Gaining Steam: Incumbent Lock-in and Entrant Leapfrogging

Richard Hornbeck
University of Chicago

Shanon Hsuan-Ming Hsu
University of Chicago

Anders Humlum
University of Chicago

Martin Rotemberg
New York University

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Abstract

We examine the long transition from water to steam power in US manufacturing, exploring how early advantages can delay the adoption of new technologies. Using newly digitized Census of Manufactures manuscripts for 1850-1880, we show that mill activity grew faster in counties with less waterpower as steam costs declined. This growth was driven by steam powered entrants and agglomeration. Waterpowered mills closed instead of switching technologies, suggesting technological lock-in. For identification, we leverage variation in US counties' waterpower potential, caused by interacting water flow and elevation changes. We estimate a dynamic model of firm entry and steam adoption, finding lock-in effects that delay technology diffusion – despite substantial entry – when the old technology remains attractive to low-productivity entrants.

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Technological innovation drives economic growth, but the widespread adoption of new technology can be slowed by firms continuing to use and invest in old technologies (Strassmann, 1959; David, 1990; Comin and Hobijn, 2010). We examine the adoption of steam power, an iconic general purpose technology (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005). Steam power broke the dependence of mechanization on local geographic characteristics, particularly local waterpower availability, and steam was a central technological driver of widespread industrialization.

Our primary goal is estimating the forces underpinning the slow transition from water to steam power in American flour mills and lumber mills, which were leading users of mechanical power across the US. Schumpeter (1942) motivates discussion of "creative destruction" using the transition from waterpower, and we show causal evidence that confirms the Schumpeterian scenario: steam created economic opportunities but crowded out water-using incumbents. In particular, not only the *potential* for waterwheel use, but the *actual prior use* of waterwheels slowed the adoption of steam power. We find that sunk costs were a crucial barrier that prevented many incumbents from upgrading technologies, who instead often closed despite their large size otherwise predisposing them to benefit from steam power.

Despite switching barriers faced by firms that existed when the technology was introduced, technology adoption could still accelerate through firm entry. We find that entry did not substantially mitigate the market-level consequences of mills' barriers to switching technologies, however, because waterpower had low purchase costs (historically named "first costs") and low overhead costs. These relatively low fixed costs made waterpower attractive to relatively smaller entrants, many of whom then became stuck when their productivity increased. A punchline is that the *interaction* of switching barriers and high fixed costs slows aggregate technology diffusion: we show that if the new technology instead had a lower fixed cost (and higher marginal costs) *or* lower switching barriers, it would have diffused much faster.

The purchase cost of steam declined from 1850 to 1880, leading to increases in aggregate steam-use in milling: in 1850, ten percent of mills were powered by steam, a share which increased to fifty percent by 1880. We find that counties with higher potential for waterpower had more initial industrial activity. However, the decline in steam costs led to an "advantage of backwardness" (Gerschenkron, 1962). Counties with less waterpower potential adopted steam faster and experienced faster growth in their number of mills and mill output. Some mills switched from water to steam power, but county growth was driven by steam powered entrants. Incumbents were more likely to exit in counties with lower waterpower, despite more overall growth in these counties.

Lumber and flour mills were at the forefront of driving the adoption of steam power in the broader US economy, which brought mechanization to new industries and spurred productivity growth.[1] We find evidence of backwards linkages (Hirschman, 1958; Baldwin and Venables, 2015), as counties with less waterpower potential experienced disproportionate growth in makers of steam equipment such as engines and boilers. Accelerating growth in upstream industries heightens the gains from early adoption of general purpose technologies like steam power, as it can encourage faster diffusion in mechanizing industries. This suggests that privately-optimal technology adoption can be socially inefficient, and we evaluate potential counterfactual policies that might counteract the technological lock-in caused by historical advantages.

Because mills' technology adoption decisions depend on choices made by their competitors, as well as potential entrants, it is difficult to assess the equilibrium implications of the reduced-form estimates without some structure. A model also helps generalize lessons from steam power, isolating specific influences on technology adoption from other features of the technology itself and its economic environment. Further, given agglomeration spillovers in the broader adoption of this general purpose technology, a model allows us to consider the potential for welfare-enhancing policies whose effects depend on equilibrium responses.

To explore counterfactual technology adoption transitions, we develop and estimate a dynamic equilibrium model of firm entry and steam adoption decisions. We use our estimated differences by county waterpower availability to identify parameters of the model, in addition to several new stylized facts about establishment level patterns in waterpower use and steam adoption. Quantitatively, the model matches several non-targeted moments related to how waterpower potential leads to entrant-driven growth, as well as 19th century accounts of the costs of steam and waterpower.

To measure plant-level technology use and switching, we digitize the complete surviving establishment level records from the US Census of Manufactures in 1850, 1860, 1870, and 1880.[2] These records include data on power use for every establishment, and we create a panel by hand-linking mills over time based on their name, industry, and location. From the states with surviving establishment level records, we construct a balanced panel of 1199 county-industries (612 lumber-mill counties and 587 flour-mill counties), covering 690 unique counties and 80,000 establishment-year observations.

[1]For discussions of the role steam power played in the Industrial Revolution, see, for instance, Ashton (1948); Kuznets (1967); Landes (1969); Rostow (1975); Atack, Bateman and Margo (2008) and Atack, Margo and Rhode (2019).

[2]Samples of these manufacturing schedules were digitized by Bateman, Foust and Weiss (1971), Atack (1976), and Bateman and Weiss (1981), see also Sokoloff (1984). Atack and Bateman (1999) provide detailed description of the samples. Recent efforts have digitized historical manufacturing microdata in a few contexts, including Japan, Russia, France, and Sweden (Braguinsky et al., 2015; Gregg, 2020; Juhász, Squicciarini and Voigtländer, 2023; Berger and Ostermeyer, 2023).

For causal identification, we use geographic variation in counties' access to waterpower. Local waterpower potential, measured in horsepower, is generated by the interaction of water flow and elevation changes. We use the geographic variation in waterpower potential, controlling for main effects of water flow and terrain ruggedness that can otherwise influence local economic activity. We also control for other local characteristics that might impact local economic activity, such as coal access and market access (Chandler, 1972; Hornbeck and Rotemberg, 2024). We measure historical local waterpower potential using modern hydrological models (McKay et al., 2012; Moore et al., 2019), which we validate with historical records.

We focus on lumber and flour mills because they were heavy users of mechanical power that relied initially on local waterpower availability (Temin, 1966). Combined, they accounted for 20% of American manufacturing revenue at the start of our sample and 60% of mechanized establishments.[3] Lumber mills and flour mills were classified by the Census as "neighborhood industries" and sold primarily to local markets. Due to high perishability of finished products and transportation costs, these mills were broadly spread across the country and dependent on local geographic endowments for access to power. As a consequence, we model each county as having a distinct market for lumber milling and flour milling. By contrast, textile mills were geographically concentrated, as textiles were more broadly traded across domestic and international markets.

A key economic force in our model rationalizes that both water and steam power were used in equilibrium: one technology had lower marginal costs, and the other had lower non-variable costs (such as overhead costs and the purchase price of the power source). We find that steam powered mills were larger than water powered mills (Atack, Bateman and Margo, 2008; Ridolfi, Salvo and Weisdorf, 2023). Correspondingly, we estimate that steam had lower marginal costs and higher fixed costs (Melitz, 2003). While the direct marginal costs of waterpower were likely low in many places, our estimates reflect the difficulty of scaling up waterpower due to capacity constraints. The size advantage of steam mills is not driven by steam allowing milling in new locations, as we find a similar pattern within counties.

Over time, as steam power diffused, the size distributions of steam and water powered mills converged. We correspondingly estimate that the fixed cost of steam adoption declined over time, since the marginal cost of steam power falling would have led to diverging size distributions. Declining steam fixed costs are consistent with qualitative histories of steam

[3] Throughout the paper, we abbreviate the official industry names of "flour and grist" to "flour" and of "lumber, sawed" and "lumber, planed" to "lumber." Similarly, we are referring to only those two sectors when we discuss "mills."

use in rural US milling, which emphasize the development of practical low-cost engines (Hunter, 1985).

A salient pattern in the data is that mill entrants were around three times more likely to use steam power than incumbent waterpowered mills, even though incumbents were typically larger and therefore predisposed to benefit more from steam. We explore the forces that made it difficult for enterprises to adopt new technologies, such as sunk costs, costs of retrofitting, and other frictions (Hall, 2004; Holmes, Levine and Schmitz Jr, 2012; Atkin et al., 2017; Verhoogen, 2023). We estimate that the barriers to switch from water to steam power were equal to about two months of revenue, and that sunk costs are responsible for 90% of the switching barrier: incumbents already had a functional power source, and most found it undesirable to abandon that sunk capital to switch to steam power.

Indeed, retrofitting costs and other frictions were relatively unimportant in this context: changing power sources did not require other substantial changes to mill production, as the power remained rotational in nature and the millstones or saws were the same regardless of the power source.[4] Difficulties changing suppliers (Farrell and Klemperer, 2007) and technological interrelatedness between components within the production process (David and Bunn, 1988; Bresnahan and Greenstein, 1996) can explain lock-in in other contexts, but are unlikely to be relevant to the transition from water to steam power. For instance, waterwheels themselves were very durable, limiting the importance of supplier relationships.

Nevertheless, switching to steam may have required an openness to new technology, as steam engines were more unfamiliar to rural America than long-used water wheels, which reflects attitudes that could have been more prevalent among entrant mill owners than incumbents. Linking the Census of Manufactures to the Census of Population, we find that the owners of steam mills were likely to be younger and also more likely to be immigrants, characteristics suggestive of an inherent willingness to change. Steam mill operators were also more likely to be professional millers rather than part-time millers (such as farmer-millers). In historical documents, we find that many mills who switched to steam power did so when sons took over from their fathers. Further, mills that added proprietors were twice as likely to switch to steam power as those that did not.

We find evidence inconsistent with other explanations for inertia in this context, such as productivity losses from changing technologies, productivity growth from using and learning about the old technology, information frictions, or permanent unobserved heterogeneity (e.g., that there were "water types" and "steam types").[5] For instance, adapting Chay, Hoynes

[4] The technologies are similar enough that some waterpowered mills used steam as an auxiliary power source (Hunter, 1985), and in our data around a third of establishments who switched from only-waterpower to steam power continued using some waterpower.

[5] For related discussions, see Lancaster and Nickell (1980); Chari and Hopenhayn (1991); Heckman (1991);

and Hyslop (1999), we show that the pattern of switching from water to steam power is inconsistent with persistence due to “types.”

We use the model to estimate how technological lock-in from counties’ waterpower potential delayed and reduced overall adoption of steam power in lumber and flour milling. Waterpower potential substantially slowed steam adoption: if the average county had one standard deviation lower waterpower potential, steam-use would have reached 50% of US mills 30 years earlier and been 20 percentage points greater in steady-state.

To quantify the role of barriers to switching, we estimate counterfactuals where we remove all sources of lock-in. We estimate that switching barriers were as important as local geography at the start of steam adoption: without any switching costs, steam-use would also have reached 30% of US mills a decade earlier. However, the importance of switching barriers becomes relatively less important as steam reached maturity, and would have increased steady-state adoption by less than 10 percentage points.[6] We also estimate the effects of counterfactual “cash for clunkers” style policies that temporarily remove switching barriers. While they raise steam adoption in the short run, our estimated agglomeration force is small enough that these programs do not have persistent effects.

Though barriers to switching slowed adoption, incumbent switching was still an important mechanism for technological transition to steam power, as the entry of new firms was not a panacea for technological lock-in. For a counterfactual scenario with infinite switching costs, we estimate that the share of plants using steam would have only been 30% by 1900.

Our establishment level panel analysis complements a large literature studying long-run technology diffusion from a more aggregate perspective (Griliches, 1957; Jovanovic and Lach, 1989; Greenwood and Yorukoglu, 1997; Comin and Hobijn, 2009, 2010). The panel microdata allow us to measure directly plants changing their technologies over an extended period of time. We estimate large, though not prohibitive, barriers to switching that place our results between standard assumptions of either infinite switching costs (Chari and Hopenhayn, 1991; Atkeson and Kehoe, 2007; Collard-Wexler and De Loecker, 2015) or no lock-in (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Greenwood, Seshadri and Yorukoglu, 2005; Beaudry, Doms and Lewis, 2010; Benhabib, Perla and Tonetti, 2021; Miller et al., 2022). Our approach has similarities to a macroeconomic literature on “vintage capital,” which considers the technology embedded in each successive generation of capital (Salter, 1960; Solow, 1962; Denison, 1964; Gilchrist and Williams, 2000; Benhabib and Rustichini, 1991; Chari

Bahk and Gort (1993); Irwin and Klenow (1994); Jovanovic and MacDonald (1994); Parente (1994) and Jovanovic and Nyarko (1996).

[6] Even in the absence of barriers to switching, steam power would would not have reached its steady state level immediately, as the technology improved over time (David, 1969; Sandberg, 1969; Atack, 1979; Manuelli and Seshadri, 2014).

and Hopenhayn, 1991; Cooley, Greenwood and Yorukoglu, 1997; Atkeson and Kehoe, 1999; Jovanovic and Yatsenko, 2012; Caunedo and Keller, 2021).

The importance of waterpower availability for power technology choices was understood contemporaneously (Montgomery, 1840), noted in the modern economics literature by Temin (1966), and occurs empirically across different contexts (Atack, 1979; Cooney, 1991; Bishop and Muñoz-Salinas, 2013; Chernoff, 2021; Gershman et al., 2022; Guilfoos, 2022).[7] Relative to this literature, our contribution is emphasize the importance of firm dynamics for technology diffusion. This approach complements research on path dependence and inertia in other contexts, including railroad gauges (Veblen, 1915), prices (Rotemberg, 1982), keyboard layouts (David, 1985), consumer choice (Klemperer, 1995), occupational choice (Artuç, Chaudhuri and McLaren, 2010), migration (Kennan and Walker, 2011), city locations (Bleakley and Lin, 2012), health care (Handel, 2013), light bulbs (Armitage, 2023), and telephone switchboards (Feigenbaum and Gross, 2023*b*). The most closely related model is from Humlum (2022), who studies robot adoption in modern firms but abstracts from entry and focuses instead on the measurement of production functions.[8]

The establishment level and aggregate economic impacts from the expansion of steam power speak to the potential for new technologies to drive economic growth. Barriers to switching technologies dampen the short-run impacts of new technologies, and change who drives technological adoption. Diffusion becomes driven by the adoption choices made by entrants, but even entrants become stuck in prior technology when the new technology has higher fixed costs and lower marginal costs. Switching costs were as influential for aggregate technology diffusion as geographic variation in waterpower potential and, while steam power and subsequent innovations have reduced the dependence of manufacturing on local geography, this period illustrates the creative destruction that accompanies industrialization.

I Context and Data Construction

I.A Water and Steam Power in US Mills

Waterpowered milling has a long history in the United States, as the Massachusetts Bay Colony built several watermills in the 1630s, some of which remained in use into the nineteenth century (Weeden, 1890). Mullin and Kotval (2021) note that Puritans believed every "town required four essential elements if it were to succeed: a meeting house with a pastor, a blacksmith, a sawmill and a grain mill." Flour and lumber mills were needed throughout the

[7] Duflo and Pande (2007), Lipscomb, Mobarak and Barham (2013), Severnini (2023), and Brey (2023) leverage geographic characteristics to understand how 20th century dams affect economic development.

[8] Frankel (1955) considers the importance of sunk costs for slow technological transitions, and Saxonhouse and Wright (1987) argue that sunk costs and durable capital led to a slow transition from spinning mules to ring-frame spinning in Lancashire, but they abstract from the role of entry.

country, using the available local waterpower, whereas textile mills could be agglomerated in major manufacturing centers in places with substantial waterpower capacity.

The carpentry and engineering skills required to build and maintain a watermill were available in almost every community in the US. Flour mills and lumber mills required less horsepower than textile mills, so they could use smaller rivers and did not typically require large installations. By the mid-1800s, waterwheels dotted the US countryside, with roughly one waterwheel or turbine in use for every 600 people (Atack, 1979). Hunter (1979, 1985) provides an overview of water and steam power in the 19th century,[9] and we summarize a few key features of this context.

Water powered and steam powered mills both used rotational power to grind grain and saw lumber, using the same millstones and saws, so the transition from waterpower to steampower did not require a substantial transformation of mill operations. By contrast, the later introduction of electricity ushered in more wholesale changes in manufacturing operations (Devine, 1983; David, 1990; Damron, 2023). The fundamental change from the arrival of steam power was a new source of mechanical power, which was less subject to the vagaries of nature (Hunter, 1985): steam power was not as expensive to scale up, and it offered consistent year-round access to power. While steam offered advantages, it was also associated with several high non-variable costs, as "the first cost of steam engines, and their annual expense, [did] not increase or diminish in proportion to the size of each engine" (Monroe, 1825). For instance, steam equipment required installation and continued maintenance oversight from trained engineers (Fisher, 1845).

Steam power was particularly useful in places with less local waterpower potential (Sharrer, 1982). These places had higher fixed costs for using water power, due to greater need for constructing dams, millponds, and riverwalls, which were generally more expensive to build than the wheels themselves (Monroe, 1825). Places with lower waterpower potential may have also required higher costs for securing water rights.[10] While waterpower technology improved moderately over the 19th century, for instance with the diffusion of the turbine (Hunter, 1979), the more-substantial forces were that steam improved substantially over time and waterpower availability varied substantially over space. For instance, a congressional report discussing options for a national armory on the "Western Waters" (Armistead, Lawson and Long, 1841) used, without updating, the estimated costs of waterpower from a previous Presidential report (Monroe, 1825).

Early steam engines were fundamental to the British industrial revolution, but were not

[9] See Howes (2022) for a description of innovations in steam power before the 19th century.

[10] Swain (1888) reports the cost of water rights for 25 counties, which are negatively (though not significantly) correlated with our measure of waterpower potential.

widely adopted in the early United States. Early Newcomen engines were coal-intensive and inefficient, wasting heat in the process of heating and cooling water to drive a piston in a cylinder. In the late 18th century, Watt introduced a separate condensing chamber so the primary cylinder never needed to be substantially cooled, which dramatically improved the efficiency and force of British engine designs. In the spirit of Arrow (1962), steam engine manufacturing was characterized by learning-by doing, as many subsequent improvements to Watt's design came as machinists gained experience and tinkered with the size and arrangement of the parts. With the introduction of the Corliss engine, patented in the US in 1849, manufacturing hubs in the US were increasingly using more-sophisticated and massive steam power systems. But these increasingly large and intricate systems were not particularly suitable for the small local mills throughout the US.

Local mills focused on relatively cheap "high-pressure" engines, patented and evangelized by Evans in the early 19th century, which did not use a condenser and instead used substantially higher pressure in the boiler. These engines were smaller and had substantially lower fixed costs, but were prone to explode (Burke, 1966; Mayr, 1975). Watt's engines were preferred to high pressure engines in Britain, partially due to this increased likelihood for explosions, but the latter became the dominant technology used in American mills.

In the second half of the 19th century, US mills began using "high-speed" engines that drew on earlier high-pressure boilers. High-speed engines were smaller and cheaper, though the parts needed to be made precisely to avoid the machine shaking dangerously and disintegrating. New high-speed engine designs were introduced by Porter and Allen in 1862, and were described contemporaneously as a "revolution in engineering" (Scientific American, 1870). Porter (1868) argued that their design required efforts that machinists "were now thoroughly accustomed to," and that the "commercial benefits" to the engine included "the saving of space and the economy in first cost."

The lower "first cost" of high-speed steam engines made them attractive to millers. Over the second half of the 19th century, many engineers adapted and improved on the Porter-Allen design, which allowed mill owners to purchase steam engines at steadily decreasing prices. Further, as local expertise in steam power spread geographically, increased local construction of steam machinery reduced shipping and installation costs (Greenberg, 1982). Although steam engines and boilers got safer over time, explosions are often described in histories of individual mills and, during the period, a plurality of steam engine explosions were in lumber mills (Scientific American, 1871, 1881).

Yet, there was hesitancy among waterpowered mills to adopt steam power. To explore potential sources of this hesitancy, we collect histories of several mills in Appendix D. Mills in places with high waterpower faced early skepticism from their neighbors, who did not view steam power as economically competitive (Flour and Feed, 1945). Many switches from water to steam power were associated with a change in management, through sons taking over from their fathers, which suggests switching frictions on the part of operators and points to the importance of management (Bloom et al., 2013; Giorcelli, 2019).

The most common reason why mills switched to steam power, we found, was they outgrew the power availability of their local waterway, or they lost their local water rights (Emery, 1883). A few millers physically moved their operations to a new structure when switching power sources, but most retrofitted their existing mills in place even after losing the original motivation for their location.

I.B County Waterpower Potential

We measure counties' waterpower potential, based on natural geographic characteristics, as a cost-shifter for local firms' use of waterpower. A key assumption for our analysis is that waterpower potential affected mills only through the costs of waterpower use. To support this assumption, we focus on variation in local waterpower potential from the interaction of particular geographic characteristics, controlling for their main effects and other local characteristics.

For any river segment, its theoretical potential for generating waterpower is given by multiplying: (1) the flow rate of water; (2) the drop in elevation (fall height); and (3) a gravitational constant equal to roughly 0.1134 when waterpower potential is measured in horsepower (which are measured in units of joules per second):

$$\text{TheoreticalWaterPower} = \underbrace{\text{FlowRate}}_{\substack{\text{Cubic Feet}\\ \text{Per Second}}} \times \underbrace{\text{FallHeight}}_{\text{Feet}} \times {}^{\text{Gravitational}}_{\text{Constant}}.$$

For each river segment in the country, we use information from the National Hydrography Dataset Plus (NHDPlusV2), which is a national database of surface water from the US EPA and USGS. For measuring fall heights, we use the difference in elevation between the maximum and minimum elevation along each river segment. Given the absence of detailed and comprehensive direct measurements of historical water flow, and the potential influence of dams and other human influences on modern rivers, we use monthly flow estimates from a USGS flow-balance model based primarily on natural and slowly changing climatic variables, such as rainfall, evaporation, and soil moisture. We use the average flow rate over the three lowest months of the year, which historical accounts argued was a key determinant of the feasibility of waterpower (Census Bureau, 1883). Figure 1 shows flow rates and fall heights for each river segment across the US, whose interaction determines waterpower potential.

We calculate waterpower potential at the county level, summing over each river segment in the county. We exclude wide river segments (more than roughly 92 feet wide) because those segments were considered at the time to be too wide for use as a practical source of waterpower, due to high dam costs, and were used instead for transportation.[11] We also exclude "seasonal" rivers with intermittent flows, which do not predict waterpower use (Appendix B).

We validate the estimates of waterflow using historical records from the 1880 Census' "Reports on the Water Power of the United States" (the "Water Census"). Consistent with the historical importance of waterpower, the US government spent resources to promote expansion of waterpower even in 1880: the stated purpose of the Water Census was to "describe the privileges actually in use and call attention to locations where power could be advantageously developed." For river segments covered in the historical Water Census, their flow rates are in close agreement with the modern data (Appendix Figure A.1).[12]

Our measurement of county waterpower potential does not directly use the Water Census, however, because the Water Census has non-random incomplete coverage based on historical economic activity (Appendix Figure A.2 Panel A). The Water Census was intended to focus on places with high waterpower potential or usage, systematically missing places that have lower waterpower potential and lower usage. Further, the Census data collection effort ran out of funds before getting to much of our sample area (Atack, Bateman and Weiss, 1980). In Section II.B, we show how relying on only the Water Census would bias estimated impacts of county waterpower potential on waterpower usage.

Appendix B describes in more detail our processing of the NHDPlusV2 data. We also collected and digitized a variety of county-level information for supplementary analysis and controls, such as access to coal deposits, which we also describe in Appendix B.

I.C Census of Manufactures, Establishment level Data

We collected and digitized all known establishment level manuscripts from the Census of Manufactures in 1850, 1860, 1870, and 1880 (see Appendix Figure A.3 for example images, and Appendix Table A.1 for the coverage of manuscripts). We classify each establishment into one of 31 industries, following Hornbeck and Rotemberg (2024), using information on self-reported "name of business" and products the establishment produced.

We restrict our main analysis to county-industries with at least one active mill in 1850

[11]For example, the 1880 Water Census writes: "...the Mississippi as it flows past New Orleans gives an exhibition of tremendous force, and by damming it up to a head of 10 feet a power of nearly 700,000 horsepower would result, but the river would be flooded back for 300 miles, and the plan is therefore impracticable." Indeed, these wide rivers are not predictive of waterpowered mills.

[12]There are some exceptions where the values diverge, which generally reflects segments where merging the two datasets is difficult (e.g., if a river splits into several sections and we are not sure how many segments to aggregate when comparing our smaller river segments to what the Census considered a river segment, or when distinct rivers in a county share a name).

and non-missing data in each decade from 1850 to 1880. Our sample covers lumber mills in 638 counties, flour mills in 604 counties, and 722 unique counties have at least one of these industries in the sample. The data include over 80,000 lumber or flour mills from 1850-1880, and cover 87% of all steam powered mills and 90% of reported steam-generated sales in the lumber and flour industries. Figure 2 Panel A shows the waterpower potential of the counties in our balanced sample.

Our data include the type of power used by each establishment, which was not geographically disaggregated in contemporaneous census tabulations (Hornbeck and Rotemberg, 2024). We also use the total annual revenue for each establishment, which inform distributions of establishment sizes that are unavailable in the previous more-aggregated data. We record establishment names that were not entered in previous samples of the establishment level manuscripts, due to punchcard width limitations (Atack and Bateman, 1999), which allows us to link mills over time.

Not all manuscripts have survived, which we can assess using contemporaneously published Census tabulations at the county level for 1850-1880 (Haines, 2010) and county-by-industry level for 1860-1880 (Hornbeck and Rotemberg, 2024). Manuscripts for some entire states and decades were lost when the original manuscripts were returned to states. Manuscripts for some counties were lost for reasons such as being used as wrapping paper when returning the surviving manuscripts (Atack and Bateman, 1999) and manuscripts for some industries (though neither lumber nor flour) were lost for 1880 (Delle Donne, 1973). To separate "missing" from "zero," we classify a county as missing data if the county has no manuscripts but the tabulations report positive establishments; otherwise, we record the county as truly having no manufacturing activity.

For counties with surviving manuscripts, Appendix Figure A.4 shows that our microdata generally aligns closely with the tabulated county-level data. However, we provide the first comprehensive information on lumber and flour mills in the period because the Census did not report county-industry statistics in 1870 and 1880 for small "local industries" (Figure A.5 Panel A). For county-industry cells above the Census tabulation threshold, our data aligns closely (Panel B). Appendix A discusses in detail our collection and processing of these data, data coverage issues, and how we group counties into time-consistent geographic units.

While mechanical power eventually diffused throughout manufacturing (Atack, Margo and Rhode, 2019, 2022), we focus on industries that had widely mechanized before steam arrived to study the transition of mechanical power from water to steam. Most waterpowered establishments in 1850 were either lumber or flour mills (Figure 3). Flour milling was the largest industrial sector in the economy during our period, by revenue, and lumber milling was the largest by number of establishments. Textile mills were also heavily-mechanized, though records for textiles in 1880 have been almost completely lost (see Appendix A and Atack and Bateman (1999)).

Among lumber and flour mills in 1850, 92% report using either water or steam power. Around 1% of mills used both water and steam power, which we classify as steam mills because they paid the fixed costs of steam and thereby benefited from the ability to scale relatively cheaply. Non-mechanized mills contributed little output share (Figure 3, Panel B), and our main analysis omits these non-mechanized mills.

A useful feature of lumber and flour mills, for our analysis, is they primarily served local demand because cut lumber and ground flour were perishable and not economical to trade, especially to rural destinations (Hunter, 1979). Indeed, an important source of revenue for flour mills was "custom milling": grinding grain that customers brought themselves (Dondlinger, 1919; Le Bris, Goetzmann and Pouget, 2019). The Census asked specifically about this practice in 1880: 95% of mills did at least some custom milling in 1880, and it represented 40% of total flour milling revenue. While milling was dependent on local geographic endowments to generate power, the material inputs for these mills were less perishable (logs and whole grains) and transported longer distances, so the local endowment of inputs was not as important for millers (Cronon, 2009).

Mills had substantial local competition. The median county-industry had 10 mills operating in a given year, considering the lumber and flour industries separately. Almost all county-industries had more than one mill (90%). Of these, 60% had at least one mill using each type of power and this share increased over time as steam power became more prevalent.

While most mills served their "local clientele" (Brown, 1923), some "merchant mills" in this era served cities and export markets (Kuhlmann, 1929). We explore the robustness of our results to excluding the cities whose mills served outside markets, but the nationalization of these industries occurred after our sample period. Flour milling began to concentrate in Minneapolis in the 1880s, after the development of less-perishable flours made possible by the the middlings purifier and the roller mill (Kuhlmann, 1929; Perren, 1990). The rise of the milled lumber trade was facilitated by the emergence of manufacturers' associations to create and maintain standards (such as regarding sapwood and knots). These associations did not exist in lumber until the 1880s, and did not reach prominence until the 1890s (Brown, 1923; National Industrial Conference Board, 1925).

Consistent with historical accounts that flour and lumber milling produced relatively non-tradable output, Appendix Figure A.6 shows that the spatial concentration of lumber and flour mills was particularly low (in the spirit of Mian and Sufi (2014)).[13] This contrasts

[13]The other least geographically concentrated sectors are leather and iron & steel (due to blacksmithing, as discussed by Atack and Margo 2019).

with clothing and textile mills, whose output was more easily traded and so was much more concentrated geographically. Lumber milling remains diffused: in the 2021 County Business Patterns data, 98% of commuting zones had a lumber mill and 25% had a flour mill.

Census schedules in 1870 and 1880 also asked mills for their installed horsepower, shown in Appendix Figure A.7: steam powered mills had slightly more horsepower than waterpowered mills, but most mills used between 10-60 horsepower with the mode around 25 horsepower.

I.D Data Linking

We create a linked panel of manufacturing establishments over time, which allows us to observe technology switching and entrant technology choices. The manuscripts do not have a time-consistent identifier for each establishment, just as in the Censuses of Population (Ferrie, 1996; Feigenbaum, 2016; Ruggles, Fitch and Roberts, 2018; Bailey et al., 2020; Abramitzky et al., 2021*a*,*b*; Price et al., 2021; Feigenbaum and Gross, 2023*a*), so we generate our own links.

We define a stable manufacturing establishment based on its owner name, industry, and place. If the owner shuts down an establishment and reopens an establishment in a different county, we consider that a new establishment. Similarly, if the owner changes their establishment to no longer be a mill, we consider the mill closed.[14] If the establishment's ownership changes entirely, with no clear link between previous and new owners, then we also consider that a new establishment. This is dictated by data availability, and also raises philosophical questions about what is an establishment. Our view is that mill owners at the time were sufficiently involved in the operation of the establishment that entire ownership changes are akin to closing operations and selling capital assets to a new venture.

We link establishments over time, within a county, using data on owner or company names, industry, product types, and (when available) nearest post office. Importantly, we do not use mills' type of power to make the panel identifiers. We hand-linked all lumber and flour mills, across each decade. Two people searched for matches for each mill, and we reconciled any disagreements. We also trained a machine-learning algorithm to predict the matches, described in Appendix A.4, which allows us to analyze robustness to different confidence thresholds. We used the ML model to re-check any hand-links that disagreed with the model's predictions. The matches are predictable: the ML model links are generally also made in the hand-links, and vice versa. We find that the distribution of predicted ML link probability for our actual matches is similar in high and low waterpower potential counties.

We also link establishment owners to the Census of Population, based on owner name,

[14]These cross-county "migrations" appear unusual for millers, based on historical society records (Appendix D), and when we hand-linked the establishments we allowed for cross-industry links and found very few outside of milling. Around 5% of surviving mills switched between lumber and flour.

industry/occupation, and place, as described in Appendix A.4.4. For our analysis, we use three owner characteristics from the Census of Population: their age; whether they were born outside the United States ("immigrant"); and if their listed occupation was a miller or manufacturer ("professional miller").[15]

II Estimating Differences by County Waterpower Potential

Figure 4 shows that steam use increased from 1850 to 1880, both in counties with average waterpower potential ("baseline") and counties with one standard deviation less potential ("low waterpower"). Mills were more likely to use steam power in counties with less waterpower in 1850, and the gap grew through 1880. Our analysis looks to estimate what factors affected this unadjusted growth of steam use in Figure 4. We then discuss the forces that encouraged steam adoption in lower-waterpower counties or, equivalently, what delayed and reduced the adoption of steam power in higher-waterpower counties. We find both that the potential for waterpower slowed steam adoption at the county level, and actual prior use of waterpower slowed it even further, in particular for incumbents.

We start by describing how we use our key source of identifying variation – spatial variation in waterpower potential – and then report our reduced-form estimates.

II.A Estimating Equations

To estimate cross-sectional effects of county waterpower potential on lumber and flour mill activity, we estimate the following regressions where each observation is a county-industry:

$$Y_{ic} = \beta LowerWaterpowerPotential_c + \gamma_i X_c + \lambda_i + \varepsilon_{ic}. \tag{1}$$

We define $LowerWaterpowerPotential_c$ as a negative standardized measure of (log) county waterpower potential per square mile, so the coefficient β can be interpreted as the effect of having one standard deviation lower waterpower potential. We focus on the estimated pooled β, across lumber and flour mills.

The estimated effect of $LowerWaterpowerPotential_c$ is conditional on industry fixed effects λ_i and a set of county controls X_c, whose effects are allowed to vary by industry i. We include three types of baseline controls, X_c, for the following reasons. Waterpower potential is the interaction of flow and height, and (1) we control for its components: total county water flow, summing over all river segments; and county ruggedness, defined as the standard deviation in county elevation.[16] Access to markets affected economic activity and

[15] The modal listed occupation for a person we link to the Census of Manufactures is "farmer," and we explore whether self-reported "professional millers" are more likely to use the more modern technology.

[16] County ruggedness is closely associated with the presence of drops in elevation, whereas fall height along river segments is not defined in the absence of rivers.

some mills got access to their material inputs through waterways (Cronon, 2009), so (2) we control for: whether the county has navigable waterways; distance to the nearest navigable waterway; and county market access in 1850 including the waterway and railroad network (Hornbeck and Rotemberg, 2024). An important source of fuel for steam mills was coal, and so (3) we control for: whether there are workable coal deposits in the county, the share of the county covered by coal deposits (Campbell, 1908), and access to coal via the transportation network.

The estimated cross-sectional differences in 1850 capture long changes in county outcomes from when there was no steam in US milling at the start of the 19th century. We also estimate some pooled cross-sectional regressions, across 1850 to 1880, for which we replace industry fixed effects with year-industry fixed effects (λ_{it}) and allow the effects of the control variables to vary by year and industry ($\gamma_{it} X_c$).

The key identifying variation comes from the interaction of river flow rates and fall heights. For the baseline cross-sectional specification, the identification assumption is that counties with lower waterpower potential would have had similar mill activity in 1850 as counties with more waterpower potential, on average, aside from differences due to power use. In practice, the identification assumption is conditional on any other differences associated with the included control variables. The control variables look to adjust for direct effects of rivers, particularly through lower transportation costs and differential impacts from the railroad network, along with different economic outcomes associated with variable elevation, access to markets, and access to coal. We discuss additional controls in Section II.D.

Our main sample is a balanced panel of county-industries, from 1850 to 1880, restricting our analysis to 722 counties with at least one lumber or flour mill in 1850 and surviving Census manuscripts in each decade. Figure 2 Panel B shows the residual waterpower potential of the counties in our sample after partialling out the baseline controls.[17]

To estimate changes over time in counties with lower waterpower potential, as steam technology improved, we estimate the following panel regressions where each observation is a county-industry-decade:

$$Y_{ict} = \beta_t LowerWaterpowerPotential_c + \gamma_{it} X_c + \lambda_{ic} + \lambda_{it} + \varepsilon_{ict}. \tag{2}$$

The estimated β coefficients report the relative change in counties with one standard deviation lower waterpower potential. We estimate the regressions separately by decade-pair, for instance estimating changes from 1850 to 1860 including only data from 1850 and 1860,

[17] The Appalachia region generally has higher waterpower potential and in Appendix E we show directly that our results are not driven by regional differences for Appalachia (with its own distinct topography and history).

which avoids interpretation issues associated with regression models that pool across many time periods (e.g., Roth et al., 2023). We include county-industry fixed effects (λ_{ic}), year-industry fixed effects ($\gamma_i t$), and interact our baseline control variables with year-industry dummies ($\gamma_{it} X_c$).

For the panel regressions, the identification assumption is that counties with lower water-power potential would have *changed* similarly to counties with more waterpower potential, on average, aside from differences due to water power and steam. This assumption is conditional on differential changes associated with our baseline county controls (river flow, terrain ruggedness, navigable rivers and market access, coal deposits). In Appendix E, we report estimates without controls, with fewer controls, or with additional controls that adjust for other factors that might be associated with differential steam adoption and growth in mill activity across counties with different waterpower potential.

For the cross-sectional and panel regressions, our main outcome variables relate to mill activity and their power source. We also examine outcomes separately for entrants and incumbents, which informs the role of switching barriers in the transition from water to steam power.

Some outcome variables are well-defined in levels, such as the share of mills using steam power, and for these outcomes we estimate Equation (2) using OLS. Shares are undefined when there are no mills, so we omit counties with no mills in one of the relevant decades. When estimating impacts on the share of mills using steam, we weight county-industries by their number of mills in the initial year to make our estimates comparable to a firm-level regression for an indicator of power adoption choice.

For outcomes such as total mills, we want to measure their elasticity with respect to waterpower potential. There are a few zeros in the sample, for county-decades where all incumbent mills closed after 1850 and there were no entrants. To estimate elasticities, and include growth on both extensive and intensive margins, we use Poisson Pseudo Maximum Likelihood (PPML) regressions (Silva and Tenreyro, 2006) rather than approaches such as $\log(1 + x)$ or inverse hyperbolic sine that are sensitive to units and therefore difficult to interpret (Chen and Roth, 2023).[18] Similarly, we use PPML to estimate the elasticity of the entry rate (entrants / previous mills) and the survival rate (incumbents / previous mills) with respect to waterpower potential.[19]

[18]Formally, PPML estimates the average effect of county waterpower potential as a percentage of the baseline mean.

[19]To estimate the elasticity of the entry rate, we use PPML regressions where the outcome in the current period is the number of entrants and the outcome in the previous period is the total number of establishments. This is equivalent to running a cross-sectional OLS regression for the log of entrants minus the log of total prior establishments, but does not require dropping counties without prior establishments or entrants. We use the same approach to estimate the elasticity of the incumbent survival rate.

