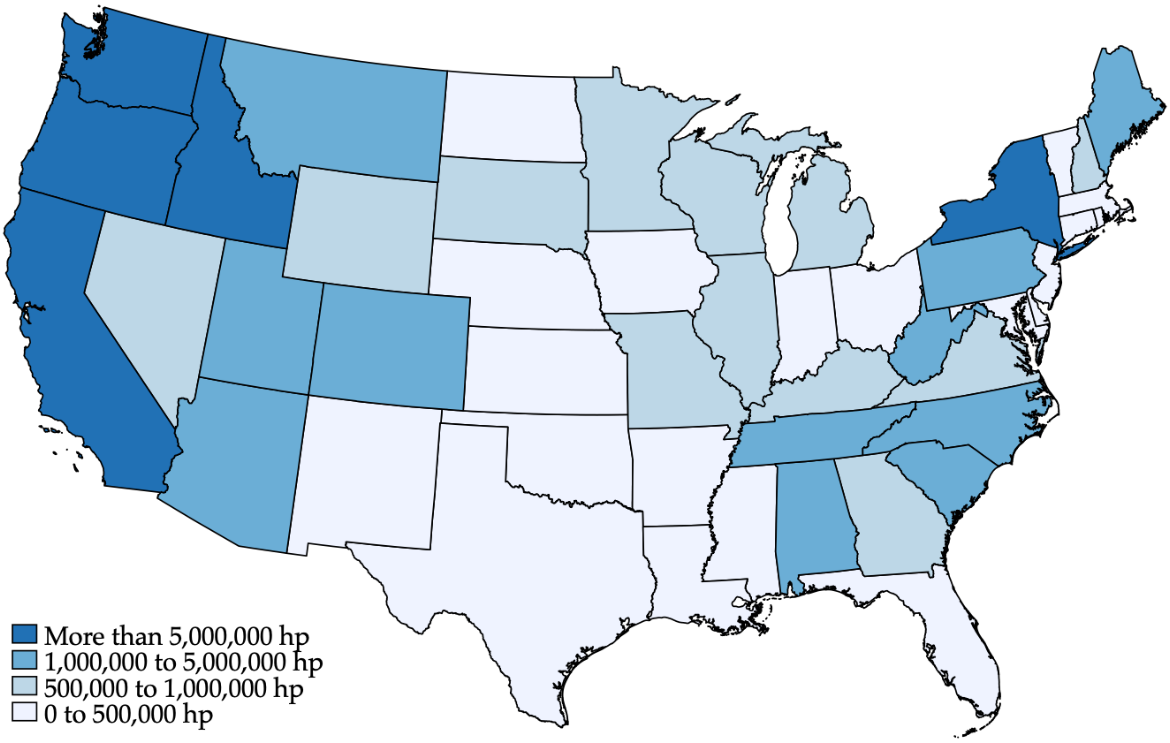
Notes: These figures show the correlation between measured income inequality in 1883 derived from local income tax data and wealth inequality as measured from wealth of decedents who were assessed for inheritance taxation. Each dot is a municipality, and the size of the dot represents the number of individuals for which we observe wealth in that municipality.

FIGURE A.4: Coal access by county



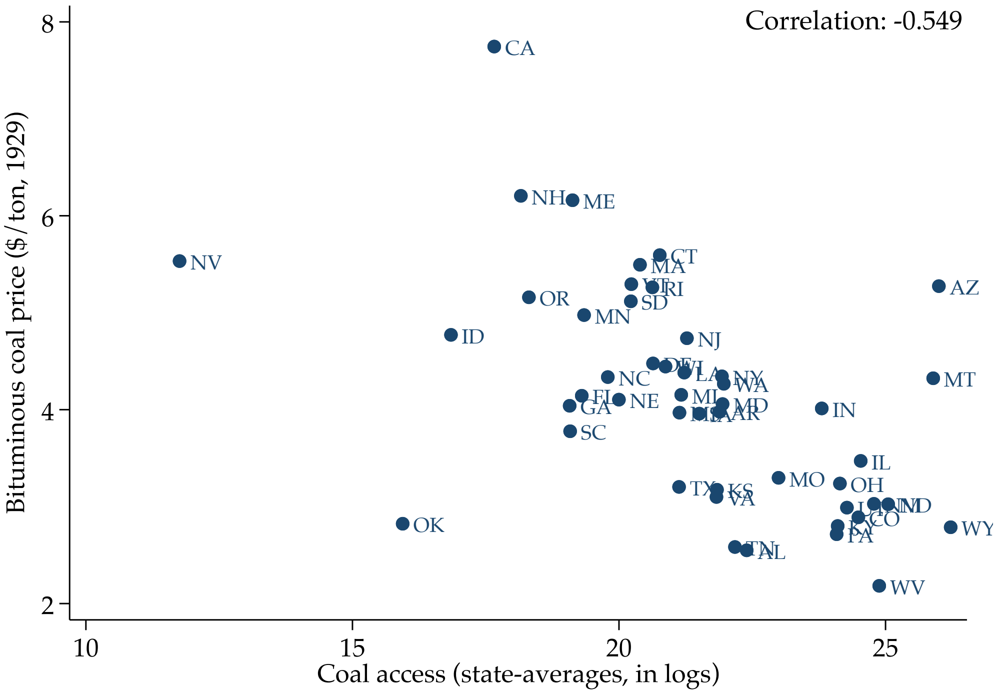
Notes: Coal access is defined in equation (16). *Sources:* US Geological Survey, Coal Resources Data System for the coal resources by county. Donaldson and Hornbeck (2016) for transportation costs by county-pair.

FIGURE A.5: Potential waterpower in horsepower available 50 percent of the time



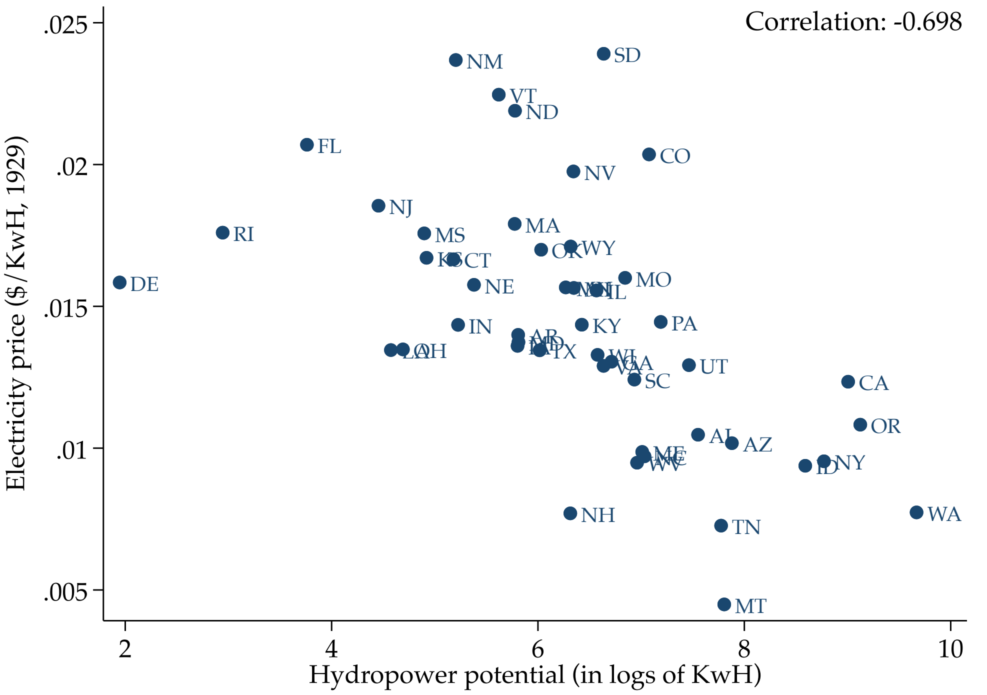
Source: US Geological Survey, (Young, 1964, Table 10).

FIGURE A.6: Correlation between coal access and coal prices



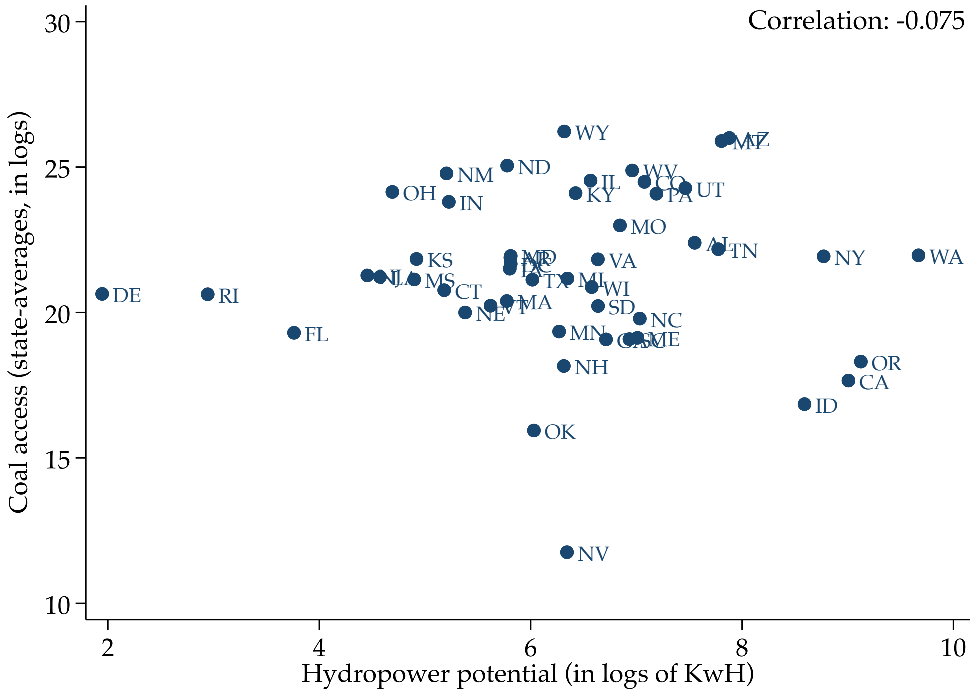
Sources: coal access: National Coal Resources Data System, US Geological Survey and Donaldson and Hornbeck (2016) for transportation costs by county-pair; coal prices: Census of Manufactures, 1929.

FIGURE A.7: Correlation between hydropower potential and electricity prices



Sources: hydropower potential: US Geological Survey, (Young, 1964, Table 10); electricity prices; Census of Manufactures 1929.

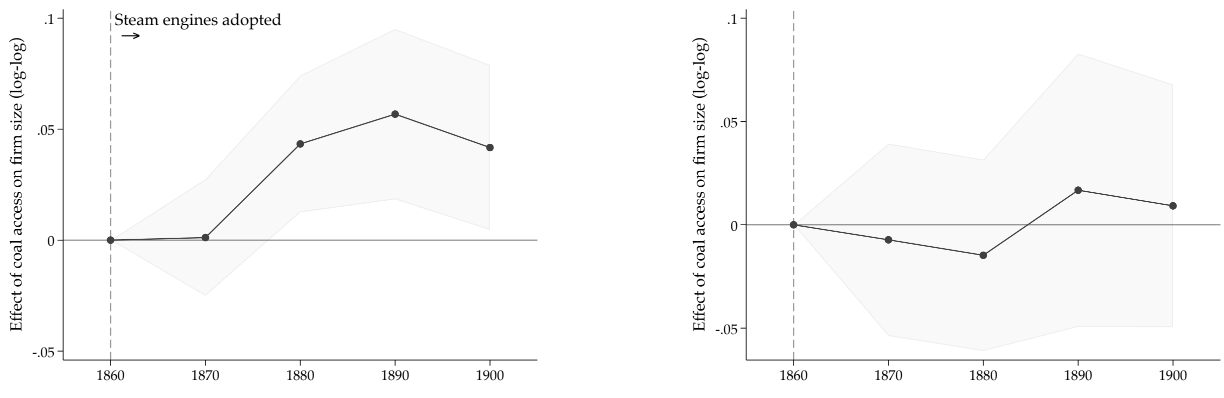
FIGURE A.8: Correlation between coal access and hydropower potential



Sources: for hydropower potential: US Geological Survey, (Young, 1964, Table 10); for coal access: US Geological Survey, Coal Resources Data System.

