Gaining Steam: Incumbent Switching and Entrant Leapfrogging

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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 as steam costs declined, mill activity grew faster in counties with less waterpower. This growth was driven by steam-powered entrants, as previously-waterpowered mills exited instead of switching technologies, suggesting technological lock-in. For identification, we leverage variation in US counties' waterpower *potential*, due to interacting water flow and elevation changes. To quantify the delay in steam adoption from technological lock-in, we estimate a dynamic model of firm entry and steam adoption.

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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.

We study 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. We estimate the role of technological lock-in, whereby the potential for waterwheel use and *actual prior use* of waterwheels slowed the adoption of steam power. Entrant mills adopted steam at higher rates and displaced incumbents, in a classic example of "creative destruction" (Schumpeter, 1942). However, entry did not substantially mitigate the market-level consequences of mills' barriers to switching technologies. This is because features of the old technology, in particular low up-front fixed costs, made it appealing to smaller entrants, who themselves became locked-in if their productivity grew. Flour and lumber mills' slowed adoption of steam, in counties with more waterpower, then had externalities on other sectors' jump from hand power to steam power.

The costs of steam declined from 1850 to 1880, leading to increases in aggregate steam use in milling: in 1850, only ten percent of mills were powered by steam, a share which increased to fifty percent by 1880. We find that, initially, counties with higher potential for waterpower had more 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 steam adoption, which brought mechanization to new industries and spurred broad productivity growth.[1] Many industries used little waterpower, and were not directly affected by local waterpower potential, but their steam adoption and mechanization was encouraged by agglomeration spillovers from lumber and flour mills. We find that, just as lumber and flour mills were more likely to use steam power in counties with little waterpower potential, so too were these mills' di-

[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).

rect neighbors in other industries. Local interactions in technology diffusion heighten the gains from early adoption of general purpose technologies like steam power. Our results suggest 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 by their competitors, as well as potential entrants, it is difficult to assess the equilibrium implications of our new facts 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 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 structural 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. The model captures how technological lock-in drives the observed pattern of entrant-driven growth, reflecting incumbents' sunk investments in waterpower and other switching costs.

A key implication of our results is that the path of technology adoption over a long time horizon depends not only on the choices made by firms that existed when the technology was introduced, but also on choices by future entrants, as these future entrants can also become incumbents stuck in an outdated technology. We show that whether firm entry mitigates the influence of switching costs depends of features of the technological environment. Because waterwheels were cheaper, they were attractive to relatively smaller entrants, who then became stuck with the older technology if their productivity increased. Had the new technology instead been characterized with a lower fixed cost (and higher marginal costs), it would have diffused faster.

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 linking mills over time based on their name, industry, and location. From the

[2]Samples of these manufacturing schedules were digitized by Bateman, Foust and Weiss (1971), Atack (1976), and Bateman and Weiss (1981), and see also Sokoloff (1984). See Atack and Bateman (1999) for more description of their 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).

states with surviving establishment-level records, we construct a balanced panel of 1241 county-industries, covering 80 thousand establishment-year observations.

For causal identification, we use geographic variation in counties' access to waterpower. Local waterpower potential, measured in horsepower, comes from 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 access to coal and market access (Chandler, 1972; Hornbeck and Rotemberg, 2023). 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 (United States Census Bureau, 1872), and 60% of mechanized plants.[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, they 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

[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."

over time, since the marginal cost of steam power falling would have led to diverging size distributions. Declining steam fixed costs is consistent with qualitative histories of steam use in rural US milling, which emphasize the importance of practical low-cost engines (Hunter, 1985).

A central pattern that we try to rationalize in the model is that mill entrants were around 3 times more likely to use steam power than incumbent waterpowered mills, despite many incumbents being large establishments that would otherwise be predisposed to benefit more from steam. We find high barriers to switching technologies generated technological lock-in. Quantitatively, we find that the barriers to switch from water to steam power were equal to about 5 months of revenue. One barrier to switching is partial irreversibility: incumbents already had a power source, and even in the absence of other frictions would need to be compensated to give it up. If we assume the purchase price of waterwheels was fully sunk, that accounts for 40% of the total switching cost.

This raises questions about the nature of the other challenges in changing technologies. (Hall, 2004; Verhoogen, 2021). The adoption of steam power by water mills did not require other substantial changes to their production technology, as the type of power remained rotational in nature and the millstones or saws were the same regardless of the power source.[4] Mills had some retrofitting costs to accommodate a new power source, but we also find evidence for a variety of other barriers to switching. One was restricted access to capital: incumbent watermills that added additional owners were more likely to switch to steam power.

Switching to steam may also 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 Manufacturers 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, 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 farmers). In historical society records, we find that many mills who switched to steam power did so when sons took over from their fathers.