We report robust standard errors clustered by county. Mill activity serves largely local markets, though waterpower potential is correlated across nearby counties, and we also estimate (Conley, 1999) standard errors that adjust for spatial correlation across counties assuming counties are independent beyond a distance cutoff (Bergé, 2018). The Conley standard errors are similar to the clustered ones for distance cutoffs within 500 miles, and are 10-30% smaller for cutoffs up to 1000 miles.

The main outcomes that we are interested in are how milling was shaped by entrants vs. incumbents, and steam vs. water users. Table 1 shows the share of milling in each decade for each type of mill. In each Census year, most mills entered during the previous decade, and entrant establishments disproportionately used more steam power than incumbent establishments.

II.B Waterpower Potential, Power Use, and Mill Growth

Table 2 reports that counties with one standard deviation lower waterpower potential had substantially fewer waterpowered mills in 1850 (Panel A) and substantially less revenue from waterpowered mills in 1850 (Panel B). Columns 2 and 3 report estimates separately for lumber mills and flour mills. The estimated coefficients of -1.0 and -1.1 imply 63% fewer waterpowered mills and and 67% less waterpowered revenue (Column 1).

By 1850, there had been faster adoption of steam power in counties with lower waterpower potential (Table 2, Panels C and D). The share of mills using steam power was 9.5 percentage points higher in lower waterpower counties in 1850 (Panel C), and the share of revenue produced using steam power was 13 percentage points higher (Panel D).

Overall mill activity was still substantially lower in counties with lower waterpower potential (Panels E and F), though somewhat muted by the increased use of steam power. Particularly in lumber milling, where there was a more substantial early shift to steam power, there are more muted effects on total revenue in 1850.

Appendix Figure A.2, Panels B and C, show that the estimated impacts on mill activity from county waterpower potential are roughly linear, so we focus on linear specifications. It is important to use our geographically comprehensive measurement of waterpower potential, though, in contrast to the 1880 Water Census that selectively omitted places with lower waterpower potential *and* lower waterpower use. Because the 1880 Water Census effectively selects on the dependent variable, we would expect estimates from that dataset to be biased toward zero, which we confirm when looking at the number of waterpowered mills in 1850 (Panel B) or 1850-1880 growth in mills (Panel C).

Table 3 reports estimated changes in counties with lower waterpower potential. From 1850 to 1860, the share of mills using steam power grew 5.9 percentage points more in counties with lower waterpower potential (Column 1, Panel A). Steam-use grew by 3.4 percentage points from 1860 to 1870 in lower waterpower counties (Panel B). From 1870 to 1880, steam adoption began to catch up in higher waterpower counties by a statistically insignificant 1.6 percentage points (Panel C). These estimates reflect a similar pattern as in Figure 4: earlier steam adoption in lower waterpower counties, with some subsequent catch-up in adoption as steam-use diffused further.

Counties with lower waterpower potential experienced substantial growth in the total number of mills and total revenue (Table 3, columns 2 and 3). The number of mills increased by 23% and revenue increased by 20%, from 1850 to 1860. Growth continued at lower rates through 1880, suggesting continued benefits from lower waterpower availability and earlier steam adoption.[20]

Table 4 shows this growth in lower waterpower counties was driven by entrant firms. The entry rate was 33% higher in lower waterpower counties, from 1850 to 1860, while the firm survival rate was 22% lower. In each period, entrants crowded-out local incumbent firms, which exited at higher rates in lower waterpower counties despite the overall growth in these counties.

We can also separate incumbents by their prior-period power use. We refer to "water incumbents" and "steam incumbents" as surviving firms who used water and steam in the previous decade, regardless of their technology in the current period. Appendix Table A.2 shows that waterpower had roughly similar effects on the exit probabilities of steam and water incumbents.

Table 5 shows that entrant firms mostly drove the greater adoption of steam power in lower waterpower counties. In each decade, entrants were 16 – 19 percentage points more likely to be using steam power in lower waterpower counties, relative to entrants in higher waterpower counties (Column 1). Among incumbent firms that had been using waterpower ("water incumbents"), these firms were a more modest 3 – 5 percentage points more likely to adopt steam power in counties with lower waterpower potential (Column 2).

Steam adoption by entrant mills was substantially more responsive than switching to steam by water incumbents (Column 3, Table 5). Water incumbents' lower steam use, combined with the increased exit of incumbents from Table 4, suggest that incumbent mills were subject to switching barriers.

In summary, the increase in steam use for lower waterpower counties was driven by: (1) more entrants in lower waterpower counties (Table 4); (2) entrants were more likely to adopt steam than water incumbents, in general (Figure 5); and (3) entrants were even more likely to

[20]These impacts on mill growth are also roughly linear in county waterpower potential (Appendix Figure A.2 Panel C).

adopt steam in lower waterpower counties (Table 5). These estimates suggest that incumbent mills faced substantial switching barriers, which particular types of firms were more able to overcome, and Section IV quantifies this technological lock-in and its implications.

II.C Non-Mill Manufacturing, Steam-Use, and Backward Linkages to Steam Production

This section shows differences by waterpower potential in broader manufacturing activity, outside lumber and flour mills. We also then narrow our focus to local steam engine production, which supported higher local steam-use across manufacturing. We restrict this analysis to 1850–1870 due to the missing Census manuscripts for some industries in 1880.

Table 6, Column 1, shows that counties with lower waterpower potential also had substantially less manufacturing activity in 1850 outside of lumber and flour mills. This is consistent with lower waterpower making locations less attractive, both due to lower waterpower use in other sectors and co-agglomeration of other sectors with milling that supported local economic activity generally. This difference declined slightly over time, as steam-use increased modestly (Column 2). In 1850, non-mills were already more likely to use steam power if located in counties with lower waterpower potential. Non-mills in these counties adopted steam power somewhat faster over the subsequent decades, though not as much as mills (shown in Table 3).

Differences in steam-use across the manufacturing sector can reflect both a direct effect, from restricted access to waterpower, and an indirect agglomeration effect from local complementarities in steam adoption. Lumber and flour milling were leading sectors for steam adoption, given their heavy initial reliance on mechanical power. Earlier steam-use by some agents could plausibly hasten steam adoption in the broader economy, given more-limited general knowledge of steam engine technology.[21] Installation and operation of steam power was not an off-the-shelf process; rather, steam was a more complicated and volatile technology, whose use might plausibly depend on the local knowledge base and, in turn, whose use might plausibly affect the local knowledge base. Delayed steam adoption by mills, in places with more waterpower availability, may have then held back steam adoption in local manufacturing more broadly.

One mechanism for these agglomeration effects is backward linkages in manufacturing of steam equipment: steam-use encouraging local manufacturing of steam equipment, which in turn encourages others to use steam power. Most manufacturing establishments purchased equipment from local manufacturers (Woodbury Report, 1838 ;Temin 1966), and a quarter of steam equipment manufacturers also report repair services in the Census of Manufactures,

[21] Indeed, Franck and Galor (2021, 2022) argue that an important driver of the diffusion of steam power in France was distance to Fresnes-sur-Escaut, the location of the first commercial steam engine in the country.

which highlights the importance of a local technical knowledge base.

Table 6, Column 3, shows that counties with lower waterpower potential had more manufacturers of steam equipment (engines, boilers, and related equipment), relative to all manufacturing establishments. The overall manufacturing sector was smaller in lower waterpower counties, but for manufacturing establishments in these counties there was a greater density of steam equipment makers to support steam adoption. This is consistent with the demand for steam power helping to create its own supply.

II.D Potential Other Forces Driving Steam Adoption

Increases in local demand could have encouraged adoption of steam power in counties with lower waterpower potential, including steam power making these counties more attractive for a variety of activities that increase local demand for milling (Benhabib and Rustichini, 1993). Appendix Table A.3, Column 1, shows that counties with lower waterpower potential experienced faster population growth during this period (6% to 12% per decade), but population is not driving our estimates on steam adoption. Appendix Table A.3, Panel A, shows that while counties with lower waterpower potential had lower population in 1850, they nevertheless had a higher share of mills using steam power (Table 2). Further, Panel B of Appendix Table A.3 shows that lower waterpower counties experienced increases in milling activity even in per capita terms. Our estimates from Table 4 are also inconsistent with population growth driving our results: if county growth were being driven by more customers, it would be difficult to rationalize the decreased survival of incumbents.

In Appendix E, we explore the robustness of our results to controlling for a variety of other features of the economic environment that may have had direct effects on steam adoption or general effects on economic activity. We summarize our approach here, and defer details to Appendix E. In Appendix Tables A.4, A.5, and A.6, we show our results are similar for flour mills only, which were the technologically less-tradable good at the time due to its perishability.

Geographic variation in waterpower potential could be correlated with other factors affecting economic activity, in levels or in changes, and in Appendix Tables A.7 and A.8 we consider how our results change when controlling for alternative local factors. In Appendix Table A.7, we show that our results are robust to including various characteristics that have been discussed as important drivers of steam power adoption across different contexts (Crafts, 1977; Floud and McCloskey, 1981; Allen, 2009; Mokyr, 2016): alternative measures of access to coal (Wrigley, 2010; Fernihough and O'Rourke, 2021; Reichardt, 2023); agricultural productivity and woodland that affect mills' material input availability (Ragnar, 1953); differences in labor availability reflected in manufacturing wages (Allen, 2009) and mechanics and engineers (Hanlon, 2022), though also potentially an outcome of mills' steam adoption; capital availability through banks (Jaremski, 2014); and all of the above controls.

In Appendix Table A.8, we show that our results are robust to other adjustments to our controlling for features of counties' economic environment. First, we show our results are robust to removing some or all of our baseline controls. Our results are robust to controlling for time-varying market access and population, which are themselves potentially endogenous to steam adoption, or growth associated with counties' fixed 1850 population. Some estimates are smaller when controlling for population, but this also introduces bias because county population is endogenous to local waterpower potential (even in 1850). Our results are robust to controlling for alternative sources of potential growth: an indicator for being in Appalachia or on the frontier (Bazzi, Fiszbein and Gebresilasse, 2020), the share of workers in agriculture (Eckert and Peters, 2023), having a portage site (Bleakley and Lin, 2012), exposure to the Civil War, and all of these time-invariant controls interacted with decade.

Our analysis focuses on county-level geographic variation in waterpower availability, though there could also potentially be within-county differences in location advantages for steam power. One salient locational characteristic could be a short distance to railroad stations, which was a source of fuel imported from other counties. We digitized historical maps of railroad station locations, which captures variation across counties in their access to railroad stations. There is locational variation within counties, as some counties had waterpower sites close to stations and in others they are far away, which could lead to differences across water incumbents in the feasibility of switching to steam power and therefore a potential source of technological lock-in. Nevertheless, Appendix Table A.9 shows that distance to railroad station is not an additional substantive source of variation in steam suitability: it does not predict steam-use, or water incumbents switching to steam, or a differential response of entrants versus incumbents.

II.E Robustness to Linkage Error

A natural question is how much our estimates might be affected by measurement error, particularly errors in the construction of panel links that we made because the historical manuscripts do not have the equivalent of a tax ID. For our main results, we invested in a resource-intensive approach that uses hand-links but there are inevitably false negatives and false positives in the links.

To explore the role of measurement error, we train a supervised machine learning algorithm on the hand-made links (see Appendix A.4 for details). We then use the estimated linking probabilities to explore the the quality of hand-links, and the sensitivity of our estimates to different rates of false negative and false positive links.

Appendix Figure A.9 Panel A shows the predicted match probability for the hand-links. For mills whose sector and ownership structure were unchanged from one decade to the next, the hand-links are very predictable: most match probabilities are above 0.8. For mills that changed sector (flour-to-lumber), and especially for mills that gained or lost some owners, the match probabilities are lower but still mostly above 0.6. For our regression analysis, a primary concern would be if linkage errors are correlated with county waterpower potential. Appendix Figure A.9 Panel B shows that the distributions of predicted match probabilities are similar for mills in counties with low and high waterpower potential, suggesting that linkage error is plausibly uncorrelated with counties' waterpower potential.

One advantage of the ML model for robustness analysis is that we can change the matching cutoff, which mechanically changes the ML survival rate along with changing the rate of false-negative and false-positive matches. Appendix Figure A.8 shows how raising the cutoff lowers the share of ML links that are not hand-links (the "false match" rate, akin to a false discovery rate) but also lowers the share of hand-links that are made by the ML model (the "found match" rate, akin to the sensitivity). Our baseline machine-learning (ML) links use a predicted match probability of 0.6 as the benchmark cutoff for classifying a mill as surviving from one decade to the next, which is close to maximizing the "found match" rate while keeping the "false match" rate relatively low.

Appendix Table A.10 shows the relationship between the ML-links and hand-links: most hand-links (67%) are also predicted by the ML model. Further, conditional on finding a match, it is rare that the ML-links and hand-links disagree on the identity of the match. However, the survival rate is higher using the ML-links, compared to the hand-links, as many mills are only classified as surviving using the ML model.

In practice, Appendix Tables A.11 and A.12 show that our results are not sensitive to changing the sample to include more or less confident matches based on the ML-link probabilities. Our results are similar if we restrict our panel sample to those mills linked by hand *and* the baseline ML model, rather than our main sample of hand-links, or use *only* the benchmark ML-links. Using the ML-links only, the results are also similar if we raise or lower the benchmark cutoff of 0.6 for classifying matches.

Another useful feature of the ML model is that it classifies whether mills have a "business name" (such as the "Rock Creek Mill") or whether mills are named after their proprietors (and might therefore be more subject to linkage error). Our estimates are similar for the sample of mills with business names only or the sample of mills with proprietor names only.

We also explore potential measurement error in the type of power source recorded for mills, which is based on Census enumerator visits to the mills. The original manuscripts contain some corrections, with scratched out and re-written information by an occasional second enumerator, so the final recorded data could also differ in some cases from mills' actual operations. For instance, we searched in historical records for mills that reported power sources other than water and steam — in particular, some suspiciously large mills without reported mechanical power — and found that these mills often did actually use water or steam power. Some report "horse" power, without specifying its source, which probably represents water or steam power rather than horse-powered mills. We cannot systematically correct these mills' recorded power use, so our baseline estimates exclude these mills; but as there are few of these mills our results are not sensitive to including them as non-steam powered mills.

Our main analysis restricts the sample to the panel of counties with at least one mill in 1850. In Appendix Table A.13, we show that our results are similar when including different sets of counties: expanding the sample to include all counties that ever had a mill, or limiting the sample to counties that have multiple mills in 1850. Our results are also similar if we exclude counties that were more involved with cross-county or international trade in mill output: the 20 largest cities at the time, or places that Kuhlmann (1929) describes as having "merchant mills" that exported their output. Our estimates are also not sensitive to dropping large county groupings, made in the construction of geographically-consistent counties, which have potentially more error in classifying local waterpower availability for mills.

III Stylized Facts

Overall, there is a stable pattern that greater waterpower potential slowed the adoption of steam power. The differences in steam adoption rates among entrants and incumbents is suggestive of technological lock-in, with barriers to steam adoption for those establishments that had previously used waterpower. We use a quantitative model, though, to estimate the magnitude of this lock-in and its implications for aggregate manufacturing outcomes given firm entry and exit. The model estimation draws on these estimated differences by county waterpower potential. The model also reflects other features of the economic environment, such as the costs and benefits of using steam power, which we describe further in Section IV. In this section, we describe stylized facts to motivate the model's structure, and these stylized facts provide moments in the model's estimation.

Our view of the technological transition from water to steam is motivated by the following intuition. Each technology was associated with marginal costs and fixed costs (where fixed costs include both purchase and overhead costs). Because neither technology was clearly more attractive to millers, throughout the 19th century, we model steam power as better on one cost dimension and waterpower as better on the other cost dimension. To see which is which, we use a logic in the spirit of Melitz (2003) (see also Olmstead and Rhode 2001; Bustos 2011). Millers have different productivities, for instance due to their ability to attract customers, manage suppliers, and operate the machinery (Huntington, Samaniego dela Parra and Shenoy, 2023). Holding fixed productivity, firms will be larger if they use the lower marginal cost technology. For a given power technology, more-productive firms will have higher sales. More-productive firms are then more likely to prefer the high fixed cost and low marginal cost technology, because they can amortize the fixed costs over more units. Both of these forces imply that whatever technology is associated with larger firms is the one with lower effective marginal costs that is easier to scale. A similar logic applies when considering how a technology varies over space or time. Technology improvements that lead to the largest users of a technology growing imply that marginal costs are falling, otherwise they imply that the fixed costs are falling. As a result, we study a variety of firm size distributions to characterize features of steam and water power in our setting. Characterizing these size distributions relies on our digitization of the micro-level Census data, as these economic patterns were previously unknown from aggregated tabulations or smaller samples of micro-data without firm names or panel links.

III.A Cost Structures for Steam and Water

Figure 6 shows that steam powered mills were larger than waterpowered mills, on average. Given the Melitz (2003)-style logic discussed above, this implies steam power has higher fixed costs and lower marginal costs than water power.

That conclusion requires some further interpretation, though, as steam engines likely had higher marginal costs in dollar terms due to expenditures for fuel and other supplies. The empirical patterns reflect the realities of running steam engines and waterwheels. In addition to high purchase prices, steam power required high overhead costs. Even small steam mills employed full time engineers and firemen and needed a baseline amount of fuel to turn on their engines (Fisher, 1845; Swain, 1888).

Waterwheels were limited by their local geography: the size, speed, seasonality, and reliability of their local waterway, as well as contractual water rights. Due to these constraints, the *effective* marginal costs of waterpower were higher than their *inframarginal* variable costs. Some water-using incumbents did grow (Appendix Figure A.10), so waterpowered mills were not completely constrained, but expanding production further could require increasingly expensive modifications to their operations.

Figure 6 shows that the size distributions for steam and water powered mills converged over time. This suggests a corresponding decline in the fixed cost of steam power, as less-productive firms started to find steam power more attractive, whereas a declining marginal cost of steam power would have increased the size premium of steam powered mills. This is consistent with our discussion of high-speed engines reducing steam fixed costs for lumber and flour mills, which contrasts with increasing efficiency and declining marginal costs of steam power in other sectors that include Corliss-style engines (Atack, 1979).

One potential explanation for these results could be that steam power shifted activity to new locations that, for unrelated reasons, had mills of different sizes. This geographic shift is not driving our results, though: Appendix Figure A.11 shows that steam powered mills are systemically larger than water powered mills even when comparing within-counties (for counties with both types of mills), and the gap falls over time.

For local waterpower potential to make waterpower use more attractive to firms (as in Figure A.2 Panel B), this implies that local waterpower potential lowered the fixed costs or marginal costs of using waterpower. If waterpower potential lowered the marginal costs of waterpower, then counties with higher waterpower potential would have larger waterpowered mills (and, due to the resulting selection, also larger steam powered mills). Figure 7 shows this was not the case and, indeed, somewhat the opposite: in most decades, counties with higher waterpower potential have more small mills. Thus, we model county waterpower potential as lowering the time-invariant fixed costs of waterpower, such as the costs of water rights and constructing millponds.

Congestion was not an important force driving differences in steam power (Gordon, 1983). In our data, almost all counties were using less than half of the available waterpower potential, so entrant mills were adopting the new steam technology at higher rates in lower waterpower counties even though there were still available water sites.[22] Further, Table 5 shows that water incumbents are more likely to switch to steam in places with lower waterpower potential (even though less than entrants). If the increased adoption of steam power was driven by difficulties finding available waterpower sites, water incumbents would be unaffected.

Figure 6 also shows there was substantial overlap in the size distributions of steam- and waterpowered mills, in every decade. This suggests a substantial idiosyncratic component to mills' technology adoption.

III.B Operating Costs

We calculate that 20-25% of mills survived from one decade to the next (Appendix Table A.14).[23] Firm exit implies that dynamic incentives are important, as only some firms will end up amortizing over a long time period any fixed costs of entry and technology adoption.

[22]Hunter 1979; Gordon 1983 report that standard estimates of waterwheel efficiency in the era were at least 50–70%.

[23]This implies an annual exit probability of around 15%, higher than modern annual exit probabilities of around 8% (Foster, Grim and Haltiwanger, 2016).

Appendix Figure A.12 shows that, on average, surviving firms are larger than exiting firms. This suggests a fixed cost of production in every period, with an additional idiosyncratic component, to rationalize exit and this correlation between firm exit and initial size. Water incumbents were also more likely to survive than steam incumbents, consistent with explosions and other operating costs associated with steam power.

III.C Barriers to Switching Technologies

Entrants' decision to adopt steam is a useful contrast to incumbents' decision, as entrant firms started with a clean slate. Figure 5 shows that entrants were four times more likely to use steam power than water incumbents.[24] The difference in steam adoption rates is not driven by differences in firm size and is slightly larger when conditioning on firm size (Appendix Table A.15). Indeed, in spite of using the technology with higher marginal costs, water incumbents who stayed with water were 2% larger than steam entrants.

This difference in steam adoption rates, between entrants and incumbents, suggests there are barriers to switching from water to steam power. A fixed cost of switching technologies also causes only the highest-productivity water incumbents to adopt steam, while relatively lower productivity entrants would use steam. Consistent with this logic, Appendix Figure A.13 shows that incumbents are larger than the entrants within each power technology: on average, incumbents are 20% larger when using water and 40% larger when using steam.

Switching barriers were not infinite, however, as both entrants and incumbents were more likely to adopt steam power over time. This is also consistent with the technological improvements in steam power over time. Over the course of our sample, steam adoption rates increased by 60 percent for both entrants and water incumbents, from a base rate of 30 percentage points for entrants and eight percentage points for water incumbents (Figure 5).

III.D Alternative Reasons for Lower Steam Adoption among Incumbents

While the data patterns are consistent with fixed costs of switching power technologies, we also consider three alternative explanations for the serial persistence in firm technology choices.

Across different contexts, one leading alternative explanation for low technology switching by incumbents is learning-by-doing. The idea would be that waterpowered incumbents could have freely adopted steam, but did not want to because they had learned to use water power and, for them, it continued to dominate steam. For this context, high rates of learning-by-doing for waterpower would be inconsistent with the longstanding use of water power in the

[24] A few firms report switching from water to steam, which is rare enough that we do not report separate statistics for these firms, though we do include these firms when we estimate the model in Section IV.

US, but we can explore this further in the data.

Learning-by-doing would also imply that water incumbents experience relatively faster growth, as they benefit both from learning and any other general economic changes that increase firm size. Thus, to test for learning in the spirit of Bahk and Gort (1993), we compare the growth rate of water incumbents who keep using water power to the change in the size distribution of entrants over the same time period. Appendix Figure A.14 shows that incumbents and successive generations of waterpowered entrants "grow" at a similar speed, consistent with no additional learning-by-doing boost for water incumbents.

We consider switching costs as consisting of actual expenditures that the firm needs to pay. An alternative modeling approach could assume a *productivity* cost from switching technologies (see, e.g., Parente and Prescott 1994). For our context, switching leading a decline in productivity is less natural because most of the day-to-day operations of milling are the same with either power source, using the same grinding/sawing machinery for the same material inputs and outputs. In the data, Appendix Figure A.10 Panel B shows that switchers grow faster than stayers, which is not consistent with productivity losses from switching. Indeed, even though water incumbents were negatively selected (because they had not entered using steam power), those that switched to steam power were 5% larger than steam entrants.

Another potential reason why incumbents would not switch technologies is permanent unobserved heterogeneity (i.e., "steam types" and "water types"). We do find some specific examples of persistent firm heterogeneity, but we do not include it in the model for reasons described below.

One natural candidate for unobserved heterogeneity is the preferences and talents of firm owners. Linking the Censuses of Manufactures and Population, Appendix Table A.16 shows that owners who were immigrants or younger were more likely to use steam power, highlighting the role of owner characteristics for technology adoption.[25] Nevertheless, these forces do not seem quantitatively important on aggregate. While immigrant owners are much more likely to use steam power, there are not very many. The effect of age is relatively small. Appendix Table A.16 also shows that professional millers were more likely to use steam power (though this presumably is not a permanent type).

Other features of the data also suggest that permanent idiosyncratic variation in costs and productivity is not driving the main data patterns. Firms grew more when they switched (Appendix Figure A.10), which is not a general prediction of models with persistent types, but is a prediction of switching barriers (as only the mills with productivity growth would

[25] McElheran et al. (2023) find that younger owners are more likely to adopt artificial intelligence technologies.

choose to change technologies). Historical accounts of mills also discuss instances of mills switching technologies after a fire destroyed their original structure (Appendix D), which suggests owners do not persistently prefer a particular technology; rather, it is more consistent with sunk fixed costs or other barriers to switching (Hornbeck and Keniston, 2017; Huesler and Strobl, 2023).

We can also use the timing of mills' water-use, steam-use, and switching to compare implications of switching barriers that generate state-dependent technology choices, compared to implications of heterogeneous types. Methods of quantifying the importance of state dependence versus types require observing agents for many periods (Chamberlain, 1985; Dano, 2023), whereas we observe mills for a maximum of four census rounds (and normally fewer). We provide two alternative tests, in the spirit of Chay, Hoynes and Hyslop (1999), which provide suggestive evidence against the presence of types driving the relatively low switching rates.

One test of state dependence is to examine firms' technology choices, conditional on their prior use of water and steam power. Consider the sample of mills over four periods who start with waterpower, end with steam power, and use steam power exactly twice. These mills use steam power half of the time, and all have the same initial and final conditions (as in Hotz and Miller, 1993; Arcidiacono and Miller, 2011). Switching barriers would make it substantially more costly for these firms to alternate between technologies twice, as opposed to using water for two periods and then steam for two periods. By contrast, under heterogeneous types, switching is driven by period-specific idiosyncratic shocks that would make both patterns equally likely. In our data, the vast majority of these mills switch technologies only once and then keep their new technology, which suggests switching barriers are driving technological choice.

In a second test, persistent firm types would imply that mill's past technology-use predicts its future technology-use, conditional on its current technology. For current water users, we find that using waterpower in the previous decade does not predict using waterpower in the next decade; which again suggests against persistent types in this context.

In Summary: Steam power allowed firms to scale production at lower effective marginal costs, which required higher fixed costs but those fixed costs declined over our sample period as steam technology improved. Both water and steam required fixed overhead costs, and millers faced some cost of switching power technologies. Counties with higher waterpower potential used relatively less steam power, due to their continued access to waterpower (direct effects of geography) and their previous use of waterpower (dynamic effects of geography, through technological lock-in). We now turn to a formal framework that fits these facts and quantifies the influence of technological lock-in.

IV A Model of Steam Adoption

It is difficult to interpret all of the estimates jointly – the stylized facts along with the estimated differences by waterpower potential – with only economic intuition. One main purpose of the model is to collect and synthesize the magnitudes of these different relationships. Further, the structural model allows us to evaluate how switching barriers – and policies aimed to alleviate them – matter for the aggregate diffusion of new technologies.

We develop a dynamic equilibrium model of technology adoption and firm entry. In the model, firms face a dynamic choice of whether to be powered by steam or water. The key tradeoff is that waterpower has a lower fixed adoption cost but a higher marginal cost that inhibits higher production levels. The only primitive that varies across counties is the cost of adopting waterpower. The only primitive that varies across time is the price of steam. A falling price of steam power drives steam diffusion but also incentivizes forward-looking firms to wait to adopt. The barriers to switching from water to steam power encourage firms to enter using steam. In this section, we describe the formal set-up of the model.

IV.A Static Choices: Production and Demand

Each firm j in county c in year t maximizes its static profit by choosing its optimal levels of variable inputs x_{jct} and price p_{jct}, given its power source R, its baseline productivity φ, and the prices of other firms.

We assume all demand for mill products takes place locally and takes a nested CES form.[26] The price index P_{ct} equals $\left[\int p_{jct}^{1-\epsilon}\, dj\right]^{\frac{1}{1-\epsilon}}$, where ϵ is the elasticity of substitution across mills' products. Local demand for mill output Y_{ct} equals $P_{ct}^{-\eta}$, where η is the elasticity of demand for mill products. If firm j charges price p_{jct}, its quantity sold is: $y_{jct} = p_{jct}^{-\epsilon} P_{ct}^{\epsilon-\eta}$.

Firms produce using a constant-returns-to-scale technology in flexible inputs x (labor and materials), which are elastically supplied at a price w:

$$y_{jct} = \exp(\varphi_{jct} + \gamma_{jct} + \alpha_{R_{jct}} s_{ct}) x_{jct}. \tag{3}$$

Firms' overall productivity is determined by their baseline productivity φ_{jct} and an additional $\gamma_{R_{jct}}$ from their power choice R, which is either water (W) or steam (S). We normalize $\gamma_W = 0$ so $\gamma_S = \gamma$. This productivity boost from steam power is also a function of contemporaneous local steam usage (αs_{ct}), where s_{ct} is the share of firms using steam and α is the strength of this agglomeration force. Agglomeration effects (α) could reflect that increased

[26] Appendix Table A.2 shows that the competitive pressure from steam entrants has similar effects on the exit probabilities of steam and water incumbents. This result is consistent with entry raising competitive pressure by lowering the aggregate price index, and less consistent with a Bertrand model, where the initially waterpowered mills would be especially unable to match the low prices of the steam mills.

local steam use generates greater local human capital in steam production.

Firms buy inputs x to maximize flow profits. Their price, output, and profit functions are:

$$p_{ct}(R,\varphi) = \frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma_R+\alpha_R s_{ct})}, \tag{4}$$

$$y_{ct}(R,\varphi) = {P_{ct}}^{\epsilon-\eta}\left(\frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma+\alpha_R s_{ct})}\right)^{1-\epsilon}, \tag{5}$$

$$\pi_{ct}(R,\varphi) = \frac{1}{\epsilon}{P_{ct}}^{\epsilon-\eta}\left(\frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma_R+\alpha_R s_{ct})}\right)^{1-\epsilon}. \tag{6}$$

The next section describes how firms choose if they produce and with what power choice.

IV.B Dynamic Choices: Firm Entry and Power Choice

We model a firm's dynamic choices in four stages (Hopenhayn, 1992; Melitz, 2003; Chernoff, 2021). In Stage 1, prospective entrants decide if they want to pay a fixed cost and enter the economy. In Stage 2, entrants draw their productivity φ_{jct} and incumbents update their productivity. In Stage 3, firms choose if they want to exit, given their revealed productivity and fixed operating cost. In Stage 4, surviving firms select their optimal power source and produce. After these four stages, the cycle starts over again. For the initial stages, we consider the possible power states to be E, W, or S (respectively for entrant, water, or steam). Entrants need to adopt water or steam power to produce in the final stage.

Stage 1: Entry. A prospective firm enters in county c in year t if its expected continuation value upon entry exceeds the fixed cost of entry:

$$\mathbb{E}_\varphi\left[V_{ct}(E,\varphi)\right] \geq f^e, \tag{7}$$

where $V_{ct}(E,\varphi)$ is the continuation value for an entrant.

Stage 2: Updating Baseline Productivity. The productivity of an incumbent mill j, φ_{jt}, follows an AR(1) process:

$$\varphi_{jt} = \pi\varphi_{jt-1} + \sigma\xi_{jt}, \tag{8}$$

where π and σ are parameters that represent the persistence and dispersion of latent productivity φ. Entrants draw their productivity from the stationary distribution of the same AR(1) process.

Stage 3: Sinking the Operating Cost. All firms pay a common deterministic operating cost f^R, given their power source $R \in \{E, W, S\}$. Furthermore, each firm j pays an idiosyncratic cost $\nu_{jct}^{R}(0)$ if it continues its operation, and $\nu_{jct}^{R}(1)$ if it chooses to exit. Each firm compares the expected value from paying the operating cost to the value from exit:

$$V_{ct}(R,\varphi) = \max\{\mathbb{E}_{\varepsilon}\left[V_{ct}^{o}(R,\varphi)\right] - f^{R} - \nu_{jct}^{R}(0), \Omega_{ct}^{R} - \nu_{jct}^{R}(1)\}, \tag{9}$$

where $V_{ct}^{o}(R,\varphi)$ is the continuation value after sinking the operating cost.

Stage 4: Choosing a Power Source and Producing. Having paid its fixed operating cost, each firm chooses its optimal power source as a function of adoption costs, switching barriers, and expectations over future productivity. The value function for an establishment with power source R and productivity φ is:

$$V_{ct}^{o}(R,\varphi) = \max_{R' \in \{W,S\}} \{\pi_{ct}(R',\varphi) - c_{ct}(R,R') - \varepsilon_{jct}(R') + \delta \mathbb{E}_{\varphi'}\left[V_{ct+1}(R',\varphi')\right]\}. \tag{10}$$

$\pi_{ct}(R,\varphi)$ is the firm's static profit from Equation (6), δ is the discount factor, and $\mathbb{E}_{\varphi'}\left[V_{ct+1}(R',\varphi')\right]$ is the expected continuation value given the law of motion for productivity in Equation (8). For each power source, the firm draws an idiosyncratic usage cost $\varepsilon_{jct}(R)$. To give some examples of idiosyncratic costs, Swain (1888) describes some millers preferring waterpower due to its "greater cleanliness, less annoyance, and less area required." If the firm chooses to change power sources, the firm pays $c_{ct}(R,R')$ to switch from power source R to power source R'. The firm then produces, charging the profit-maximizing price described in Equation (4).

IV.C Equilibrium

Firms make forward-looking decisions anticipating improvements in steam power and the competition from other firms in their local product market. For example, while lower steam costs create an option value for incumbents to switch to steam, these firms understand that cheaper steam may also induce other firms to enter, adopt steam, and compete for customers. We study the local economies along their transition path as steam power becomes available at lower costs.

Definition 1 (Dynamic Equilibrium)**.** An equilibrium for county c is a time path for the mass of entrants M_{ct}, the mass of operating firms $F_{ct}(R,\varphi)$, and the policy functions for operation/exit $O_{ct}(R,\varphi)$ and power $R'_{ct}(R,\varphi)$, taking the time path of steam costs $c_{ct}(S)$ as given, such that:

1. Firms enter, exit, and adopt power sources to maximize expected discounted profits (Equations 7, 9, and 10).

2. Firms source inputs x to maximize flow profits period-by-period (Equation 6).

3. Output markets clear:

$$P_{ct}Y_{ct} = wX_{ct} + \Pi_{ct}, \tag{11}$$

where $\Pi_{ct} = \int \pi_{ct}(R,\varphi)dF_{ct}(R,\varphi)$ are total local profits, and $X_{ct} = \int x_{ct}(R,\varphi)dF_{ct}(R,\varphi)$ is local demand for inputs.

4. The free entry condition holds:

$$\mathbb{E}_{\varphi}\left[V_{ct}(E,\varphi)\right] \leq f^{e}. \tag{12}$$

5. The evolution of firm masses $\{F_{ct}\}_t$ is consistent with the policy functions $\{O_{ct}, R'_{ct}\}_t$.

IV.D The Arrival of Steam

We initiate the model in 1830, before steam power became broadly available to mills in the US. We assume the economy was in a steady state before steam, with differences across counties reflecting their different water costs.[27] In 1830, firms receive the news that steam will become increasingly available. After the surprise of steam power, firms have perfect foresight about the path of falling steam costs.[28] In particular, steam power first becomes purchasable at a high price in 1830, and its fixed adoption cost then monotonically declines until reaching its steady-state level in 1900.[29]

The falling steam cost is the only driving force along the transition path. In particular, we assume water technology is comparatively unchanged over this period, as it was a comparatively mature technology. Rosenberg and Trajtenberg (2004) estimate that horsepower per waterwheel was largely stable over time.

IV.E Parametric Assumptions

We make a series of parametric assumptions to take the model to the data. Firm operating/exit costs are drawn from a Gumbel distribution with dispersion parameter ρ_o^R, and the adoption costs for each power source are drawn from Gumbel distributions with dispersion

[27] The Census of Manufactures was professionalized and comprehensive beginning in 1850 (United States Census Bureau, 1900; Atack and Bateman, 1999), after the first introduction of steam power. Hence, we cannot use our first period, 1850, as the steady state before steam power. Instead, we initiate the model simulations in 1830, when very few steam engines were used in US milling (Woodbury Report, 1838), and estimate the model to match steam diffusion from 1850 to 1880.

[28] Humlum (2022) adopts a similar approach to modeling the arrival of robots in modern manufacturing.

[29] Steam power reached its peak adoption in US manufacturing around 1890-1900 (Jovanovic and Rousseau, 2005), prior to the large-scale arrival of electricity in milling (Fenichel, 1966).

parameter ρ:

$$\nu^R_{jct}(\text{OPERATE/EXIT}) \overset{\text{iid}}{\sim} \mathit{GEV1}(\rho_o) \tag{13}$$

$$\varepsilon_{jct}(R) \overset{\text{iid}}{\sim} \mathit{GEV1}(\rho). \tag{14}$$

The productivity innovations are drawn from a standard-normal distribution

$$\xi_{jt} \overset{\text{iid}}{\sim} \mathcal{N}(0,1), \tag{15}$$

which implies that entrants draw their productivities from the normal distribution

$$\varphi_{jct} \sim \mathcal{N}\left(0, \frac{\sigma^2}{(1-\pi)^2}\right). \tag{16}$$

The resale value of each technology is a share of the current purchase price:

$$\Omega^R_{ct} = \omega^R c_{ct}(R). \tag{17}$$

The costs of switching power sources reflect buying prices, resale values, and other costs:

$$c_{ct}(R,R') = \begin{cases} 0 & \text{if } R = R' \\ c_{ct}(R') & \text{if } R = E \\ c_{ct}(R') + c(R,R') - \Omega^R_{ct} & \text{otherwise.} \end{cases} \tag{18}$$

Mills keeping their existing technology do not pay any further costs. Mills purchasing technology R' have to pay a fixed purchase price $c_{ct}(R')$. Switchers face two additional forces. First, incumbents face an additional switching cost to change power sources, $c(R,R')$, which captures all costs of changing technologies. Second, while firms may sell their pre-existing technology, due to partial irreversibility (if $\omega^R < 1$), the scrap value may not be equal to the purchase price of their old technology (Bertola and Caballero, 1994; Ramey and Shapiro, 2001; Baley and Blanco, 2022).