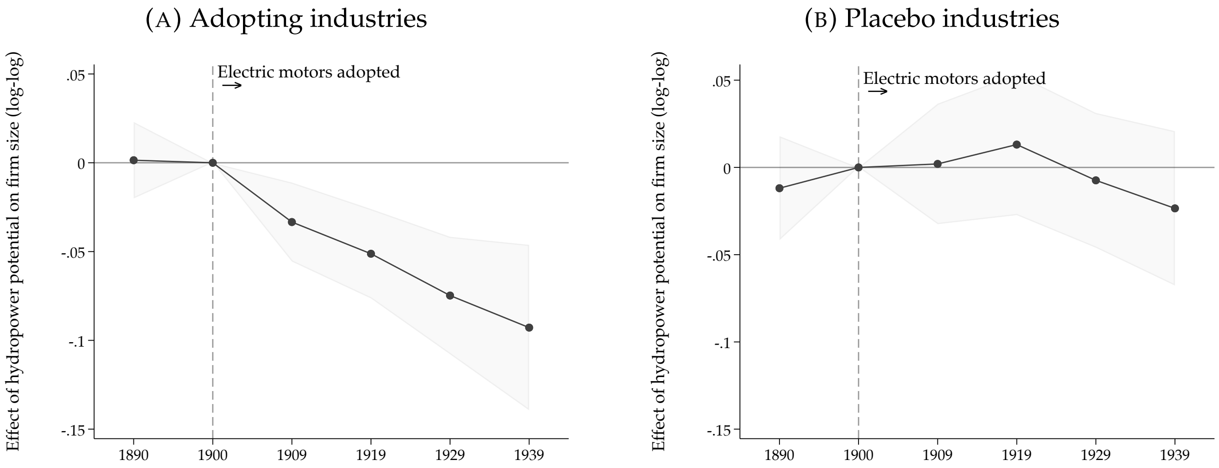
FIGURE A.9: Heterogeneous effects of coal access across industries

(A) Adopting industries (B) Placebo industries



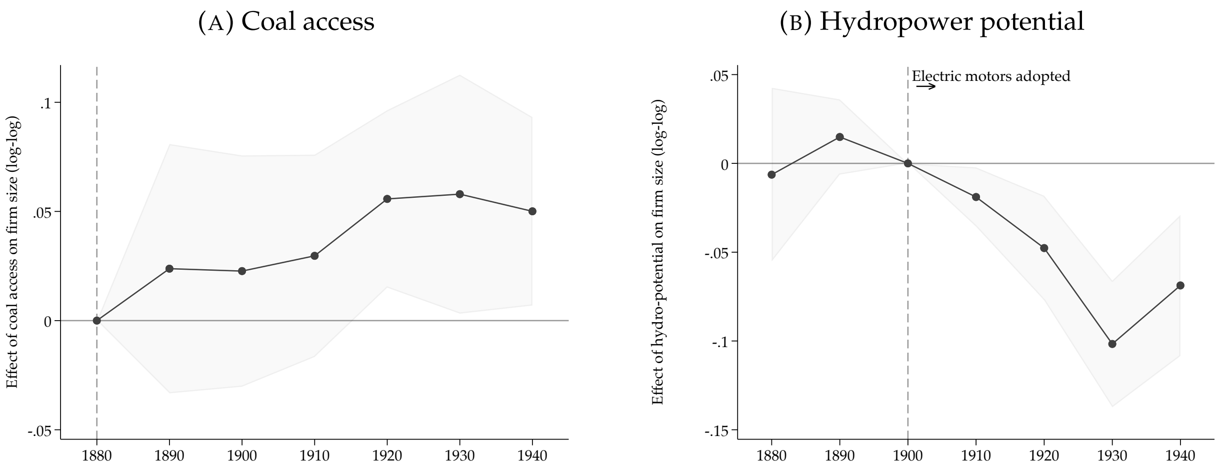
Notes: This figure shows estimated of the reduced form effects of coal access. Panel A shows the effect estimated on a subset of industries that adopt any power nationally in 1890 (measured as being above the 25th percentile in share of establishments reporting the use of power). Panel B shows the effect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

FIGURE A.10: Heterogeneous effects of hydropower potential across industries



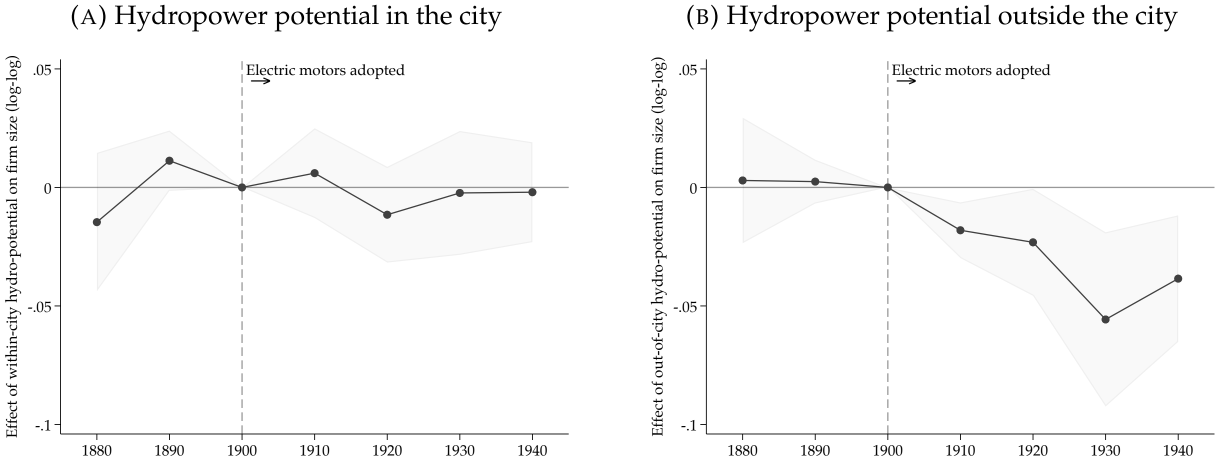
Notes: This figure shows estimated of the reduced form effects of hydropower potential on establishment sizes. Panel A shows the effect estimated on a subset of industries that adopt electric motors nationally in 1939 (measured as being above the 25th percentile in share of fuel costs that is electric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

FIGURE A.11: Effects of coal access and hydropower potential on the city-industry level



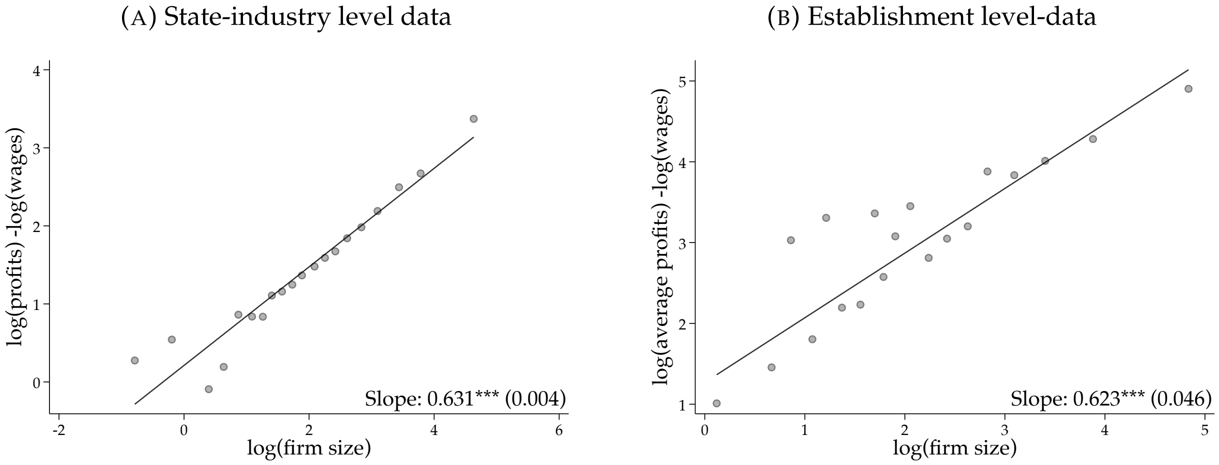
Notes: Panel A and B of this figure show estimates of the reduced form effects of coal access and hydropower potential on on establishment sizes on the city-industry level. Estimates in Panel A and B are jointly estimated in one specification (see equation (19) for the econometric specification), the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

FIGURE A.12: Effects of hydropower potential on the city-industry is mostly through state-level hydropower



Notes: Panel A and B of this figure show estimates of the reduced form effects of hydropower potential on on establishment sizes on the city-industry level. Estimates in Panel 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.

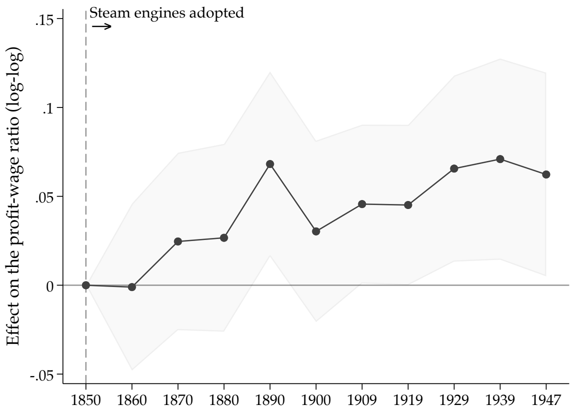
FIGURE A.13: Free entry condition: correlation between profit-wage ratio and firm size



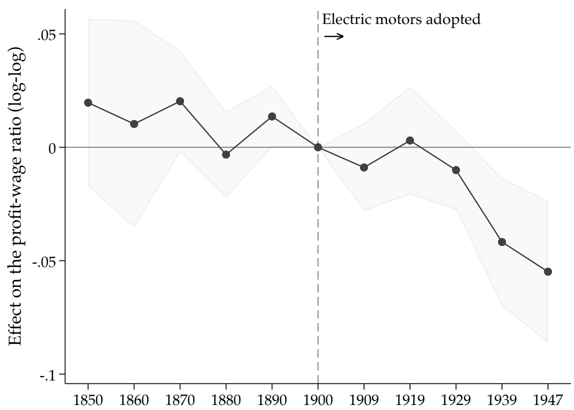
Notes: Panel A and B show binscatters of firm sizes and the ratio between average profits and wages by industry (each in logs). Each observation is an industry-state-year combination. Average profits are approximated by dividing total output minus cost of raw materials, labor costs, capital costs, and 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.14: Effects of coal access and hydropower potential on the profit-wage ratio