We find evidence inconsistent with other explanations for inertia, including productivity losses from changing technologies, productivity growth from using and learning about the old technology, or permanent unobserved heterogeneity (e.g., that there were "water types" and "steam types").[5] For instance, in the historical records we find that many mills changed

[4]The technologies are similar enough that some waterpowered mills used steam as an auxiliary power source (Hunter, 1985).

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

technologies after fires destroyed the original capital, which is broadly at odds with those three potential explanations.

There was substantial entry of new mills in this era, which might seemingly minimize the aggregate influence of technological lock-in, but smaller entrants were still predisposed to use the low-initial-cost and high-marginal-cost technology. These entrant firms then faced costs of switching from water to steam power in future periods. This feature of the model – that switching costs can matter for the pattern of aggregate technology adoption even with substantial entry – would explain a general slow diffusion of new technologies that particularly benefit larger firms, rather than many recent experiences with quickly-embraced innovations that allow small firms to use new technologies without having to build them from scratch.[6]

We use the model to estimate how technological lock-in and waterpower potential delayed and reduced overall adoption of steam power in lumber and flour mills. Waterpower 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 (including retrofitting and sunk costs). We estimate that these costs were as important as local geography: without any switching costs, steam-use would also have reached 50% of US mills 30 years earlier and been 20 percentage points greater in steady-state.[7]

Though barriers to switching slowed adoption, the possibility to switch was still important for the aggregate transition from water to steam. For a counterfactual scenario with infinite switching costs, we estimate that the share of plants using steam would have only been 30% by 1900. 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. While steam adoption would have been slower if there had not been entry and exit, we estimate that switching costs matter almost as much when there is entry/exit as when there is not entry/exit because even entrants succumb to switching costs in later periods.

We estimate that barriers to switching were large enough that incumbent firms actually

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

[6]Examples include Amazon Web Services, that allows firms access to storage space without needing to buy a server; or ChatGPT, that allows firms access to AI technologies without needing to code and train them in-house.

[7]Note that 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; Atack, 1979; Manuelli and Seshadri, 2014).

suffered overall from the introduction of steam power. While incumbents directly benefited from the option to switch to the new technology, this force is smaller than the increased competition from entrants. Even in a counterfactual with no lock-in, the general equilibrium effects from entry completely mitigate the direct benefits for incumbents. However, in an alternative counterfactual with neither lock-in nor entry, incumbent firms benefit modestly from steam power.

Our establishment-level panel estimates complement 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 allows 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; Benhabib and Rustichini, 1991; Chari and Hopenhayn, 1991; Cooley, Greenwood and Yorukoglu, 1997; Atkeson and Kehoe, 1999; Jovanovic and Yatsenko, 2012; Caunedo and Keller, 2021), though our empirical setting allows a more-specific focus on technology choice (rather than aggregation and input ratios) and exploits cross-sectional implications of the new technology.

Schumpeter (1942) discusses the creative destruction associated with the transition away from waterpower, and we show causal evidence that steam created economic opportunities but crowded out water-using incumbents in confirmation of the Schumpeterian argument. Our finding of technology spillovers across sectors, within nearby areas, complements a large literature on agglomeration (Stokey, 1984; Young, 1991; Irwin and Klenow, 1994; Greenstone, Hornbeck and Moretti, 2010; Cabral, Wang and Xu, 2018; Allen and Donaldson, 2022).

The fact that waterpower availability impacts 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).[8] Relative to this literature, our contribution is to highlight the dynamic effects that geography can have on technology adoption due to actual prior technology-use and not only different contem-

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

poraneous technology options. 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), and health care (Handel, 2013). 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.

I Context and Data Construction

I.A Water and Steam Power in US Mills

By the mid-nineteenth century, waterpower had long been used in the United States. 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." While flour and lumber mills were needed locally throughout the country, textile manufacturing was agglomerated in major manufacturing centers, in places with substantial local 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 the large textile mills, so they could use smaller rivers and did not typically need 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). See Appendix Figure A.4 for a diagram of a traditional gristmill. Hunter (1979, 1985) provides an overview of water and steam power in the 19th century,[9] and we summarize a few key features of the 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 steam-power did not require a substantial transformation of mill operations. By contrast, the later introduction of electricity ushered in more wholesale changes in manufacturing operations, which no longer used rotational power (Devine, 1983; David, 1990; Damron, 2023). The fundamental change from the arrival of steam power was a new source of mechanical power, that 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 many advantages, it was 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

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

of each engine" (Monroe, 1825). Even small steam mills required installations from trained engineers, and then needed to employ full time engineers and firemen (Fisher, 1845).