We parameterize the fixed cost of steam adoption declining over time as follows:

$$c_t(S) = \kappa s_{ct} + c_S^{(init)} + (c_S^{(term)} - c_S^{(init)}) \exp\left(-c_S^{(slope)}(t - T_0)\right), \tag{19}$$

where the cost at period T_0 is $c_{T_0}(S) = c_S^{(init)}$, and $\lim_{t\to\infty} c_t(S) = c_S^{(term)}$. This set-up implies that the price of steam varies over time but not space. Conversely, the price of waterpower varies over space due to local waterpower potential, but does not vary over time. Finally, we allow the price of steam power to be a function of local steam use (κ), capturing the potential for agglomeration (or congestion) in power adoption, such as information sharing.[30]

Given these distributional assumptions, the firm-level expected continuation value is:

$$\mathbb{E}_\nu[V_{ct}(R,\varphi)] = \rho_o^R \log\left[\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right) + \exp\left(\frac{\mathbb{E}_\varepsilon\left[V_{ct}^o(R,\varphi')\right] - f^R}{\rho_o^R}\right)\right], \tag{20}$$

while the expected continuation value after sinking the operating cost is:

(21)

$$\mathbb{E}_\varepsilon[V_{ct}^o(R,\varphi)] = \rho \log\left[\sum_{R'\in\{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R,R') + \pi_{ct}(R',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(R',\varphi')]\right)\right].$$

The probability of exit, given the existing power source R and the baseline productivity φ, is:

$$\Pr_{ct}\left(\text{OPERATE/EXIT}|R,\varphi\right) = \frac{\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right)}{\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right) + \exp\left(\frac{\mathbb{E}_\varepsilon[V_{ct}^o(R,\varphi')] - f^R}{\rho_o^R}\right)}. \tag{22}$$

The conditional probability of choosing power source $R' \in \{W,S\}$, given a mill is starting with power source R, is:

$$\Pr_{ct}\left(R'|R,\varphi\right) = \frac{\exp\left(\frac{1}{\rho}(-c_{ct}(R,R') + \pi_{ct}(R',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(R',\varphi')])\right)}{\sum_{R''\in\{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R,R'') + \pi_{ct}(R'',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(R'',\varphi')])\right)}. \tag{23}$$

IV.F Solution Algorithms

The equilibrium for each economy is a complicated fixed point: heterogeneous firms make forward-looking decisions about entry, exit, and power adoption, and firms' decisions are interlinked through their competition in local product markets. We study the transition path of the economy, where falling steam costs drive the transition from water to steam power.

Appendix F describes our solution algorithms. In brief, we solve firms' dynamic programs by combining value function iteration (in the steady states) with backward recursion (along the transition path). We solve the dynamic equilibrium using a fixed-point shooting

[30] While we formally model κ as affecting the price of steam power, it also serves as a local shifter for the *relative* price of steam. For instance, if the price of local waterpower falls in the local use of steam, due to a move along the supply curve for waterpower, we would estimate a positive κ.

algorithm in the aggregate state variables.

IV.F.1 Existence and Uniqueness

Appendix F discusses the properties of our solution algorithm, including the existence and uniqueness of the equilibrium. The convergence of our iterative algorithm is ensured by a congestion force due to competition in the product market, which in turn ensures the existence of an equilibrium. The congestion force behind the convergence property also tends to make the equilibrium unique. Strong steam agglomeration forces (κ and α_S) could, however, lead to multiple equilibria: a "low steam" equilibrium where few mills adopt steam (because the agglomeration force is weak) and a "high steam" equilibrium where many mills use steam (because the agglomeration force becomes strong). We check for multiple equilibria in our terminal steady state (when steam power is fully available and more firms are at the margin of steam use) by initiating our solution algorithm at different starting values for the equilibrium steam share.

V Structural Estimation

In this section, we describe the quantification of the model developed in Section IV. We consider two counties: a baseline county with the average amount of waterpower in the United States, and a "lower waterpower" county with one standard deviation less waterpower potential. We assume that the only fundamental difference between the counties is the cost of waterpower $c_c(W)$. This structural modeling mirrors the identifying assumption in our reduced-form analysis in Section II, using waterpower potential as a cost-shifter for local firms' use of waterpower (after controlling for county water flow, elevation changes, and other characteristics). In particular, the differences between the model counties corresponds to our reduced-form regression coefficients β_t in Equations (1)-(2). One feature of our setting is that the transition to steam power had already started when comprehensive manufacturing census data started to be collected in 1850, as by then 10% of mills used steam power. We model the diffusion curve directly, allowing us to interpret the reduced-form regressions as estimates of the effect of waterpower potential at different dates along the diffusion curve.

V.A Estimation Strategy

In this section, we describe the set of structural parameters and the target moments used for estimation. We estimate the structural model to match the stylized facts and the reduced-form estimates from Section II. In particular, we target a mix of estimates within county-industries (our stylized facts) and between counties (our reduced-form estimates). We estimate the parameters simultaneously using the Method of Simulated Moments (MSM). Appendix G provides details on the MSM estimation procedure.

V.A.1 Within-County Moments

Most of the moments we match in the model come from predicting the value of a typical baseline county (denoted B). We have data on two sectors (flour and lumber), while in the model we consider one composite "milling" sector. To create this composite, we calculate the relevant moment Y_{ict} for each sector separately. We then predict Y_{ict} using our reduced-form specification in Equation (1).[31] We then take the average to generate Y_{ct}, weighting by the number of mills. Specifically, the moment we match is then the predicted outcome for a county with average waterpower potential:

$$Y_{Bt} \equiv \mathbb{E}_i \left[\mathbb{E}_c[Y_{ict}] \right] = \mathbb{E}_i \left[{\gamma_{it}}' \mathbb{E}_c[X_{ic}] \right], \tag{24}$$

where X_{ic} consists of our baseline controls, our standardized measure of local waterpower potential (whose average is normalized to zero), and an industry fixed effect.

For some moments, we compare outcomes in the baseline county to those in a "lower water power" county (denoted L). The counterfactual moments for county L are identified under the assumption that local waterpower potential is a cost-shifter for local firms' use of waterpower (conditional on our included control variables). To calculate outcomes in county L, we follow Equation 24 but predict outcomes for a county with one standard deviation lower waterpower potential (while holding all of the other characteristics fixed at their average levels). The difference in moments between counties B and L corresponds to our estimated reduced-form impacts of lower waterpower, $\hat{\beta}_t$.

While the parameters are estimated jointly, many have an intuitive mapping to specific moments, which we discuss below. Appendix G supports these intuitive explanations with a formal analysis of our sources of identification, using the local relationships between structural parameters and simulated moments, following Andrews, Gentzkow and Shapiro (2017).

Steam productivity. If steam is relatively more productive, so the steam productivity parameter γ is positive, steam users will have higher sales in our model. We therefore use the sales differential between steam and water users within each county, as in Figure 6, to help identify γ. Importantly, the observed difference in sales between steam and water users also reflects selection, as productive mills are more likely to use steam power. We model this selection directly and account for it when estimating γ jointly with the other parameters.

[31] We weight by the number of mills in each county-industry, for estimating these moments, because some of our moments relate to dispersion and we want these to reflect aggregate dispersion.

Baseline productivity process. We estimate the persistence of the baseline productivities π by matching the auto-correlation of log sales at the establishment level, reported in Appendix Table A.17. To help estimate the dispersion of productivities σ, we use the standard deviation of log sales within each county.

Operating costs. Given the dynamics of productivity, higher operating costs f_o^R will make firms more likely to exit. We therefore use the share of water (or steam) users that subsequently exit the market, as in Table A.14, to help estimate f_o^R.

Startup costs. Entrants have to pay $f_o^E + c(R)$ to start producing. A higher startup cost toughens the selection upon entry, increasing the relative sizes of entrant mills. We use the sales differential between incumbents and entrants (as in Figure 6) to help pin down $f_o^E + c(R)$.

Power adoption costs: Water power. We split the startup costs into general milling capital f_o^E and power-specific capital $c(R)$ by comparing water mills (who pay $f_o^E + c(W)$) to hand-powered mills (who only pay f_o^E) in our data.[32] The capital premium for water users is 0.5 log points, implying $\frac{c(W)}{f^E + c(W)} = 0.4$.

Power adoption costs: Steam power. A higher adoption cost of steam power $c_t(S)$ leads fewer firms to choose steam over water power. We use the share of establishments using steam power in 1850 and 1880, as in Figure 5, to help estimate $c_t(S)$.

Power switching barriers. Higher power out-switching barriers lead incumbents to switch power technologies less often. To help estimate the barriers that incumbents face to switch technologies, we follow Equation (23) and use the (within-county) difference in adoption shares for entrants versus incumbents, as in Figure 5:

$$\log \frac{\Pr(R|R,\varphi)}{\Pr(R'|R,\varphi)} - \log \frac{\Pr(R|E,\varphi)}{\Pr(R'|E,\varphi)} = \frac{1}{\rho} \times \left(c(R,R') + (1-\omega^R) c_{ct}(R) \right). \tag{25}$$

Entry costs. A higher entry cost will deter mills from entering the market. We use the share of producers who are entrants, as in Table 1, to inform our estimate of f^e.

V.A.2 Across-County Moments

The comparison across counties is crucial for identifying key model parameters, including the demand elasticity for milling and the strength of the steam agglomeration forces. We match four moments that are generated by comparing counties of different waterpower potentials.

[32] We do not include hand-powered mills in our broader analysis, as these mills only constitute 0.6% of total output in flour and lumber milling.

Regional cost of waterpower. The additional fixed cost of waterpower in low waterpower potential places, $c_L(W) - c_B(W)$, lowers the attractiveness of using waterpower. We, therefore, help estimate it using the relationship between waterpower potential and the share of mills using waterpower (as in Table 2).

Total demand elasticity. The total demand elasticity η determines how sensitive the demand for milling output is to milling prices. The primary moment used to identify η is the initial (1850) relationship between lower waterpower potential (which increases milling costs) and local milling activity.

Agglomeration in steam adoption. An agglomeration force in steam adoption costs (negative κ) will further boost the diffusion of steam power in the low-water region. Hence, to identify the agglomeration in power costs, we target the impact of lower waterpower on the observed use of steam power from 1850 to 1880, as in Table 3.

Agglomeration in steam productivity. An agglomeration force in steam productivity (positive α_S) will further boost economic growth in the low-water region (where steam is diffusing faster). Hence, to identify the agglomeration in steam productivity, we target the impact of lower waterpower on output growth from 1850 to 1880, as in Table 3.

V.A.3 Calibrated Parameters

We calibrate the following parameters outside the estimation routine.

Firm demand elasticity. In our model, mills charge a constant sales-to-cost markup $\frac{1}{\epsilon-1}$ over variable costs (materials and labor). In Appendix A, we calculate that the median sales-to-cost markup among flour and lumber mills is 20%, implying a firm demand elasticity of 6. In comparison, modern estimates range between 3 and 11 (Asker, Collard-Wexler and De Loecker, 2014; Coşar, Guner and Tybout, 2016; Sedláček and Sterk, 2017; Felbermayr, Impullitti and Prat, 2018; Acemoglu et al., 2018; Buera et al., 2021), and are relatively large in milling (Broda and Weinstein, 2006).

Time discounting. The discount factor (denoted as δ) is calibrated to reflect an annual interest rate of 6%. In Section V.C.2, we support the forward-looking assumption by demonstrating that ignoring future returns (a scenario with $\delta = 0$) would imply an implausibly low estimate for the startup capital cost of milling.

Sunk costs. Our baseline setup assumes that water and steam capital is fully sunk and sets ω^R to zero. We also explore robustness to allowing for partial recovery of these costs, setting ω^R to 0.35 based on modern estimates by Kermani and Ma (2023).

Convergence rate for steam technology. The parameter $c_S^{(slope)}$ governs how fast steam adoption costs fall from its initial state $c_S^{(init)}$ to its mature state $c_S^{(term)}$. We set the convergence rate to 4% per year, which implies that steam power matures by 1890. This assumption is consistent with the long-run diffusion patterns in Jovanovic and Rousseau (2005) and aligns with the power cost estimates presented in Atack (1979). We show that the estimated model can match the steam diffusion patterns in all decades from 1850 to 1880, despite fixing the convergence rate to this literature-informed value.

Dispersion of cost shocks. We set the dispersion parameters ρ and ρ_o to 2, equivalent to about 6.5% of median 1850 sales. These values fall within the range of estimates in the literature (Chernoff, 2021; Humlum, 2022) and imply a limited amount of idiosyncratic variation in power and operation costs. We verify that our results are robust to both halving and doubling the dispersion parameters. As a validation of the amount of idiosyncrasies in power and exit choices, we validate that our estimated model can match the observed overlap in firm size distributions between steam and water users (as in Figure A.12) as well as the overlap between exiting and surviving firms (as in Figure 6).

V.A.4 Estimation Procedure

We use an adapted Newton-Rhapson method to estimate our structural model. Appendix G.1 details the algorithm and validates the method's robustness. In particular, we ensure that the estimated model satisfies the parameter-moment relationships predicted in Sections V.A.1-V.A.2 above and that the algorithm converges to the same best-fit estimates from a wide variety of starting values.

V.B Estimation Results

V.B.1 Model Fit

Table 7 shows the targeted moments and how well the model does at matching the data. We exactly identify and estimate 15 parameters using 15 target moments. Due to the robust and monotone relationships between parameters and moments described in Sections V.A.1-V.A.2, our estimation procedure matches the target moments exactly. In Section V.C, we conduct overidentification tests of the model by comparing model simulations to the non-targeted regressions from Section II.B.

V.B.2 Parameter Identification

Appendix G.2 conducts a formal analysis of our sources of parameter identification, following the local sensitivity measures proposed by Andrews, Gentzkow and Shapiro (2017). In particular, we verify that the relationship between moments and parameters have the signs and magnitudes predicted in Sections V.A.1-V.A.2. The analysis also highlights the importance of estimating the model parameters jointly, as many parameters affect multiple target moments simultaneously.

V.B.3 Parameter Estimates

Table 8 reports our estimated parameters. We discuss the estimated magnitudes below and, when possible, compare them to estimates in the literature and from contemporaneous sources.

Productivity. Steam power γ lowers marginal production costs by about 9.3%. This structural estimate falls within the range of existing estimates of the efficiency of steam engines vs. waterwheels in the 19th century (Atack, 1979; Crafts, 2004; Chernoff, 2021). Our estimated parameters for the baseline productivity process (π, σ) are remarkably close to estimates from modern data (Bachmann and Bayer, 2014; Coşar, Guner and Tybout, 2016; Schaal, 2017; Ottonello and Winberry, 2020).

Operating costs. The operating costs of steam power f_o^S are larger than those of water power f_o^W, constituting 30% and 10% of 1850 median sales, respectively. Large operating costs of steam are consistent with the qualitative evidence that steam engines required more upkeep and reflect the fact that steam users exit at a higher rate, despite being larger and more productive (as in Table A.2 and Figure A.11). Swain (1888) estimates that the annual fixed costs of steam and waterpower were around \$20 and \$10 dollars per horsepower, which applied to 1850 firm medians are around 16% and 8% of annual sales.

Startup costs. The startup cost of setting up a watermill f_o^E is around 44% of annual sales. These inferred costs are close to the capital stocks of water users directly observed in our data, as the capital stock of the median water mill in 1850 represents 41% of its annual sales.

Power adoption costs. Figure A.15 plots the estimated adoption costs of water and steam power over time. Waterpower in the baseline region $c_B(W)$ had an upfront cost of around 425 dollars in 1850, equivalent to about 18% of 1850 median sales. Steam initially had a higher upfront cost, as the availability of steam engines was limited. In 1850, the upfront cost of steam power $c_{1850}(S)$ was about 625 dollars or 26% of median sales. By comparison, in our 1850 data, the typical water and steam mills had, respectively, around \$500 and \$2000 more capital installed than the hand-powered mills. As steam became more available and adaptable, the upfront cost of steam fell below water, converging to a level of around 9% of annual sales. Our estimated magnitudes are somewhat smaller than contemporaneous accounts that 20 horsepower engines – including the boiler and other associated equipment – cost \$2,500 in the 1840s and \$2,000 in the 1880s (Armistead, Lawson and Long, 1841; Emery, 1883; Atack, Bateman and Weiss, 1980). Nevertheless, Emery (1883) reports that the purchase prices of steam and waterpower were similar in 1880, which is consistent with our estimates. The continued use of waterpower in this later period reflects lower operating costs, idiosyncratic shocks, and switching costs.

Power switching barriers. The barrier to switching from water to steam includes sunk capital $(1-\omega^W)c(W)$, and other switching costs $c(W,S)$. This total switching barrier from water constitutes 19% of 1850 median annual sales or just above two months' worth of revenue. Notably, fully sunk water capital ($\omega^W = 0$) can account for the vast majority of these switching barriers (93%), as residual switching costs $c(W,S)$ only represent 1.4% of annual sales. Sunk steam capital ($\omega^S = 0$) similarly accounts for the majority (82%) of switching barriers from steam to waterpower, though we estimate larger costs of switching from steam to water, perhaps due to the importance of location for waterpower.

Regional cost of waterpower. The additional water cost in the low-water region $c_L(W)$, 106 dollars, is around a quarter of the cost in the baseline region. By comparison, Atack, Bateman and Weiss (1980) estimate that the average water-horsepower for all manufacturing in 1850 cost 67 percent more in the Midwest compared to New England.[33] One reason why our numbers might be smaller is that millers were relatively small power users, and therefore less affected by more-limited local waterpower.

V.C Model Validation

In this section, we examine the validity of our estimated model of steam adoption. First, we reproduce a series of non-targeted regressions from Section II.B on how waterpower potential shapes steam adoption and economic growth of incumbents and entrants. Second, we examine the validity of two key model features: the forward-looking behavior of establishments and agglomeration effects in steam power.

V.C.1 Testing the Model: Reproducing Regressions

In Table 9, we compare the data patterns in Tables 3, 4, and 5 to the patterns we find when we run equivalent regressions on simulated data from our model.

Table 3 shows that higher water costs cause faster steam adoption, and Table 5 shows that this is driven by entrants. However, over time the effect of local waterpower potential diminishes. Our estimated model demonstrates the same pattern. This is because higher costs of water affect steam adoption among incumbents by: making steam power a comparably cheaper technology (a *technology cost* effect), strengthening the selection of operating mills (a productivity *selection* effect), and weakening competition in local product markets (a *competition* effect). These effects are reinforced by an *agglomeration* effect in steam power. The *technology cost*, *selection*, *competition*, and *agglomeration* effects all lead to more steam

[33] On average, counties in the Midwest have around 1.1 standard deviations less waterpower potential than counties in New England.

use in places with higher water costs. Incumbents differ from entrants due to switching barriers, which make their steam adoption decisions less responsive to the cost of waterpower. Places with less waterpower potential approach their steady-state use of steam power earlier. As a result, along the diffusion curve, the effect of waterpower potential on the *growth* in steam use diminishes and reverses over time, though in *levels* places with less waterpower potential are always more likely to use steam power.

Table 3 also shows that higher water costs cause faster output growth, and Table 5 again shows that this is driven by entrants. Our estimated model replicates this pattern. As described above, cheaper steam costs affect operating values through the *technology cost*, *agglomeration*, *competition*, and *continuation value* channels. While the negative *competition* effect is shared among all establishments, the positive *technology cost* and *agglomeration* effects depend on steam adoption, and on net lead to increased steam use and output growth.

Our estimated model is also able to match the two potentially incongruous facts that incumbents in low waterpower places are both (1) more likely to invest and switch to steam power (Table 5) and (2) more likely to exit (Table 4). This reflects countervailing forces that dominate in different parts of the firm-productivity distribution: incumbents in places with low waterpower potential places are relatively high productivity, and this selection means that (all else equal) they are more likely to choose to switch from steam power. However, the increased entry and greater steam-use in places with low waterpower potential lowers the local price index, which lowers survival rates for the marginal incumbents (of which there are more in places with less waterpower potential).

V.C.2 Validating Model Features

Forward-looking behavior. Forward-looking expectations are at the heart of our adoption model: some establishments adopt steam power even though they anticipate that adoption costs will continue to fall, and other establishments choose water power, even knowing that they will face switching barriers if they later want to scale up production with steam power.

To illustrate the importance of allowing for expectations, we re-estimate the model assuming that establishments are fully myopic ($\delta = 0$) and compare our estimates to external benchmarks. We find that myopia would imply an implausibly low estimate for the startup capital cost of milling. Intuitively, firms would not be willing to pay high fixed startup costs if they did not care about the future. In particular, under myopia, we estimate that the total startup costs $f_o^E + c(W)$ would need to be less than 10% of median firm sales to rationalize the firms we see enter. By contrast, the median water mill in our data has a capital stock worth 41% of annual sales. Importantly, this external estimate is much closer to the 44% of sales we estimate in Table 8 when allowing decisions to incorporate future returns ($\delta > 0$).

Agglomeration. Agglomeration effects in steam power are one prominent reason why adoption may be inefficiently slow, motivating a potential role for policy intervention. While Section II.C provides suggestive evidence of agglomeration spillovers, through backward linkages, we can now use the estimated model to directly assess the quantitative importance of agglomeration effects in driving the economic impacts of steam power.

Increasing the local share of steam users from 0 to 100% further boosts the productivity of steam power by $\alpha = 2.5\%$ (over its baseline level of 9.3%). This agglomeration effect on marginal costs, potentially due to the increased local knowledge base as evidenced by the relative increase in steam makers, has a meaningful impact on the aggregate economic growth from steam power. In particular, in Table A.18 we estimate the model while forcing $\alpha = 0$, and find that this constrained model can only account for around half of the differential growth we observe in the low-water region.

By contrast, we do not find economically significant agglomeration effects in steam purchase prices. Increasing the local share of steam users from 0 to 100% slightly increases the steam adoption cost by 1.8% of 1850 median sales (over a baseline level of 18%). In particular, in Table A.18 we estimate the model while forcing $\kappa = 0$, and find that the constrained model can nevertheless still explain the differential steam adoption and economic growth in the low-water region. One interpretation of this result is that it suggests that information about the existence of steam, and it's broad costs and benefits, was not a barrier to adoption: having more steam using neighbors did not make mills more likely to adopt, other than through the measured productivity spillover.

VI Counterfactual Experiments

In this section, we use our estimated model to assess the determinants of technology diffusion and to evaluate policies aimed at alleviating barriers to adoption. In Section VI.A, we first evaluate the importance of establishment level water costs and switching barriers for the aggregate diffusion of steam power. In Section VI.B, we evaluate a "cash-for-clunkers" style program that pays mills to switch from water to steam by buying the mills' sunk water capital. Finally, in Section VI.C, we show how the interaction of switching barriers and the new technology's high fixed costs leads to slow aggregate technological diffusion, whereas technology diffusion is much faster if there is only one of these.

VI.A Power Costs and Switching Barriers

Our results in Section II.B show the importance of local waterpower potential for the adoption of steam power. In Figure 8, Panel A, we simulate the share of mills using steam power in the baseline region, and in a region with one standard deviation lower waterpower potential. Higher costs of waterpower induce the use of steam: low waterpower places reach the value of the baseline steady-state steam share around 20 years faster, and ultimately experience a 20% higher steady-state steam share.

Our findings in Section II.B suggest that switching barriers prevented incumbents from benefiting from steam power. In Figure 8, we evaluate the importance of establishment-level switching barriers for the aggregate diffusion of steam power. We simulate the arrival of steam in two counterfactual worlds: one where water mills face no switching barriers and choose power sources as freely as entrants ($\omega^W = 1, c(W, S) = 0$), and one where water mills face insurmountably high costs of switching ($c(W, S) \to \infty$), respectively labeled "No Water Lock-In" and "Full Water Lock-In." Entrants are free to choose their power source in either of the scenarios.

Figure 8, Panel B, plots the diffusion curves for steam power in these counterfactual worlds. The simulations yield several insights into the role of switching barriers for aggregate steam diffusion. Switching barriers substantially delay steam adoption despite substantial entry and exit in the economy. For example, compared to the scenario with full water lock-in, the economy is 25 years faster to reach a steam adoption rate of 30% when water mills face no switching barriers (1850 vs. 1880). Switching barriers matter the most in the middle of the diffusion curve, when more establishments are on the margin of choosing steam power. Nevertheless, switching barriers never cease to be important and lower steam adoption by about eight percentage points even in the terminal steady state.

Our baseline economy falls about halfway in between the "Full Water Lock-In" and "No Water Lock-In" scenarios. Hence, to understand steam adoption in our data, it is important to both allow for switching but also acknowledge that these actions are subject to substantial barriers. Our baseline economy is closer to the "Full Water Lock-In" scenario early on the diffusion curve but then, over time, converges to the "No Water Lock-In" scenario. This suggests that technology switching is particularly important for the acceleration in steam adoption that we see in our data period from 1850 to 1880.

VI.B Cash-for-Clunkers Policy Counterfactual

The existence of agglomeration spillovers could make steam adoption inefficiently slow. Section VI.A showed that switching barriers cause substantial delays in steam diffusion. Further, these barriers may bar incumbents from benefiting from steam, ultimately driving them out of business.

This section evaluates counterfactual policies intended to address these concerns. In particular, we evaluate policies that subsidize water incumbents to switch to steam power by fully offsetting the switching barriers: purchasing the incumbents' waterpower infrastructure and covering any further switching costs. These policies are motivated by the 2009 "cash-for-clunkers" program (Blinder, 2008), which lasted for two months and incentivized drivers to trade in old (fuel-inefficient) cars for new ones. We consider the effects of temporary policies and a permanent policy.

Figure 9 shows the effect of different counterfactual policies, as well as their annual costs. Panel A shows the counterfactual effects of a one-year-only policy, implemented in 1850. Many establishments take advantage of the subsidy, and the share of mills using steam power instantaneously doubles. However, the share falls over time and, by 1865, there is no legacy of the program on the share of establishments using steam power. While agglomeration can lead to short-run subsidies having persistent effects, in principle, our estimated agglomeration effects are too small for "big-push" effects to occur.

Panel C shows the counterfactual effects of a policy lasting for 20 years, again starting in 1850. As with the one-year program, many marginal establishments switch instantaneously, but fewer because some prefer to wait (understanding that they can still take advantage of the policy later). This counterfactual policy highlights the importance of allowing for forward-looking entrepreneurs, as there is a spike in steam adoption (and therefore program cost) in the last year of the policy.[34] While the programs are effective in raising contemporaneous steam adoption, these effects fully disappear within two decades because the agglomeration benefits from steam are too small to lead to persistent effects.

Panel E shows that with a permanent policy, steam diffusion is exactly the same as in the counterfactual with no-switching barriers (shown in Figure 8). While the steady-state increase in steam-use is small, the costs are very high because many subsidized steam switchers would have entered with steam power, without the subsidy, to avoid future switching barriers.

VI.C Fixed Costs and the Speed of Diffusion

The aggregate importance of switching barriers may seem surprising given the substantial amount of entry and exit observed in our data. For example, from one decade to the next, about 80-85% of establishments go out of business and are replaced by new entrants who can choose power sources freely. How can switching barriers continue to matter if most establishments are entrants? The answer is that waterpower continued to appeal to entrants far along the transition path to steam. In particular, waterpower had lower purchase prices (at the start of our sample) and lower fixed costs of operation, which appealed to less-productive entrants who did not yet have the scale to benefit from steam power. However, when some of these entrants later became successful businesses with higher productivity, they faced switching barriers to scaling up with steam power. Importantly, these "entrant lock-

[34]This is consistent with modern evidence on bunching at the expiration of subsidy policies (Chen, 2024).

ins" are not indicative of "mistakes" in adoption decisions. On the contrary, entrants in our model choose waterpower fully anticipating that they will be locked in if their productivity increases in the future.

To conclude our counterfactual analysis, we explore how the interaction of fixed costs and switching costs affects technology diffusion. We show that a higher fixed purchase price slows adoption of a new technology, in the presence of switching costs, holding fixed the overall attractiveness of the new technology. To do this, we consider two hypothetical technologies that are equally attractive (so their steady-state adoption rates are 50%), but they have different purchase prices and different marginal costs. Specifically, technology 1 ("High FC & low MC") has a marginal cost advantage equal to our estimated steam marginal cost advantage over water, while technology 2 ("Low FC & high MC") has a lower fixed adoption cost chosen such that its steady-state adoption rate is 50%. Otherwise, we hold all parameters fixed at those we estimate for water power (such as demand elasticities, overhead costs, and idiosyncratic shocks).

Figure 10 plots the diffusion speed of new technologies in this environment. As a benchmark, the gray line shows the importance of switching costs: if the economy starts with technology 2, and we introduce an *identical* technology, it takes 16 years for the new technology to approximately reach steady-state penetration. The black line shows that higher fixed costs slow adoption: if technology 1 is introduced into an economy that only has technology 2, the adoption shares take 36 years to reach 50% each. Conversely, the dashed line shows that lower fixed costs raise adoption speed: if technology 2 is introduced into an economy that only has technology 1, the adoption shares take only two years to reach 50% each.[35] These estimates are all driven by the interaction of fixed costs and switching barriers: in the absence of switching barriers, diffusion would be instantaneous regardless of the relative costs of the technologies.

VII Conclusion

This paper studies the diffusion of steam power in milling in the late 19th century. Steam power was a general purpose technology that alleviated the dependence of mechanized power on local geography. The adoption of steam power, and its impacts, depended on places' access to water power. Indeed, a general feature of new technologies is their impacts vary with differences in access to previously-available alternative technologies. Even as steam technology improved, and became increasingly more cost-effective than water power in more places and for more firms, incumbents were resistant to change.

[35]In this case, technology 2 even overshoots and reaches over 50% penetration in the short-run. This is because, initially, the price index is relatively high and so low-productivity establishments (who prefer technology 2) are briefly able to profitably produce before getting crowded out in steady-state.

To understand the effect of steam power on milling, this paper makes several contributions. We compile a previously undigitized full panel microdataset of manufacturing plants in the United States during the Second Industrial Revolution. We link the data to the geographic distribution of waterpower potential, which allows insights into the diffusion of steam power: places with less waterpower potential adopted more steam power, earlier, and steam adoption was driven predominantly by entrant mills.

We emphasize dynamic effects: that prior use of waterpower created lock-in effects, which discouraged steam adoption, and generated leapfrogging by entrants. We estimate a dynamic equilibrium model of entry and investment to characterize the forces that determine technology use across space and time.

There was substantial entry of new mills in this era, which might seemingly minimize the aggregate influence of technological lock-in. Nevertheless, technological diffusion was slow. We show that technological diffision was slowed by incumbent sunk costs and other switching costs – despite substantial entry – because the new technology was a relatively high fixed cost technology (and scalable with low marginal cost). The interaction of high fixed costs and switching barriers is what slows aggregate technology adoption, whereas either feature on its own has little effect on adoption speeds. High fixed costs made smaller entrants predisposed to use the old technology (the low-initial-cost and high-marginal-cost technology). These entrant firms became stuck with waterpower, even if their productivity grew, due to switching barriers that were even anticipated by entrants.

This feature of the model – that switching costs influence the pattern of aggregate technology adoption even with substantial entry – can explain a general slow diffusion of new technologies that particularly benefit larger firms. In contrast, many recent quickly-embraced innovations, such as cloud computing (Lu, Phillips and Yang, 2023), allow small firms to use new technologies without substantial fixed investments. Technologies that Comin, Hobijn and Rovito (2006) document as having diffused the fastest are often characterized by having low switching costs (ATMs, credit card readers, pesticides). Steam power illustrates the slow diffusion of technology, from switching costs, when the new technology has high fixed costs.

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Figure 1. Components of County Waterpower Potential

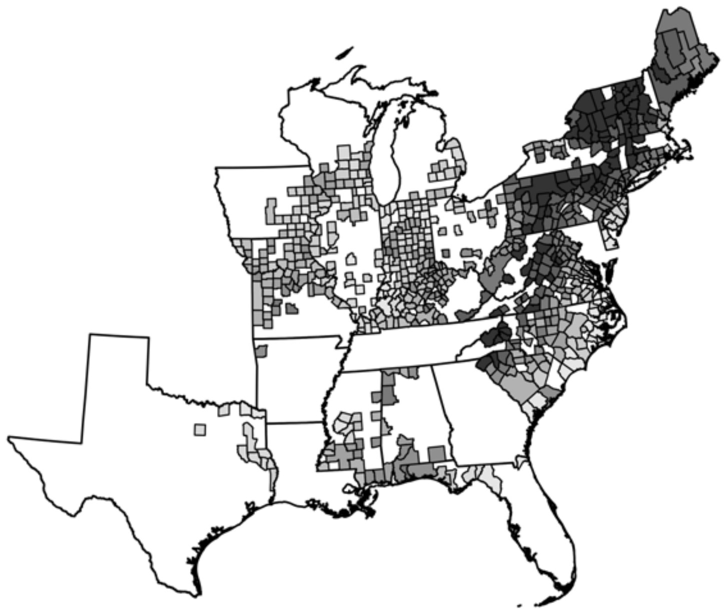
Panel A. Flow Rate of River Segments

Panel B. Fall Height of River Segments

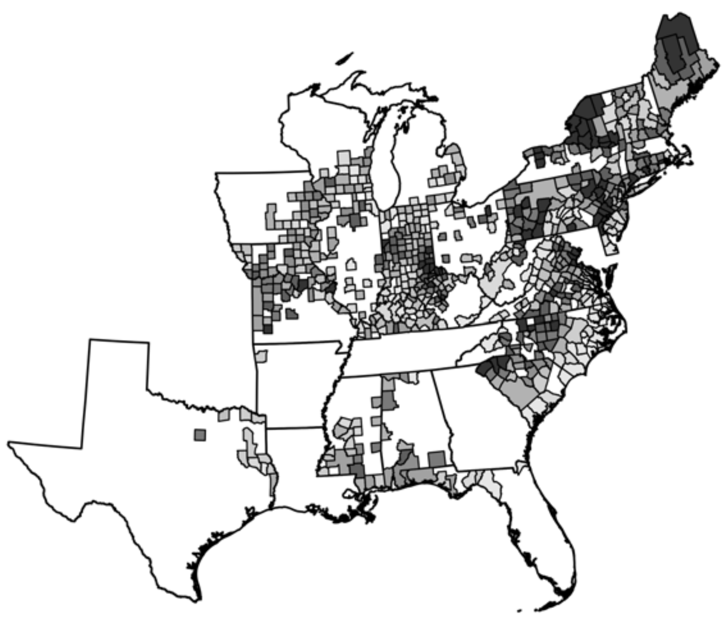
Notes: This figure plots the sources of waterpower potential in the United States, with darker shares corresponding to greater flow rates or fall heights. Panel A plots our estimated flow rates for each river segment, in cubic feet per second. Panel B plots the drop in elevation for each river segment, in feet per mile. Data from NHDPlusV2.

Figure 2. County Waterpower Potential, Measured and Residualized

Panel A. County Waterpower Potential, Measured



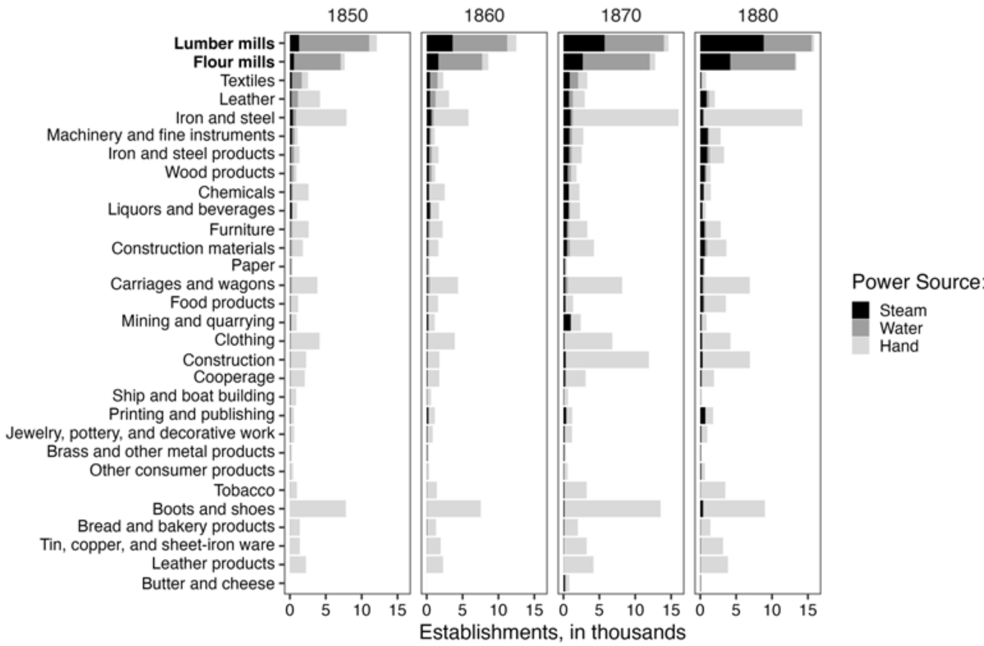
Panel B. County Waterpower Potential, Residualized



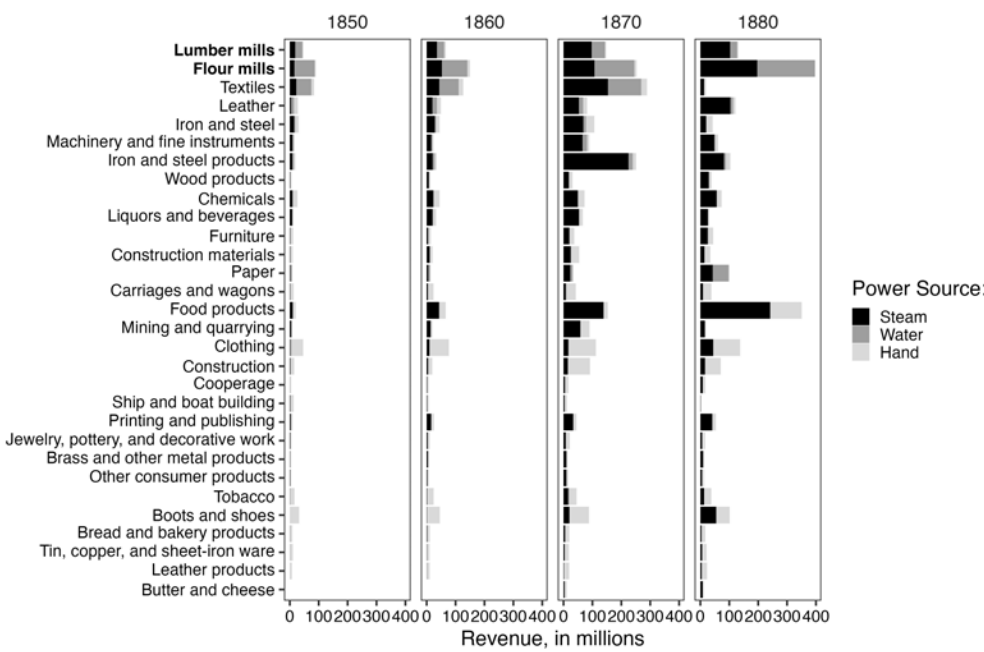
Notes: This figure shows our estimated county waterpower potential, with darker shares corresponding to greater waterpower potential deciles. The sample is restricted to our main balanced panel of 690 counties. Panel A shows our measure of county waterpower potential: summing across all river segments in the county the flow rate of the river segment times its fall height (and a gravitational constant), per square mile. Panel B shows the residual county waterpower potential, after controlling for our main baseline controls: total county water flow and terrain ruggedness; the presence of a navigable waterway, distance to the nearest navigable waterway, and county market access in 1850; the presence of coal in the county, the share of county area covered by coal deposits, and market access to coal deposits. Data from NHDPlusV2.