(A) Coal access



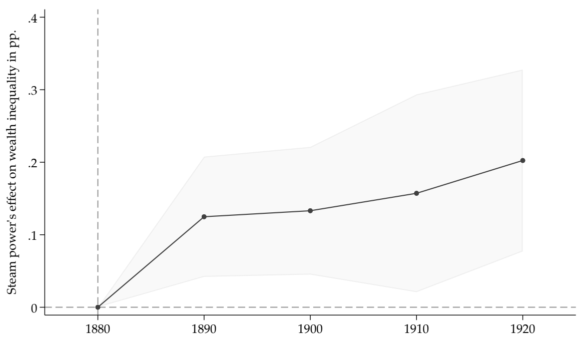
(B) Hydropower potential



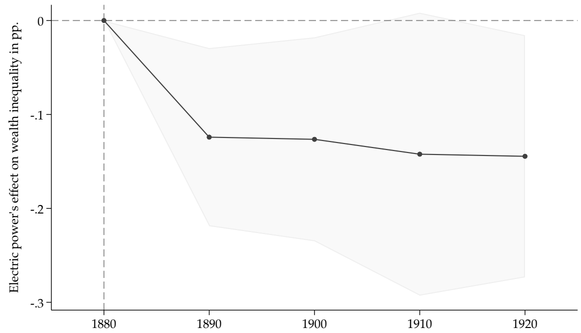
Notes: Panel A and B of this figure show estimates of the reduced form effects of coal access and hydropower potential on the ratio between average profits and average wages relative to the base year, accounting for industry and state fixed effects. Estimates in Panel A and B are jointly estimated in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

FIGURE A.15: Robustness to using weighted wealth inequality measures

(A) Steam power effect

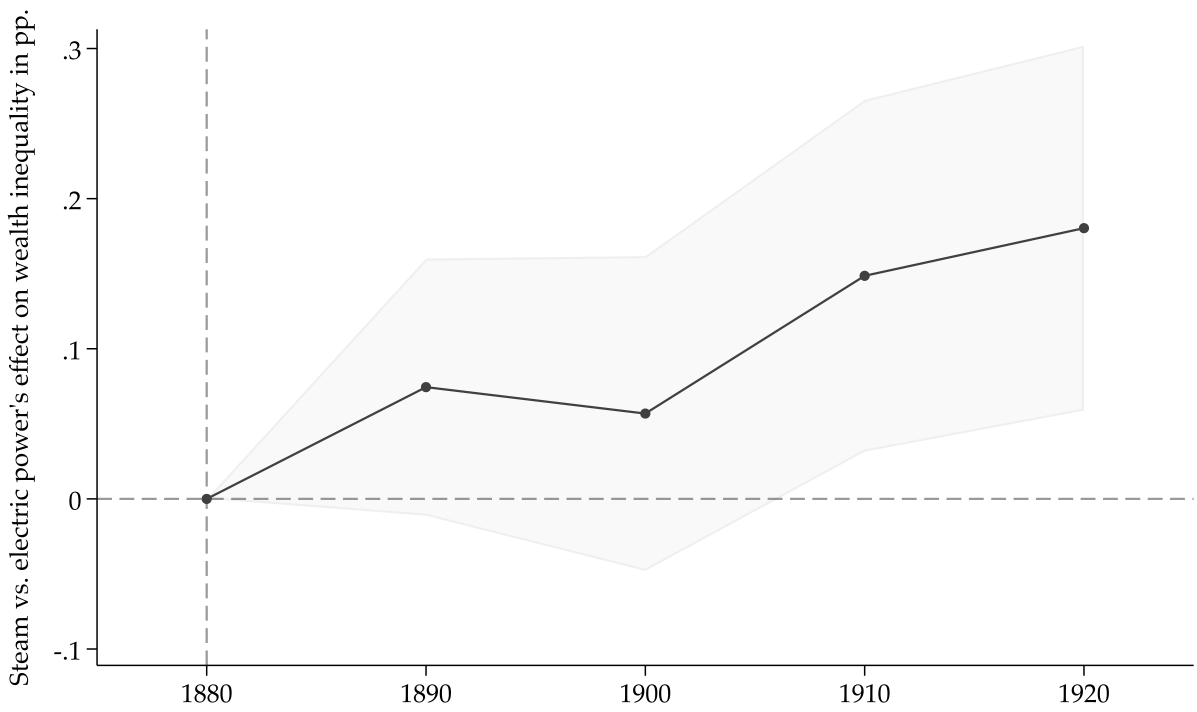


(B) Electric power effect



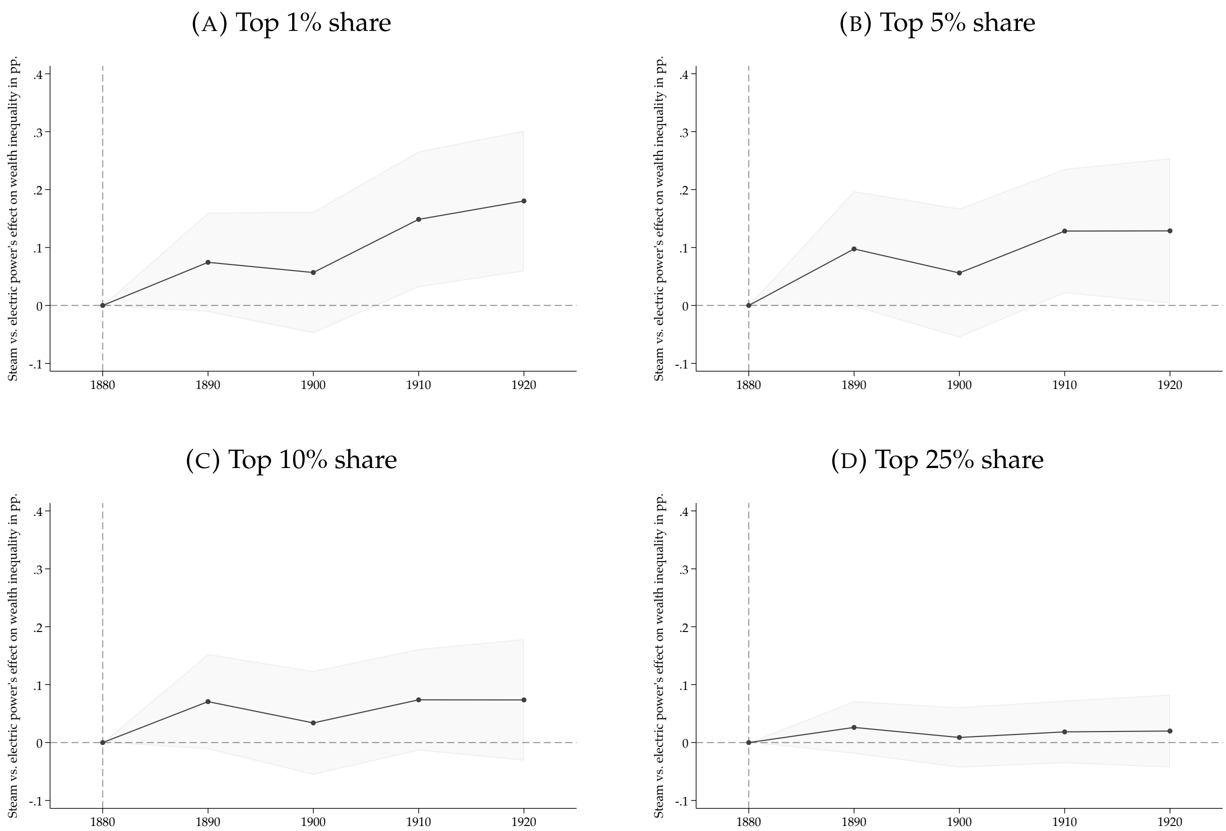
Notes: This figure shows the estimated effects in percentage points of steam power (in panel A) and electric power adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The only difference with 9 is that wealth inequality is computed by weighting individuals by the inverse probability of death as estimated by their age. The econometric specifications are detailed in equations (23) and (24). Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

FIGURE A.16: 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.

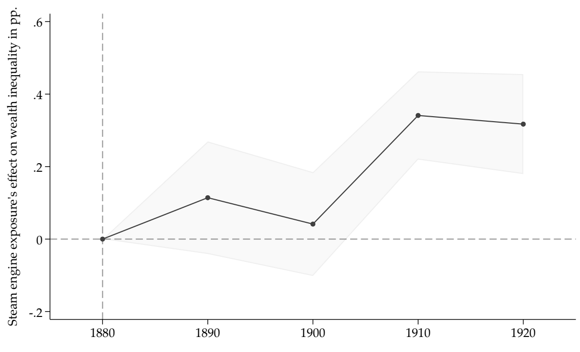
FIGURE A.17: Steam vs. electric power is most correlated with increased wealth inequality at the very top



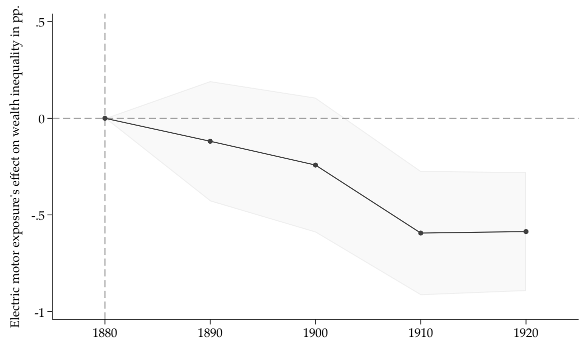
Notes: This figure shows the estimated effects in percentage points of steam power (in panel A) and electric power adoption (in panel B) on within-municipality top wealth inequality for each decade relative to 1880. The econometric specifications are detailed in equations (23) and (24). Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

FIGURE A.18: 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 percentage points of pre-industrial exposure to steam power (in panel A) and electric power adoption (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 which is computed on the basis of the local industry composition in 1816 and adoption rates by industry in 1930. Observations are weighted by the number of individuals on which the inequality measure is based. Shaded areas represent 95% confidence intervals.