Figure 3. Power Source By Industry

Panel A. Number of Establishments, by Power Source

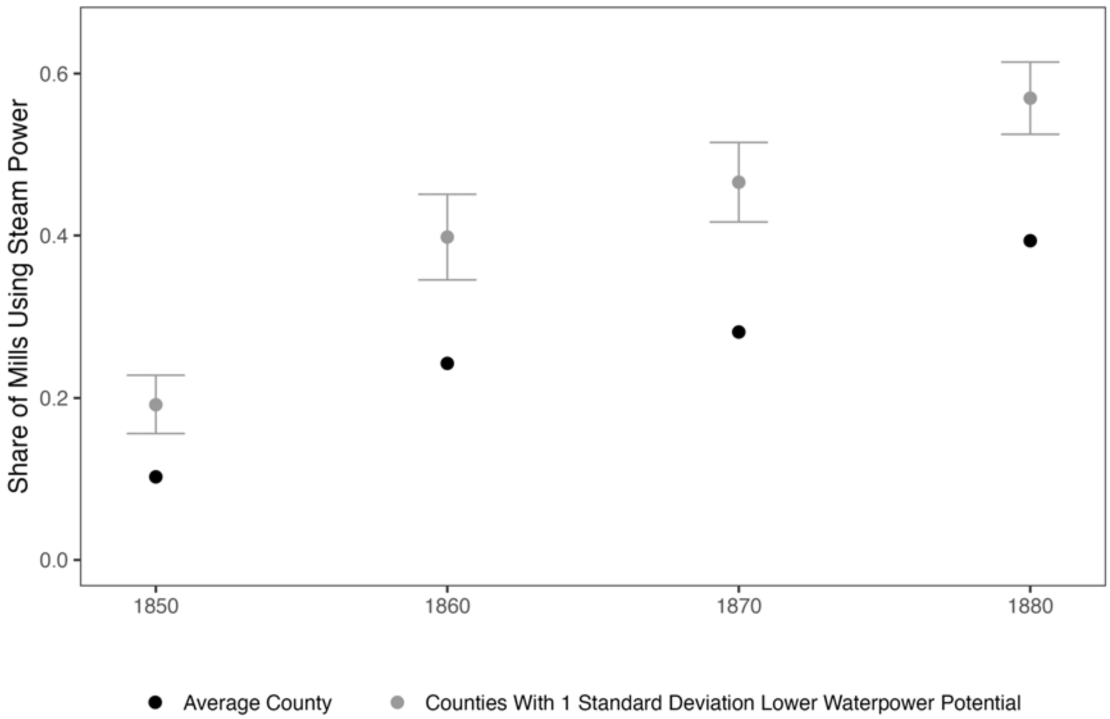


Panel B. Total Revenue, by Power Source



Notes: This figure plots power-use, by industry and decade. Industries are sorted by the number of establishments using either steam or water power in 1850 (in decreasing order). Panel A shows the number of establishments in each industry using steam, water, and hand power. Panel B shows the total revenue produced in establishments using steam, water, and hand power. We define "steam" to include all establishments using any steam power; "water" includes establishments using water power and no steam power; "hand" includes the remaining establishments that use neither steam nor water. Data from our digitized establishment-level Census of Manufactures (1850-1880).

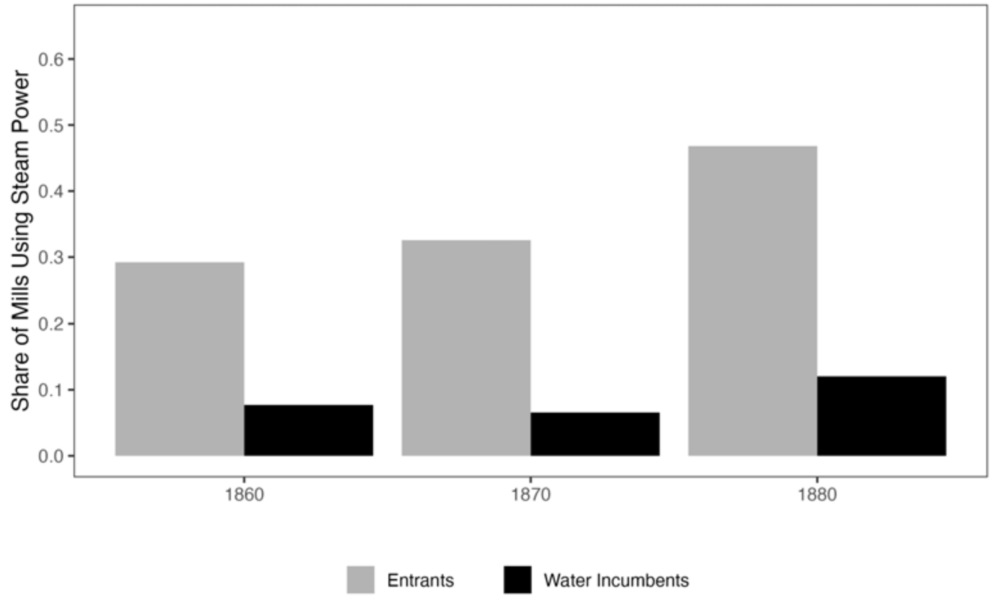
Figure 4. Share of Mills using Steam Power, by Decade and County Waterpower Potential



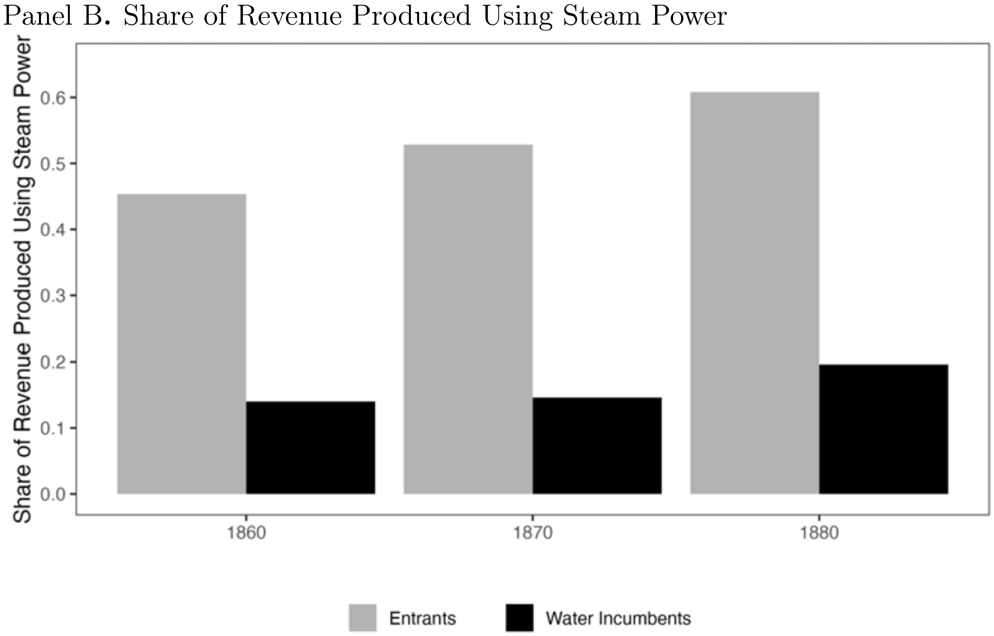
Notes: Darker circles represent the share of mills using steam power in the average county (or "baseline"). For the lighter circles, we add the estimated increase in steam share from a one standard deviation decrease in county waterpower potential (or "low waterpower") as in Table 2, with an indicated 95% confidence interval. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Figure 5. Steam-use Share, for Entrants and Water Incumbents

Panel A. Share of Mills Using Steam Power

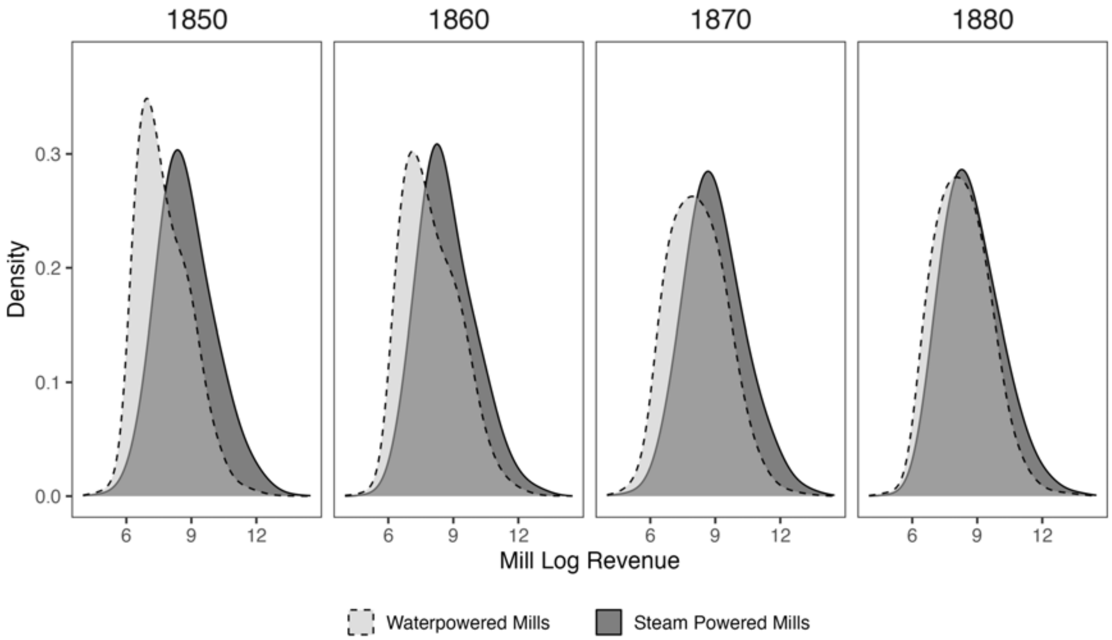


Panel B. Share of Revenue Produced Using Steam Power



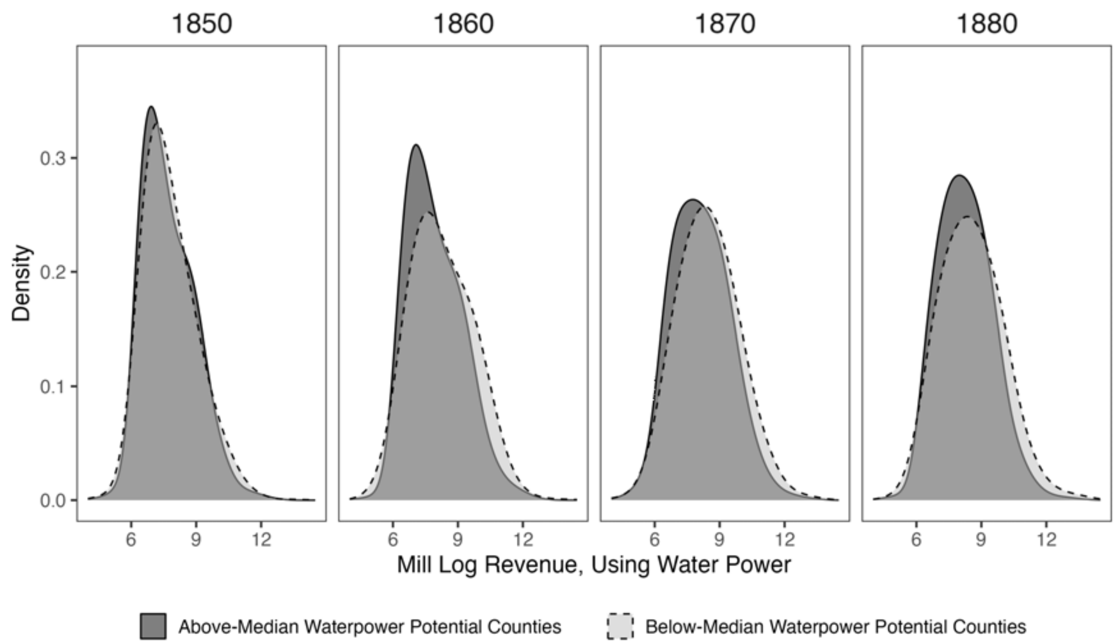
Notes: This figure shows steam-use rates, by mill type ("Entrant Mills" and "Water Incumbent Mills"). Entrants began operations after the prior Census. Water Incumbents used water power in the prior Census. Panel A shows the share of mills using steam power, for each mill type. Panel B shows the share of revenue produced using steam power, for each mill type. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure 6. Mill Size Distribution, by Power Source

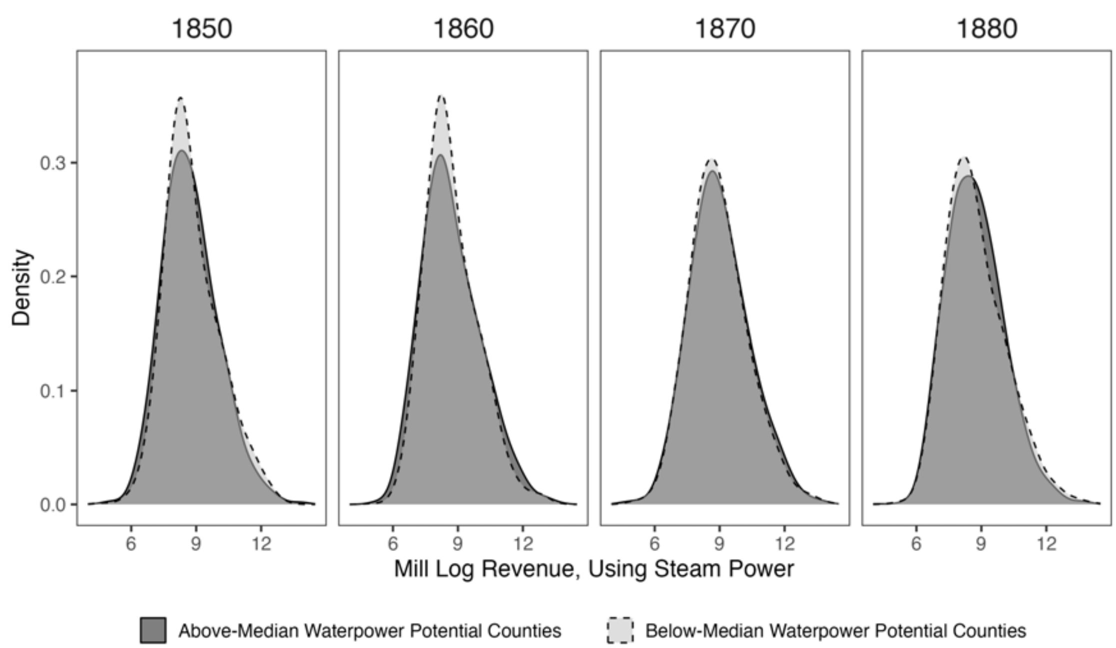


Notes: This figure shows the distribution of mill revenue, by power source, in each decade. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure 7. Mill Size Distribution, by County Waterpower Potential
Panel A. Revenue Distribution of Water-Using Mills



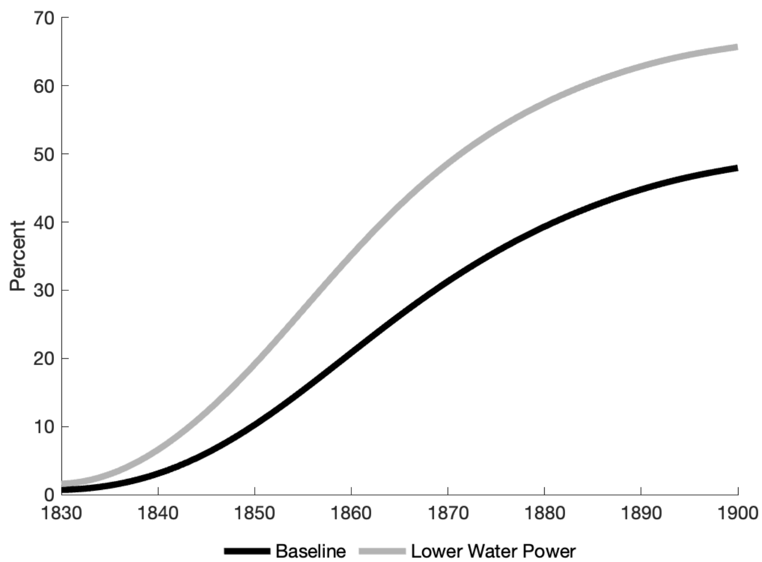
Panel B. Revenue Distribution of Steam-Using Mills



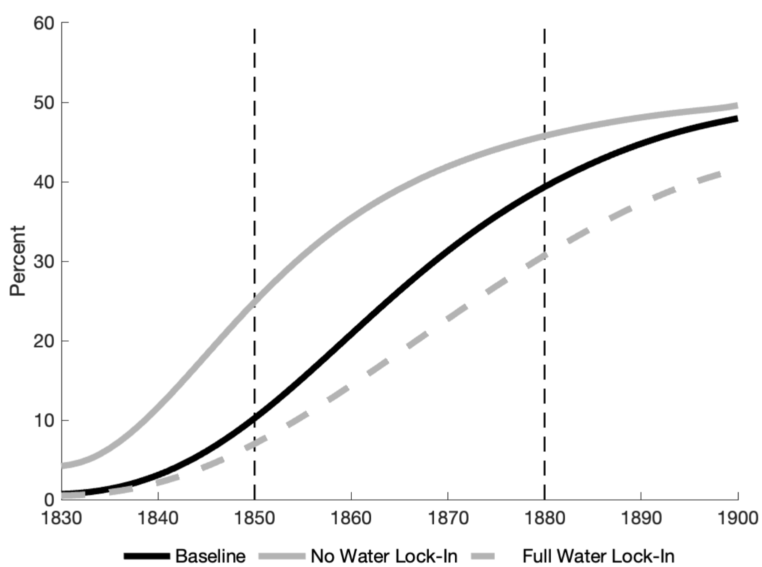
Notes: This figure shows the distribution of mill revenue in each decade, separately for counties with above-median and below-median waterpower potential. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Figure 8. Switching Barriers and the Diffusion of Steam Power

Panel A. Water Costs and Steam Adoption

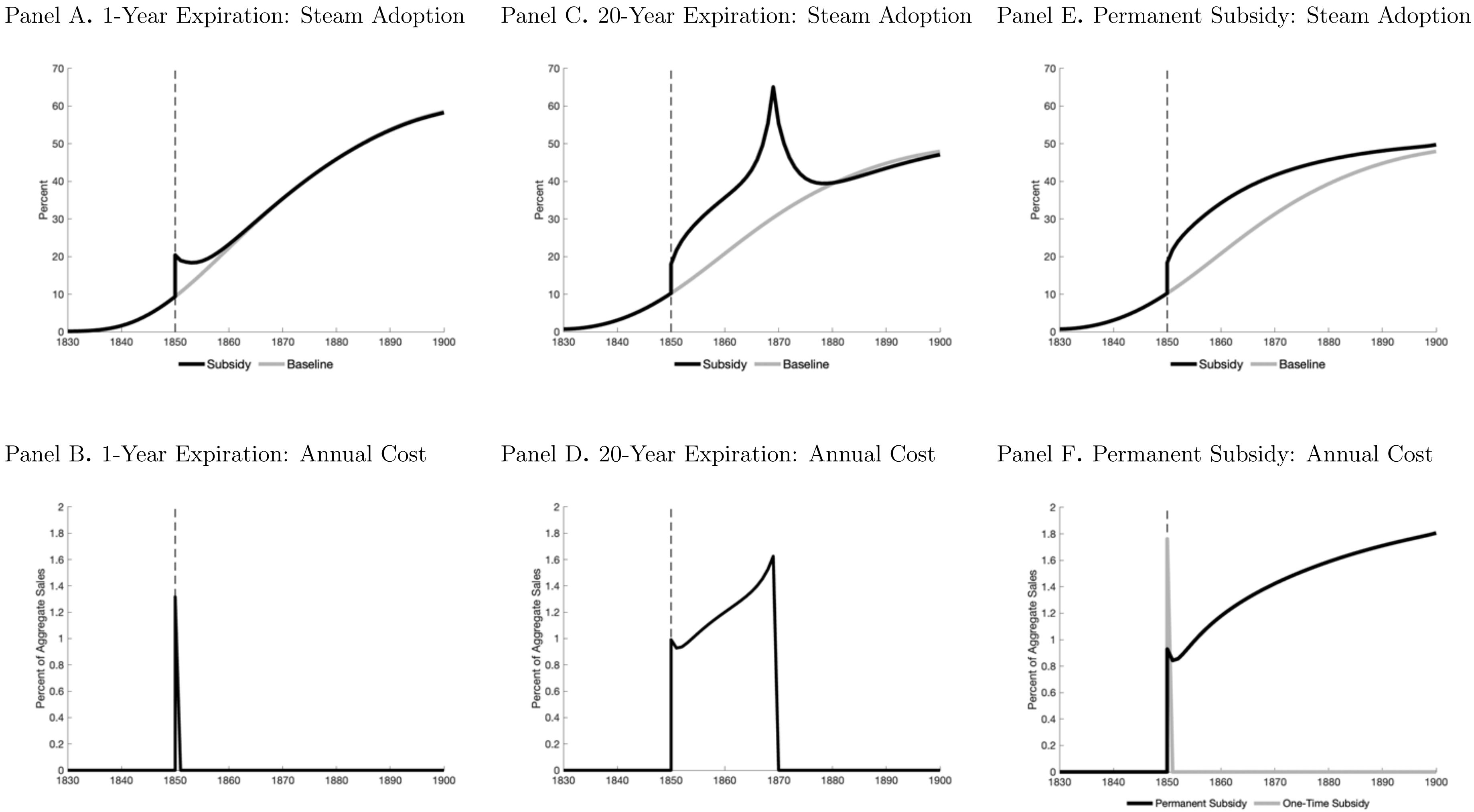


Panel B. Switching Barriers and Steam Adoption



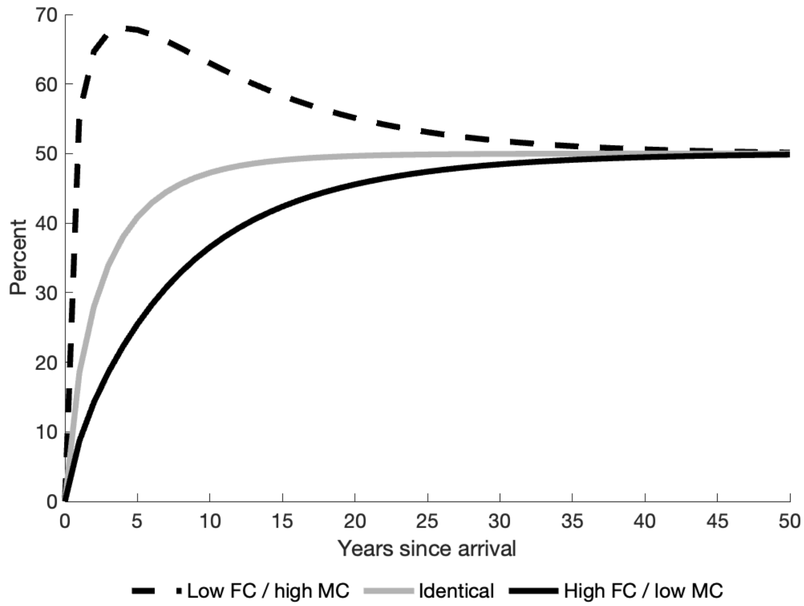
Notes: Panel A plots the model estimates for the share of steam users in the average county and the typical county with one standard deviation less waterpower potential. The only parameter difference between the dark gray line (baseline) and light gray line (low waterpower potential) is the fixed cost of waterpower adoption. Panel B plots the model estimates for the share of steam users as a function of switching barriers. The dark gray line shows diffusion for our baseline estimates, the light gray line removes switching barriers ($\omega^W = 1, c(W, S) = 0$) and the dashed line represents prohibitive switching barriers ($c(W, S) \to \infty$). Data from the 1850-1880 Census of Manufacturers and NHDPlusV2

Figure 9. Water-to-Steam Switching Subsidies: Steam Adoption and Annual Costs



Notes: This figure simulates counterfactual "cash-for-clunkers" policies that pay water incumbents ($c_{ct}(W,S)$) to switch to steam power (exactly offsetting the switching barriers). Panel A shows the diffusion of steam power with a one-year-only policy in 1850, and Panel B shows its annual costs. Panel C shows the diffusion of steam power after a policy that starts in 1850, and Panel D shows its annual costs. Panel E shows the diffusion of steam power after a permanent policy introduced in 1850, and Panel F shows its annual costs. All three panels compare the counterfactual diffusion of steam power (in black) to the factual diffusion (in gray). Panel E shows the annual cost of the policies, as a share of total revenue in milling.

Figure 10. Technology Diffusion and Fixed Costs



Notes: This figure simulates the diffusion speed of new technologies under various scenarios. One technology ("High FC/ low MC") has a marginal cost advantage equal to our estimated steam's marginal cost advantage over water in 1900, while the other technology ("Low FC/ high MC") has a lower fixed cost, chosen such that in an economy with both, the steady-state adoption rate of each is 50%. Otherwise the technologies have the same parameters as those we estimate for waterpower. The gray line shows the diffusion of introducing the latter technology in an environment that already has its equivalent (so the old and new technologies are identical other than for idiosyncratic shocks). The black line shows the diffusion of the former technology in an environment that already has the latter. The dashed line shows the diffusion of the latter technology in an environment that already has the former. The x-axis is years (the new technology is introduced in year 0), and the y-axis is the share of establishments using the new technology. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 1. Composition of Milling

	Share of Total Milling					Share of Steam Milling		
	Steam Entrants (1)	Water Entrants (2)	Steam Incumbents (3)	Water Incumbents (Switchers) (4)	Water Incumbents (Stayers) (5)	Entrants (6)	Steam Incumbents (7)	Water Incumbents (8)
Panel A. Establishments								
1860	0.23	0.56	0.01	0.01	0.18	0.90	0.05	0.06
1870	0.28	0.58	0.03	0.01	0.11	0.90	0.07	0.03
1880	0.37	0.42	0.06	0.02	0.14	0.84	0.11	0.05
Panel B. Revenue								
1860	0.36	0.43	0.04	0.02	0.15	0.85	0.09	0.06
1870	0.43	0.38	0.08	0.02	0.09	0.83	0.14	0.03
1880	0.44	0.29	0.10	0.03	0.14	0.77	0.17	0.06

Notes: Columns 1–5, in Panel A, show the share of total mills that are steam entrants, water entrants, steam incumbents, or water incumbents (distinguishing between those who switched to steam and those who stayed with waterpower). Columns 6–8 show the share of steam mills in each decade that are steam entrants, steam incumbents, or water incumbents. Panel B reports corresponding numbers for the share of total revenue produced by each mill type. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Table 2. Mill Activity in 1850, by County Waterpower Potential

	All Mills (1)	Only Lumber Mills (2)	Only Flour Mills (3)
Panel A. Number of Waterpowered Mills			
Lower Waterpower	-1.055	-1.246	-0.783
	(0.130)	(0.173)	(0.109)
Panel B. Revenue of Waterpowered Mills			
Lower Waterpower	-1.127	-0.974	-1.178
	(0.249)	(0.215)	(0.302)
Panel C. Steam Share of Mills			
Lower Waterpower	0.089	0.107	0.060
	(0.015)	(0.019)	(0.016)
Panel D. Steam Share of Revenue			
Lower Waterpower	0.123	0.160	0.060
	(0.022)	(0.031)	(0.021)
Panel E. Total Number of Mills			
Lower Waterpower	-0.956	-1.100	-0.738
	(0.119)	(0.156)	(0.105)
Panel F. Total Revenue of Mills			
Lower Waterpower	-0.876	-0.704	-0.973
	(0.215)	(0.173)	(0.291)
# County-Industries	1,199	612	587

Notes: This table shows the relationship between mill activity in 1850 and county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Each panel shows the effect of waterpower potential on a different outcome in 1850: the total number of waterpowered mills (Panel A); the total revenue of waterpowered mills (Panel B); the share of mills using steam power (Panel C); the share of milling revenue from using steam power (Panel D); the total number of mills (Panel E); and total mill revenue (Panel F). Column 1 reports pooled estimates from county-industry regressions, for lumber and flour milling; Column 2 restricts the sample to lumber mills only; and Column 3 restricts the sample to flour mills only. Panels A, B, E, and F use (pseudo) Poisson maximum likelihood estimation (PPML), which approximate percent differences. Panels C and D are OLS regressions, weighting county-industries by their number of mills, which reflect percentage point differences in the shares.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850) and NHDPlusV2.

Table 3. Steam Diffusion and Mill Growth, by County Waterpower Potential

	Steam Share of Mills (1)	Total Mills (2)	Total Mill Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.067	0.220	0.183
	(0.016)	(0.062)	(0.081)
# County-Industries	1,084	1,199	1,199
From 1860 to 1870	0.034	0.113	0.203
	(0.013)	(0.052)	(0.097)
# County-Industries	1,061	1,199	1,199
From 1870 to 1880	-0.009	0.092	0.140
	(0.013)	(0.036)	(0.087)
# County-Industries	1,138	1,199	1,199

Notes: This table shows the relationship between growth in mill activity and county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcomes are the share of mills using steam power (column 1), the total number of mills (column 2), and total mill revenue (column 3). Each row corresponds to growth over the indicated decade, using only data from the indicated years.

Column 1 reports OLS estimates, restricting the sample to county-industries with at least one mill in both decades (for the steam share to be defined) and weighting by the number of mills in that county-industry in 1850. These estimates reflect percentage point differences in the shares. Columns 2 and 3 report PPML estimates for a balanced panel of county-industries (including zeros), which approximate percent differences.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 4. Entry Rates and Survival Rates, by County Waterpower Potential

	Entry Rate (1)	Survival Rate (2)	Difference (1) − (2) (3)
Elasticity with Respect to Lower Waterpower:			
In 1860	0.323	-0.230	0.554
	(0.074)	(0.065)	(0.089)
# County-Industries	1,199	1,199	
In 1870	0.168	-0.266	0.434
	(0.058)	(0.057)	(0.072)
# County-Industries	1,199	1,199	
In 1880	0.158	-0.158	0.316
	(0.045)	(0.040)	(0.061)
# County-Industries	1,199	1,199	

Notes: This table shows the elasticity of mill entry and mill survival, over the previous decade, with respect to county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Column 1 reports results for entry, column 2 reports results for incumbent survival, and column 3 reports the difference in these estimates. Each row corresponds to a different PPML regression, using data from the indicated Census year and previous Census year, which approximates percent differences in the rates.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 5. Steam Adoption Shares for Entrants and Water Incumbents, by County Waterpower Potential

	Entrants (1)	Water Incumbents (2)	Difference (1) − (2) (3)
Adoption in Lower Waterpower Counties:			
In 1860	0.169	0.034	0.135
	(0.024)	(0.021)	(0.023)
# County-Industries	1,076	607	
In 1870	0.188	0.049	0.139
	(0.022)	(0.018)	(0.025)
# County-Industries	1,151	560	
In 1880	0.172	0.051	0.121
	(0.022)	(0.024)	(0.025)
# County-Industries	1,169	685	

Notes: This table shows the relationship between county waterpower potential and the steam use of entrant mills and water incumbent mills. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is the share of entrants using steam power, restricted to county-industries with at least one entrant in that year. Column 2 reports the share of "water incumbents" (mills that used waterpower in the previous Census year) who switched to steam power. For column 2, the sample is restricted to county-industries with at least one surviving water incumbent. Column 3 reports the difference between the estimates in columns 1 and 2. Each row corresponds to a different OLS regression, using data from the indicated Census year only, which report percentage point differences in the shares.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

For each row, each observation is a county-industry, weighted by the number of mills in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 6. Non-Mill Manufacturing Establishments, Non-Mill Steam-Use, and Steam Manufacturing, by County Waterpower Potential

	Total Non-Mill Establishments (1)	Steam User Share of Non-Mill Establishments (2)	Steam Makers, Relative to All Establishments (3)
Differences in Lower Waterpower Counties:			
In 1850	-0.546	0.016	0.410
	(0.229)	(0.005)	(0.162)
# Counties	690	674	690
In 1860	-0.428	0.023	0.326
	(0.328)	(0.008)	(0.211)
# Counties	690	661	690
In 1870	-0.525	0.035	0.501
	(0.234)	(0.010)	(0.242)
# Counties	690	678	690

Notes: This table shows the relationship between county waterpower potential and local non-mill manufacturing activity (i.e., outside the flour mill and lumber mill industries). "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is the total number of non-mill manufacturing establishments. The outcome in column 2 is the share of non-mill establishments using steam power. The outcome in column 3 is the number of steam makers (establishments reporting making engines or boilers) relative to the number of all manufacturing establishments. Each row corresponds to a different regression, using data from the indicated year only. Columns 1 and 3 report PPML estimates, including zeros, which approximate percent differences. Column 2 reports OLS estimates, weighting by the number of non-mills in that county in 1850, which reflects percentage point differences in the shares.

All regressions include our baseline controls: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

For each row, each observation is a county. We exclude 1880 because data for several non-mill industries are mostly lost for 1880. Robust standard errors are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 7. Model Fit to Target Moments

	Moment	Years	Model	Data
	Baseline Region			
$c(W,S)$	Water Choice Differential: Water Incumbents vs. Entrants	1850-1880	0.552	0.553 (0.062)
$c(S,W)$	Steam Choice Differential: Steam Incumbents vs. Entrants	1850-1880	0.977	0.977 (0.123)
$c_S^{(init)}$	Steam Adoption Rate	1850	0.102	0.103 (0.006)
$c_S^{(term)}$	Steam Adoption Rate	1880	0.393	0.393 (0.011)
f_e	Entry Rate	1820-1830	0.737	0.750 (0.006)
f_o^E	Log Sales Differential: Incumbents vs. Entrants	1850-1880	0.132	0.131 (0.015)
f_o^W	Water Exit Rate	1850-1880	0.789	0.789 (0.003)
f_o^S	Steam Exit Rate	1850-1880	0.835	0.835 (0.006)
γ	Log Sales Differential: Steam vs. Water Users	1850-1880	0.855	0.855 (0.029)
Π	Log Sales Autocorrelation	1820-1830	0.412	0.412 (0.019)
Σ	Log Sales Standard Deviation	1820-1830	1.019	1.019 (0.011)
	Differences Between Low Water and Baseline Region			
$c_L(W)$	Steam Adoption Rate	1850	0.089	0.089 (0.016)
η	Log Total Output	1850	-0.876	-0.876 (0.215)
κ	Change in Steam Adoption Rate	1850,1880	0.092	0.092 (0.019)
α	Growth of Output	1850,1880	0.525	0.525 (0.118)

Notes: This table shows each parameter of the model (column 1) and the moment that most closely targets it (columns 2 and 3). Column 4 reports the model-simulated moments, and Column 5 is the empirical estimates with standard errors in parentheses.

Table 8. Parameter Estimates

Parameter	Description	Value	Dollars	Source
	Power Costs			
$c(W,S)$	Switching costs from water	0.014	36	Table 7
$c(S,W)$	Switching costs from steam	0.058	145	Table 7
$c_S^{(init)}$	Steam cost (initial)	0.263	658	Table 7
$c_S^{(term)}$	Steam cost (terminal)	-0.093	-233	Table 7
$c_S^{(slope)}$	Steam cost (time-slope)	0.040		Section V.A.3
$c_L(W)$	Additional water cost in low-water region	0.043	106	Table 7
κ	Agglomeration in steam adoption	0.018	44	Table 7
ρ	Dispersion in power costs	0.064	159	Table 7
	Entry and Operating Costs			
f_e	Entry costs	0.004	10	Table 7
f_o^E	Startup cost	0.444	1110	Table 7
f_o^W	Operating cost of water user	0.103	257	Table 7
f_o^S	Operating cost of steam user	0.299	748	Table 7
ρ_o	Dispersion in operating costs	0.064	159	Table 7
	Productivity			
γ	Steam productivity premium	0.093		Table 7
Π	Autocorrelation in baseline productivities	0.966		Table 7
Σ	Dispersion in baseline productivities	0.088		Table 7
α	Agglomeration in steam production	0.025		Table 7
	Demand			
ϵ	Elasticity of firm demand	6.000		Section V.A.3
η	Elasticity of local demand	5.877		Table 7
	Other Parameters			
β	Water share in startup cost	0.400		Section V.A.3
ω	Power resale value	0.000		Section V.A.3
δ	Discount factor	0.940		Section V.A.3

Notes: This table shows the estimated values of our model parameters.

Table 9. Non-Targeted Differences Between Low Water and Baseline Region

Moment	Years	Model	Data
Steam Diffusion and Mill Growth (Table 3)			
Change in Steam Share of Mills	1850-1860	0.054	0.067
			(0.016)
Change in Steam Share of Mills	1860-1870	0.030	0.034
			(0.013)
Change in Steam Share of Mills	1870-1880	0.008	-0.009
			(0.013)
Total Mills	1850-1860	0.184	0.220
			(0.062)
Total Mills	1860-1870	0.157	0.113
			(0.052)
Total Mills	1870-1880	0.142	0.092
			(0.036)
Total Revenue	1850-1860	0.217	0.183
			(0.081)
Total Revenue	1860-1870	0.169	0.203
			(0.097)
Total Revenue	1870-1880	0.139	0.140
			(0.087)
Entry Rates and Survival Rates (Table 4)			
Entry rate	1850-1860	0.218	0.323
			(0.074)
Entry rate	1860-1870	0.189	0.168
			(0.058)
Entry rate	1870-1880	0.170	0.158
			(0.045)
Survival rate	1850-1860	-0.047	-0.230
			(0.065)
Survival rate	1860-1870	-0.102	-0.266
			(0.057)
Survival rate	1870-1880	-0.127	-0.158
			(0.040)
Steam Adoption of Entrants and Water Incumbents (Table 5)			
From Entrants	1850-1860	0.145	0.169
			(0.024)
From Entrants	1860-1870	0.173	0.188
			(0.022)
From Entrants	1870-1880	0.181	0.172
			(0.022)
From Water Incumbents	1850-1860	0.068	0.034
			(0.021)
From Water Incumbents	1860-1870	0.088	0.049
			(0.018)
From Water Incumbents	1870-1880	0.089	0.051
			(0.024)

Notes: This table shows differences for non-targeted regressions run on the simulated model as well as the observed data (each panel reports the regression estimates from a different table). Standard errors in parentheses of the *Data* column.