FIGURE A.19: Top 1% wealth share in Enschede, Netherlands

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

B Tables

TABLE B.1: The effect of coal access on steam engine adoption (1890)

	Steam hp per worker (asinh)			Steam as share of total hp		
Coal access (logs)	0.022***	0.022***	0.023***	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)
Hydropower 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: The effect 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 electricty 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: The effect of steam power and electric power adoption on firm sizes

	$\Delta \ln(\text{firm size}_{is})$					
	1860-1890			1900-1940		
$\text{STEAM}_{is,1890}$	1.058**	1.152**	1.089**			
	(0.450)	(0.465)	(0.483)			
$\text{ELECTRICITY}_{is,1939}$				-0.386***	-0.383***	-0.353***
				(0.094)	(0.104)	(0.113)
$\Delta \ln(\text{population density}_s)$		X	X		X	X
$\Delta \ln(\text{income/wealth p.c.}_s)$			X			X
Observations	1900	1900	1900	2117	2117	2117
Kleibergen-Paap F-stat.	42.9	33.4	24.7	16.8	14.1	13.3

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

TABLE B.5: The effect of steam power and electric power adoption on the profit-wage ratio

	$\Delta \ln\left(\frac{\text{average profits}_{is}}{\text{wage}_{is}}\right)$					
	1860-1890			1900-1939		
$\text{STEAM}_{is,1890}$	1.134**	1.297**	1.020*			
	(0.529)	(0.533)	(0.512)			
$\text{ELECTRICITY}_{is,1939}$				-0.543**	-0.524**	-0.474*
				(0.250)	(0.250)	(0.254)
$\Delta \ln(\text{population density}_s)$		X	X		X	X
$\Delta \ln(\text{income/wealth p.c.}_s)$			X			X
Observations	1869	1869	1869	1935	1935	1935
Kleibergen-Paap F-stat.	42.8	33.4	24.8	6.6	6.4	5.8

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 horse power in 1890 and megawatt-hour of purchased electricity per worker in 1939. The adoption variables are instrumented with coal access (first three columns) and hydropower potential (last three columns). Observations are weighted by the number of establishments in the base year. Standard errors in parentheses are clustered at the state-level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.6: Adoption rates by 2-digit ISIC industry in 1930

ISIC	Name	$\text{STEAM}_{1930,i}$	$\text{ELEC}_{1930,i}$	Employment
11	Beverages	0.50	0.44	4374
13	Textiles	0.50	0.47	44750
19	Coke and petroleum	0.47	0.42	1129
17	Paper and paper products	0.40	0.57	11000
24	Basic metals	0.35	0.64	6305
23	Other non-metallic mineral products	0.33	0.56	22733
20	Chemicals and chemical products	0.32	0.64	11558
21	Pharmaceuticals	0.29	0.64	1126
22	Rubber and plastics products	0.27	0.71	2540
16	Wood and wood products	0.25	0.40	19081
10	Food products	0.24	0.62	103220
28	Machinery and equipment n.e.c.	0.16	0.82	5313
27	Electrical equipment	0.16	0.84	22380
33	Repair and installation of machinery	0.08	0.89	7030
30	Other transport equipment	0.07	0.87	18723
25	Fabricated metal products	0.07	0.80	34951
15	Leather and related products	0.04	0.40	26855
18	Printing	0.03	0.92	31740
31	Furniture	0.03	0.68	12820
32	Other manufacturing	0.01	0.63	7163
26	Computer and electronic products	0.01	0.32	3748
12	Tobacco products	0.01	0.65	21160
14	Wearing apparel	0.00	0.37	53939

Source: Dutch Census of Companies 1930.

TABLE B.7: First stage: pre-industrial exposure and technology adoption

	$\text{STEAM}_{1930,m}$	$\text{ELECTR}_{1930,m}$
$\text{STEAM\_EXP}_{1816,m}$	0.535^{***}	
	(0.061)	
$\text{ELECTR\_EXP}_{1816,m}$		0.497^{***}
		(0.088)
Constant	0.043^{*}	0.254^{***}
	(0.023)	(0.046)
Observations	835	835

Standard errors in parentheses. Observations are weighted by total manufacturing employment in 1930.
* $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

C Model appendix

Proof of Proposition 1. I prove Proposition 1 by proving its elements (a) to (c) sequentially.
Proposition 1(a): Recall that optimal technology adoption implies that the profit gain of adopting a higher fixed, lower marginal, cost relative to a lower fixed, higher marginal cost technology is increasing in productivity ψ. Formally, $\Delta\pi_{jk}(\psi)$ (defined in equation (6)) is strictly increasing in ψ if $\kappa_j > \kappa_k$ and $\alpha_j < \alpha_k$. This implies that the least productive entrepreneur uses technology with the highest marginal and lowest fixed cost of all adopted technologies. Also, the least productive entrepreneur has productivity ψ equal to the lowest zero-profit cut-off of all available technologies, $\min_{j\in 1,2,..,J} \bar{\psi}_j$. From equation (8), technology t_j is the lowest zero-profit cut-off technology if and only if

$$\alpha_j \kappa_j^{\frac{1}{\sigma-1}} = \min_{k\in\{1,2,..,J\}} \left\{ \alpha_k \kappa_k^{\frac{1}{\sigma-1}} \right\}.$$

The marginal entrepreneur is indifferent between any two technologies t_j and t_k such that $\bar{\psi}_j = \bar{\psi}_k = \bar{\psi}$ as they both give them zero-profit. But since $\Delta\pi_{jk}(\psi)$ in (6) is strictly increasing, any entrepreneur with $\psi > \bar{\psi}$ would strictly prefer the technology with higher fixed cost and lower marginal cost. Therefore, out of any technology t_j that minimizes $\bar{\psi}_j$, only the technology with lowest marginal cost is adopted (in the sense of having a strictly positive probability measure of entrepreneurs adopting the technology).
Proposition 1(b): Note that $\Delta\pi_{jk}(\psi) \to \infty$ in (6) as $\psi \to \infty$ if and only if $\alpha_j < \alpha_k$. This means that if the marginal cost of a technology is lower than that of any another, there exists a productivity level high enough such that it is profitable to adopt this technology. The assumption that the productivity distribution has semi-infinite support implies that for any $C > 0$, $\Pr(\psi > C) > 0$. Therefore, there always exists a strictly positive share of households that adopt the technology with lowest marginal cost. Note that is true regardless of the fixed cost. Of course, in case there is more than one technology that minimizes marginal cost, the technology with lowest fixed costs amongst those will be adopted. Since no technology can be adopted that is trivially dominated, this must also be the adopted technology with highest fixed cost.
Proposition 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. Note that condition is 3) is redundant given condition 1) since it can only dominate technology t_1^* if $\psi > \bar{\psi}$ and t_1^* yields positive profits for all $\psi > \bar{\psi}$. Also, recall that technologies in T are arranged in order of increasing fixed costs ($\kappa_1 < .. < \kappa_J$) and thus decreasing marginal costs ($\alpha_1 > .. > \alpha_J$). Therefore, technology t_j is adopted if there exists a $\psi > \psi_m$ such that $\Delta\pi_{jk}(\psi) > 0$ for all $k \in \{1, .., j-1\}$ and $\Delta\pi_{jl}(\psi) > 0$ for all

$l \in \{j+1, .., J\}$. Using equation (6), this yields the following two restrictions:

$$\frac{Y}{\sigma}(\rho\psi)^{\sigma-1} > \frac{\kappa_j - \kappa_k}{\alpha_j^{1-\sigma} - \alpha_k^{1-\sigma}} \text{ for all } k \in \{1, .., j-1\} \text{ and;} \tag{27a}$$

$$\frac{Y}{\sigma}(\rho\psi)^{\sigma-1} < \frac{\kappa_l - \kappa_j}{\alpha_l^{1-\sigma} - \alpha_j^{1-\sigma}} \text{ for all } l \in \{j+1, .., J\} \tag{27b}$$

Hence, for (27a) and (27b) to hold for some $\psi > \bar{\psi}$, it is necessary and sufficient that the lower bound in (27a) is strictly lower than the upper bound in (27b). Thus, technology j is adopted if and only if for all $k \in \{1, .., j-1\}$ and $l \in \{j+1, .., J\}$

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

□

Proposition 2 (Closed-form equilibrium). *Suppose that the distribution of productivity ψ is Pareto with shape parameter ξ and a minimum productivity level of $\psi_m > 0$ such that $\xi > 1$ and $\xi > \sigma - 1$. Then, the competitive equilibrium is given in closed-form by*

$$L = \frac{\xi}{1+\xi} \tag{28}$$

$$\bar{\psi} = \bar{B}(\xi, \sigma, \psi_m)\left(\bar{\kappa}^{\frac{\sigma-2}{\sigma-1}}\alpha_1^*(\kappa_1^*)^{\frac{1}{\sigma-1}}\right)^{\frac{\sigma-1}{\bar{A}(\xi,\sigma)}} \tag{29}$$

$$Y = \bar{C}(\xi, \sigma, \psi_m)\left(\frac{\bar{\kappa}^{\frac{1}{\xi}}}{\alpha_1^*(\kappa_1^*)^{\frac{1}{\sigma-1}}}\right)^{\frac{\xi(\sigma-1)}{\bar{A}(\xi,\sigma)}} \tag{30}$$

$$C = \frac{\xi\sigma - \xi + \sigma - 1}{\xi\sigma}Y \tag{31}$$

$$w = \rho\frac{1+\xi}{\xi}Y \tag{32}$$

$$\bar{\pi} = \frac{\sigma - 1}{\xi - \sigma + 1}\bar{\kappa} \tag{33}$$

where $\bar{A}(\xi, \sigma)$, $\bar{B}(\xi, \sigma, \psi_m)$, and $\bar{C}(\xi, \sigma, \psi_m)$ are strictly positive functions of the exogenous (non-

technological) parameters ξ, σ, and ψ_m:

$$\bar{A}(\xi,\sigma) \equiv (1+\xi)(\sigma-1)-\xi$$

$$\bar{B}(\xi,\sigma,\psi_m) \equiv \left(\psi_m^{\xi}\,(1+\xi)^{\frac{1}{\sigma-1}}\,\frac{\sigma}{\xi-\sigma+1}\left(\frac{\xi\psi_m^{\xi}}{\xi-\sigma+1}\right)^{\frac{1}{1-\sigma}}\right)^{\frac{\sigma-1}{\bar{A}(\xi,\sigma)}}$$

$$\bar{C}(\xi,\sigma,\psi_m) \equiv \bar{B}(\xi,\sigma,\psi_m)^{-\xi}\frac{\psi_m^{\xi}\xi\sigma}{\xi-\sigma+1}\frac{1}{1+\xi}$$

and $\bar{\kappa}$ is the average fixed cost of all producing entrepreneurs:

$$\bar{\kappa} = \begin{cases} \kappa_1^* & \text{if } J^*=1 \\ \kappa_1^* + \left(\alpha_1^*\,(\kappa_1^*)^{\frac{1}{\sigma-1}}\right)^{\xi}\sum_{j=2}^{J^*}\left((\alpha_j^*)^{1-\sigma}-(\alpha_{j-1}^*)^{1-\sigma}\right)^{\frac{\xi}{\sigma-1}}\left(\kappa_j^*-\kappa_{j-1}^*\right)^{\frac{\sigma-1-\xi}{\sigma-1}} & \text{if } J^*>1. \end{cases}$$

Proof of Proposition 2. We first derive the adopting set Ψ_j^* for each technology $t_j^* \in T^*$. Note that we can restrict ourselves to technologies that are adopted in equilibrium (see Proposition 1), since the adopting set is empty otherwise.