Online Appendices

Gaining Steam: Incumbent Lock-in and Entrant Leapfrogging

Richard Hornbeck
University of Chicago

Shanon Hsuan-Ming Hsu
University of Chicago

Anders Humlum
University of Chicago

Martin Rotemberg
New York University

A Establishment-level Manuscripts from the Census of Manufactures

We have digitized establishment-level data from the original published manuscripts of the Census of Manufactures for 1850, 1860, 1870, and 1880 . We are grateful to Jeremy Atack for providing us many manuscripts; the rest we located in a variety of state, non-profit, and university archives. Most manuscripts were already microfilmed, and the rest we photographed or acquired photos from archive staff. Our data include some manuscripts that had not been found during the construction of previously-digitized samples described in Atack and Bateman (1999), including Rhode Island and Nevada.

The Census of Manufactures was professionalized and comprehensive beginning in 1850 (Atack and Bateman, 1999). Before 1880, Census enumeration was done in person by U.S. Marshals and all establishments received the same questionnaire, though it changed slightly over time. In 1880, the Census of Manufactures was split into three broad parts: (1) a "general" schedule; (2) a "special agent" schedule; and (3) a "special" schedule. First, many industries received a "general" schedule, similar to that used in 1850, 1860, and 1870. Second, some important sectors were given "special agent" schedules, which involved sector-specific questions and specially trained enumerators. These "special agent" manuscripts for 1880 are all believed to be lost (Delle Donne, 1973), which include most manufactures of: cotton, wool, and worsted goods; silk and silk goods; iron and steel; the coke industry; the glass industry; the mining of metals, coal, and petroleum; distilleries and breweries; shipbuilding; and fisheries.[36] Some establishments in these industries were included in the "general" schedule (Atack, Bateman and Margo, 2004).

A third category of sectors were given "special schedules" with sector-specific questions, but these were not administered by special agents and these manuscripts were not lost along with the "special agent" schedules. For 1880, these special schedules include "Lumber and Saw Mills" and "Flouring and Grist Mills," along with other manufacturing sectors: agricultural implements; paper mills; boots and shoes; leather; brick and tile; cheese and butter; and slaughtering and meat packing. For example, the additional sector-specific questions include: "number of runs of stone" for flour mills; and whether a lumber mill does its own logging.

A.1 Variable Coverage

The 1860 Census instructions to enumerators discuss the data collection guidelines in useful detail. In addition to establishment count, our main variables of interest are:

Manufacturing Revenue. Products were valued at the factory gate, excluding transporta-

[36] In 1880, cities with over 8,000 inhabitants were surveyed separately from their counties, also by special agents. While Delle Donne (1973) also reports that the special agent city records were lost, we found the city manuscripts and they are included in our samples (the city manuscripts were with the other records, so we are not sure why they were considered lost).

tion costs to customers: "In stating the value of the products, the value of the articles *at the place of manufacture* is to be given, exclusive of the cost of transportation to any market" (emphasis original, United States Census Bureau 1860*a*). We consider a mill active if it reports positive revenue, and include only active mills in our analysis.

Input Expenditure. To estimate the demand elasticity ϵ, we need a measure of variable input expenditure. We calculate variable input expenditure as the sum of reported labor costs and materials. Total wages paid are reported directly in 1870 and 1880. In 1850 and 1860, we calculate labor costs as the sum (for men and women) of the monthly wage bill times twelve. Materials expenditures are reported directly in the data. For estimating the demand elasticity, we need the input expenditure, so for this calculation we only include mills that report all inputs (94% of the sample). Equation 5 shows that prices are a multiple $\frac{\epsilon}{\epsilon-1}$ of marginal costs, so $\epsilon = \frac{\frac{y_{jct}}{x_{jct}}}{\frac{y_{jct}}{x_{jct}}-1}$. We find that for the median mill, revenues are around 20% higher than expenditures, which implies $\epsilon = 6$. At the time, for the custom milling of flour millers were paid in wheat, keeping a fraction of what their customers brought. The "millers toll" (the price that could be charged for custom flour milling) was regulated, ranging across regions from a quarter to a sixteenth. The markup for wheat sold on the market was higher (Dondlinger, 1919). Consistent with these regulations, we estimate lower markups in flour (10%) than lumber (33%)

Power Source. The Census also asked all establishments for their number of horsepower used in 1870 and 1880. The kind of power source was asked about in every year. Across manufacturing, the most common responses were variations on "steam," "water," "horse," and "hand," which we processed to make those broad categories (as well as "other" and "nothing"). Wind power was relatively rare, and by the time of our sample most American enterprises using tides for power had closed (Charlier and Menanteau, 1997). In milling, "steam" and "water" were by far the most common power sources. For our main analysis, we exclude mills who report other categories, mostly because there are very few and so are difficult to model, but also due to concerns about measurement error for the larger ones. We found historical records for steam or waterpower use for several suspiciously-large self-reported "non-mechanized" mills. Since we cannot systematically correct these non-mechanized mills' recorded power-use, we drop them from the main analysis. The one exception is that some mills use "steam" or "water" in their industry name (e.g., "steam mill"), but do not also directly report steam or water as their power source, and for those mills we assume they used the named power source. We do use the reported capital stock of "hand" and "manual" mills in order to estimate the share of the capital for waterpowered mills that was due to waterpower (as opposed to other milling equipment or structures))

Industry. In all years, the general schedule Census asked establishments to report the type of business that they were in. Before 1880, the general schedule Census also asked for the types of products they made. In 1880, most flour mills and lumber mills were surveyed on their own special schedules. 2% flour and lumber mills in 1880 were recorded in the general schedule, and we include those mills in our analysis unless the same mill was already also recorded in the special schedule. Below, we describe our processing of the industry strings.

For Table 6, we define "steam makers" as follows. First, we search for establishments whose products are variations on "steam", "engine", "heat", or "boiler". We then constrained the set to establishments who self-reported being in a potentially relevant industry: "iron and steel", "iron and steel products", "brass and other metal products", "machinery and fine instruments", or have industry unclassified/unknown. Finally, we manually verified that the product strings plausibly related to steam products and were not false positives. For instance, we found several establishments that passed these criteria but also produced baked goods, which we did not classify as steam makers. Because product names are not available in the 1880 general schedule, we only classified steam makers in 1850, 1860, and 1870.

Location. The manuscripts record county and state, in each decade based on contemporaneous county names and boundaries. In addition, the name of the closest post office is available for 90% of establishments in 1860, 1870, and the 1880 general schedule. Post office is rarely recorded on the 1850 manuscripts and 1880 special schedules. Establishments with the same post office are surveyed on the same page, consistent with our assumption that firms surveyed on the same page are nearby each other within counties.

A.2 Digitization and Processing of the Census Manuscripts

We worked with Digital Divide Data to double-enter and reconcile data from the manuscript images. In total, there were 63,802 manuscript images with manufacturing establishments, including 27,071 pages from 1880. The average page had 7 establishments. Appendix Table A.1 shows the coverage for which states and decades we were able to find and digitize. When we have records for a state and decade, the records are normally complete for the entire state. For some states and decades, there are some entire counties missing or parts of counties from comparing our establishment totals to the published county-level tabulations.[37] We track each establishment's decade, state, county, page, and row.

To help clean the data, we received assistance from many UChicago undergraduates, graduate students, and full-time research professionals. The team randomly checking many

[37]There are 7 counties that, in the manuscripts and tabulated data, have more than 10 firms in an initial decade, have no firms in the subsequent decade, and then have more than 10 firms. We drop these counties, given our concerns for enumeration error (or the manuscripts being lost contemporaneously). This is in the spirit of Allcott, Collard-Wexler and O'Connell (2016), who similarly drop firms with observations in a given year that are very different from both adjacent observations.

entries, finding a very low error rate. We also used a useful feature of the manuscripts to verify numeric entries on many sheets: many 19th century enumerators entered some *totals*, such as writing the total production value for the entire page or for a given firm. We also digitized these row totals and page totals, and compared the entered total with the sum of the relevant responses. Consistent with our general verification of the data, the most common sources for discrepancies were that the total was calculated incorrectly by the enumerator or the total reflected a sum of values that were later crossed out and replaced with other values. In these cases, we made no changes. We also manually checked entries when a ratio seemed highly unusual, such as the output to employment ratio, which was inspired by the data cleaning processes at the current U.S. Census (Fellegi and Holt, 1976; Thompson and Sigman, 1999). We manually changed any cells where we found a difference between entered values and the manuscripts themselves, but did not otherwise "correct" the original written entries.

We manually processed the entered strings for product names, material inputs, and self-reported industry, along with categorizing the entered power strings based on relevant information such as "water" and "steam." The overall goal was to standardize misspellings and British spellings, expand abbreviations, and assign strings to broader categories. To clean industries, we also used the product strings.

The data include many self-reported industries in each decade, which we group together for our analysis. Following Hornbeck and Rotemberg (2024), we homogenized industry names into 31 categories, using additional information on products when needed. Our analysis focuses on flour and lumber milling, which were relatively straightforward to classify since they had unique outputs. To give a sense of the raw data, there were 1630 distinct industry strings in the original manuscripts that we associate with the flour industry and 2476 distinct industry strings that we associate with lumber, including: "grist," "flower mill," "wood & lumber," "steam saw mill," and "mill" (for the last, we could only identify the industry because of their products).

Some values for string variables were entered in the "wrong place," when the surveyor had run out of room, which we manually corrected. Similarly, we corrected when numeric variables were entered in a string column. Some entries were marked with a question mark, when the data processing team could not read part or all of a cell, particularly for some string values. We looked at those entries, and were rarely able read them either.

The Census recorded an enterprise as one establishment even if it contained multiple locations within the same Census subdivision, if these activities across sites were for the "same concern, and all engaged in the same manufacture" (United States Census Bureau, 1860*a*). There were also some lines in the Census that were associated with one owner but different industries (for instance, below we discuss the case of E. E. Locke & Co, which operated a distillery and a mill). We split each establishment into multiple industries, so as to consider only the output of each industry. For instance, when we consider the revenue of E. E. Locke & Co, we only consider the revenue of the mill and not that of the distillery. This is particularly relevant for the mills in the period that produced both cut lumber and flour, which we classify as separate mills in our analysis. This approach follows historical Census practice to, for multi-industry establishments, "[separate] the two parts of the business and [assign] each to its appropriate place in the Statistics of Industries" (United States Census Bureau, 1870*a*). We often refer to "firms" for convenience, though note that the Census enumeration is at the establishment level (unless there were multiple buildings within the same enumeration area) and activity is recorded where it takes place, not at headquarters, so we are then referring to single-establishment "firms."

A.3 Adjustment for County Border Changes

Some county borders change over our sample period, and we group together counties with overlapping geographies to create time-consistent borders. This approach is preferable for our analysis of individual mills and establishment-level panel-linking. This differs from an alternative approach of splitting aggregate county activity based on geographic area and aggregating to baseline county borders (Hornbeck, 2010), which would make it difficult to interpret split shares of individual establishments in establishment-level data.

Our baseline county boundaries start with 1850 borders. Issues arise when county polygons from 1860, 1870, or 1880 overlap with multiple 1850 county borders. We group together 1850 counties so that every county from 1860 to 1880 corresponds to a unique grouped 1850 cell. The first step is to group together all of the 1850 counties that overlap with at least 5% of the area of a given county (in a subsequent decade). The second step is then grouping together all of the 1850 counties that were linked in the previous step. As an example, suppose 1860 county a overlaps with 1850 counties i and j, and 1870 county b overlaps with 1850 counties j and k. Our 1850 county group would cover i, j, and k, which is a conservatively large county grouping because we do not want to split individual establishments across counties and we want to find the same establishments in subsequent decades. Two grouped counties have an area larger than a circle with a radius of 50 miles, which is too large to be well-captured by our model, so we drop them from our analysis. We focus on our analysis on counties east of the 98th meridian (Webb, 1931). For simplicity, we continue to call the grouped geographies "counties." Our baseline sample covers 750 counties using the actual 1850 borders, which we group into 690 consistent geographies. This covers 83951 flour and lumber mills, and around 90% of all steam-generated sales in those industries.

A.4 Creating a Linked Panel of Mills

We link mills by hand, from one decade to the next, in combination with a machine-learning linkage model. We employed a team of data associates to compare a mill in one decade to plausible matches in the subsequent decade. We matched mills on name and location, but did not force establishments to be in the same industry in every decade. Because mills rarely switched between lumber and flour, and we consider working in a different manufacturing sector to be part of the outside option in our model, we consider industry switches to be "exits." We never make links using information on power source, or other establishment characteristics.

To guide the large-scale hand-links, we first matched a few counties ourselves and compared every mill to every manufacturing establishment in the subsequent decade. We then trained a machine learning algorithm on those matches. For the large-scale hand-linking, we then only considered potential matches with a relatively high linking probability. For the possible matches, we mostly included all candidates with over a 9% linking probability. For mills with many potential links, we only sent the top twenty; for mills with few potential links, we sent the top 5 as long as their linking probabilities were above 5%. In practice, the potential links with a low match probability were rarely hand-chosen as an actual match. For the analysis in the paper, we then retrained the machine-learning model on the full set of matches. Below, we describe our approach in more detail.

A.4.1 Hand-linking Procedure

Our first step was to create some panel links by hand, linking establishments in 1860 to their 1870 counterparts in 97 counties. We chose relatively small counties, to start, so it was feasible to compare all possible matches in the same county. We matched 2,709 establishments in 1860 to 5,518 establishments in 1870, adding up to 282,341 comparisons.

To make the links, we considered each establishment's name, industry classification (including the self-reported string and our own cleaned industry measures), and the nearest post office. We also had access to the original CMF manuscript images for each establishment to double-check mistakes, either in the original handwriting or its transcription. Each hand-linking sheet was completed by two UChicago students, and assigned to a third person to reconcile any discrepancies. For each 1860 establishment, we sorted all 1870 candidates by Jaro-Winkler (JW) name similarity, and by whether or not their broad industries matched, to increase the likelihood that links were at the top of each block of names.

Broadly, we made two types of matches in the data. "Direct" matches are when the establishment names in both periods are close matches. This is similar to common practice in literature linking men across decades in the Census of Population (Ferrie, 1996; Feigenbaum, 2016; Ruggles, Fitch and Roberts, 2018; Bailey et al., 2020; Abramitzky et al., 2021*a*,*b*). However, an important difference between linking men and linking establishments is that many mills *actually* changed their names somewhat when ownership changed slightly. While additional data would be needed to link women who change their last names, our Census of Manufactures data can tolerate moderate changes in ownership. For instance, Appendix Figure A.3 shows the manuscript images for a mill that was initially owned by Alson Rogers, which later passed to his son Lucian. To account for "ownership transfers," we also match establishments where part of the name is very similar but another part is different in a manner consistent with a partial change in ownership. In practice, this second category includes partnership formation or newer members taking on the family business.[38]

A.4.2 Model Specification

From hand-linking establishments, we noticed there were broadly four categories for how the establishment's name was reported (consistent with guidance from Jeremy Atack). These were not formal rules, and the way names were written down varied across time and space, but we list the categories below along with our interpretation of their meaning.

1. Establishments with sole proprietorship contain a single owner's name. Names were sometimes initialized, and the names did not consistently follow a first/last name order.

2. Establishments owned by families normally appeared as a person's name followed by *& sons* or *& brothers.* Others appeared with two first names separated by an ampersand, followed by a last name.

3. Establishment that were a partnership or expanded partnership reported two or more names of the proprietors; limited partnerships reported one or more people's names followed by *& co.*

4. Establishments that reported names that were impersonal, and often included tokens related to the business and location.

For our mills, in particular, there were two broad types of naming patterns: those with general company names, sometimes including the name of the waterpower source; and those named after people. Across Census decades, the order of people's names can change. Even for establishments with a single owner, the order of first and last names can change, along with changes in the use of initials.

[38] In our replication files, we denote direct matches as "y", ownership transfer matches as "o", and non-matches as "n". We denote direct matches where the industry changed as "s."

These features motivate us to build two separate linking models: one matching the whole establishment name, and one matching owners' names with flexibility in their ordering.[39] We use two random forest models to predict establishment pairs, either tracking the company as a whole or tracking individual owners.[40] Both linking models predict establishment pairs to be: a same-owner match, an ownership transfer match, or not a match. We describe this approach in more detail below.

Name Classifier. We built a name classifier to categorize establishments by their naming pattern type, extract the name of the owners, and identify the name order. While owner names are embedded in establishments owned by sole proprietors, families, partners, or expanded partnerships, the names were often initialized and would switch first-last name orders.

We first use a list of company tokens to identify establishments with impersonal names, which includes: names of locations, such as state and county names; and tokens related to their product or business, such as tanning, manufacturing, lumber, etc.

For establishments without those company tokens, we implement the following steps to extract and format the owner names. First, we remove the non-name tokens, such as "& co" or "& sons," and split the establishment names into owners' names. For a family-owned establishment with two first names and one last name, we assign the last name to both owners (e.g., turn "J & D. Taflinger" into "J Taflinger" and "D. Taflinger.") We then standardize common nicknames and abbreviations to their original names (e.g., Wm to William and Geo to George.) We determine the name order using the first and last name frequency in the 1880 Census of Population. When both names can be first or last names, we keep both orders and look for both of them in the next Census decade.

Owner Linking Model. Our owner-linking model predicts links based on three sets of information: establishment name, industry, and post office. We define several sets of variables for each of the first, middle, and last names: Jaro-Winkler string distance, whether the name is initialized, and whether the initial matches exactly. When there are missing values, which are incompatible with the random forest model, we assign the median value and define an indicator flag for missing. For industry, we use our industry classification based on the raw industry string to create matching indicators for broad and detailed industries. We also

[39] We are grateful toJeremy Atack for suggesting this approach.

[40] We generated linking models based on several classifier families, including logistic regression, random forests, and extreme gradient boosting (Chen and Guestrin, 2016). After evaluating their performance on the validation data, we settled on a random forest trained using the R library `ranger`. The random forest model provided the most reliable output, with respect to false positive and negative rates, and the empirical distribution of predicted probability does not concentrate on the two ends which leaves room for setting the probability threshold and varying the false positive and false negative errors.

create a measure of industry distance based on the industry classification and similarity in their reported kinds of materials. For post office, we use the Jaro-Winkler string distance between post office names and an indicator for missing values.

For establishments with multiple owners, the model predicts matches at the establishment-owner level. At the training stage, we manually select the owner pairs that match and drop the others to avoid confusing the model. At the predicting stage, we take the maximum of the predicted probability for each establishment pair (from all owner pairs) to let the output be at the establishment-pair level. This process allows a firm to match when one owner is the same, even if other owners are different, which mimics how humans generally make links.

Company Linking Model The company-linking model also predicts links based on establishment name, industry, and post office. However, instead of extracting the owner information from the establishment names, this model uses the full string of establishment names and looks for establishments with similar whole names. We use the Jaro-Winkler string distance for the full names, in addition to string distance after removing business and location tokens and the minimum string distance between those remaining tokens among all token pairs. The remaining name distances measure the name similarity unrelated to the business itself, which removes false matches that only have closer string distances on the full name because of common tokens (e.g., "Eagle Mill" and "James Mill").

A.4.3 Model prediction reconciliation and hand-linking

We use both models to predict matches, separately, and then take the maximum of the predicted probability. For the set of potential matches that we consider when making hand-links, we select all pairs with a linking probability above 9% (after piloting different thresholds, trading off missed potential matches with the capacity to consider many potential matches).

We worked with Digital Divide Data (DDD) to hand-link the matches, at scale. Our full-time research pre-docs traveled to Kenya to help train their team in person, who also had experience linking individuals across waves of the Census of Population. We then continued to work closely with them remotely, handling the data process ourselves while their managers handled HR.

We sent DDD lists of all potential matches with identifying information: establishment name, industry, post office, and product kinds produced. We did not include the estimated linking probabilities. Two separate members of the DDD team found the best match for each establishment, or indicated no close match, and a third member reconciled any disagreements between the original two members.

We then iterated on these hand-links using the machine-learning model, asking them to manually check "unlikely" matches or "likely" non-matches. We used the same protocol as for the original data, sending DDD the information about the firm but nothing else about the linking probability. For links that were made for which the algorithm predicted link probability was below 40%, we asked a DDD member if they agreed with the link. For mills with no links, but for which the algorithm predicted at least a link probability above 40%, we asked a DDD member if they agreed with any of the predicted links. Finally, if DDD and the highest-predicted link were different (and the predicted link probability of the actual match was at least 0.1 lower than the best predicted match), we sent both to DDD. After iteration, the "unlikely" hand-linked matches were generally found to be reasonable matches (and missed by the machine-learning model) and the predicted "likely" matches were also generally decided to be matches after a second look. The automated linking model performed relatively worse in identifying ownership transfers, compared to the hand-links.

Using this final hand-linked data, after iteration with the original model, we re-estimate the model to create final model-predicted links for our analysis. We consider two mills linked if the predicted match probability is above 0.6. To eliminate a small number of multiple links (3% of all links), we keep the mostly likely period 2 link for every period 1 establishment and then keep the most likely period 1 link for every period 2 establishment. There are a few tied matches (0.8% of all links), in cases where adjacent establishments in the same industry have the same owners; in these cases, we randomly select one of the establishments.

A.4.4 Linking Mill Owners to the Census of Population

We link mill owners to the complete Census of Population , using a similar procedure to our panel links. We construct an owner-name dataset with each probable person name ordering in the establishment name. For each owner-name, we keep up to 20 most likely matches in the Census from the same year and county who: were over 18 years old; had a matching first initial or first name Jaro-Winkler distance less than 0.3; and had a last name Jaro-Winkler distance less than 0.3. In rare cases when more than 20 individuals meet these criteria, we keep people with milling-adjacent occupations and those with the lowest string distances.

We sent the list of potential matches to Digital Divide Data, where two team members selected the best match (or no match) and a third team member reconciled all disagreements. Team members matched on the basis of: mill owner name and Census name; mill industry and Census person occupation.

Using the final match list, we first collapse between multiple matches, where for every owner name, we take the top match, sorting by milling status, last name distance, first name distance, and, for very rare cases, a seeded random variable. The same is done to collapse between multiple name orderings of the same owner, such that there is a list of unique owners paired to a single census person.

For mills with multiple owners who match to the Census of Population, we use all matches to characterize firm-level ownership characteristics: average owner age, whether any owner was born outside the United States (immigrant), and whether any owner has a self-reported occupation associated with being a "professional miller."[41] In most cases, only one owner name is linked to the Census of Population.

B Measuring County Waterpower Potential

This section describes how we measure county waterpower potential. We start with data on rivers in the United States (Section B.1); define theoretical waterpower potential (Section B.2); discuss our exclusion of rivers that were impractical for waterpower (Section B.3); and aggregate flowline-level waterpower to the county-level, including adjustment for river segments that cross county boundaries (Section B.4).

B.1 NHDPlusV2 Data

National Hydrography Dataset Plus is a national geospatial surface water framework for water resource analysis, developed and maintained by the U.S. EPA in partnership with the U.S. Geological Survey (USGS).

We use NHDPlus Version 2 (NHDPlusV2), released in 2012 (McKay et al., 2012).[42] NHDPlusV2 is built from multiple data sources, including: the medium-resolution (1:100,000) National Hydrography Dataset (NHD), 30 meter National Elevation Dataset (NED), and the National Watershed Boundary Dataset (WBD).

We generate waterpower potential for each "flowline" or "river segment," which is the basic unit in the NHD linear surface-water network. We use the two types of flowlines that represent natural rivers: "Stream Rivers" and "Artificial Paths." A Stream River (SR) is a river segment, often extending between tributary confluences. An Artificial Path (AP) represents a flow-path through a waterbody in the surface water network: for particularly wide rivers, normally those wider than 50 feet and longer than 2640 feet, an "artificial path" is drawn to represent the flow-path within the waterbody.

[41] These occupations, listed in decreasing prevalence among the owners, are: Millers; Lumbermen and raftsmen; Sawyers; Manufacturers; Saw and planing mill operatives; Carpenters and joiners; Traders and dealers in lumber; Machinists; Mill and factory operatives (not specified); Mechanics (not specified); Traders and dealers in produce and provisions; Woolen mill operatives; Paper mill operatives; Cotton-mill operatives; Employees in manufacturing estabs. (not specified); and Traders and dealers in coal and wood.

[42] Another version is NHDPlus High Resolution (NHDPlus HR), which is at a higher resolution (1:24,000-scale or better) (Moore et al., 2019), but does not currently include monthly streamflow estimates. The resolution of NHDPlusV2 is sufficient for us, particularly given that we later aggregate data to the county level.

B.2 Theoretical Waterpower

For each river segment r, the theoretical waterpower generated from the flow of water along this segment can be derived using the following formula (assuming no friction):

$$\text{TheoreticalWaterPower}_r = \underbrace{\text{FlowRate}_r}_{\substack{\text{Cubic Feet}\\\text{Per Second}}} \times \underbrace{\text{FallHeight}_r}_{\text{Feet}} \times \substack{\text{Gravitational}\\\text{Constant}}, \tag{26}$$

where the gravitational constant roughly equals 0.1134 when the theoretical water-power is measured in horsepower. This formula closely approximates horsepower calculations in the 1880 Water Census.

Intuitively, the theoretical waterpower available is proportional to the flow rate of water (volume per second) and its falling height.

Flow Rate. Our data from NHDPlusV2 is based on the Enhanced Unit Runoff Method (EROM), a five-step procedure, to estimate mean monthly flow rates of rivers under natural conditions:

Step 1. Unit runoff based on a flow-balance model, taking into account: precipitation, potential evapotranspiration, evapotranspiration, and soil moisture.

Step 2. Adjustment for excessive evapotranspiration.

Step 3. Adjustment in a log-log regression estimated using reference gauge.

Step 4. Adjustment for flow transfers, withdrawals, and augmentations.

Step 5. Gage-adjustment based on actual observed flow at the gauge.

Step 4 is notable, for our purposes, because the model predicts waterpower potential in the absence of various hydrological infrastructure built in the United States since the 19th century. The modeled water volume reflects natural waterflows, close to those observed in the 19th century (verified in Appendix Figure A.1).

Fall Height. NHDPlusV2 data also provides the maximum and minimum elevation values for each river segment. Following the hydrology literature, we approximate the fall height (or hydraulic head) using the difference in elevation along each river segment.

B.3 Practical Waterpower.

As discussed in the 1880 Water Census: "There is a sharp distinction to be made between *theoretical* and *actually available* waterpower" (emphasis original). Some sources of water-power were infeasible (e.g., the Mississippi River). We discuss two reasons why theoretical waterpower was not usable in practice – river width and seasonality – and how this enters into our calculations of county waterpower potential.

B.3.1 River Width

We exclude wide rivers, such as the lower Mississippi River, that were impractical to dam for the purposes of generating waterpower. These rivers were also used for water transportation, which crowded out waterpower for manufacturing because millers had to provide rights of way. We obtain the "top" (surface) width of rivers for NHD segments from the National Water Model (NWM), developed by NOAA (2016).[43]

As an exact cutoff for impractically wide rivers, we calculate county waterpower potential excluding rivers with maximum widths above the 95th percentile and estimate the relationship between county waterpower potential and the number of water mills in 1850 (as in Table 2). Appendix Figure A.16 plots the coefficient on Lower Waterpower against the Xth percentile of maximum river width. For wide rivers, around the 95th percentile, there is a sharp attenuation in the relationship. Our main measure of county waterpower potential excludes rivers that are wider than the 96th percentile (106.3 feet). This cutoff mostly excludes Artificial Paths, including most of the lower Mississippi River network, which were impractical for waterpower-use. We also exclude Niagara Falls from our analysis, as water-wheels were "inadequate" for the magnitude of the falls (Adams, 1927) and there was only one nearby water-mill in our sample that opened in the late 1870s.

B.3.2 Seasonality

The seasonality of water flow rates is also important for the practical use of waterpower, in addition to average flow rates, because it determines whether watermills can be active throughout the year. Some mills were more seasonal, using waterpower when available, but the strong tendency was for mills to focus on year-round waterpower availability. Seasonal rivers were also generally too small for practical waterpower-use.

Our analysis calculates county waterpower potential using only "perennial" rivers, indicated in NHDPlusV2 data to have steady water flow throughout the year, and excludes "intermittent" rivers. NHDPlusV2 includes this indicator for only "Stream Rivers," but it depends closely on variation in monthly flow rates so we can also classify "Artificial Paths." Consistent with historical mill activity focused on "perennial" rivers, county waterpower potential from "interittent" rivers is not systematically associated with county waterpower use in 1850 (Appendix Table A.19, Column 2).

Even for "perennial" rivers, water flow rates vary some over the year. We use the average flow rate over the three lowest months of the year, as historical accounts viewed this as a key

[43] For more details of the National Water Model, see `https://water.noaa.gov/about/nwm`.

determinant of feasible waterpower (Census Bureau, 1883). By contrast, average flow rates across all 12 months are less predictive of county waterpower-use in 1850 (Appendix Table A.19, Column 3).

B.4 Aggregating to County Waterpower Potential

The above procedure constructs river segment waterpower potential, which we aggregate to the county level for our analysis of US Census data. For flowlines that intersect county boundaries, we split flowlines into multiple segments that are contained entirely within county boundaries. We allocate the total river segment waterpower potential in proportion to the share of its length inside each county. We then sum across all river segments in a county.

C Other County-Level Data

This section provides additional detail on some of our supplementary data sources.

Market Access, Navigable Waterways, and Railroad Stations. We use measures of county "market access" in 1850, and decadal changes from 1850 to 1880 (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024). Market access is approximated as:

$$MA_c = \sum_{d \neq c} (\tau_{cd})^{-\theta} L_d. \tag{27}$$

The market access of county c is the trade cost weighted sum of population in other counties d, where the iceberg trade cost τ is raised to the power of the trade elasticity. We set $\theta = 3.05$, following Hornbeck and Rotemberg (2024), and control for the log of county market access in 1850 and decadal changes in log county market access.

Measured transportation costs are based on least-cost routes using railroads, navigable waterways, and wagon transportation. We also control directly for whether the county is on a navigable river (as defined by Fogel (1964)) or other navigable waterway (canal, lake, ocean), and log distance to the nearest navigable waterway (based on average distance from 200 random points in the county to the nearest navigable waterway). Using maps of the railroad network in Colton (1882), we also collect detailed locations of railroad stations.

Coal Access. We digitized maps of workable coal deposit locations from Campbell (1908), a survey run by the United States Geological Survey. In addition to using measures of coal in the county, we also calculate the lowest-cost "iceberg" transportation cost from any workable deposit to each county along the transportation network from (Hornbeck and Rotemberg, 2024).

Local Milling Material Availability. We define counties' wheat suitability using crop suitability data from the Global Agro-Ecological Zones project of the Food and Agriculture

Organization (GAEZ-FAO), from Rusanov (2021). We also use counties' acreage share in woodland in YYYY (Haines, 2010).

Portage Site Locations. Following Bleakley and Lin (2012), we use data from Semple (1903) and Fenneman (1946) to measure whether counties contain actual or potential portage sites based on the fall line. We also included the historic location of portage sites along the Ohio, Missouri, and Mississippi rivers collected by Bleakley and Lin (2012).

The Water Census We digitized the "detailed tables" of the water census, which gives us information of waterpower potential at the level of the site, which we then aggregate to the county level as we do with the NHDPlusV2.

D Switching Case Studies from Historical Society Records

For some cases in which incumbent water mills adopted steam power, we looked through historical society records (and other documents, when possible) for guidance on why these mills adopted steam and what impediments to steam adoption may have confronted incumbent water mills. This qualitative history of switching helps motivate assumptions of our model for why water incumbents faced higher costs of steam power than entrants.[44] The available historical detail was limited in most cases, or we were unable to find records for the mills, though we could generally see that most millers did not change locations and verify Census data on when mills switched to steampower.

Below, we provide some examples of millers (in alphabetical order) for whom we were able to find more-detailed information. These case studies suggest some of the push and pull factors behind mills switching from water to steam power:[45]

The Blanchards Brick Mill was built in 1842 in Watertown, Wisconsin (Watertown Historical Society, 2022). Due to concerns about low flow from the Rock River, the proprietors started construction of a steam mill (next door to their original mill) in the 1840s, though in our data the mill did not switch to steam until the 1860s.

The Canal Mill in Erie, Pennsylvania was sold by Jehiel Towner to Oliver & Bacon in 1865, who immediately converted it to a steam mill (Bates, 1884). Oliver & Bacon had previously operated a mill called Hopedale, located in the same county but outside the city, but left it to purchase the Canal Mill.

The Ellis Mill was built around 1838 by Moses Ellis, in Fayette County, Indiana (Barrows, 1917). After Moses' death in the 1840s, his son Lewis operated the mill for a few years, until he abandoned the watermill in the 1850s and built a steam mill in nearby Bentonville.

Elhanan Garland owned a waterpowered mill on the East bank of a stream in Kenduskeag,

[44] We are particularly grateful to David Kirchenbauer and Tony Li for outstanding research assistance in finding these historical sources. We also include examples of switching that we found in secondary sources.

[45] We provide an additional example in Appendix Figure A.3.

Maine, and Moses Hodson owned a waterpowered mill on the West bank of that same stream (Hubbard, 1861). After a lawsuit, it was determined that Garland had the senior water rights for using two stones of grist mill, but Hodson's rights were prior to Garland's for other purposes (such as a saw mill). Garland subsequently switched to steam power, but did not change locations.

Charles Gwinn, who was already a prominent miller exploiting high waterpower availability in Baltimore, built a steam powered mill there in 1813. He did not use steam power for very long, though, as it became clear that steam was "too costly to operate for milling flour" relative to water, in Baltimore at that time (Scharf, 1874; Sharrer, 1982).

The Graue Mill in Oak Brook, Illinois (which is now a museum, conveniently close to Chicago) was a gristmill that opened in 1852 (York Township Historical Society, 2023). The ground was relatively flat, so the immigrant owner (Frederick Graue) had to construct a dam to create a three foot fall. In order to expand, Graue spent three years retrofitting his mill for steam use (including the help of a visiting millwright). Graue had also made his own bricks on site, for the building, and seemed quite entrepreneurial and adventurous in further modifications prior to the steam engine's explosion.

The Hardesty Brothers inherited a profitable grist mill in Canal Dover, Ohio after their father died in 1869 (Hardesty, 2019). Within a decade, they borrowed money to buy a steam engine (without changing the location of their mill). The mill dissolved a few years later, and Hardesty (2019) speculates that one possible reason was due to the heavy financing needs.

Chauncey B. Knight inherited a waterpowered flour and grist mill built by his grandfather Nicholas Knight in Monroe, New York (Flour and Feed, 1945). Close to what is now Harriman State Park, the location has excellent access to waterpower. Knight converted the mill to run on steam power, which was the first steam mill in the county. Knight recounted that "it was freely predicted that it would be a failure," as many thought steam "could not compete with water power which was so much cheaper." Knight's mill was large enough to process corn meal, wheat bran and middlings, and malt sprouts by the "carload," with the bulk discounts allowing his mill to sell meal much more cheaply than his competitors.

E. E. Locke & Co operated a distillery along with a mill in Mifflin, Pennsylvania (Ellis and Hungerford, 1886). The mill only used water power in 1850 and only used steam power in 1860. The distillery and mills of E. E. Locke were destroyed by a fire in 1857. The rebuilding and the restoration was finished by 1858. We suspect that the mill switched from water to steam after the fire, and because of the fire, and otherwise the broad site of the mill stayed the same.

David and Andrew Luckenbach purchased a grist mill from their father in 1861 in Bethlehem, Pennsylvania (Jackson, 1975). As the business expanded, "the water power provided by Monocacy Creek was found unsatisfactory," and they installed steam engines in 1877 after a fire destroyed the original mill.

J.S. Manning owned a mill in Columbus, Wisconsin that used only waterpower in 1870 and used only steam power in 1880 (Jones, 1914). He purchased the mill in 1849, which was already the busiest mill in Central Wisconsin. It is described that the wait for grist work was often weeks. Manning is described as switching to steam power to keep up with demand. When the mill switched from water to steam power, the location of the mill did not change, though new machinery was added to the pre-existing mill.

John Orf purchased a mill in Allen County, Indiana in 1856 (Bates, 1945). Water from the Wabash and Erie Canal was taken into a mill pond just east of the St. Mary's aqueduct and run across an overshot wheel. Anticipating the canal's closure, Orff retrofitted the mill to be able to run on either steam or water power in the 1870s. The canal closed in the 1880s, at which point Orf's mill used steam power exclusively.

The Phoenix Mill in Millwakee, Wiscosin was built by brothers William and Edward Sanderson in 1847 (Andreas, 1881). William died in 1868, and Edward added Isaac Van Schnaick as a partner. They expanded the business, and switched to steam power.

The Shoemaker Mill was built in 1746 on a mill race off Tookany Creek in Montgomery County, Pennsylvania Rothschild (1976). The family operated the mill for 100 years before it was purchased by Charles Bosler, an employee. After Charles died, his son Joseph enlarged the mill and converted to steam power.

Williams & Lufbury owned a waterpowered lumber mill in Rahway, NJ (International Publishing Co, 1887). The mill used waterpower in the 1850 Census and steam power in the 1860 Census, without changing location. During that time, dams were abolished within the city limits.

Emery (1883) describes an (unnamed) water mill forced to switch to steam power because it lost its water rights. Emery (1883)'s goal was to describe the cost of switching to steam power, as testimony for a hearing to determine how much the mill should be compensated.

E Alternative Specifications

In this section, we discuss in more detail the robustness specifications described in Section II.D. In each table, the first row corresponds to our main specification for comparison.

Appendix Tables A.7, and A.8 consider other county-level characteristics that could affect the relative diffusion of steam power across counties with different waterpower potential. Correspondingly, the outcomes in these tables are our main county-level outcomes: the number of water establishments (column 1) and the steam share (column 2) in 1850, the growth in total establishments over each decade (columns 3-5), and the change in the share of mills using steam power (columns 6-8).

Appendix Tables A.7 and A.8 include additional controls for potential drivers of county-level steam adoption and economic growth. Appendix Table A.7, rows 2 and 3, include additional controls for county access to coal (in addition to our baseline controls that include an indicator for any workable coal in the county, the share of the county covered by workable coal deposits, and access to workable coal deposits via the transportation network). Row 2 includes separate controls for each type of coal (lignite, subbituminous, bituminous, and anthracite). Row 3 controls for a cubic polynomial in the share of the county covered by workable coal deposits. Because different access to material inputs may have influenced flour and lumber mills' steam adoption (Ragnar, 1953), row 4 controls for county wheat suitability (from FAO-GAEZ data provided by Rusanov 2021) and row 5 controls for share of the county covered by woodland (as in Hornbeck 2010). Rows 6–8 control for county access to labor and capital inputs: row 6 controls for local wages in manufacturing in our Census data Allen (2009); row 7 controls for the share of county population who report being engineers or mechanics Hanlon (2022); row 8 controls for the number and total capital of local banks (Jaremski, 2014). Row 9 includes all of the above controls. Our results are broadly robust across these specifications, though the point estimates fall in row 9.

Appendix Table A.8 adjusts our baseline controls for different influences on county growth. Rows 2–4 use subsets of our baseline controls: row 2 excludes our baseline controls for market access and navigable rivers; row 3 excludes our baseline controls for coal; and row 4 excludes both sets of controls. Row 5 controls for contemporaneous market access. Row 6 controls for contemporaneous population, which is itself an endogenous outcome to waterpower availability and the arrival of steam power, so this is not our preferred specification but gives a sense of how much the evolution of overall economic activity matters as a control. Rows 7–12 alternatively control for time-invariant county characteristics (interacted with year), which adjust for potentially differential growth patterns across counties with different waterpower potential, though even 1850 county outcomes are influenced by county waterpower potential. Rows 7–10 control for variation in counties' initial settlement, which may have been associated with differential growth subsequently: row 7 controls for 1850 population; row 8 controls for being in Appalachia; row 9 controls for being on the frontier Bazzi, Fiszbein and Gebresilasse (2020); and, given the historical pattern of spatial convergence in structural transformation, row 10 controls for the 1850 population share in agriculture (Eckert and Peters, 2023). Row 11 controls for whether counties had historical portage sites, which less directly relevant by our sample period but had persistent path-dependent effects on economic activity (Bleakley and Lin, 2012).[46] Exposure to the Civil War had direct effects on economic activity (Margo, 2002; Feigenbaum, Lee and Mezzanotti, 2022), and so row 12 includes controls for differential exposure to the Civil War, following Hornbeck and Rotemberg (2024): whether there was a battle in the county; the number of battles; the total number of casualties; an indicator for if the number of casualties was over 500; if the county was on the Union/Confederacy border; if the state had legal slavery in 1864; if the state seceded from the union; and the share of industrial activity in broadly war-related industries.[47] Row 13 controls for all of the time-invariant controls listed in rows 8–12, and row 14 controls for all of the time-invariant controls listed in rows 7–12.

The estimates are broadly robust across these specifications in Appendix Tables A.7 and A.8, though the estimated initial differences in 1850 are more sensitive to controls for population.[48] We view time-varying population as an example of "bad controls" that introduce bias (Angrist and Pischke, 2009), as county population is endogenous to our mechanism: milling in lower waterpower potential places benefited more from the diffusion of steam power, lowering the local price index and drawing population to those places. Indeed, Appendix Table A.3 shows that population grew more in counties with lower waterpower potential, so controls for population potentially capture the direct effects of steam power. Row 7, columns 1 and 2, suffers from the same issue: population in 1850 is also endogenous to county waterpower potential and the existing steam power, which makes it difficult to interpret the effects counditional on counties' contemporaneous population. For this reason, we only include the time-invariant controls in our omnibus regressions (rows 13 and 14). Row 13, which does not control for 1850 population, is our preferred omnibus regression.

Appendix Tables A.11 and A.12 explore the influence of linkage error for our results. These tables compare entrant and incumbent outcomes, which are the estimates most likely affected by linkage errors. Appendix Table A.11 shows how the entry rate (columns 1–3) and incumbent survival rate (columns 4–6) vary with county waterpower potential, in each decade. Appendix Table A.12 shows results for steam-use by entrants (columns 1–3) and

[46] Conceptually, there are two differences between waterpower potential and portage sites, which create independent variation in the two. First, portage sites were on navigable rivers, whereas local waterpower potential can also come from non-navigable rivers. Second, portage sites reflect any discrete drops in elevation, whereas waterpower potential varies more continuously in terrain ruggedness. For example, the Falls of Ohio by Louisville are 26 feet, whereas the St. Anthony Falls in Minneapolis are twice as high. Both were portage sites, but the latter was more useful for waterpower.

[47] These broad war-related industries include: artificial limbs and surgical appliances; awnings and tents; coffins; cutlery, edge tools, and axes; drugs; chemicals and medicines; explosives and fireworks; flags and banners; gun- and lock-smithing; gunpowder; lead; military goods; ship and boat building; bronze; canning and preserving; carriage and wagon materials; carriages and wagons; clothing (general); cooperage; gloves and mittens; and hats and caps.

[48] The controls related to the Civil War also lower the point estimates in 1850, though by a smaller and statistically insignificant amount.

water incumbents (columns 4–6). The rows correspond to the same alternative specifications across the two tables. For rows 2–5, we use the machine-learning (ML) links described in Appendix A.4. Our benchmark ML model considers mills linked across decades if they have a match probability of at least 0.6. In row 2, we limit the panel links to only mills that are matched *both* by hand and by the benchmark ML model. In row 3, we use only the benchmark ML links. Row 4 restricts the matches to those with a ML-link probability of 0.8, and row 5 expands the matches to those with a ML-link probability of at least 0.4. Rows 2–5 change the survival and entry rates, mechanically, but do not qualitatively change the relationship between waterpower potential and entry or survival. In rows 6 and 7, our estimates are similar for mills with a predicted "business name," often based on a local geographic feature, or other mills named after their proprietors. Our baseline regression sample includes mills who report positive sales, regardless of their input costs, though we further limit the sample to mills who report all inputs to calculate the elasticity of substitution. Rows 8 and 9 show that our regression results are robust to these sample choices: row 8 restricts the sample to mills who report all inputs, and row 9 expands the sample to include the mills with unreported output (who were likely inactive at the time). Finally, row 10 includes mills that do not explicitly report using water or steam power (and for Appendix Table A.12, we consider a mill as steam powered only if it explicitly mentions steam).

Appendix Table A.13 shows the robustness of our results to changes in the county sample. Rows 2–5 consider the role of zeros in the data. Row 2 expands the sample to an unbalanced panel of all counties that ever had a mill in our sample period. Rows 3 and 4 constrain the sample to counties that had at least 3 or 5 mills in 1850, which are counties that are substantially less likely to report no mills in subsequent decades. When we limit the sample to at least 3 mills or 5 mills in 1850, we exclude 94 and 175 counties, respectively. Our baseline sample drops the two grouped counties with areas larger than a circle with a radius of 50 miles, and row 5 shows that our similar when we include them. Rows 6 and 7 exclude counties with more extreme values of measured water power potential: row 6 drops the 1% largest and smallest values, and row 7 drops the 5% largest and smallest values. Rows 8 and 9 exclude counties that were more involved in trading mill output: row 8 drops the 20 largest cities in our sample, and row 9 drops cities that Kuhlmann (1929) describes as having export-oriented "merchant mills."

F Solution Algorithms

F.1 Dynamic Programming

The expected operating values $\mathbb{E}_{\varepsilon}[V^{o}_{ct}(R,\varphi)]$ are the key determinant of firms' forward-looking decisions. Once firms know the operating values, their optimal decisions about entry, exit, and power adoption in Equations (7)-(10) are only determined by contemporaneous features of the economy.

The expected operating values satisfy the Bellman equation:

$$\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)] = \mathbb{E}_\varepsilon \max_{R'} \left\{ \begin{array}{l} \pi_{ct}(R,\varphi) - c_{ct}(R,R') - \varepsilon_{jct}(R) \\ + \delta \mathbb{E}_{(\varphi'|\varphi)} \mathbb{E}_\nu \max \left\{ \mathbb{E}_\varepsilon \left[V^o_{ct+1}(R',\varphi') \right] - f^{R'} - \nu^{R'}_{jct}(0), \Omega^{R'}_{ct} - \nu^{R'}_{jct}(1) \right\} \end{array} \right\}. \tag{28}$$

Equation (28) involves two maximization steps over distributions of idiosyncratic cost shocks (for adoption ϵ and operation/exit ν, respectively). The parametric assumptions in Section IV.E simplify these steps. In particular, when the cost shocks follow Gumbel distributions, Equation (28) simplifies to:

$$\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)] = \rho \log \left[\sum_{R'} \exp \left\{ \frac{1}{\rho} \left(\pi_{ct}(R,\varphi) - c_{ct}(R,R') + \delta \mathbb{E}_{(\varphi'|\varphi)} \rho_o \log \left[\exp \left(\frac{\mathbb{E}_\varepsilon \left[V^o_{ct+1}(R',\varphi') \right] - f^{R'}}{\rho_o} \right) + \exp \left(\frac{\Omega^{R'}_{ct}}{\rho_o} \right) \right] \right) \right\} \right], \tag{29}$$

which uses the log-sum expression for the expected maximum (EMAX) when idiosyncratic shocks are drawn from a Gumbel distribution (Train, 2009; Keane, Todd and Wolpin, 2011).

We use the recursive scheme in Equation (29) to solve for the expected operating values in the steady states and along the transition path between the steady states. We assume that firms have perfect foresight about the price index and steam share (our two aggregate state variables) up to unanticipated aggregate shocks to the economy (e.g., the first arrival of steam power).

F.1.1 Steady State

Equation (29) is a contraction mapping when operating values are stationary, $\mathbb{E}_\varepsilon[V^o_{ct+1}(R,\varphi)] = \mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)]$, so we can solve for the unique fixed point $\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)]$ by iterating on Equation (29) until convergence. Convergence of the value function iteration procedure is ensured by Blackwell's sufficient conditions for contraction mappings (Stokey, Lucas and Prescott, 1989, Theorem 4.6).

F.1.2 Transition Path

Starting from the terminal steady-state values $\mathbb{E}_\varepsilon[V^o_{cT_1}(R,\varphi)]$, we may solve for the operating values along the transition path $\{\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)\}_{t=T_0}^{T_1-1}$ using backward recursion on Equation (29) from $T_1 - 1$ to the initial period T_0.

F.2 Dynamic Equilibrium

This section discusses how we solve for the dynamic equilibrium of our economy.

We first describe our algorithms for solving the equilibrium in steady states and along a transition path. In brief, we use a shooting algorithm that iterates on the time paths for the mass of operating firms and entrants to find a fixed point of the equilibrium policy functions.

We then discuss the properties of our solution algorithm, including the existence and uniqueness of equilibrium. In brief, the convergence of our iterative algorithm is ensured by a congestion force in the product market. The convergence property also ensures the existence and uniqueness of the equilibrium.

F.2.1 Steady State

We use a shooting algorithm that iterates on the mass of operating firms $F_{ct}(R,\varphi)$ and entrants M_{ct} to find a fixed point of the equilibrium policy functions. Our solution algorithm reads as follows.

1. Set an initial guess for the mass of firms $F_{ct}^{(0)}(R,\varphi)$ and entrants $M_{ct}^{(0)}$. For each iteration $(i) = 0, 1, 2, ...,$:

2. Solve for the expected operating values $\mathbb{E}_{\varepsilon}[V_{ct}^{o(i)}(R,\varphi)]$ by iterating on the contraction mapping in Equation (29).

3. Simulate the mass of operating firms: given $F_{ct}^{(i)}$ and $M_{ct}^{(i)}$, use the policy functions for exit and power adoption (Equations (9)-(10)) to simulate the firm mass $F_{ct}^{(NEW)}(R,\varphi)$.

4. Predict the mass of entrants that closes the free entry condition:

   (a) Compute entry values $\mathbb{E}_{\varphi}\left[V_{ct}^{(i)}(E,\varphi)\right]$ by plugging $\mathbb{E}_{\varepsilon}[V_{ct}^{o(i)}(R,\varphi)]$ into Equation (9) and integrating over the stationary distribution for φ.

   (b) Use automatic differentiation to compute the elasticity of entry values with respect to the mass of entrants:

   $$\mathcal{E}^{(i)} = \frac{d \log \mathbb{E}_{\varphi}\left[V_{ct}^{(i)}(E,\varphi)\right]}{d \log M_{ct}^{(i)}}. \tag{30}$$

   (c) Predict the mass of entrants that closes the free entry condition:

   $$M_{ct}^{(NEW)} = \exp\left(\log M_{ct}^{(i)} + h\left(\frac{1}{\mathcal{E}^{(i)}}\right)\left(\log f^e - \log EV_{ct}^{(i)}\right)\right), \tag{31}$$

   where $h : \mathbb{R} \to \mathbb{R}$ is a shrinkage function with $h(0) = 0, h'(x) \in [0,1], h''(x) \leq 0$. We use the inverse hyperbolic sine function.

5. Update the mass of entrant and operating firms:

$$M_{ct}^{(i+1)} = \lambda M_{ct}^{(NEW)} + (1-\lambda) M_{ct}^{(i)} \tag{32}$$

$$F_{ct}^{(i+1)}(R,\varphi) = \lambda F_{ct}^{(NEW)}(R,\varphi) + (1-\lambda) F_{ct}^{(i)}(R,\varphi), \tag{33}$$

   where $\lambda = 0.5$ is the relaxation parameter in the Gauss-Seidel update.

6. Repeat Steps 2-5 until $\sum_{R,\varphi} |F_{ct}^{(i+1)}(R,\varphi) - F_{ct}^{(i)}(R,\varphi)| \leq tolerance_F$ and $|M_{ct}^{(i+1)} - M_{ct}^{(i)}| \leq tolerance_M$ for some small positive numbers *tolerance*.

We solve for the initial steady state (before $T_0 = 1830$) and the terminal steady state (after $T_1 = 1900$). In the initial equilibrium, water power is the only available power source, which we model with a prohibitively high cost of steam adoption $c_{T_0}(S)$. In the terminal equilibrium, the cost of steam power has reached its new steady-state level.

F.2.2 Transition Path

This section describes how we solve for the transition path between the initial steady state ($T_0 = 1830$) and the terminal steady state ($T_1 = 1900$).

The dynamic equilibrium along the transition path is a technically challenging fixed point: we simulate a transition path of 70 years where heterogeneous firms make forward-looking decisions about entry, exit, and power adoption, and their decisions are interlinked through their competition in product markets.

We assist the solution algorithm based on our knowledge that: (i) the economy transitions between the steady states found in Section F.2.1, and (ii) the only driving force along the transition path is a steadily falling steam cost. In particular, we know that lower steam costs induce more entry, more steam adoption, and a lower price index. Hence, we search for a transition path where the mass of entrants, the distribution of operating firms, and the price index evolve smoothly between the steady states.

We use a nested shooting algorithm, where the outer loop searches for a time path for the mass of entrants that closes the free entry condition, and the inner loop iterates over the mass of operating firms to find a fixed point of the equilibrium policy functions for exit and power adoption. Our solution algorithm reads as follows.

1. Assume that the mass of entrants evolves smoothly between the steady states:

$$M_{ct}(\xi) = \exp\left(\log M_{cT_0} + \left(\frac{t-T_0}{T_1-T_0}\right)^{\xi} (\log M_{cT_1} - \log M_{cT_0})\right) \quad t \in [T_0, T_1], \tag{34}$$

where $\xi > 0$ governs the speed of convergence to the terminal steady state. Our goal is to find the value ξ^* that satisfies free entry and the other equilibrium conditions.

2. Define a grid $0 < \xi^{(1)} < \xi^{(2)} < ... < \xi^{(J)}$. Perform Steps 3-7 for each value of $\xi^{(j)}$.

3. Set an initial guess for the time paths of the price index and mass of operating firms:

$$Y_{ct}^{(0)} = Y_{cT_0} + \frac{t - T_0}{T_1 - T_0}(Y_{cT_1} - Y_{cT_0}) \quad \text{for} \quad Y_{ct} \in \{P_{ct}, F_{ct}(R, \varphi)\}, \tag{35}$$

where Y_{cT_0} and Y_{cT_1} correspond to the initial and terminal steady states from Section F.2.1. For each iteration $(i) = 0, 1, 2, ...,$:

4. Simulate the mass of operating firms:
   (a) Solve for the expected operating values $\mathbb{E}_\varepsilon[V_{ct}^{o(i)}(R, \varphi)]$ by backward recursion on Equation (29) from $T_1 - 1$ to the initial period T_0.
   (b) Given $F_{T_0}(R, \varphi)$ and $\{M_{ct}(\xi^{(j)})\}_t$, use the policy functions for exit and power adoption (Equations (9)-(10)) to simulate the firm mass $\{F_{ct}^{(NEW)}(R, \varphi)\}_t$.

5. Calculate the new price index:

$$P_{ct}^{(NEW)} = \left[\int p_{ct}^{(i)}(R, \varphi)^{1-\epsilon} dF_{ct}^{(NEW)}(R, \varphi)\right]^{\frac{1}{1-\epsilon}}. \tag{36}$$

6. Update the mass of operating firms and the price index:

$$F_{ct}^{(i+1)}(R, \varphi) = \lambda F_{ct}^{(NEW)}(R, \varphi) + (1 - \lambda) F_{ct}^{(i)}(R, \varphi) \tag{37}$$

$$P_{ct}^{(i+1)} = \lambda P_{ct}^{(NEW)} + (1 - \lambda) P_{ct}^{(i)}, \tag{38}$$

   where $\lambda = 0.5$ is the relaxation parameter in the Gauss-Seidel update.

7. Repeat Steps 4-6 until $|P_{ct}^{(i+1)} - P_{ct}^{(i)}| \leq tolerance_P$ for some small positive number *tolerance*.

8. Pick the value of ξ to close the free entry condition (Equation (7)) along the transition path:

$$\Delta(\xi) = \min_{\xi' \in \{\xi^{(1)}, .., \xi^{(J)}\}} \sum_{t=T_0}^{T_1} \left| \mathbb{E}_\varphi \left[V_{ct}(E, \varphi) | \xi = \xi' \right] - f^e \right|. \tag{39}$$

9. Conduct consistency checks of the equilibrium:

- Verify that the associated equilibrium closes the free entry condition $\Delta(\xi^*) < tolerance_\xi$ for some small positive number *tolerance*.
- Verify that the mass of operating firms has reached its terminal steady-state values by T_1. Otherwise, the time horizon T_1 has to be expanded.

F.2.3 Existence of Equilibrium

The convergence of our iterative algorithm (and thus the existence of an equilibrium) is ensured by the competition between firms in product markets, creating a congestion force (as summarized by the price index P_{ct}). For intuition, we describe a few practical examples of the congestion force.

First, suppose entry values exceed the fixed entry cost (such that the free entry condition in Equation (12) is not met) at our initial guess. More firms will then enter the market. The additional entrants strengthen the competition (i.e., lower the price index P_{ct}), which lowers profits ($\frac{\partial \pi_{ct}(R,\varphi)}{\partial P_{ct}} > 0$ in Equation (6)) and the value of entry.

Similarly, suppose the optimal survival rates exceed our initial guess. More firms will then stay in business. The additional operating firms lower the price index P_{ct}, which decreases operating values and, thus, optimal survival rates.

Finally, suppose the optimal steam adoption rates exceed our initial guess. More firms will then adopt steam power. The additional steam users lower the price index P_{ct} (when steam has lower marginal costs, $\gamma > 0$), which decreases optimal steam adoption (because of the profit complementarities between steam power and the price index, $\frac{\partial \pi_{ct}(S,\varphi)}{\partial P_{ct}} > \frac{\partial \pi_{ct}(W,\varphi)}{\partial P_{ct}}$ when $\gamma > 0$).

F.2.4 Uniqueness of Equilibrium

As Section F.2.3 describes, the convergence of our solution algorithm relies on a monotone relationship between the mass of firms (steam users) and the price index: a higher price index induces more entry/survival (steam use), which in turn lowers the price index. This monotone relationship also tends to ensure the equilibrium of the economy is unique.

To see this, suppose – for the sake of contradiction – that the economy could sustain two equilibria with different masses of entrants. The price index in the "low entry" equilibrium would then be higher, all else equal. However, that higher price index would induce more entry, contradicting its "low entry" nature.

A strong steam agglomeration force (a high α_S) could, however, lead to multiple equilibria. For example, suppose that the agglomeration force is so strong that a higher steam share s_{ct} makes even more mills want to adopt steam (i.e., $\frac{d\pi_{ct}(S,\varphi)}{ds_{ct}} \geq \frac{d\pi_{ct}(W,\varphi)}{ds_{ct}}$). In this case, the economy could sustain multiple equilibria: a "low steam" equilibrium where few mills adopt steam (because the agglomeration force is weak) and a "high steam" equilibrium where many mills use steam (because the agglomeration force becomes strong).

The potential for multiple equilibria is larger when steam is more available so that more firms are at the margin of steam adoption. We check for multiple equilibria in our terminal steady state (when steam power is fully available) by initiating our solution algorithm at different starting values for the equilibrium steam share. We also provide simulations of the agglomeration force (value of α_S) needed to create multiple equilibria, given our estimated values for the other parameters.

G Structural Estimation

G.1 Estimation Procedure

We estimate the structural model using a Newton-Rhapson algorithm that leverages the relationships between parameters and moments discussed in Sections V.A.1-V.A.2. The method iteratively adjusts the parameter values $\theta \in \mathbb{R}^K$ to match model-simulated moments $f(\theta) \in \mathbb{R}^K$ to their target values $y^* \in \mathbb{R}^K$.

Starting from an initial value θ_0, the Newton method updates the parameter estimates as follows:

$$\theta_{n+1} = \theta_n - \lambda J_f(\theta_n)^{-1}(f(\theta_n) - y^*), \tag{40}$$

where $J_f(\theta_n)$ is the Jacobian of the moment function f, evaluated numerically around θ_n, and $\lambda = 0.5$ is a dampening parameter that mitigates overshooting and ensures stable convergence to the target values.

The theoretical relationships between parameters and moments described in Sections V.A.1-V.A.2 are critical for the performance of the Newton method. In particular, the method works well when parameters and moments have smooth (most easily when linear) relationships (such that J_f does not change too rapidly) and the parameters have distinct (most easily when one-to-one) mappings to each target moment (such that J_f is well-conditioned and non-singular).

We make three adjustments to the estimation procedure to ensure these regularity conditions are robustly met.

First, we estimate the baseline productivity process (π, σ) and entry costs f^e in an initial step to match their target moments before the arrival of steam power. Second, we implement an adaptive grid search in the steam production parameters (γ, f_o^S), executing the Newton method on each grid point. Third, we adopt a dimensional continuation strategy for our Newton method, gradually adding parameter-moment pairs to the estimation problem in steps:

(a) *Steam adoption within regions:* estimate $(c_S^{(init)}, c_S^{(term)}, c(R, R'))$ to match their target moments.

(b) *Steam adoption between regions:* add $(c_L(W), \kappa)$ and their target moments to the estimation problem.

(c) *Output between regions:* add (η, κ) and their target moments to the estimation problem.

(d) *Startup and fixed costs*: add (f_o^E, f_o^W) and their target moments to the estimation problem.

Our estimation algorithm only proceeds to the next step once the incorporated moments are sufficiently close to their target values. These adjustments ensure that our estimation algorithm is well-behaved. We validate that J_f, at all iterations n, has the signs and magnitudes predicted in Sections V.A.1-V.A.2.

G.2 Identification of Structural Parameters

We now further analyze the local relationships between parameters and moments around the best-fit values θ^*. We also ensure that the algorithm converges to the same parameter estimates θ^* from a wide variety of starting values θ_0.

Local identification. Table A.20 and A.21 report two standard measures of parameter identification: the Jacobian of the moment function, which captures how simulated moments change with parameter values;[49] and the sensitivity measure of Andrews, Gentzkow and Shapiro (2017), which captures how estimated parameters change with target moments.[50]

We show these relationships for our Newton-based estimation, which relies directly on the Jacobian for the estimation (see Section G.1). We order the table rows and columns such that the diagonal elements capture the relationship between parameters and their target moments, as discussed in Sections V.A.1-V.A.2. The tables yield several insights into the identification of our structural model.

First, the simulated moments are highly sensitive to our parameters, suggesting that our parameter estimates are tightly identified. For example, increasing the water-to-steam switching costs by 1% of firm sales brings the incumbent-to-entrant steam switching rate 0.XX percentage points away from its perfectly fitted target values.

[49] The Jacobian is a commonly used diagnostic to assess the empirical properties of structural models (see, e.g., Berger and Vavra (2015); Ottonello and Winberry (2020); Balke and Lamadon (2022)).

[50] The sensitivity matrix M is related to the Jacobian J as follows: $M = (J'WJ)^{-1}J'W$, where W is a weighing matrix that does not matter in our exactly-identified case.

Second, there is a particularly strong link between model parameters and each of their target values, as the Jacobian and sensitivity matrices have pronounced excess mass along their diagonals. This suggests that the selected target moments are particularly important for identifying each of the parameters.

Third, and reassuringly, all the diagonal elements have the theory-predicted signs, as the relationship between moments and parameters have the directions predicted in Sections V.A.1-V.A.2.

Finally, the Jacobian and sensitivity matrices also have important off-diagonal elements, which highlight the importance of estimating the model parameters jointly. For example, Table A.21 shows that a higher water exit rate implies that steam costs must be higher to rationalize the observed level of steam adoption.

Global identification. To assess global identification, we follow Berger and Vavra (2015) by initiating our estimation routine at different starting values. Reassuringly, our estimation routine converges to the same best-fit values for many different starting values.

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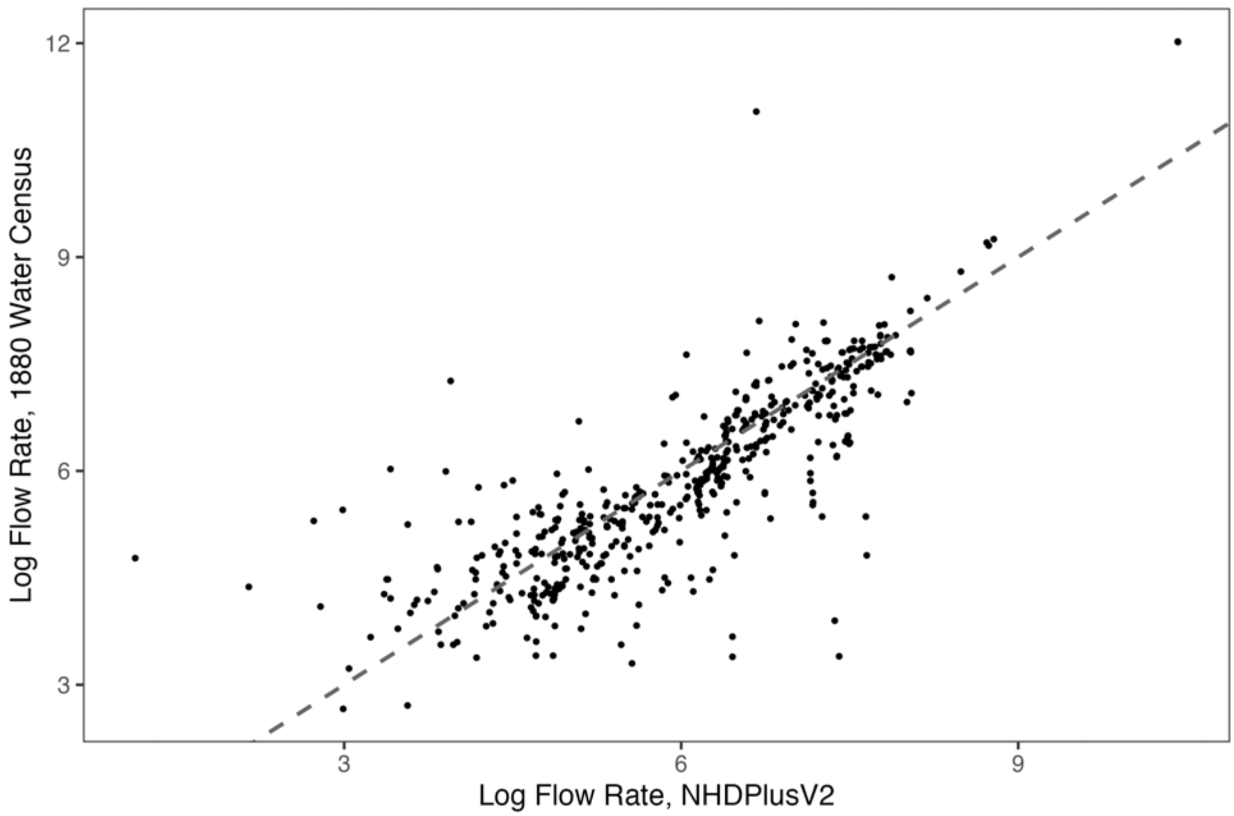
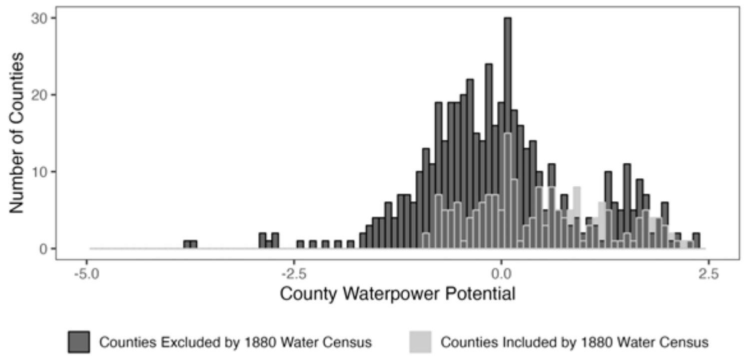
Figure A.1. River Segment Flow Rates, in the 1880 Water Census compared to NHDPlusV2



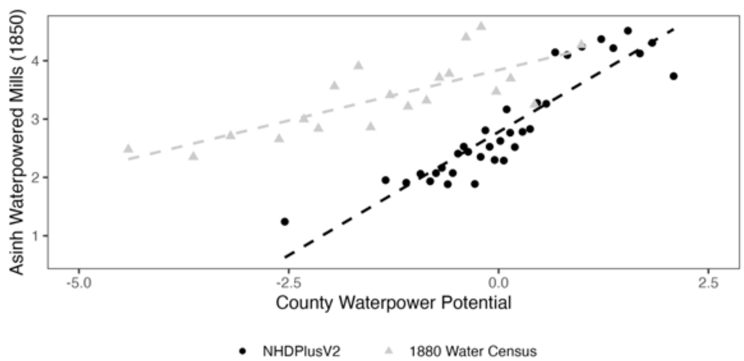
Notes: This figure compares the water flow rates of river segments that we linked by name from the 1880 Water Census and the National Hydrography Dataset Plus Version 2.0 (NHDPlusV2). Each point represents one linked river segment. Data from NHDPlusV2 and Census Bureau (1883).

Figure A.2. Selected coverage in the 1880 Water Census, compared to comprehensive NHDPlusV2 Data

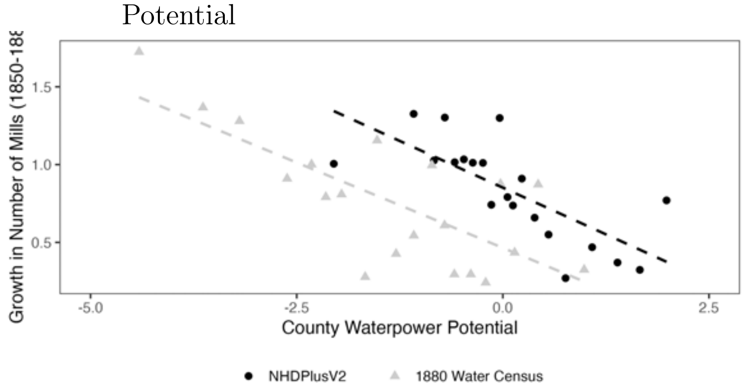
Panel A. Distribution of County Waterpower Potential, for Counties Included and Excluded by 1880 Water Census



Panel B. Measured Relationship Between 1850 Waterpowered Mills and County Waterpower Potential



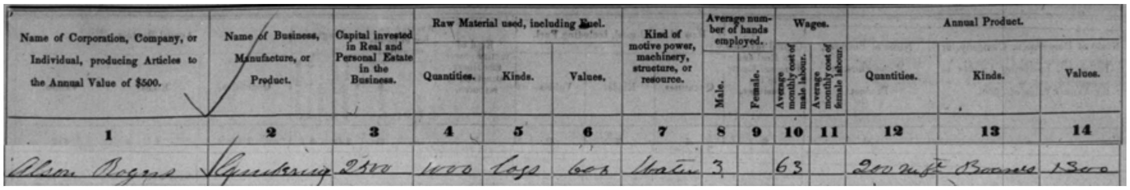
Panel C. Measured Relationship Between 1850-1880 Mill Growth and County Waterpower Potential



Notes: Panel A shows the distribution of country waterpower potential, measured using NHDPlusV2 data, for counties included by the 1880 Water Census (light gray) and counties excluded by the 1880 Water Census (dark gray). Panel B shows the unadjusted relationship between the number of waterpowered mills in 1850 and county waterpower potential, using the full NHDPlusV2 data and the Water Census data. Panel C shows the unadjusted relationship between the growth in the number of mills between 1850 and 1880 and county waterpower potential, using the full NHDPlusV2 data and the Water Census data. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880), NHDPlusV2, and Census Bureau (1883).

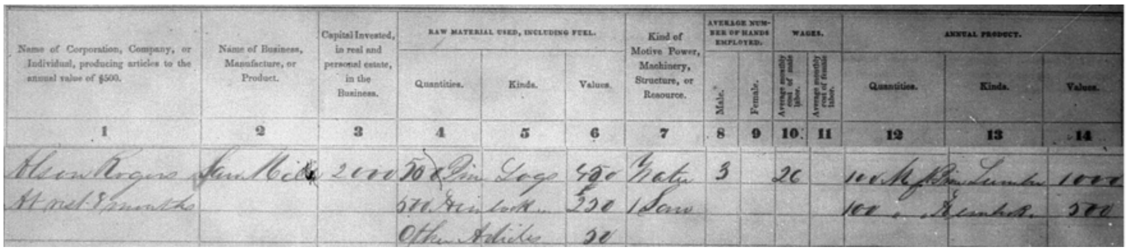
Figure A.3. Example Census Images: The Rogers' Lumber Mill

Panel A. 1850



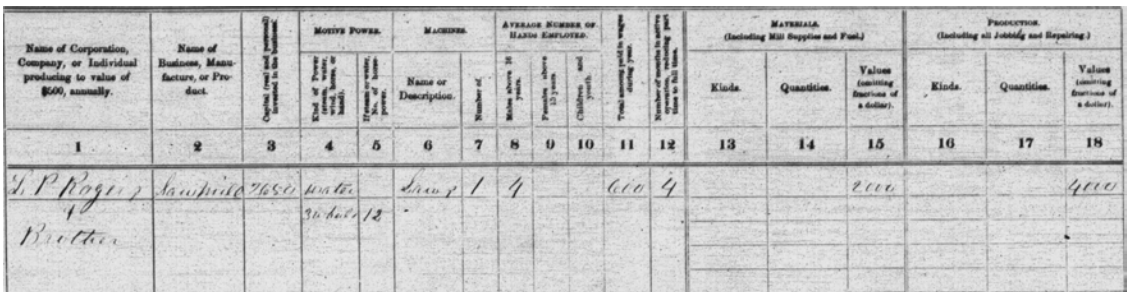
Name of Corporation, Company, or Individual, producing Articles to the Annual Value of $500.	Name of Business, Manufacture, or Product.	Capital invested in Real and Personal Estate in the Business.	Raw Material used, including Fuel. Quantities.	Kinds.	Values.	Kind of motive power, machinery, structure, or resource.	Average number of hands employed. Male.	Female.	Wages. Average monthly cost of male labour.	Average monthly cost of female labour.	Annual Product. Quantities.	Kinds.	Values.
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Alson Rogers	Lumbering	2500	1000	Logs	605	Water	3		63		200 M ft	Boards	1300

Panel B. 1860



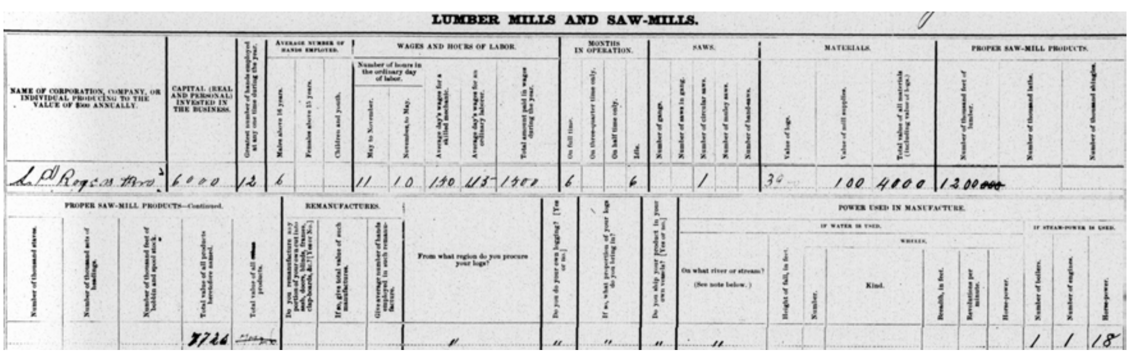
Name of Corporation, Company, or Individual, producing articles to the annual value of $500.	Name of Business, Manufacture, or Product.	Capital Invested, in real and personal estate, in the Business.	Raw Material Used, Including Fuel. Quantities.	Kinds.	Values.	Kind of Motive Power, Machinery, Structure, or Resource.	Average Number of Hands Employed. Male.	Female.	Wages. Average monthly cost of male labor.	Average monthly cost of female labor.	Annual Product. Quantities.	Kinds.	Values.
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Alson Rogers	Saw Mill	2000	700 Pine	Logs	450	Water	3		26		100 M ft Pine	Lumber	1000
At mill 8 months			500 Hemlock		250	1 Saw					100 "	Hemlock	500
			Other Articles		50								

Panel C. 1870



Name of Corporation, Company, or Individual producing to value of $500, annually.	Name of Business, Manufacture, or Product.	Capital (real and personal) invested in the business.	Motive Power. Kind of Power (steam, water, wind, horse, or hand).	If steam or water, No. of horse-power.	Machines. Name or Description.	Number of.	Average Number of Hands Employed. Males above 16 years.	Females above 15 years.	Children and youth.	Total amount paid in wages during year.	Number of months in active operation, reducing part time to full time.	Materials (Including Mill Supplies and Fuel.) Kinds.	Quantities.	Values (omitting fractions of a dollar).	Production (Including all Jobbing and Repairing.) Kinds.	Quantities.	Values (omitting fractions of a dollar).
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
L. P. Rogers & Brother	Sawmill	7650	water		Saws	1	4			600	4			2000			4000
			3 wheels	12													

Panel D. 1880



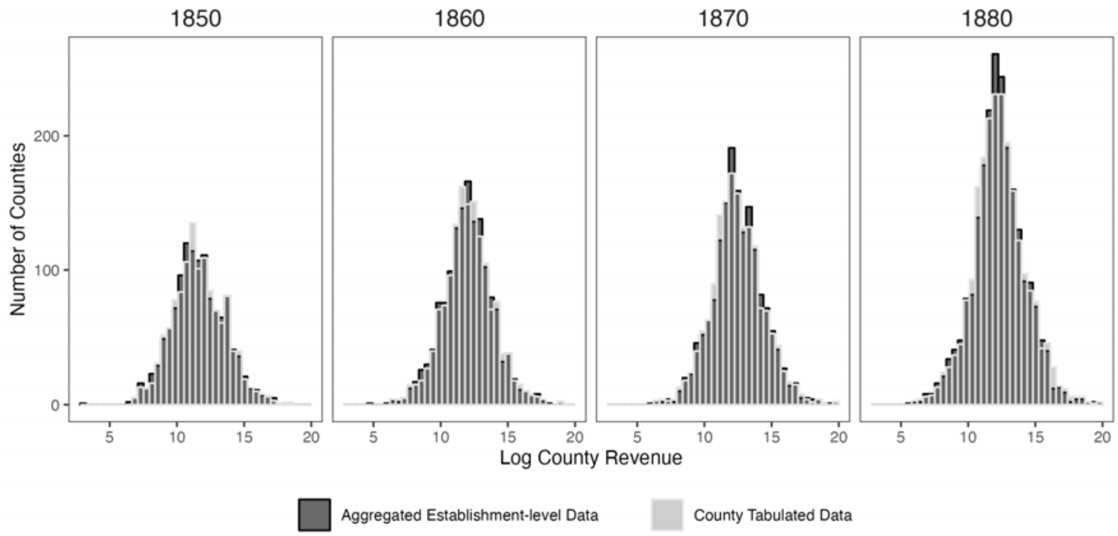
LUMBER MILLS AND SAW-MILLS.