By definition, if T^* is a singleton set, then Ψ_1^* is $[\bar{\psi},\infty)$. Now suppose $J^* \equiv |T^*| > 1$. From equation (6), it follows that an entrepreneur with productivity ψ is indifferent between adopting t_j^* and t_{j+1}^* if and only if $G(\psi,t_{j+1}^*,t_j^*)=0$. Define $\bar{\psi}_{j,j+1}$ implicitly by

$$G(\psi,t_{j+1}^*,t_j^*)=0$$

which implies that

$$\bar{\psi}_{j,j+1} = \left(\frac{\kappa_{j+1}^*-\kappa_j^*}{(\alpha_{j+1}^*)^{1-\sigma}-(\alpha_j^*)^{1-\sigma}}\right)^{\frac{1}{\sigma-1}}\left(\frac{\sigma}{Y}\right)^{\frac{1}{\sigma-1}}\frac{w}{\rho} = \bar{\psi}\frac{\left(\frac{\kappa_{j+1}^*-\kappa_j^*}{\left(\alpha_{j+1}^*\right)^{1-\sigma}-\left(\alpha_j^*\right)^{1-\sigma}}\right)^{\frac{1}{\sigma-1}}}{\alpha_1^*(\kappa_1^*)^{\frac{1}{\sigma-1}}}. \tag{34}$$

Since $G(\psi,t_{j+1}^*,t_j^*)$ is increasing in ψ (see proof of Proposition 1(a)), the more productive entrepreneur chooses the technology that entails higher fixed cost. Specifically, an entrepreneur would choose t_{j+1}^* over t_j^* if and only if $\psi > \bar{\psi}_{j,j+1}$. This means that all entrepreneurs with productivity between $\bar{\psi}$ and $\bar{\psi}_{1,2}$ choose t_1^*, all entrepreneurs with productivity between $\bar{\psi}_{1,2}$ and $\bar{\psi}_{2,3}$ choose t_2^*, and so on and so forth. Formally,

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

Combining equation (8) (definition of $\bar{\psi}$) and equation (11) (labor market clearing) with the Pareto assumption, the probability of being an entrepreneur conditional on entry is

$$1 - F(\bar{\psi}) = \psi_m^{\xi} \bar{\psi}^{-\xi} = \frac{L}{1-L} \frac{\xi - \sigma + 1}{\xi(\sigma - 1)} \frac{w}{\bar{\kappa}} \tag{35}$$

where $\bar{\kappa}$, the average fixed cost across producing entrepreneurs, is

$$\bar{\kappa} = \kappa_1 + \left(\alpha_1^* \left(\kappa_1^*\right)^{\frac{1}{\sigma-1}}\right)^{\xi} \sum_{j=2}^{J^*} \left(\left(\alpha_j^*\right)^{1-\sigma} - \left(\alpha_{j-1}^*\right)^{1-\sigma}\right)^{\frac{\xi}{\sigma-1}} \left(\kappa_j^* - \kappa_{j-1}^*\right)^{\frac{\sigma-1-\xi}{\sigma-1}}.$$

Also, labor market clearing in (11) combined with the aggregate price equation in (13), implies that the labor share is constant and independent of technology:

$$\frac{Lw}{Y} = \rho. \tag{36}$$

Combining the constant labor share with equation (35), shows that the share of output devoted to the fixed costs is constant and independent of technology:

$$\frac{(1-L)\psi_m^{\xi} \bar{\psi}^{-\xi} \bar{\kappa}}{Y} = \frac{\xi - \sigma + 1}{\xi \sigma}. \tag{37}$$

Then, by goods market clearing, the profit share must be constant too:

$$\frac{(1-L)\psi_m^{\xi} \bar{\psi}^{-\xi} \bar{\pi}}{Y} = 1 - \rho - \frac{\xi - \sigma + 1}{\xi \sigma} = \frac{\rho}{\xi}. \tag{38}$$

Equation (39) also implies that consumption is a fixed share of output, as in equation (31):

$$C = \frac{\xi \sigma - \xi + \sigma - 1}{\xi \sigma} Y. \tag{39}$$

Together with the free entry condition in equation (9) and the labor share in equation (36), the constant profit share implies that the share of entrants is constant and independent of technology too:

$$L = \frac{\xi}{1+\xi}. \tag{40}$$

Lastly, the pricing equation in (13) combined with the Pareto distribution yields

$$\left(\frac{w}{\rho}\right)^{\sigma-1} = (1-L)\left(\frac{\xi \psi_m^{\xi}}{\xi - \sigma + 1}\right) \bar{\psi}^{\sigma-1-\xi} \frac{\bar{\kappa}}{\left(\alpha_1^*\right)^{\sigma-1} \kappa_1^*} \tag{41}$$

Equations (35), (36), (40), (41) together lead to the closed-form solutions for L, $\bar{\psi}$, Y, and w in equations (28), (29), (30), and (32), respectively. Lastly, the solution for $\bar{\pi}$, the average profits, in (33) results from equations (39) and (38). $\square$

Lemma 1. Suppose that the assumptions in Proposition 2 (Pareto distribution) hold and that $\sigma > 2$. Then, if a new technology t_{new} is added to the technology set T and it is adopted in equilibrium, it increases output Y, wages w, and total profits $(1-L)\psi_m^{\xi}\bar{\psi}^{-\xi}\bar{\pi}$.

Proof of Lemma 1. Suppose towards contradiction that output Y does not increase. Since Y and wages w are positively linearly related (equation (32)), the profit function can be rewritten as

$$\pi_j(\psi) = \frac{1}{\sigma}\left(\frac{\xi}{1+\xi}\right)^{\sigma-1} Y^{2-\sigma}\left(\frac{\psi}{\alpha_j}\right)^{\sigma-1} - \kappa_j. \tag{42}$$

Given $\sigma > 2$, if Y does not increase, it means that profits can not go down for any productivity level and for any technology choice. Also, given that the technology is adopted, it must yield strictly higher profits for some entrepreneurs. Therefore, total profits must go up. But by equation (38), profits are a fixed share of output. Hence, the increase in total profits implies that output Y *increases*, a contradiction. Therefore, output must increase in response to a new technology that is adopted. Since output, wages, and total profits are positively and linearly related, wages and total profits must also go up in response to an adopted new technology. $\square$

Proof of Proposition 3. I prove Proposition 3 by proving its elements (a) and (b) sequentially.

Proposition 3(a): If t_{new} is adopted and has the highest fixed cost, it must have lowest marginal cost. By the reasoning in Stage 3 (equation (6)), this technology is only adopted by the entrepreneurs above a certain threshold for ψ. The entrepreneurs above this threshold reduce their marginal cost and thus increase their total factor productivity.

Because it becomes the highest fixed cost technology, the average fixed cost among producing entrepreneurs, $\bar{\kappa}$, increases.[49] Since $\bar{\kappa}$ increases, the entry threshold $\bar{\psi}$ increases too (seen from equation (29)). Hence, the technical change would lead some entrepreneurs to no longer produce, i.e., decreasing their total factor productivity to 0. It also means that the thresholds above which an entrepreneur uses technology $j+1$ instead of j increase for each j (see equation (34)): at least some entrepreneurs that do not adopt the new technology "downgrade" their technology, because the increased total output (see Lemma 1) by those using the new technology reduces their demand. Hence, for all entrepreneurs that do not adopt the new technology, the marginal cost either decreases or remains unchanged. This proves that technical change is large-scale-biased *if* the new technology has higher fixed than any other adopted technology.

[49] To see this formally, note that output increases by Lemma 1. By equation (30), if output increases while the entry technology, i.e. $\alpha_1^*(\kappa_1^*)^{\frac{1}{\sigma-1}}$ remains unchanged, $\bar{\kappa}$ must increase.

Now suppose the new technology does not have highest fixed cost of all adopted technologies. Then, entrepreneurs that previously adopted the technology with lowest marginal cost can not decrease their marginal cost. For any $k > \psi_m$, there exists a subset of entrepreneurs with $\psi > k$ that adopts the technology with lowest marginal cost before and after the technical change. Hence, there does not exist a k such that all entrepreneurs with $\psi > k$ strictly increase total factor productivity, so that the technical change can not be large-scale-biased, which proves that technical change can be large-scale-biased *only if* the new technology has higher fixed than any other adopted technology.

Proposition 3(b): If t_{new} is adopted and has the lowest fixed cost, it must have highest marginal cost. First, the entry threshold $\bar{\psi}$ in equation (29) decreases because both κ_1^* (the fixed cost of the lowest adopted fixed-cost technology) and $\bar{\kappa}$ decrease. Therefore, there exists a range of entrepreneurial productivities $[\bar{\psi}_{new}, \bar{\psi}_{old}]$ such that entrepreneurs within that range exited before the technical change and enter after. Therefore, these entrepreneurs increase their total factor productivity from 0 to a strictly positive value. For any $\psi > \psi_{old}$, none chooses a technology that has lower marginal cost than before the technical change, because the increased total output (see Lemma 1) reduces their demand for any given price. Hence, some entrepreneurs with $\psi > \psi_{old}$ "downgrade" their technology relative to before the technical change and others do not change their adoption choice. This proves that technical change is small-scale-biased *if* the new technology has lower fixed than any other adopted technology.

Now suppose the new technology does not have lowest fixed cost of all adopted technologies. By Lemma 1, output and wages increase as a result of the technical change. Also, output and wages are positively linearly related (equation (32)). Thus, if output goes up while the entry technology remains unchanged, $\bar{\psi}$ must increase by equation (8). That is, $\bar{\psi}(T_{new}) > \bar{\psi}(T_{old})$. This means the range of entrepreneurs with $\psi \in (\bar{\psi}(T_{old}), \bar{\psi}(T_{new}))$ see their TFP decrease. Hence, such technical change can not be small-scale-biased, which proves that technical change can be small-scale-biased *only if* the new technology has lower fixed than any other adopted technology. □

Proposition 3A (Scale-biased technical change with obsolescence). Suppose that the assumptions in Proposition 2 (Pareto distribution) hold, that $\sigma > 2$ and that $T^*_{new} = \tilde{T}_{old} \cup \{t_{new}\}$ where $\tilde{T}_{old} \subset T^*_{old}$ (the new technology makes at least of one of the previously adopted technologies obsolete), then

(a) the technical change is large-scale-biased if and only if the conditions a.1 and either a.2 or a.3 are satisfied:

(a.1) $\alpha_{new} < \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j$

(a.2) $\alpha_{new}\kappa_{new}^{\frac{1}{\sigma-1}} > \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j \kappa_j^{\frac{1}{\sigma-1}}$

(a.3) $\alpha_{new}\kappa_{new}^{\frac{1}{\sigma-1}} \leq \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j\kappa_j^{\frac{1}{\sigma-1}}$ and $\alpha_{new}\kappa_{new} > \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \left[\alpha_j\kappa_j^{\frac{1}{\sigma-1}}\right] \bar{\kappa}_{old}$

(b) the technical change is small-scale-biased if and only if the conditions b.1, b.2, and b.3 are satisfied:

(b.1) $\alpha_{new} \geq \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j$

(b.2) $\alpha_{new}\kappa_{new}^{\frac{1}{\sigma-1}} < \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j\kappa_j^{\frac{1}{\sigma-1}}$

(b.3) $\alpha_{new}\kappa_{new}^{\frac{1}{\sigma-1}}\bar{\kappa}_{new} \leq \min_{\{\alpha_j,\kappa_j\}\in T^*_{old}} \alpha_j\kappa_j^{\frac{1}{\sigma-1}}\bar{\kappa}_{old}$

Proof of Proposition 3A. I prove Proposition 3A by proving its elements (a) and (b) sequentially.

Proposition 3A(a): If the new technology satisfies a.1 it is the technology with lowest marginal cost. Therefore, it is adopted by all entrepreneurs above a certain threshold of productivity. This range of entrepreneurs would see TFP increase. If a.2 is true (besides a.1), it means the new technology does not become the entry technology. From there, the same reasoning as in the proof of Proposition 3(a), proves that the technical change is large-scale-biased. If a.3 is true (besides a.1), the new technology becomes the only technology that is adopted in equilibrium by Proposition 1 and the entry threshold increases by Proposition 2. Therefore, every entrepreneur with productivity above the new entry threshold increases TFP, while those below the threshold lose out. That is, $\bar{\psi}(T_{new}) > \bar{\psi}(T_{old})$. This means the range of entrepreneurs with $\psi \in (\bar{\psi}(T_{old}), \bar{\psi}(T_{new}))$ see their TFP decrease, while those with $\psi > \bar{\psi}(T_{new})$ see their TFP increase. This proves that technical change is large-scale-biased if the conditions a.1 and either a.2 or a.3 are satisfied.