Name of corporation, company, or individual producing to the value of $500 annually.	Capital (real and personal) invested in the business.	Greatest number of hands employed at any one time during the year.	Average number of hands employed. Males above 16 years.	Females above 15 years.	Children and youth.	Wages and hours of labor. Number of hours in the ordinary day of labor. May to November.	November to May.	Average day's wages for a skilled mechanic.	Average day's wages for an ordinary laborer.	Total amount paid in wages during the year.	Months in operation. On full time.	On three-quarter time only.	On half time only.	Idle.	Saws. Number of gangs.	Number of saws in gang.	Number of circular saws.	Number of muley saws.	Number of band-saws.	Materials. Value of logs.	Value of mill supplies.	Total value of all materials (including value of logs.)	Proper saw-mill products. Number of thousand feet of lumber.	Number of thousand laths.	Number of thousand shingles.
L. P. Rogers & Bro.	6000	12	6			11	10	150	115	1400	6			6			1			30	100	4000	1200		

Proper saw-mill products—Continued. Number of thousand staves.	Number of thousand sets of headings.	Number of thousand feet of bobbin and spool stock.	Total value of all products heretofore named.	Total value of all products.	Remanufactures. Do you remanufacture any portion of your own cut into sash, doors, blinds, frames, clap-boards, &c.? [Yes or No.]	If so, give total value of such manufactures.	Give average number of hands employed in such remanufacture.	From what region do you procure your logs?	Do you do your own logging? [Yes or no.]	If so, what proportion of your logs do you bring in?	Do you ship your product in your own vessels? [Yes or no.]	Power used in manufacture. If water is used. On what river or stream? (See note below.)	Height of fall, in feet.	Wheels. Number.	Kind.	Breadth, in feet.	Revolutions per minute.	Horse-power.	If steam-power is used. Number of boilers.	Number of engines.	Horse-power.
			7726	~~7726~~				"	"	"	"	"							1	1	18

Notes: This figure shows example images for the Census of Manufactures in each decade, and follows the Rogers' Mill across each decade. Alson Rogers settled in Warren, Pennsylvania and started in the lumber business after marrying in 1835. After he passed away in 1867, his sons Lucian (the "L.P." seen in the 1870 and 1880 Census images) and Burton took over the business. Sources: Schenck and Rann (1887), Census of Manufacturers (1850-1880), Census of Population (1850-1880).

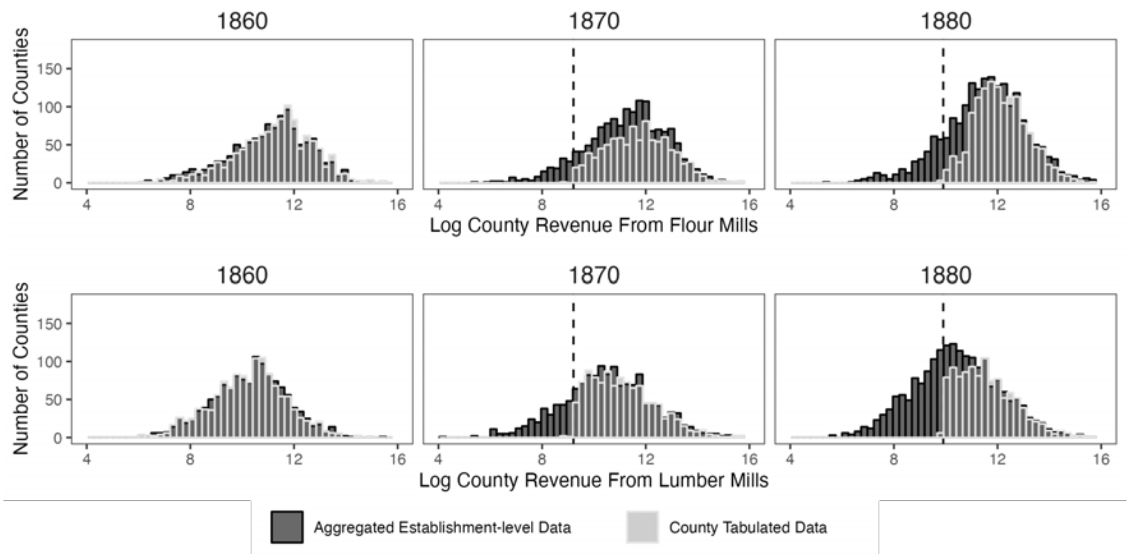
Figure A.4. Distribution of County-Level Manufacturing Revenue, in County-level Tabulations and Aggregating Our Establishment-level Data



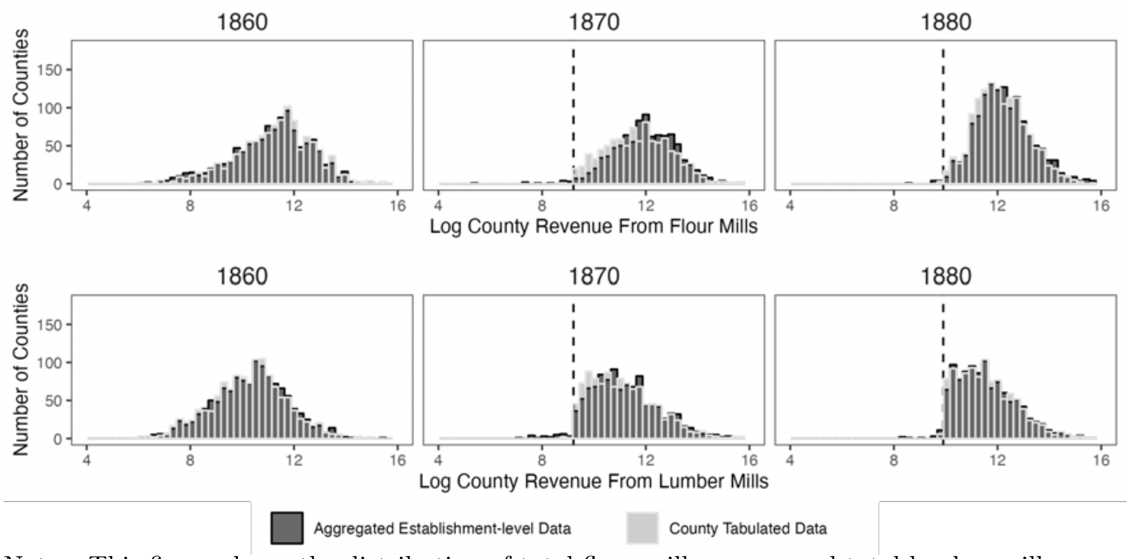
Notes: This figure shows the distribution of total recorded manufacturing revenue by county, comparing county-level tabulations made contemporaneously by the Census and aggregating to the county-level our digitized establishment-level data from Census manuscripts. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880), county-level tabulations (Haines, 2010).

Figure A.5. Unreported Data in County-Industry Tabulations, for Flour Mills and Lumber Mills, Compared to Aggregated Establishment-Level Data

Panel A. Distribution of County Revenue for Flour Mills and Lumber Mills, in County-Industry Tabulations or Aggregated Establishment-level Data

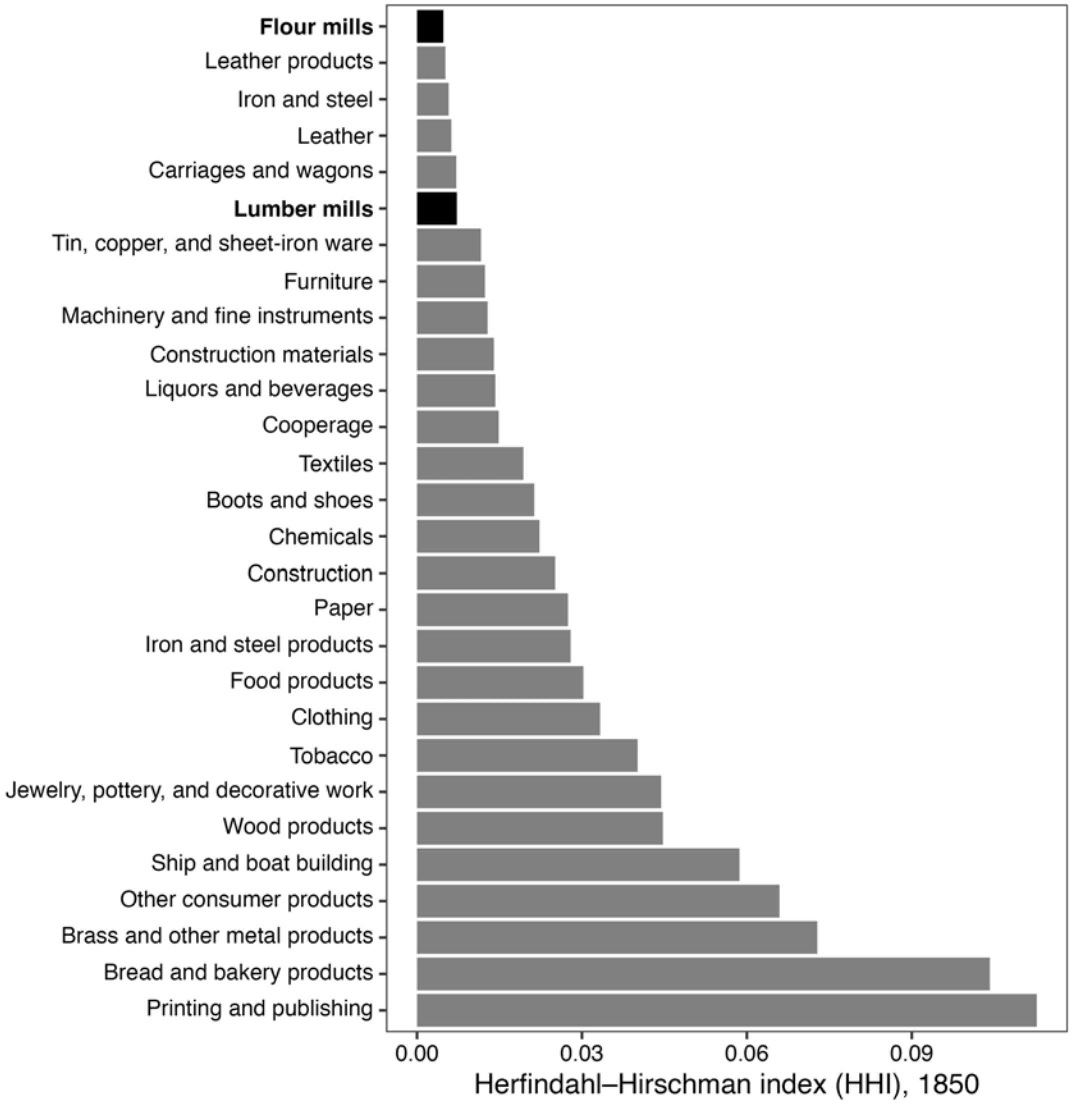


Panel B. Restricted to the Same Counties: Distribution of County Revenue for Flour Mills and Lumber Mills, by Data Source



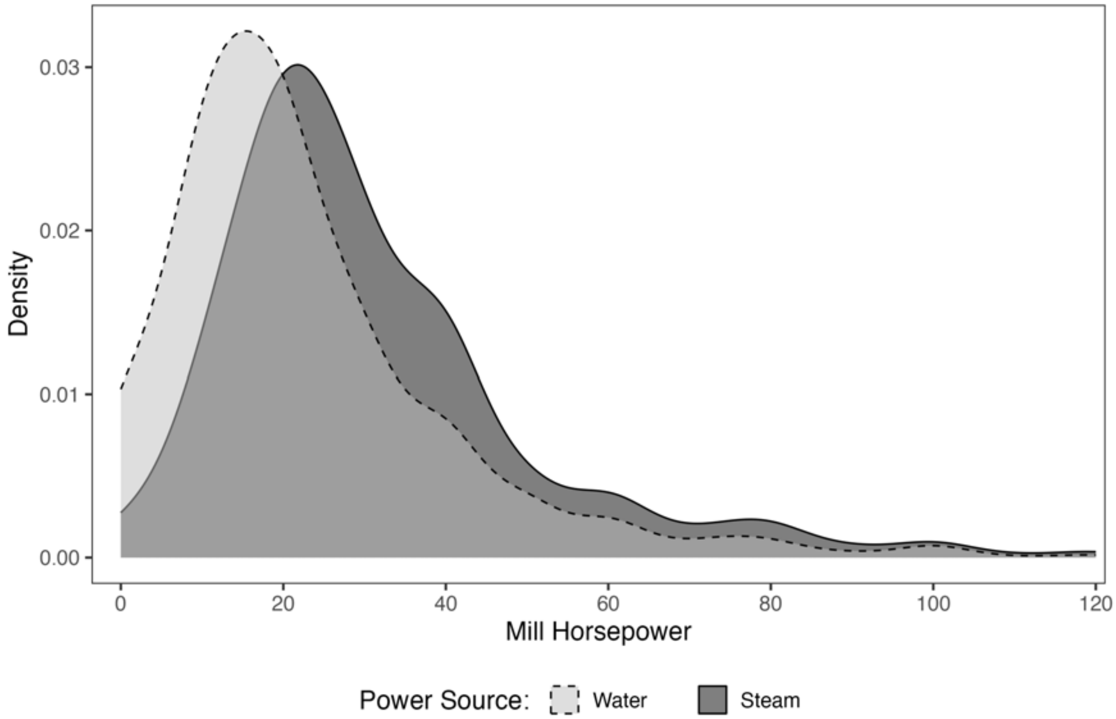
Notes: This figure shows the distribution of total flour mill revenue and total lumber mill revenue, by county, comparing county-industry tabulations for 1860-1880 made contemporaneously by the Census and aggregating to the county-industry-level our digitized establishment-level data from Census manuscripts. Panel A reports the distribution of values for county-industries with data in either source. Panel B reports the distribution of values for only those county-industries for which we have data from both sources. The Census had a *de jure* minimum value of total revenue for reporting county-industry values in 1870 and 1880, which correspond to the vertical lines, and also omitted tabulations for some other county-industry cells. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1860-1880) and county-industry-level tabulations digitized by Hornbeck and Rotemberg (2024).

Figure A.6. Geographic Concentration of Production in 1850, by Industry



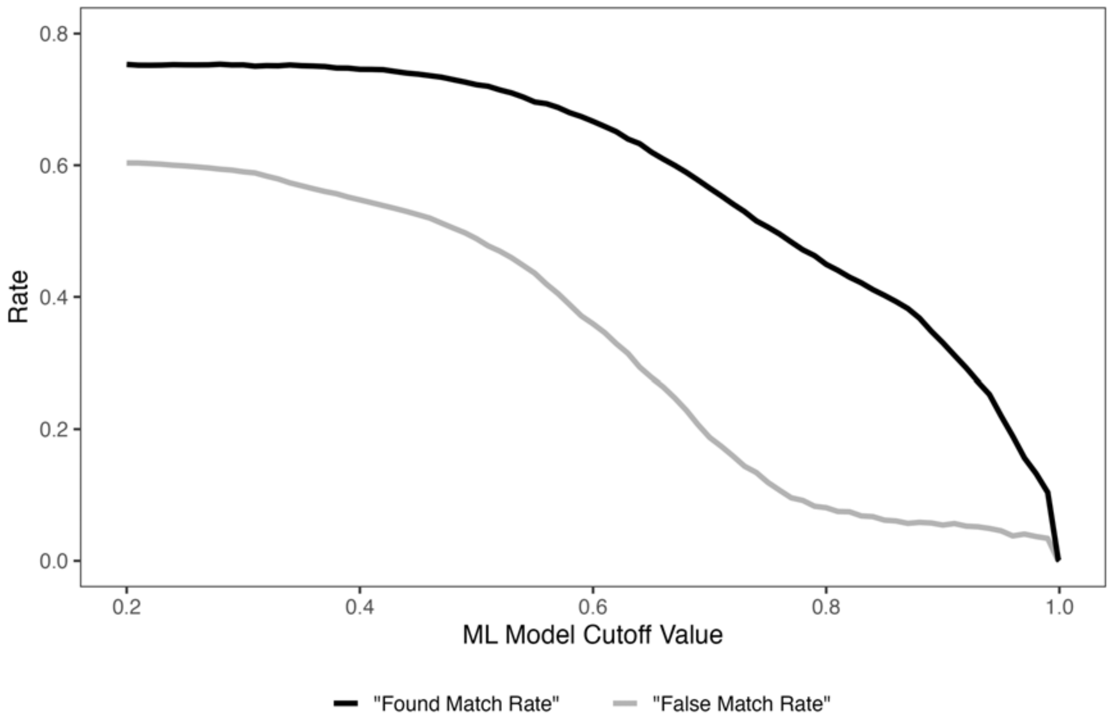
Notes: For each sector, this figure shows the Herfindahl–Hirschman index of revenue across counties in 1850 (sorted in increasing order). Data restricted to counties in our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850).

Figure A.7. Distribution of Total Horsepower Installed, by Power Source



Notes: This figure shows the distribution of horsepower installed for flour mills and lumber mills in 1870 and 1880, pooled across both industries and decades. For this figure, we truncated the data at 120 horsepower. Data restricted to counties in our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1870 and 1880).

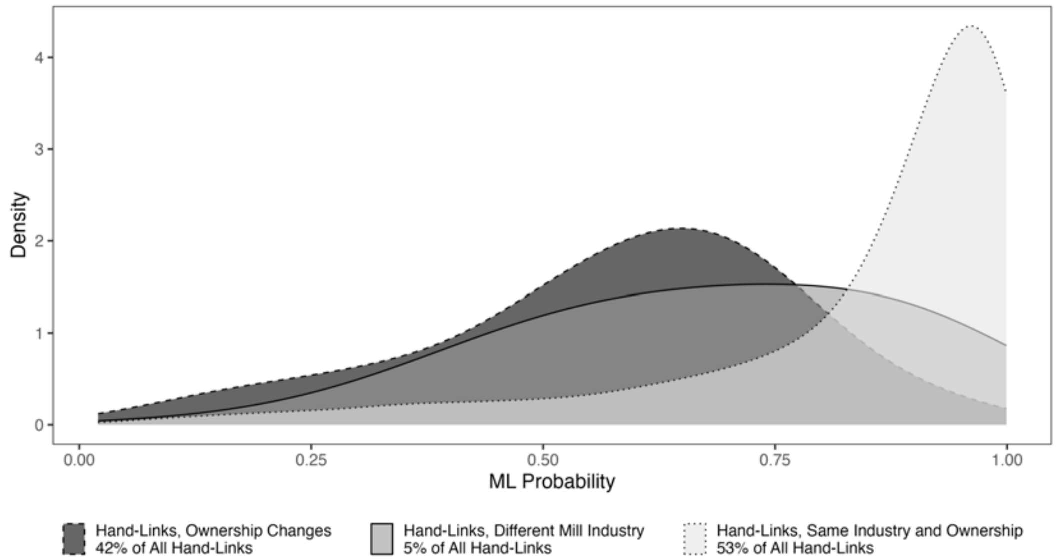
Figure A.8. "False Match Rate" and "Found Match Rate" of Machine-Learning Model, Compared to Hand-Links, by Chosen ML-Model Cutoff Value



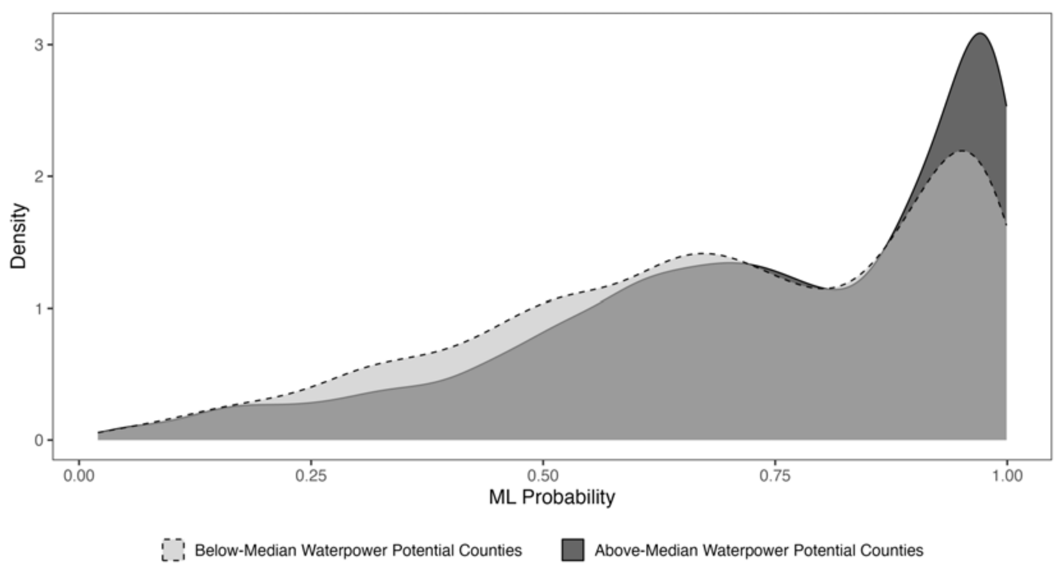
Notes: For different cutoff values used by the machine-learning model, the light gray line shows the share of links made by the machine-learning model that are not hand-links ("False Match Rate," if hand-links are assumed correct). The black line shows the share of hand-links made by the machine-learning model ("Found Match Rate"). The ML-model reports a probability that mills in adjacent decades are the same, and the chosen ML-model cutoff value is the lowest probability that we would classify as a match. If there are multiple mills above the cutoff, we match only the highest probability mill. The ML-Linking model is described in Appendix A.4. Data is for all lumber and flour mills in our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.9. Distribution of Hand-Links' ML-Model Probability, by Type and Waterpower Potential

Panel A. Distribution of Hand-Links' ML-Model Probability, by Hand-Link Type

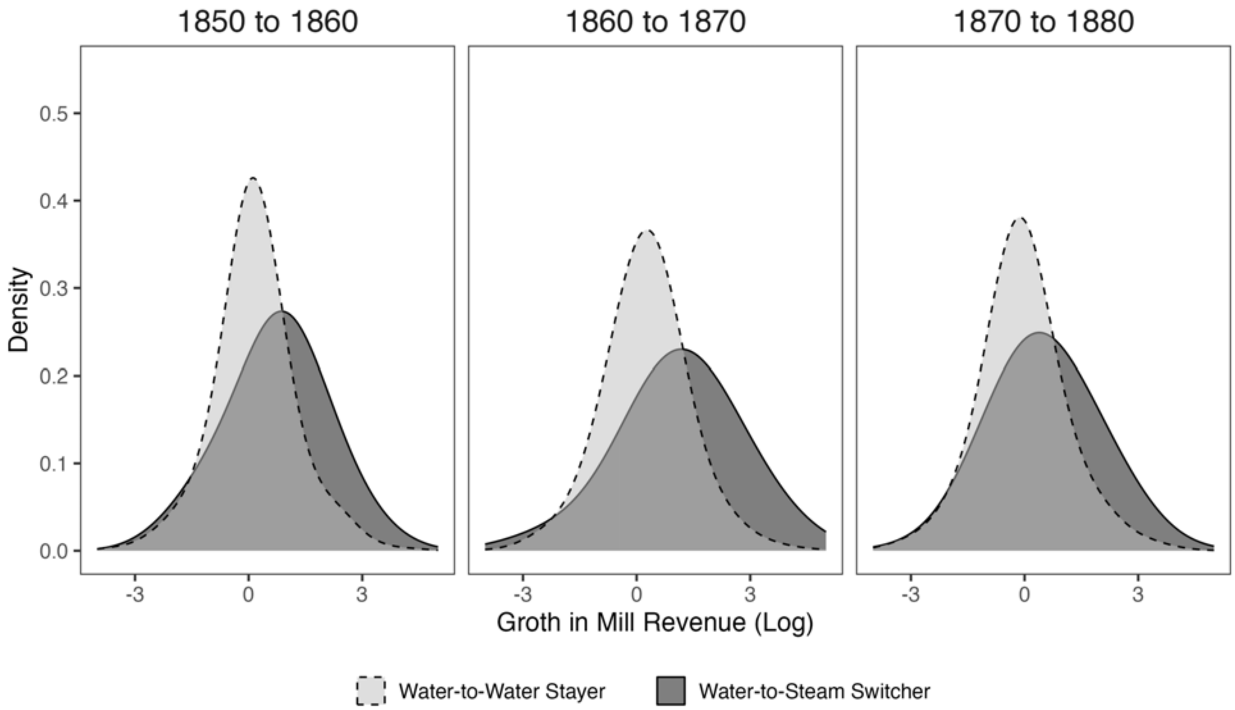


Panel B. Distribution of Hand-Links' ML-Model Probability, by County Waterpower Potential



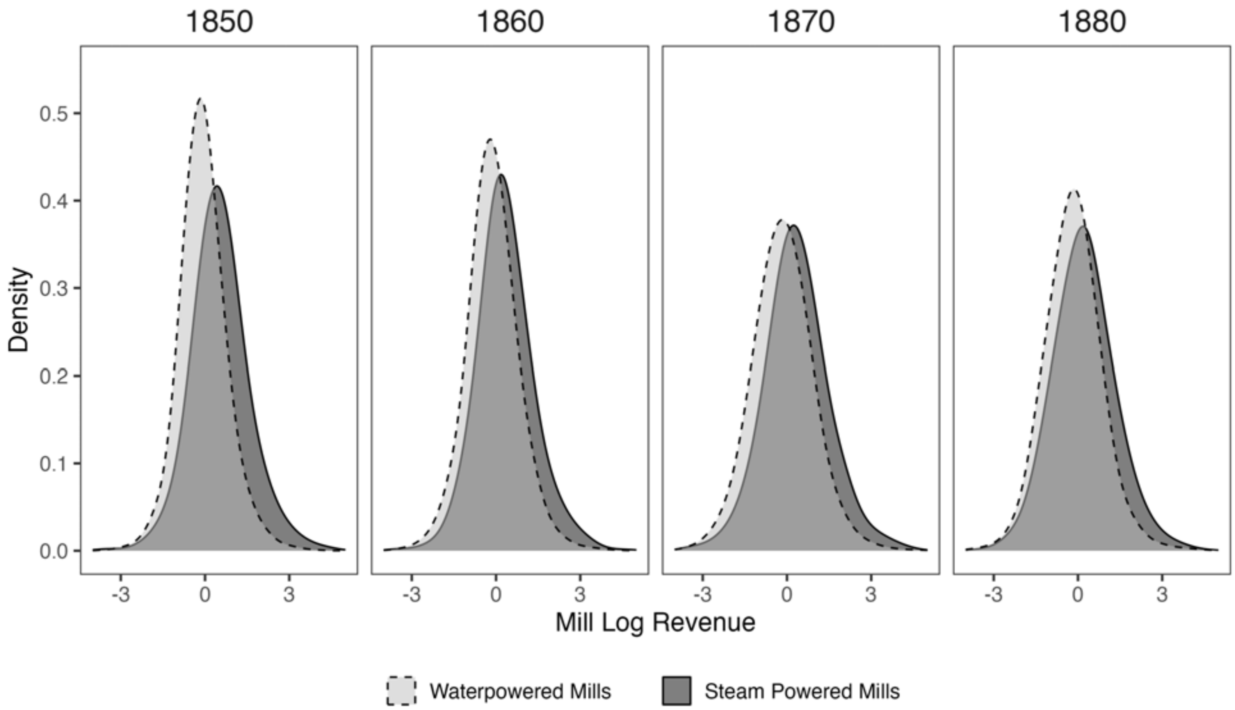
Notes: Panel A shows the distribution of hand-links by machine-learning probability, separately by the type of hand-link: those in the same industry and same ownership structure; those in a different mill industry (i.e., switched from flour to lumber milling); and those with ownership changes (i.e., added/removed some owners or changes to first names/initials). Panel B shows the distribution of machine-learning probabilities assigned to hand-links, separately for counties with above-median waterpower potential and below-median waterpower potential. The ML-Linking model is described in Appendix A.4. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Figure A.10. Growth in Mill Revenue (Log), by Steam Adoption Choice



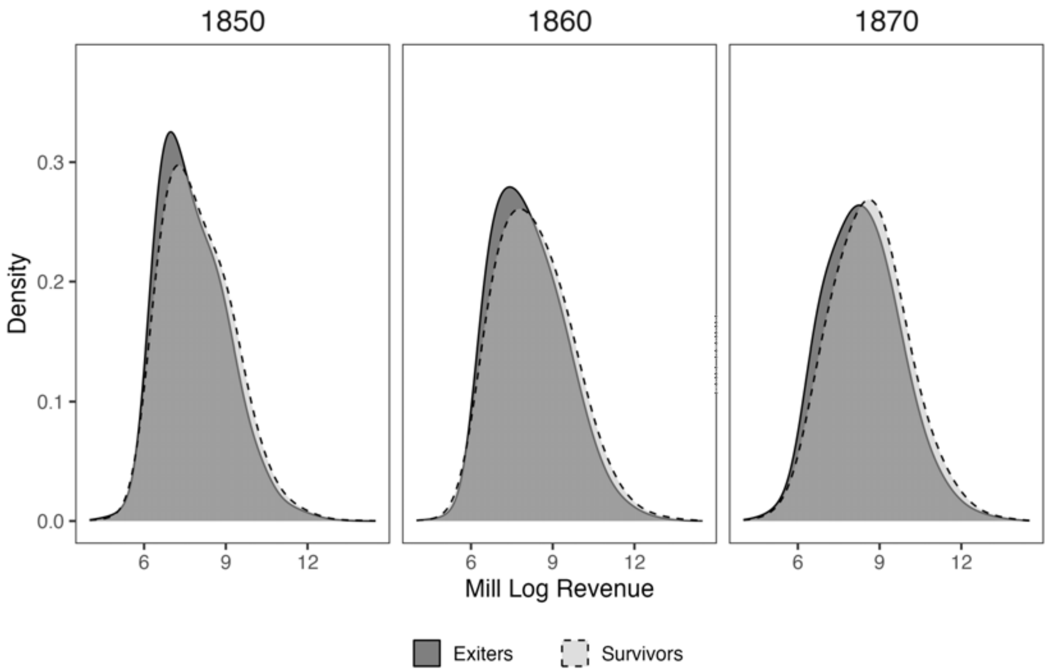
Notes: This figure shows the growth in mill revenue, by decade, for water incumbents who (1) kept using waterpower or (2) switched from water to steam power. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.11. Mill Size by Power Source, Within-County



Notes: This figure shows the distribution of mill revenue, in each decade, for each type of power source (steam or water). For each mill, we subtract mean log revenue in their county and industry (flour or lumber). Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

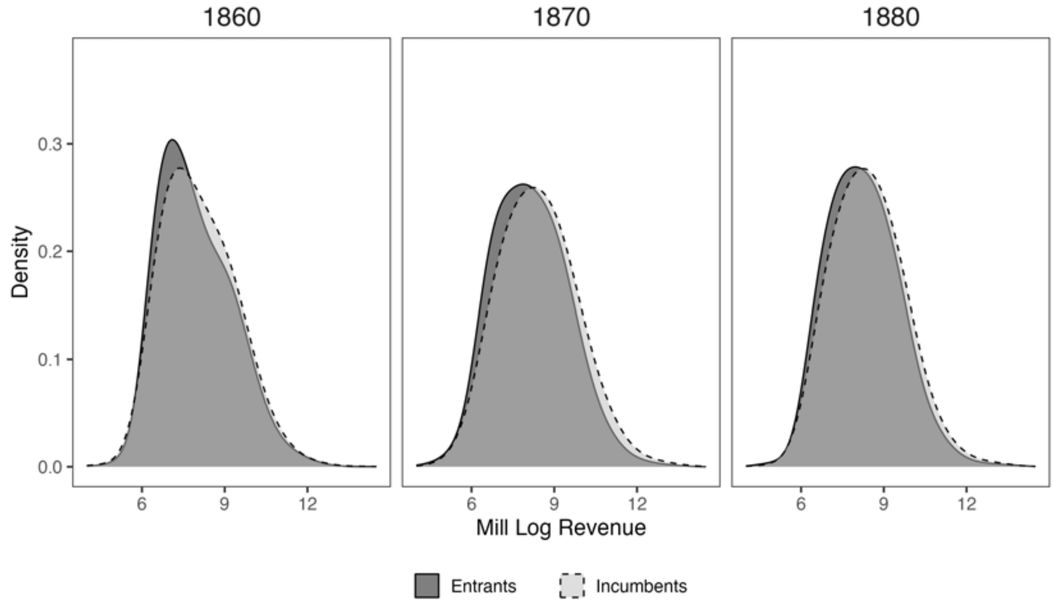
Figure A.12. Initial Mill Size, for Exiters and Survivors



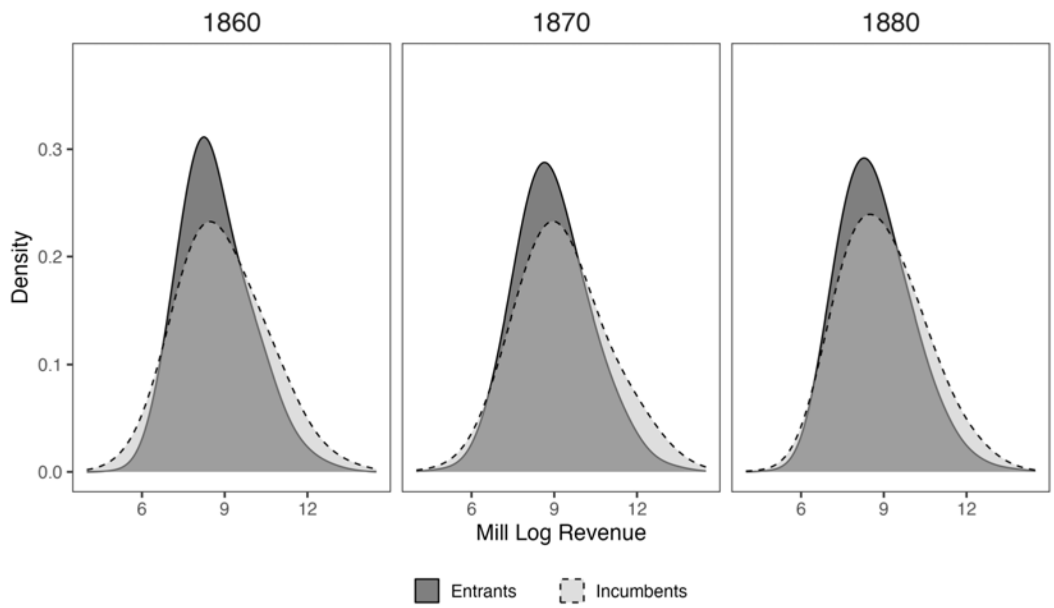
Notes: This figure shows the distribution of mill revenue in each baseline decade, separately for: "Exiters" who close in the subsequent decade, and "Survivors" who remain in operation by the next Census. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.13. Mill Size for Entrants and Incumbents, within Power Source

Panel A. Log Revenue of Entrants and Incumbents Using Water Power



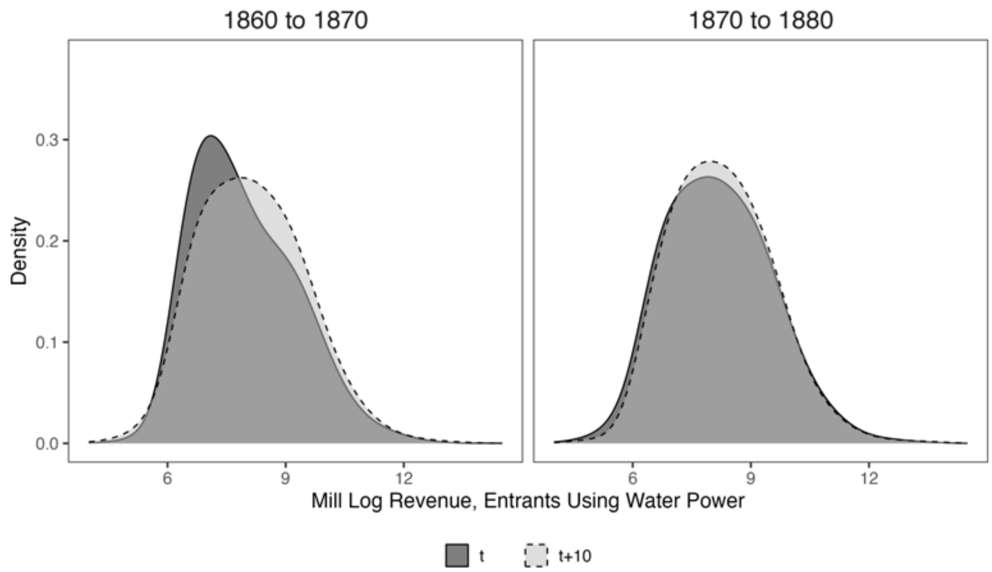
Panel B. Log Revenue for Entrants and Incumbents Using Steam Power