To prove that technical change is large-scale-biased only if the conditions a.1 and either a.2 or a.3 are satisfied, now suppose technical change is large-scale-biased. By definition, the new technology increases TFP for all entrepreneurs above a certain productivity threshold $k > \min\{\bar{\psi}(T_{new}), \bar{\psi}(T_{old})\}$. Therefore, the marginal cost of the new technology must be lower than any previously adopted technology, such that a.1 is satisfied. Also, by definition of large-scale bias, TFP does not increase for all entrepreneurs with $\psi < k$. Therefore, if the new technology becomes the only technology that is adopted in equilibrium (such that a.2 is not satisfied), it must be that the entry threshold increases, hence a.3 is satisfied. This proves that technical change is large-scale-biased only if the conditions a.1 and either a.2 or a.3 are satisfied.

Proposition 3A(b): Suppose conditions b.1, b.2, and b.3 are satisfied. Then, because the new technology does not have the lowest marginal cost (b.1), it is not adopted by the most productive entrepreneurs. Because b.2 is satisfied, it is adopted by the least productive entrepreneurs. Because b.3 is satisfied, it reduces the entry threshold (by Proposition

2). Therefore, it increases TFP for a range of entrepreneurs that did not enter before the technical change. If it increases TFP for some $\psi' > \bar{\psi}_{old}$, it also increases TFP for any $\bar{\psi}_{new} > \psi'' > \psi' > \bar{\psi}_{old}$. This can be seen by realizing that the new technology can only increase TFP for ψ' if it is adopted by ψ', in which case it must also be adopted by any entrepreneur with lower productivity (since it is adopted by the marginal entrepreneur). Also, because it is not adopted by the most productive entrepreneurs, there is a productivity threshold above which the new technology is not adopted and therefore does not increase TFP. This proves that technical change is small-scale-biased if the conditions b.1, b.2, and b.3 are satisfied. This proves that technical change is large-scale-biased only if the conditions b.1, b.2, and b.3 are satisfied.

Now suppose technical change is small-scale-biased. Since there exists a productivity threshold above which the technical change does not increase TFP, its marginal cost must not be lower than the lowest marginal cost of any existing technology (b.1). Also, since there exists a productivity threshold below which it increases TFP, it must be adopted by the marginal entrepreneur (so that b.2 is satisfied by Proposition 1). Lastly, again since there exists a productivity threshold below which it increases TFP, it cannot increase the entry threshold (so that b.3 must be satisfied by Proposition 2). □

Proof of Proposition 4. I prove Proposition 4 by proving its elements (a), (b), and (c) sequentially.

Proposition 4(a): If technical change is large-scale-biased, it increases average fixed cost: $\bar{\kappa}_{new} > \bar{\kappa}_{old}$ (see the proof of Proposition 3(a)). Since it increases the average fixed cost without affecting $\alpha_1^*(\kappa_1^*)^{\frac{1}{\sigma-1}}$, it increases $\bar{\psi}$ by equation (29). The average employment by firm is the number of workers divided by the number of entrepreneurs. The number of workers L is constant in equilibrium by equation (28). The number of entrepreneurs is $(1-L)(1-F(\bar{\psi}))$ which is decreasing in $\bar{\psi}$. Therefore, the average employment size increases in response to large-scale-biased technical change.

If technical change is small-scale-biased the entry threshold $\bar{\psi}$ in equation (29) decreases because both κ_1^* (the fixed cost of the lowest adopted fixed-cost technology) and $\bar{\kappa}$ decrease. Therefore, the average employment size decreases in response to large-scale-biased technical change.

Proposition 4(b): By Proposition Proposition 4(a), if technical change is large-scale biased, it increases $\bar{\psi}$. Thus, by the free-entry condition in equation (9), it increases the ratio between average profits of producting entrepreneurs and wages. The opposite is true for small-scale-biased technical change.

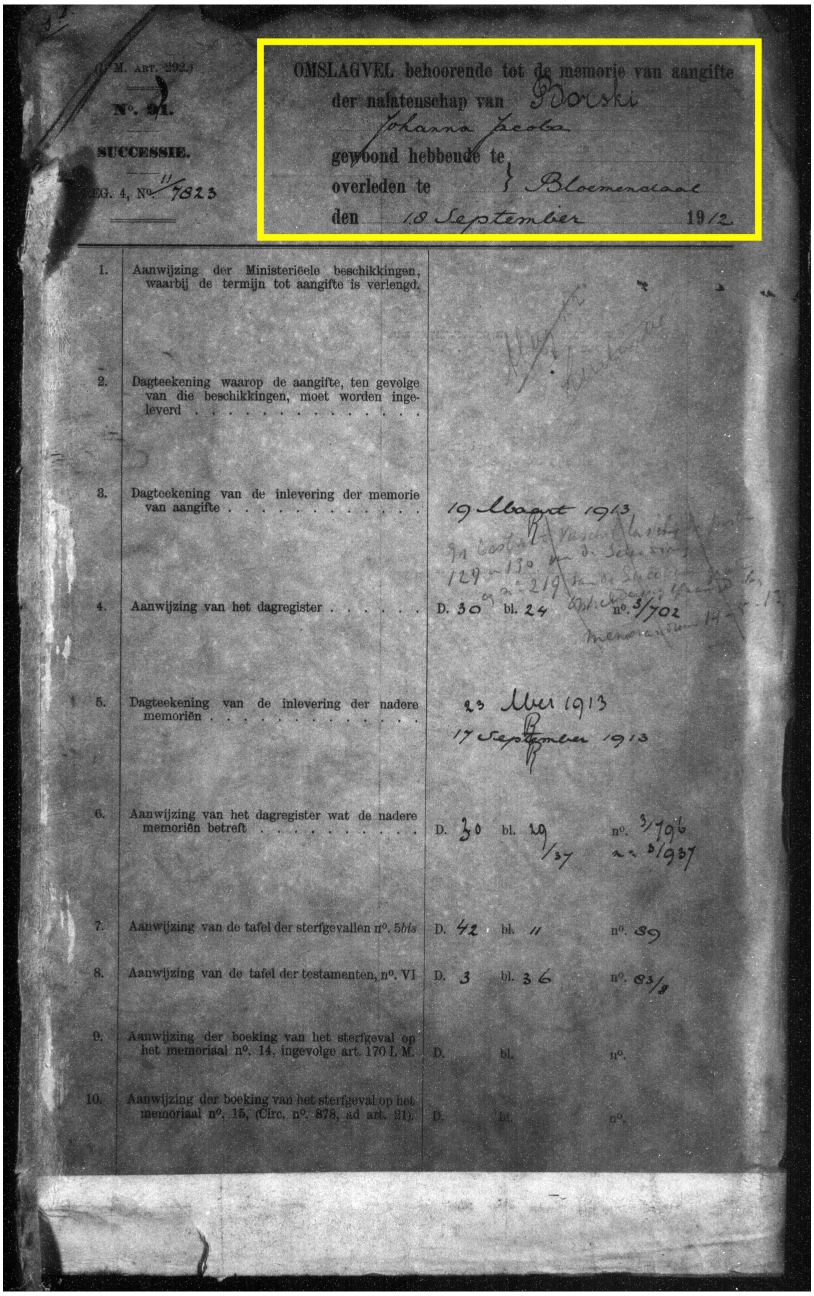
Proposition 4(c): Any entrepreneur that does not adopt the technology, sees a reduction in profits as a result of technical change. This can be seen by noting that equation (42) is decreasing in output Y and output increases when a new technology is added by Lemma 1. If technical change is small-scale-biased, entrepreneurs above a certain productivity threshold do not adopt the technology and their profits must therefore decline. However, total output and wages go up. Hence, there exists a $\bar{k} \in (0, 100)$ such that average income growth of the top k% of incomes is lower than average income growth of the bottom $(100 - k)$% of incomes for all $k < \bar{k}$.

If technical change is large-scale-biased, it increases profits of entrepreneurs above a certain productivity threshold, while it decreases profit for those below it. Because the profit share of output is constant (see equation (38)) and wages are a linear function of output (32), total profit growth equates wage growth. Because only adopting entrepreneurs experience a profit increase, while other entrepreneurs' profit decline, their income growth must exceed wage growth. Furthermore, even among adopting entrepreneurs, proportional profit growth is increasing in ψ. Therefore, there exists a $\bar{k} \in (0, 100)$ such that average income growth of the top k% of incomes is higher than average income growth of the bottom $(100 - k)$% of incomes for all $k < \bar{k}$. □

D Data appendix

D.1 Examples of source files

FIGURE D.1: Example of a source image of the Dutch inheritance tax files.



M. ART. 292.
N°. 91.
SUCCESSIE.
REG. 4, N°. 11/7823

OMSLAGVEL behoorende tot de memorie van aangifte
der nalatenschap van Borski
Johanna Jacoba
gewoond hebbende te
overleden te } Bloemendaal
den 18 September 1912

1. Aanwijzing der Ministerieele beschikkingen, waarbij de termijn tot aangifte is verlengd.

2. Dagteekening waarop de aangifte, ten gevolge van die beschikkingen, moet worden ingeleverd . . . .

3. Dagteekening van de inlevering der memorie van aangifte . . . . 19 Maart 1913

4. Aanwijzing van het dagregister . . . . . . D. 30 bl. 24 n°. 3/702

5. Dagteekening van de inlevering der nadere memoriën . . . . 23 Mei 1913
17 September 1913

6. Aanwijzing van het dagregister wat de nadere memoriën betreft . . . . D. 30 bl. 19 1/37 n°. 3/796 n°. 3/937

7. Aanwijzing van de tafel der sterfgevallen n°. 5*bis* D. 42 bl. 11 n°. 89

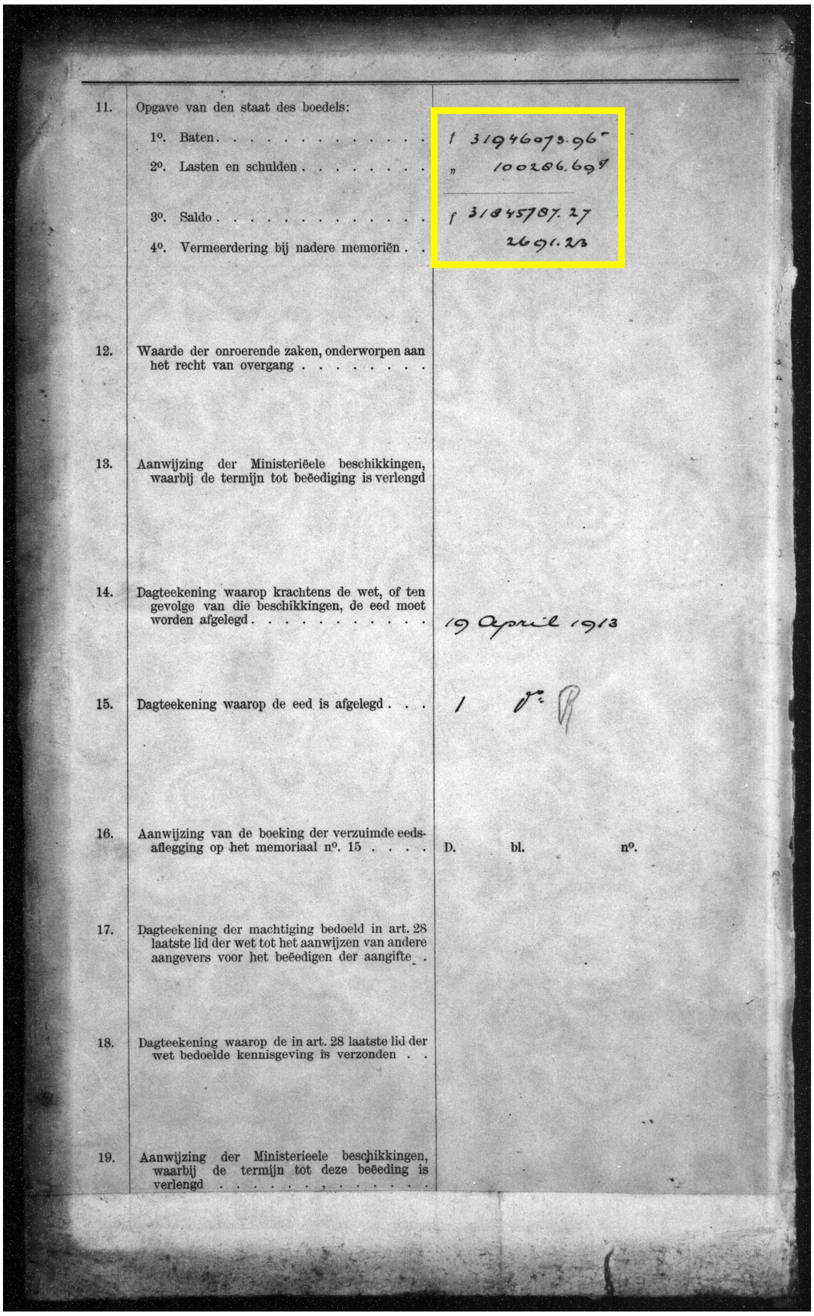
8. Aanwijzing van de tafel der testamenten, n°. VI D. 3 bl. 36 n°. 83/8