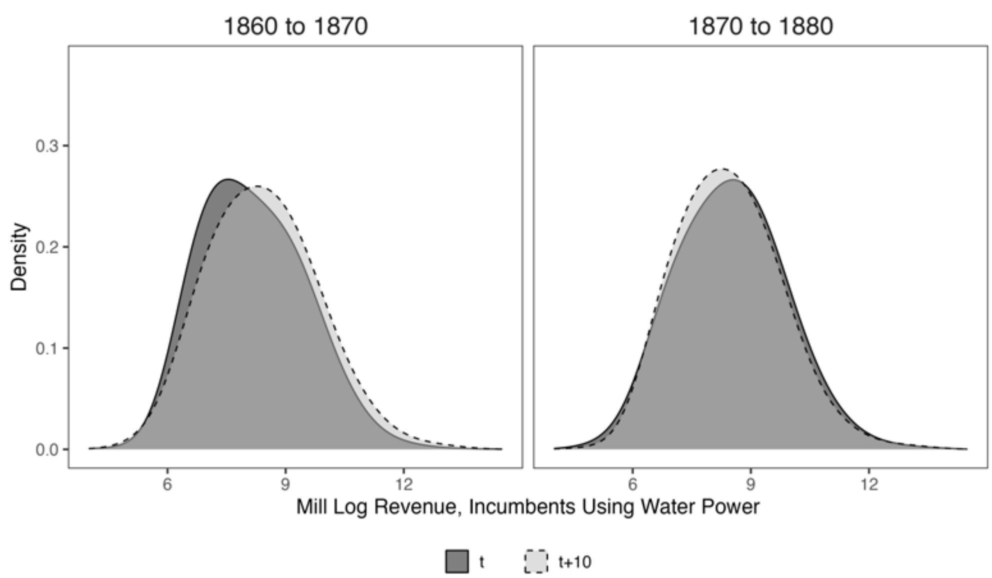
Notes: This figure shows the distribution of mill revenue, in each decade, comparing entrant mills and incumbent mills using the same power source (water power in Panel A, steam power in Panel B). Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.14. Mill Growth For Incumbents and Successive Generations of Entrants

Panel A. Log Revenue of Entrants Using Water Power



Panel B. Log Revenue of Incumbents Using Water Power



Notes: This figure plots the distribution of mill revenues for all water mills, by decade. The top panel shows the size distributions of water entrants in t and $t+10$. The bottom panel shows the size distributions of the water incumbents (who do not subsequently switch to steam power) in t and $t+10$. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Figure A.15. Water and Steam Adoption Costs: Structural Estimates

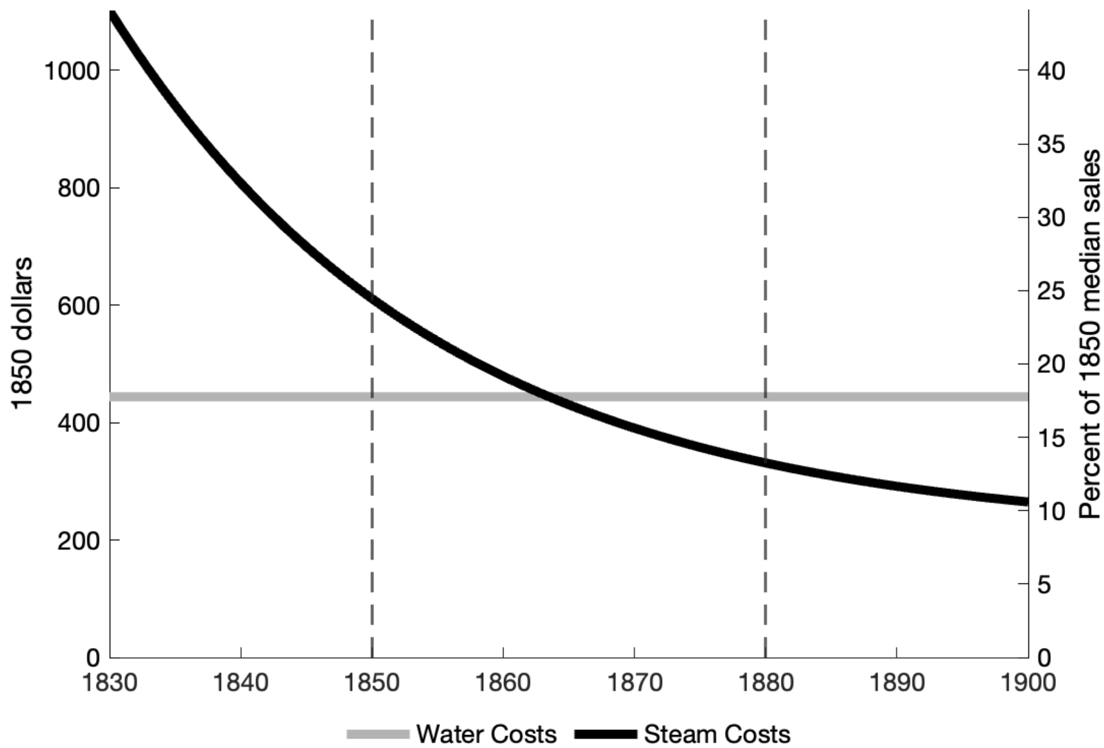
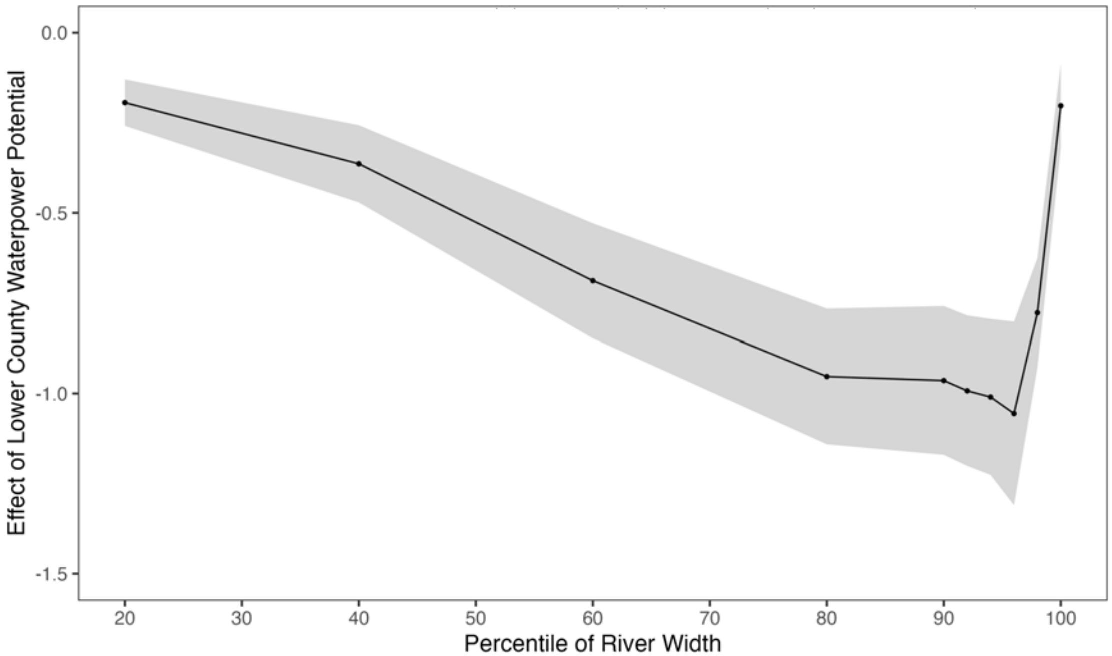


Figure A.16. Estimated Relationship between Waterpowered Mills in 1850 and County Waterpower Potential, Excluding Rivers with Widths Above Different Cutoffs



Notes: This figure shows the estimated relationship between a county's number of waterpowered mills in 1850 and county waterpower potential, where county waterpower potential is measured excluding rivers that are wider than the indicated cutoff percentile of river widths. We sort rivers into percentile bins, based on their width, estimate our main specification from Panel A of Table 2, and plot the estimated coefficient on Lower Waterpower along with its 95% confidence interval. All regressions include our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county, distance to the nearest navigable waterway, county market access in 1850, an indicator for workable coal deposits in the county, the share of the county covered by coal deposits, and access to coal via the transportation network. Data from our main sample (Figure 2), using our digitized establishment-level Census of Manufactures (1850) and NHDPlusV2.

Table A.1. Coverage Rates

State	1850	1860	1870	1880	State	1850	1860	1870	1880
AL	✓	✓	✓	✓	MT	-	-	✓	✓
AR	✓	✓	✓	✓	NE	-	✓	✓	✓
CA	✓	✓	✓	✓	NV	-	-	✓	✓
CO	-	-	✓	✓	NH	✓	✓	✓	✓
CT	✓	✓	✓	✓	NJ	✓	✓	✓	✓
DE	✓	✓	✓	✓	NY	✓	✓	82%	99%
DC	✓	✓	✓	✓	NC	✓	84%	✓	✓
FL	✓	✓	✓	✓	ND & SD	-	-	0%	18%
GA	0%	0%	0%	✓	OH	✓	26%	74%	68%
IL	✓	✓	46%	✓	OR	✓	✓	✓	✓
IN	✓	✓	✓	✓	PA	✓	✓	✓	✓
IA	✓	✓	✓	✓	RI	✓	✓	✓	✓
KS	-	✓	✓	✓	SC	✓	✓	✓	✓
KY	✓	✓	✓	✓	TN	✓	30%	35%	✓
LA	0%	0%	0%	✓	TX	✓	✓	85%	✓
ME	✓	✓	✓	✓	UT	-	✓	✓	✓
MD	✓	✓	0%	✓	VT	✓	✓	✓	✓
MA	✓	✓	32%	✓	VA	✓	✓	✓	✓
MI	✓	✓	49%	✓	WA	-	✓	✓	✓
MN	✓	✓	✓	✓	WV	-	-	✓	✓
MS	✓	✓	✓	✓	WI	✓	✓	✓	✓
MO	✓	✓	✓	✓					

Notes: This table shows our coverage of counties. Percents indicate estimates of the share of establishments that we digitized, given the published county-level tabulations. In 1850, the Census records for three counties in California (Contra Costa, San Francisco, and Santa Clara) were lost and never tabulated, we have complete coverage of the remaining counties in California. Dashes indicate that no survey was conducted, checkmarks indicate that we have complete coverage.

Table A.2. Survival Rates, by County Waterpower Potential and Initial Power Source

	Water Survival Rate (1)	Steam Survival Rate (2)	Difference (1) − (2) (3)
Elasticity with Respect to Lower Waterpower:			
In 1860	-0.215	-0.515	0.300
	(0.072)	(0.179)	(0.185)
# County-Industries	1,199	1,199	
In 1870	-0.265	-0.158	-0.107
	(0.064)	(0.109)	(0.122)
# County-Industries	1,199	1,199	
In 1880	-0.217	-0.162	-0.055
	(0.049)	(0.080)	(0.092)
# County-Industries	1,199	1,199	

Notes: This table shows the elasticity of survival in both water and steam mills, over the previous decade, with respect to county waterpower potential from 1860-1880. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Column 1 reports results for waterpowered incumbents, column 2 reports results steam powered ones, and column 3 reports the difference. Each row corresponds to a different PPML regression, using data from the indicated Census year and previous Census year, which approximates percent differences in the rates.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1860-1880) and NHDPlusV2.

Table A.3. Per Capita Manufacturing Growth and Steam Diffusion by Waterpower

	Population (1)	Mills Per Capita (2)	Mill Revenue Per Capita (3)
Panel A. Differences in Lower Waterpower Counties:			
In 1850	-0.284	-0.672	-0.592
	(0.226)	(0.233)	(0.232)
Panel B. Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.094	0.126	0.088
	(0.029)	(0.065)	(0.082)
From 1860 to 1870	0.067	0.046	0.136
	(0.040)	(0.060)	(0.066)
From 1870 to 1880	0.075	0.017	0.065
	(0.024)	(0.044)	(0.101)
# County-Industries		1,199	1,199

Notes: This table shows the relationship between per capita growth in mill activity and county water power potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is (log) population, the outcome in column 2 is mills per capita, and the outcome in column 3 is milling revenue per capita. Panel A reports cross-sectional differences in 1850. Panel B reports growth rates over the following decades. Each row corresponds to a different regression, using only data from the indicated years. Column 1 reports OLS estimates, and columns 2-3 report PPML estimates, which approximate percent differences.

All regressions industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network. Panel B regressions also include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.4. Steam Diffusion and *Flour* Mill Growth, by County Waterpower Potential

	Steam Share of Mills (1)	Total Mills (2)	Total Mill Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.018	0.114	0.154
	(0.020)	(0.069)	(0.110)
# Counties	535	587	587
From 1860 to 1870	0.038	0.163	0.194
	(0.019)	(0.072)	(0.088)
# Counties	531	587	587
From 1870 to 1880	0.013	0.053	0.160
	(0.015)	(0.041)	(0.120)
# Counties	574	587	587

Notes: This table shows the relationship between growth in mill activity and county waterpower potential, limiting the sample to flour mills. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcomes are the share of flour mills using steam power (column 1), the total number of mills (column 2), and total mill revenue (column 3). Each row corresponds to growth over the indicated decade, using only data from the indicated years.

Column 1 reports OLS estimates, restricting the sample to counties with at least one flour mill in both decades (for the steam share to be defined) and weighting by the number of flour mills in that county in 1850. These estimates reflect percentage point differences in the shares. Columns 2 and 3 report PPML estimates for a balanced panel of counties (including zeros), which approximate percent differences.

All regressions include county fixed effects, year fixed effects, and our baseline controls interacted with year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.5. ***Flour*** **Mill Entry Rates and Survival Rates, by County Waterpower Potential**

	Entry Rate (1)	Survival Rate (2)	Difference (1) − (2) (3)
Elasticity with Respect to Lower Waterpower:			
In 1860	0.183	-0.153	0.336
	(0.084)	(0.093)	(0.120)
# Counties	587	587	
In 1870	0.203	-0.117	0.320
	(0.082)	(0.071)	(0.101)
# Counties	587	587	
In 1880	0.129	-0.223	0.352
	(0.050)	(0.057)	(0.079)
# Counties	587	587	

Notes: This table shows the elasticity of mill entry and mill survival, over the previous decade, with respect to county waterpower potential, limiting the sample to flour mills. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Column 1 reports results for entry, column 2 reports results for incumbent survival, and column 3 reports the difference in these estimates. Each row corresponds to a different PPML regression limited to flour mills, using data from the indicated Census year and previous Census year, which approximates percent differences in the rates.

All regressions include county fixed effects, year fixed effects, and our baseline controls interacted with year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.6. Steam Adoption of Entrants and Water *Flour* Mills, by County Waterpower Potential

	From Entrants (1)	Water Incumbents (2)	Difference (1) − (2) (3)
Adoption in Lower Waterpower Counties:			
In 1860	0.091	0.033	0.059
	(0.029)	(0.033)	(0.037)
# Counties	530	333	
In 1870	0.103	0.063	0.040
	(0.022)	(0.027)	(0.035)
# Counties	575	326	
In 1880	0.126	0.047	0.079
	(0.026)	(0.023)	(0.027)
# Counties	577	416	

Notes: This table shows the relationship between county waterpower potential and the steam use of entrant mills and water incumbent mills, limiting the sample to flour mills. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is the share of entrants using steam power, restricted to county-industries with at least one entrant in that year. Column 2 reports the share of "water incumbents" (mills that used waterpower in the previous Census year) who switched to steam power. For column 2, the sample is restricted to county-industries with at least one surviving water incumbent. Column 3 reports the difference between the estimates in columns 1 and 2. Each row corresponds to a different OLS regression, using data from flour mills in the indicated Census year only, which report percentage point differences in the shares.

All regressions include our baseline controls: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

For each row, each observation is a county, weighted by the number of flour mills in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.7. Robustness to Alternative Drivers of Steam Use

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.055	0.089	0.220	0.113	0.092	0.067	0.034	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
2. Each type of coal separately	-1.056	0.089	0.221	0.113	0.091	0.067	0.034	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
3. Square and cubic in county coal shares	-1.046	0.086	0.202	0.131	0.097	0.069	0.030	-0.007
	(0.129)	(0.015)	(0.061)	(0.053)	(0.035)	(0.016)	(0.012)	(0.013)
4. FAO suitability for wheat	-1.065	0.088	0.203	0.127	0.100	0.065	0.033	-0.011
	(0.130)	(0.015)	(0.061)	(0.052)	(0.037)	(0.017)	(0.013)	(0.013)
5. Woodland share in county	-1.004	0.093	0.182	0.097	0.086	0.059	0.030	-0.017
	(0.131)	(0.015)	(0.065)	(0.054)	(0.037)	(0.017)	(0.013)	(0.014)
6. 1850 local MFG wages	-1.045	0.094	0.230	0.116	0.080	0.059	0.035	-0.010
	(0.133)	(0.015)	(0.063)	(0.055)	(0.037)	(0.017)	(0.013)	(0.014)
7. 1850 engineers and mechanics	-1.063	0.091	0.216	0.115	0.093	0.069	0.031	-0.007
	(0.129)	(0.015)	(0.062)	(0.052)	(0.036)	(0.017)	(0.013)	(0.013)
8. 1850 access to banks	-1.044	0.086	0.219	0.115	0.090	0.067	0.034	-0.008
	(0.129)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
9. All above	-0.983	0.082	0.138	0.140	0.090	0.050	0.023	-0.011
	(0.123)	(0.015)	(0.066)	(0.058)	(0.037)	(0.018)	(0.013)	(0.014)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and growth 1850-1880. This table focuses on additional controls for alternative factors which may have driven steam adoption.

All regressions include our baseline controls interacted with year and industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.8. Robustness to Alternative Drivers of County Growth

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.055	0.089	0.220	0.113	0.092	0.067	0.034	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
2. No controls for MA/navigable rivers	-1.253	0.078	0.288	0.120	0.104	0.083	0.036	-0.011
	(0.136)	(0.015)	(0.063)	(0.051)	(0.036)	(0.017)	(0.012)	(0.013)
3. No controls for coal	-1.060	0.096	0.238	0.110	0.098	0.080	0.038	-0.005
	(0.125)	(0.016)	(0.064)	(0.052)	(0.036)	(0.019)	(0.012)	(0.014)
4. No extra controls	-1.270	0.080	0.306	0.125	0.114	0.087	0.036	-0.010
	(0.131)	(0.015)	(0.063)	(0.050)	(0.035)	(0.018)	(0.012)	(0.015)
5. Time-varying market access	-1.049	0.088	0.211	0.114	0.103	0.066	0.035	-0.008
	(0.126)	(0.015)	(0.059)	(0.052)	(0.034)	(0.016)	(0.013)	(0.013)
6. Time-varying population	-0.764	0.090	0.149	0.101	0.072	0.053	0.024	-0.013
	(0.108)	(0.015)	(0.064)	(0.057)	(0.037)	(0.017)	(0.013)	(0.014)
7. 1850 population	-0.815	0.094	0.179	0.112	0.078	0.056	0.032	-0.011
	(0.115)	(0.016)	(0.061)	(0.054)	(0.036)	(0.016)	(0.013)	(0.014)
8. Appalachia	-1.039	0.088	0.220	0.114	0.092	0.066	0.034	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
9. Frontier	-1.050	0.089	0.215	0.110	0.095	0.066	0.035	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.017)	(0.013)	(0.013)
10. 1850 agricultural share	-1.041	0.093	0.207	0.103	0.084	0.065	0.032	-0.012
	(0.129)	(0.015)	(0.062)	(0.052)	(0.035)	(0.016)	(0.012)	(0.013)
11. Portage sites	-1.063	0.091	0.219	0.114	0.091	0.069	0.032	-0.008
	(0.129)	(0.015)	(0.062)	(0.052)	(0.036)	(0.017)	(0.012)	(0.014)
12. Civil war controls	-0.920	0.087	0.225	0.127	0.051	0.061	0.033	-0.009
	(0.122)	(0.015)	(0.063)	(0.055)	(0.037)	(0.017)	(0.013)	(0.013)
13. Time-invariant controls from rows 8-12	-0.914	0.091	0.217	0.110	0.052	0.062	0.033	-0.008
	(0.121)	(0.015)	(0.063)	(0.055)	(0.036)	(0.017)	(0.012)	(0.013)
14. All time-invariant controls (rows 7-12)	-0.667	0.092	0.184	0.123	0.045	0.055	0.032	-0.006
	(0.100)	(0.016)	(0.063)	(0.056)	(0.036)	(0.017)	(0.012)	(0.013)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and growth 1850-1880. This table focuses on additional controls for alternative factors which may have driven county growth.

Unless otherwise specified (in rows 2-5), all regressions include our baseline controls interacted with year and industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850, an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.9. Steam use, by Distance to Railroad Station

	From Entrants (1)	From Water Incumbents (2)	Difference (1) − (2) (3)
Lower Waterpower	0.177	0.045	0.132
	(0.021)	(0.014)	(0.017)
Log Distance, WPP-to-RR Station	0.017	-0.033	0.050
	(0.042)	(0.028)	(0.041)
Log Distance, to RR Station	-0.017	0.035	-0.052
	(0.047)	(0.032)	(0.045)
# County-Industries	1,190	841	

Notes: This table shows the relationship between waterpower potential, railroad station placement, and the steam use of entrant and incumbent mills from 1860-1880. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential. "Log Distance, WPP-to-RR Station" is the log of the average distance from water segments to the closest railroad stations, weighting by potential horsepower. "Log Distance, to RR Station" is the average distance from railroad stations from all points in the county.

The outcome in column 1 is the share of entrants using steam power, the outcome in column 2 is the share of water incumbents (incumbents who used waterpower in the previous decade) who switched to steam power, and column 3 reports the difference. Each row corresponds to different regressions, using only data from the indicated year. The sample is restricted to all county-industry-years at least one current entrant (in column 1) or incumbent (in column 2).

All regressions include our baseline controls interacted with year and industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network. Regressions are weighted by the number of mills in the county in 1850.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.10. Confusion Matrix: Hand Links vs. Predicted Links

	Machine Learning Links			
	Linked (Same)	Linked (Different)	Not Linked	Total
Hand Links	(1)	(2)	(3)	(4)
Panel A. 1850 to 1860				
Linked	2,590	69	942	3,601
Not Linked	-	217	14,114	14,331
Panel B. 1860 to 1870				
Linked	2,313	256	816	3,385
Not Linked	-	2,237	11,885	14,122
Panel C. 1870 to 1880				
Linked	3,486	187	1,849	5,522
Not Linked	-	1,096	16,697	17,793

Notes: This table shows the confusion matrix for the panel links. The rows report matches made by the hand-linking procedure, and the columns correspond to matches made by the machine-learning model, both of which are described in Appendix A.4. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.11. Robustness to Measurement and Linking Error: Entry and Survival

	Entry Rate			Survival Rate		
	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)
1. Baseline	0.323	0.168	0.158	-0.230	-0.266	-0.158
	(0.074)	(0.058)	(0.045)	(0.065)	(0.057)	(0.040)
2. Links that are both ML and hand-linked	0.274	0.142	0.134	-0.165	-0.229	-0.193
	(0.068)	(0.055)	(0.041)	(0.079)	(0.069)	(0.048)
3. Only ML links	0.287	0.143	0.135	-0.211	-0.212	-0.179
	(0.069)	(0.056)	(0.042)	(0.078)	(0.068)	(0.046)
4. Raising ML linking threshold to 0.8	0.256	0.139	0.126	-0.179	-0.349	-0.258
	(0.065)	(0.054)	(0.040)	(0.089)	(0.073)	(0.057)
5. Lowering ML linking threshold to 0.4	0.320	0.143	0.130	-0.242	-0.192	-0.110
	(0.073)	(0.056)	(0.042)	(0.068)	(0.066)	(0.043)
6. Only business-name mills	0.308	0.244	0.124	-0.241	-0.258	-0.172
	(0.070)	(0.058)	(0.049)	(0.083)	(0.078)	(0.058)
7. Only non-business name mills	0.270	0.043	0.173	-0.205	-0.290	-0.229
	(0.083)	(0.072)	(0.052)	(0.097)	(0.084)	(0.064)
8. Only mills with all positive inputs	0.341	0.198	0.142	-0.207	-0.253	-0.124
	(0.079)	(0.061)	(0.047)	(0.068)	(0.061)	(0.043)
9. Include inactive mills with zero output	0.313	0.174	0.148	-0.240	-0.282	-0.157
	(0.072)	(0.057)	(0.045)	(0.067)	(0.058)	(0.039)
10. Include mills using manual/other power	0.314	0.164	0.150	-0.212	-0.244	-0.152
	(0.073)	(0.057)	(0.045)	(0.066)	(0.057)	(0.040)

Notes: This table shows the robustness of the relationship between waterpower potential and the entry rate and the survival rate. This table focuses on linking and measurement error.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.12. Robustness to Measurement and Linking Error: Steam Use

	Entrant Steam Share			Incumbent Steam Share		
	1860	1870	1880	1860	1870	1880
	(1)	(2)	(3)	(4)	(5)	(6)
1. Baseline	0.169	0.188	0.172	0.034	0.049	0.051
	(0.024)	(0.022)	(0.022)	(0.021)	(0.018)	(0.024)
2. Links that are both ML and hand-linked	0.167	0.188	0.168	0.022	0.042	0.062
	(0.023)	(0.022)	(0.021)	(0.021)	(0.019)	(0.027)
3. Only ML links	0.166	0.188	0.168	0.029	0.045	0.064
	(0.023)	(0.022)	(0.021)	(0.022)	(0.019)	(0.027)
4. Raising ML linking threshold to 0.8	0.162	0.185	0.169	0.001	0.019	0.049
	(0.023)	(0.022)	(0.021)	(0.024)	(0.020)	(0.027)
5. Lowering ML linking threshold to 0.4	0.168	0.188	0.171	0.027	0.045	0.056
	(0.024)	(0.022)	(0.021)	(0.021)	(0.018)	(0.024)
6. Only business-name mills	0.161	0.175	0.159	0.031	0.082	0.070
	(0.027)	(0.025)	(0.024)	(0.029)	(0.035)	(0.033)
7. Only non-business name mills	0.149	0.177	0.164	0.034	0.005	0.050
	(0.030)	(0.023)	(0.024)	(0.022)	(0.021)	(0.031)
8. Only mills with all positive inputs	0.164	0.188	0.164	0.035	0.045	0.065
	(0.023)	(0.023)	(0.022)	(0.023)	(0.018)	(0.026)
9. Include inactive mills with zero output	0.167	0.189	0.171	0.035	0.052	0.052
	(0.024)	(0.021)	(0.021)	(0.021)	(0.017)	(0.023)
10. Include mills using manual/other power	0.166	0.187	0.169	0.035	0.047	0.059
	(0.024)	(0.022)	(0.021)	(0.021)	(0.017)	(0.024)

Notes: This table shows the robustness of the relationship between waterpower potential and the share of entrants and water incumbents using steam. This table focuses on linking and measurement error.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.13. Robustness to Sample

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.055	0.089	0.220	0.113	0.092	0.067	0.034	-0.009
	(0.130)	(0.015)	(0.062)	(0.052)	(0.036)	(0.016)	(0.013)	(0.013)
2. Include extensive margin of counties	-1.152	0.088	0.298	0.092	0.118	0.070	0.034	-0.009
	(0.132)	(0.015)	(0.062)	(0.050)	(0.035)	(0.017)	(0.013)	(0.013)
3. At least 3 mills in 1850	-0.957	0.081	0.170	0.112	0.070	0.069	0.038	-0.010
	(0.133)	(0.016)	(0.064)	(0.057)	(0.042)	(0.017)	(0.013)	(0.014)
4. At least 5 mills in 1850	-0.859	0.073	0.135	0.113	0.057	0.067	0.048	-0.013
	(0.136)	(0.017)	(0.069)	(0.063)	(0.047)	(0.018)	(0.014)	(0.015)
5. Exclude large grouped counties	-1.105	0.099	0.227	0.111	0.092	0.071	0.031	-0.009
	(0.129)	(0.015)	(0.062)	(0.053)	(0.037)	(0.017)	(0.012)	(0.014)
6. Exclude top and bottom 1% WPP counties	-1.161	0.088	0.238	0.121	0.113	0.072	0.036	-0.010
	(0.127)	(0.016)	(0.064)	(0.056)	(0.039)	(0.017)	(0.013)	(0.014)
7. Exclude top and bottom 5% WPP counties	-1.131	0.085	0.238	0.117	0.120	0.061	0.039	-0.014
	(0.147)	(0.019)	(0.075)	(0.063)	(0.042)	(0.020)	(0.015)	(0.016)
8. Exclude largest 20 cities in 1850-1880	-1.048	0.088	0.225	0.100	0.098	0.072	0.038	-0.012
	(0.130)	(0.015)	(0.064)	(0.055)	(0.039)	(0.016)	(0.013)	(0.014)
9. Exclude merchant mill cities	-1.011	0.091	0.211	0.101	0.095	0.064	0.034	-0.007
	(0.126)	(0.015)	(0.064)	(0.055)	(0.038)	(0.017)	(0.014)	(0.014)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and growth 1850-1880. This table focuses on alternative choices for the sample of counties in the analysis.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Except for the stated modifications in each row, data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.14. Survival Rates

	Survival Rate By Initial Power Source		
	All (1)	Water (2)	Steam (3)
From 1850 to 1860	0.201	0.208	0.138
From 1860 to 1870	0.194	0.214	0.136
From 1870 to 1880	0.237	0.257	0.194

Notes: This table shows the measured survival rate in each decade of mills. Column 1 reports the share of all mills that survive in each decade, column 2 reports survival for waterpowered mills, and column 3 reports survival for steam powered mills. We denote a mill as surviving if we can find a record for it in the subsequent Census.

Each observation is a county-industry-year. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880).

Table A.15. Incumbency, Size, and Steam Use

	Steam Adoption		
	(1)	(2)	(3)
Water Incumbent	-0.175		-0.177
	(0.009)		(0.009)
Mill Log Revenue		0.091	0.091
		(0.004)	(0.004)
# Mill-Years	63,755	63,755	63,755

Notes: This table shows how incumbency and size predict steam use. Column 1 shows the bivariate relationship of (water) incumbent status and steam use, Column 2 the bivariate relationship between revenue and steam use, and Column 3 includes both as independent variables.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850, an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.16. Steam Use and Characteristics of the Owner

	Mean Value	Uses Steam			
	(1)	(2)	(3)	(4)	(5)
Immigrant	0.069	0.076			0.075
	[0.253]	(0.015)			(0.015)
Age, in years	44.7		-0.0018		-0.0016
	[13.3]		(0.0002)		(0.0002)
Professional Miller	0.395			0.041	0.035
	[0.489]			(0.006)	(0.006)
# Mills	30,777	30,777	30,777	30,777	30,777
Mean of Dependent Variable		0.203	0.203	0.203	0.203

Notes: This table shows the relationship between owner characteristics and steam use. We link (when possible) Census of Manufacturers establishments to the Census of Population, as described in the text.

Column 1 shows the mean characteristic of the linked millers in the sample. Column 2 shows the relationship between steam use and immigrant status, column 3 the relationship with age, and column 4 the relationship with the owner self-reporting their occupation as a miller (or milling-related). Column 5 includes all covariates jointly.

All regressions include our baseline controls interacted with year and industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a mill-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.17. Persistence of Productivity

	Mill Log Revenue, Current (1)
Mill Log Revenue, Last Decade	0.424 (0.017)
# Mills	9,800

Notes: This table shows the relationship between current log sales (as the dependant variable) and lagged log sales (the independent variable).

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a mill-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.18. Model Fit without Agglomeration

	Moment	Years	Model $\alpha = 0$	Model $\kappa = 0$	Data
		Baseline Region			
$c(W,S)$	Water Choice Differential: Water Incumbents vs. Entrants	1850-1880	0.546	0.558	0.553 (0.062)
$c(S,W)$	Steam Choice Differential: Steam Incumbents vs. Entrants	1850-1880	0.983	0.934	0.977 (0.123)
$c_S^{(init)}$	Steam Adoption Rate	1850	0.100	0.105	0.103 (0.006)
$c_S^{(term)}$	Steam Adoption Rate	1880	0.393	0.416	0.393 (0.011)
f_e	Entry Rate	1820-1830	0.750	0.750	0.750 (0.006)
f_o^E	Log Sales Differential: Incumbents vs. Entrants	1850-1880	0.134	0.147	0.131 (0.015)
f_o^W	Water Exit Rate	1850-1880	0.789	0.792	0.789 (0.003)
f_o^S	Steam Exit Rate	1850-1880	0.834	0.838	0.835 (0.006)
γ	Log Sales Differential: Steam vs. Water Users	1850-1880	0.853	0.841	0.855 (0.029)
Π	Log Sales Autocorrelation	1820-1830	0.412	0.412	0.412 (0.019)
Σ	Log Sales Standard Deviation	1820-1830	1.019	1.019	1.019 (0.011)
	Differences Between Low Water and Baseline Region				
$c_L(W)$	Steam Adoption Rate	1850	0.089	0.095	0.089 (0.016)
η	Log Total Output	1850	-0.882	-0.817	-0.876 (0.215)
κ	Change in Steam Adoption Rate	1850,1880	0.093	0.097	0.092 (0.019)
α	Growth of Output	1850,1880	0.250	0.594	0.525 (0.118)

Notes: This table shows each parameter of the model (column 1) and the moment that most closely targets it (columns 2 and 3). Column 4 reports the model-simulated moments, and Column 5 is the empirical estimates with standard errors in parentheses.

Table A.19. Lumber and Flour Mill Activity in 1850, by County Waterpower Potential, by Different River Classifications

	Baseline (1)	Intermittent River (2)	12-Month Average (3)
Panel A. Number of Waterpowered Mills			
Lower Waterpower	-1.055	0.023	-0.553
	(0.130)	(0.036)	(0.106)
Panel B. Revenue of Waterpowered Mills			
Lower Waterpower	-1.127	0.017	-0.678
	(0.249)	(0.059)	(0.170)
Panel C. Steam Share of Mills			
Lower Waterpower	0.089	-0.005	0.048
	(0.015)	(0.003)	(0.015)
Panel D. Steam Share of Revenue			
Lower Waterpower	0.123	-0.007	0.052
	(0.022)	(0.005)	(0.023)
Panel E. Total Number of Mills			
Lower Waterpower	-0.956	0.018	-0.496
	(0.119)	(0.035)	(0.095)
Panel F. Total Revenue of Mills			
Lower Waterpower	-0.876	-0.003	-0.474
	(0.215)	(0.051)	(0.151)
# County-Industries	1,199	1,191	1,199

Notes: This table shows the relationship between 1850 milling activity and waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text) with standard deviation of one.

Column uses the benchmark measure of waterpower potential from the main text, as in Table 2 column 1 (as proportional to the fall height times the average flow rate in the three lowest months in the year). Column 2 instead uses the 12-month average flow rate, and column 3 calculates waterpower potential only from intermittent rivers. Each panel shows the effect of waterpower potential on a different outcome. Panel A shows total number of waterpowered mills and Panel B shows the total revenue of waterpowered mills. Panel C shows the share of mills using steam power, and Panel D shows the share of milling revenue from steam power. Panel E shows the total number of mills, and Panel F shows total milling revenue. Panels A, B, E, and F use (pseudo) Poisson maximum likelihood estimation. Panels C and D weight counties by their number of mills.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 2), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.20. Jacobian: Effect of Parameter on Moments, $\frac{dM}{d\theta_k}$

	$c(W,S)$	$c(S,W)$	$c_S^{(init)}$	$c_S^{(term)}$	f_o^E	f_o^W	$c_L(W)$	η	κ	α
Water Use: W-Inc – Ent	**6.40**	0.05	0.38	-0.05	0.62	-27.32	0.00	0.11	-0.22	-10.13
Steam Use: S-Inc – Ent	0.57	**9.98**	1.32	4.78	4.38	30.78	0.00	-0.10	1.82	9.39
Steam Share 1850	-0.33	-0.03	**-0.53**	-0.57	0.27	9.30	0.00	0.07	-0.10	1.60
Steam Share 1880	-0.30	0.53	-0.35	**-2.10**	0.50	18.82	0.00	0.07	-0.92	9.38
Firm Size: Inc – Ent	-0.80	0.33	-0.43	-1.57	**-3.02**	11.28	0.00	0.21	-0.62	3.83
Water Exit	-0.22	0.03	-0.12	-0.33	-0.27	**4.52**	0.00	-0.00	-0.12	1.41
Steam Share: L – B	0.00	0.07	-0.35	-0.40	0.25	6.70	**2.23**	0.13	-0.22	3.25
Output: L – B	0.33	0.65	-1.85	-2.73	5.12	46.92	-10.95	**-6.92**	-2.33	33.31
Steam Share Growth: L – B	0.43	-0.07	0.35	0.38	-0.12	-7.17	1.27	-0.12	**-0.22**	-0.08
Output Growth: L – B	1.38	0.33	0.83	-0.25	-0.07	-7.03	9.40	4.07	-3.05	**17.53**

Notes: This table shows the Jacobian of the moment function, capturing how simulated moments change with parameter values. All parameters except η and α are measured in percent of 1850 median firm sales.

Table A.21. Sensitivity: Effect of Moment on Parameters, $\frac{d\theta}{dM_k}$

	Water Use: WI – E	Steam Use: SI – E	Steam Share 1850	Steam Share 1880	Firm Size: I – E	Water Exit	Steam Share: L – B	Output: L – B	Steam Share Growth: L – B	Output Growth: L – B
$c(W,S)$	**0.21**	-0.00	-0.86	-0.27	-0.24	2.93	0.35	0.03	-0.69	0.04
$c(S,W)$	-0.05	**0.09**	0.88	0.35	0.62	-4.68	-0.12	-0.01	0.52	-0.06
$c_S^{(init)}$	0.04	0.01	**-1.27**	0.55	-1.14	8.27	-1.02	-0.15	1.29	-0.10
$c_S^{(term)}$	0.02	0.05	0.93	**-0.84**	-0.30	3.58	-0.65	0.05	0.53	0.15
f_o^E	-0.04	0.00	0.63	0.30	**-0.18**	-1.25	-0.22	-0.02	0.37	-0.02
f_o^W	0.01	0.00	0.11	-0.03	-0.09	**0.86**	-0.11	-0.01	0.14	-0.00
$c_L(W)$	-0.01	0.00	0.03	0.06	-0.02	-0.01	**0.30**	-0.03	0.35	-0.04
η	0.03	-0.01	-0.44	-0.09	-0.05	-0.04	-0.05	**-0.03**	-1.41	0.17
κ	0.04	-0.08	-5.64	-0.03	0.02	-0.80	3.34	0.05	**-4.88**	-0.07
α	-0.01	-0.01	-0.73	-0.05	0.04	-0.27	0.40	0.03	-0.66	**0.03**

Notes: This table shows the sensitivity measure of Andrews, Gentzkow and Shapiro (2017), capturing how parameter estimates change with moment values. All parameters except η and α are measured in percent of 1850 median firm sales.