9. Aanwijzing der boeking van het sterfgeval op het memoriaal n°. 14, ingevolge art. 170 L. M. D. bl. n°.

10. Aanwijzing der boeking van het sterfgeval op het memoriaal n°. 16, (Circ. n°. 878, ad art. 21). D. bl. n°.

Notes: This form shows the first page of the estate tax form. I extracted information within the yellow rectangular on the name of the decedents, their place of residence and death, and the date of death. I detected and extracted the relevant part of the image using a self-trained object detection algorithm. The template form was consistent nationally and over time between 1879 and 1927. *Source*: Noord-Hollands Archief (provincial archive), record group 178, inventory number 2884, image 403.

FIGURE D.2: Example of a source image of the Dutch inheritance tax files.



11. Opgave van den staat des boedels:

1°. Baten . . . . ƒ 31946073.96

2°. Lasten en schulden . . . . „ 100286.69

3°. Saldo . . . . ƒ 31845787.27

4°. Vermeerdering bij nadere memoriën . . 2691.23

12. Waarde der onroerende zaken, onderworpen aan het recht van overgang . . . .

13. Aanwijzing der Ministerieele beschikkingen, waarbij de termijn tot beëediging is verlengd

14. Dagteekening waarop krachtens de wet, of ten gevolge van die beschikkingen, de eed moet worden afgelegd . . . . 19 April 1913

15. Dagteekening waarop de eed is afgelegd . . .

16. Aanwijzing van de boeking der verzuimde eedsaflegging op het memoriaal n°. 15 . . . . D. bl. n°.

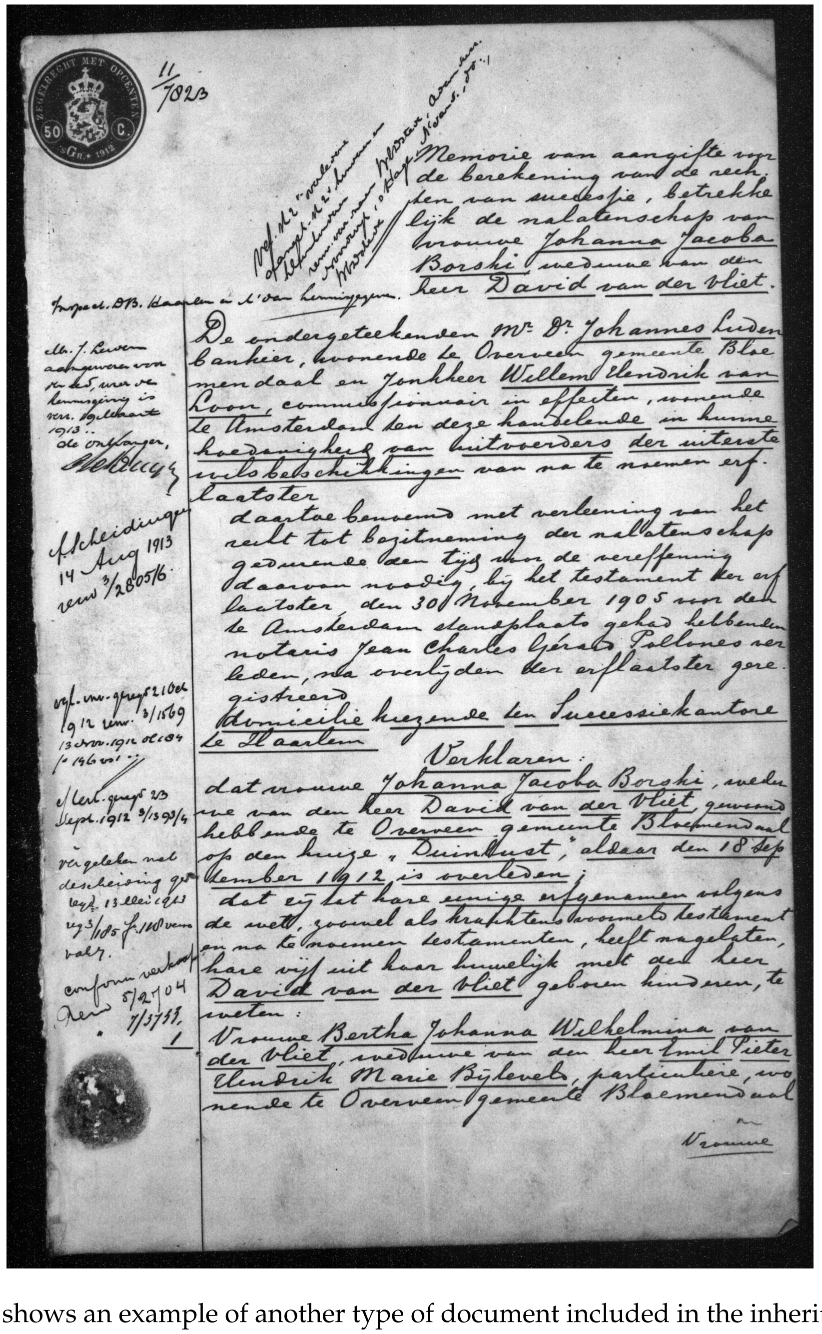
17. Dagteekening der machtiging bedoeld in art. 28 laatste lid der wet tot het aanwijzen van andere aangevers voor het beëedigen der aangifte .

18. Dagteekening waarop de in art. 28 laatste lid der wet bedoelde kennisgeving is verzonden . .

19. Aanwijzing der Ministerieele beschikkingen, waarbij de termijn tot deze beëeding is verlengd . . . .

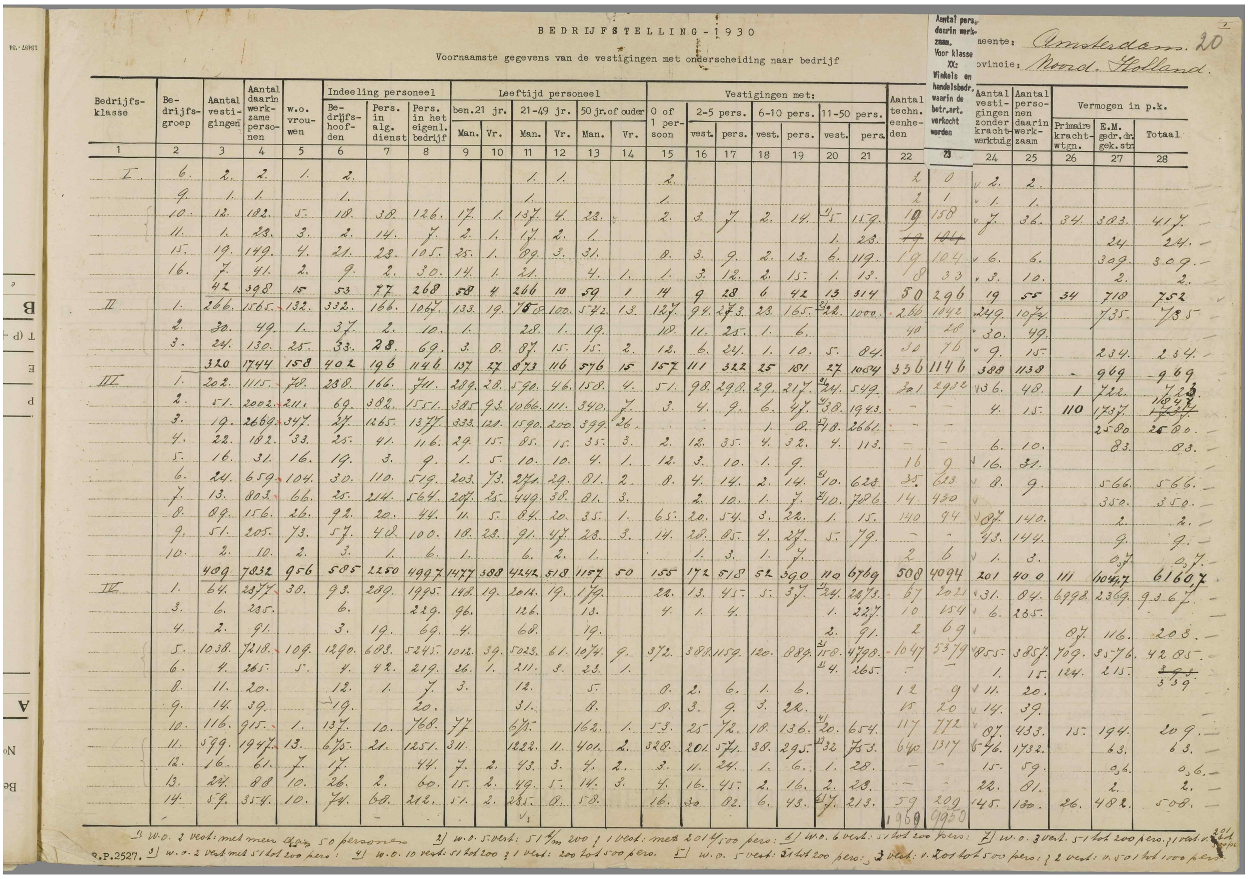
Notes: This form shows the second page of the estate tax form. I extracted information within the yellow rectangular on the assets, liabilities, and net worth of the decedent. I detected and extracted the relevant part of the image using a self-trained object detection algorithm. The template form was consistent nationally and over time between 1879 and 1927. *Source*: Noord-Hollands Archief (provincial archive), record group 178, inventory number 2884, image 404.

FIGURE D.3: Example of a source image of the Dutch inheritance tax files.



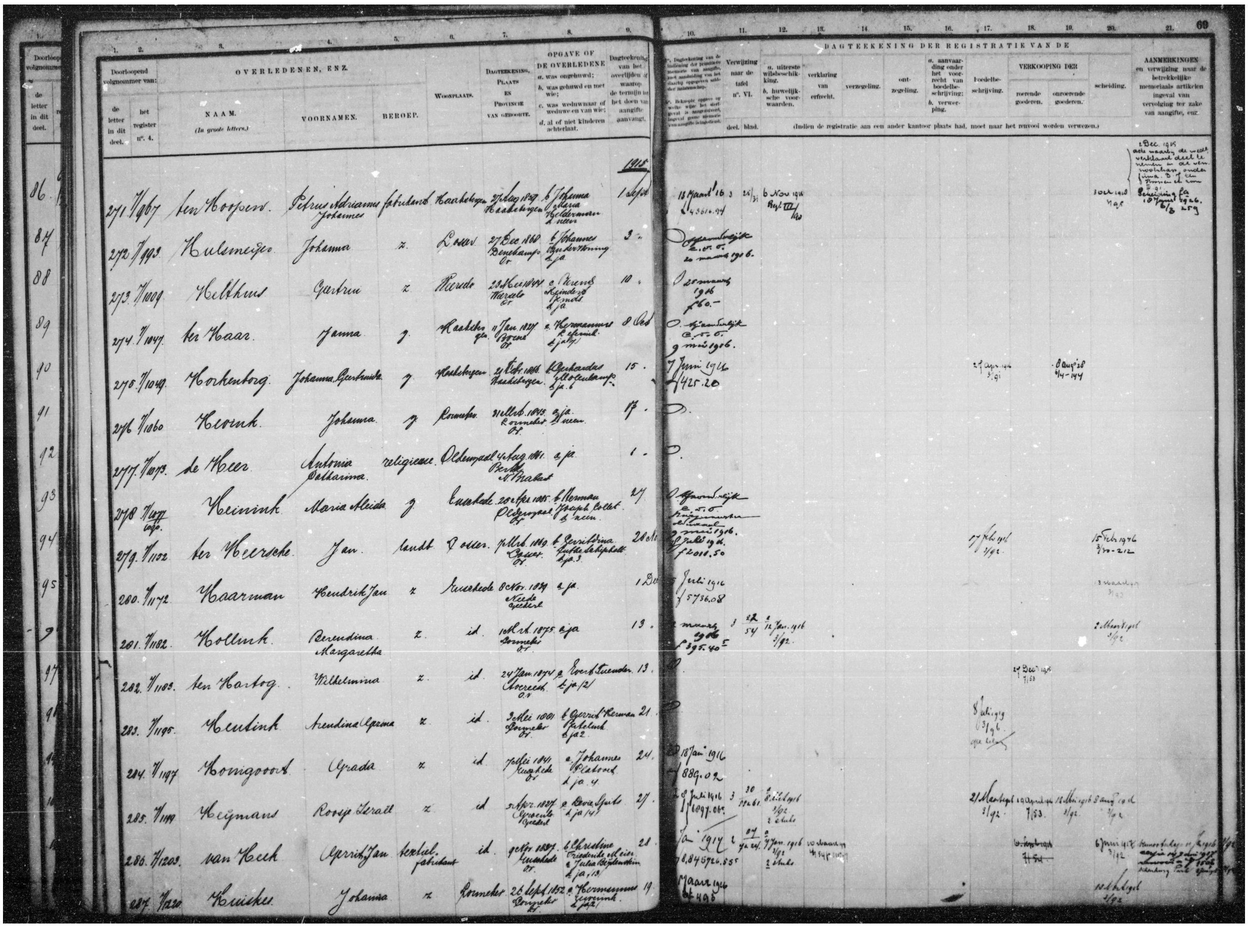
Notes: This image shows an example of another type of document included in the inheritance tax files that I do not use in the analysis. I filtered out these documents using a self-trained object detection algorithm. *Source*: Noord-Hollands Archief (provincial archive), record group 178, inventory number 2884, image 405.

FIGURE D.4: Example of a source image of the 1930 Census of Companies by municipality



Notes: The example is for Amsterdam. The data contains the broad and detailed industry classification (columns 1 and 2), the number of establishments and workers by size (columns 15-21), and information on power adoption (columns 24-28). *Source*: (Statistics Netherlands, 2010).

FIGURE D.5: Example of a source image of the tables of decedents' and their wealth



Notes: The image is an example of the tables containing names of and information on decedents that I digitized for Enschede. The data contain information such as names (columns 3 and 4), occupation (column 5), residence (column 6), and, importantly, wealth (column 10). The original source of the wealth data are the inheritance tax records that I digitized on a large scale. *Source*: Collectie Overijssel (provincial archive), record group 0136.4, inventory number 644, image 70.

D.2 Income distribution by Dutch municipality (1883)

The main source of the data reports the income distribution of 79 municipalities. I added data on the income distribution for 8 large municipalities with an income tax. The data for each additional cities derives from the same source as the other 79 municipalities. Table D.1 documents the relevant year that the income distribution was measured and the source of the data.

TABLE D.1: Sources of income distribution data for 8 additional cities

City	Year	Archive	Source
Breda	1881	Stadsarchief Breda	Municipal year report ("Gemeenteverslag") 1880
Delft	1893	Stadsarchief Delft	Municipal year report ("Gemeenteverslag") 1893
Eindhoven	1885	RHC Eindhoven	Original assessment lists, archive number 10246.925
Enschede	1880	Stadsarchief Enschede	Original assessment lists, archive number 1.1226
Hilversum	1880	Archive Prof. Van Zanden	Original assessment lists
Nijmegen	1880	Regionaal Archief Nijmegen	Overview by income class, archive number 2.14167
Utrecht	1888	Utrechts Archief	Municipal year report ("Gemeenteverslag") 1900
Vlissingen	1883	Zeeuws Archief	Original assessment lists, available here.

D.3 Matching the inheritance tax records to the civil registry

I first download all deaths recorded between 1879 and 1927 in the civil registry databases from five regional archives, each covering the near-universe of deaths in their province: Brabants Historich Informatie Centrum (Noord-Brabant), Collectie Overijssel (Overijssel), Gelders Archief (Gelderland), Noord-Hollands Archief (Noord-Holland), and Zeeuws Archief (Zeeland). These datasets contain high quality hand-collected information on each deaths. 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. Amsterdam is the only place in the regions covered for which digitized records of the civil death registry are not available. 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.

The inheritance tax records were ordered by place and date of death. I use this to narrow down the possible matches in the civil registry data for each person in the inheritance tax data. 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.

E Details on steam engines and electric motor costs

In this section, I explain in detail the sources, assumptions and computations underlying the average and marginal cost curves of steam engines and electric motors shown in Figures 4 and A.2. The underlying data for steam engines, taken directly from (Emery, 1883), are displayed in Table E.1. The data for electric motors, from (Bolton, 1926), are displayed in Table E.2. I take these to be a full description of the costs.

TABLE E.1: Cost parameters (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
15	1487	30	618.00		83.43	52.53	568.33
20	1981	30	618.00		92.70	67.98	647.14
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
150	13046	30	772.50	463.50	145.23	309.00	2718.00
200	16785	30	772.50	463.50	169.95	383.16	3603.86
250	20426	30	849.75	463.50	200.85	454.23	4504.68
300	23899	30	927.00	463.50	247.20	525.30	5406.08
400	29958	30	927.00	695.25	293.55	679.80	7207.72
500	36220	30	927.00	927.00	355.35	886.83	9009.94

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

Both the coal and electricity input costs are based on the assumption that the engine/motor is run at capacity 309 days per year, 10 days per hour. For steam engines, coal input data comes directly from (Emery, 1883). For electric motors, I computed the cost using electricity prices. For example, running a 1 horsepower electric motor at full capacity for 309×10 hours requires 3090 horsepower-hour, which corresponds to $0.7457 \times 3090 \approx 2304$ kWh. The price of electricity per kWh in the UK in 1925 was £0.00687.

From the data in Tables E.1 and E.2, I compute the annualized cost of purchase and renewal using the sinking fund formula:

$$\text{Annualized purchase cost} = \text{Price} \times \frac{r}{(1+r)^{\text{Life}} - 1}. \tag{43}$$

I set the interest rate r equal to 0.05. Then, for example, the annualized cost of renewal of a 5 horsepower steam engines every 30 years becomes \$9.71. In other words, with an

TABLE E.2: Cost (in £, 1925) of electric motors (squirrel-cage induction motors) of different capacities

		Purchase costs		Electricity input	
hp	Efficiency	Price (£)	Life (yrs)	kWh	£
1	0.770	12.90	15	2304	15.83
2	0.787	14.50	16	4608	31.66
3	0.800	16.20	17	6913	47.49
5	0.820	22.20	18	11521	79.15
7.5	0.833	26.80	18	17282	118.72
10	0.840	31.50	19	23042	158.30
15	0.853	39.25	19	34563	237.45
20	0.860	46.20	20	46084	316.60
25	0.870	52.80	20	57605	395.75
30	0.875	58.80	20	69126	474.90
40	0.885	69.90	20	92169	633.20
50	0.890	81.25	20	115211	791.50
60	0.900	92.00	20	138253	949.80
80	0.910	110.50	20	184337	1266.40
100	0.915	132.20	20	230421	1582.99

Notes: The price of electricity per kWh in 1925 was £0.00687 (Hannah, 1979). *Source of all other data*: (Bolton, 1926, p. 344).

interest rate of 5 percent, a deposit of $9.71 each year would yield $645 every 30 years. From there, the total annual costs per horsepower per year are calculated as the sum of the annualized purchase costs and the yearly operating costs. Figure 4 illustrates the data on cost per horsepower per year tabulated in Table E.3.

TABLE E.3: Total and per horsepower annualized cost of purchase, renewal, maintenance and operation (including and excluding of fuel) of a steam engine and electric motor of different sizes at capacity for 309 days, 10 days per hour.

	Steam engines (in 1874 $)				Electric motors (in 1925 £)			
	Excl. fuel		Incl. fuel		Excl. fuel		Incl. fuel	
hp	Total	Per hp	Total	Per hp	Total	Per hp	Total	Per hp
1					0.60	0.78	16	21
2					0.61	0.39	32	21
3					0.63	0.26	48	20
5	652	130	879	176	0.79	0.19	80	19
7.5					0.95	0.15	120	19
10	682	68	1095	109	1.03	0.12	159	19
15	776	52	1345	90	1.29	0.10	239	19
20	808	40	1456	73	1.40	0.08	318	18
25	917	37	1670	67	1.60	0.07	397	18
30					1.78	0.07	477	18
40					2.11	0.06	635	18
50	1378	28	2581	52	2.46	0.06	794	18
60					2.78	0.05	953	18
80					3.34	0.05	1270	17
100	1659	17	3557	36	4.00	0.04	1587	17
150	1887	13	4605	31				
200	2042	10	5646	28				
250	2276	9	6780	27				
300	2523	8	7929	26				
400	3047	8	10254	26				
500	3641	7	12651	25				

Notes: To compute the cost per horsepower per year for electric motors, an efficiency loss relative to capacity that varies across sizes is taken into account (see Table E.2).

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.

BLANKEN, I. AND H. LINTSEN (1981): "Mechanische kracht in de industrialisatie van Nederland (1850-1950)," .

BOLTON, D. (1926): "The variation of efficiency with size, and the economic choice of electrical machinery," *Journal of the Institution of Electrical Engineers*, 64, 337–348.

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

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.

HANNAH, L. (1979): *Electricity before nationalisation*, Springer.

STATISTICS NETHERLANDS (2001): "Tweehonderd jaar statistiek in tijdreeksen 1800–1999," The Hague, Netherlands.

——— (2010): "Bedrijfstelling 1930," .

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.