Given its costs and benefits, steam power was particularly useful in places with less local waterpower potential (Sharrer, 1982; Rosenberg and Trajtenberg, 2004; Chernoff, 2021). These places had higher fixed costs for using water power, due to greater need for constructing dams, millponds, and riverwalls (which were generally more more expensive to build than the wheels themselves) (Monroe, 1825). Places with lower waterpower potential potentially 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, Armistead, Lawson and Long (1841) use, without updating, the estimated costs of waterpower from Monroe (1825).

Early steam engines were fundamental to the British industrial revolution, but were not 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 machinests 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 (Mayr, 1975). Watt's engines were preferred to high pressure engines in Britain, partially due to this increased likelihood for explosions, but they became the dominant technology used in American mills. Improvements in metallurgy made high-pressure engines safer over time, though explosions are often described in histories of individual mills and, from 1867 to 1879, a plurality of steam engine explosions were in lumber mills (United States Census Bureau, 1880*a*).

[10]Swain (1888) reports the cost of water rights for 22 counties, which are negatively (though not significantly) correlated with our measure of waterpower potential.

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." See Appendix Figure A.5 for a diagram of the original Porter-Allen design.

The lower "first cost" of high-speed steam engines made them attractive to millers, especially in lumber. 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, increasing local construction of steam machinery reduced shipping and installation costs (Greenberg, 1982).

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 C. 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 when 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.

Because the costs of watermills were site-specific, we were unable to find definitive numbers for the market price of setting up a waterwheel. From official reports, our best estimates are that a steam engine of around 20 horsepower, including the boiler and other associated equipment, cost $2,500 in the 1840s and around $2,000 in the 1880s (Armistead, Lawson and Long, 1841; Emery, 1883; Atack, Bateman and Weiss, 1980).

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):

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

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). Appendix 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 (those in the top 5%, roughly 92 feet or wider) as these 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 that flow intermittently, 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" ("Water Census"). Consistent with the historical importance of waterpower, the US government spent resources to promote

[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 horse-power 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.

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.6).[12]

Our measurement of county waterpower potential does not directly use the Water Census, however, because it has non-random incomplete coverage based on historical economic activity (Appendix Figure A.7 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).[13] 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, 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 Manufacturers in 1850, 1860, 1870, and 1880 (see Appendix Figure A.8 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 (2023), 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 mill in 1850 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 underlying data includes over 80 thousand lumber or flour mills from 1850-1880, and covers 87% of all steam-powered mills and 90% of reported steam-generated sales in the lumber and flour industries. Figure 3 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, 2023). We also use the total annual revenue for each establishment, which inform distributions of

[12]There are some exceptions where the datasets diverge, which generally reflects segments where merging 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).

[13]Bleakley and Lin (2012) digitized the "summary tables" from the introduction of the Water Census; for our purposes, we digitized the "detailed tables."

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), 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, 2023). 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 entire industries 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.9 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 disaggregated industry statistics in 1870 and 1880 for counties with small "local industries" (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 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 2). 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, but 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, therefore benefiting from the ability to scale relatively cheaply. Non-mechanized mills contributed little output share (Figure 2, 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 grinding grain that customers brought themselves (Le Bris, Goetzmann and Pouget, 2019), called "custom milling." The Census asked specifically about this practice in 1880. 95% of mills did at least some custom milling in 1880, and it represented 68% 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 9 mills operating in a given year, considering lumber and flour mills separately.[14] 94% of county-industries had more than one mill. Of these, 53% had mills using both types 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. 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.11 shows that the spatial concentration of lumber and flour mills was particularly low (in the spirit of Mian and Sufi (2014)).[15] This contrasts 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.

Mill-specific Census schedules in 1880 asked for their installed horsepower, shown in Appendix Figure A.12: steam powered mills had slightly more horsepower than waterpowered mills, but most mills used between 10-50 horsepower with the mode for steam power around 25 horsepower.

[14]We aggregate counties to make consistent geographies. The number of operating mills per actual administrative county-industry was 8.

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

I.D Data Linking

One contribution of our project is creating 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 population censuses (Ferrie, 1996; Feigenbaum, 2016; Bailey, Cole and Massey, 2020; Abramitzky et al., 2021*a*,*b*), 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.[16] 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, products, 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 research assistants 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 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 predicted ML link probability of our actual matches is not correlated with waterpower potential nor steam use.

We also link establishment owners to the Census of Population, based on owner name, industry/occupation, and place, as described in Appendix A.4.4. For our analysis, we use three owner characteristics: their age; whether they were born outside the United States ("immigrant"); and if their listed occupation was a miller or manufacturer ("professional miller").[17]

[16] These cross-county "migrations" appear unusual for millers, based on historical society records (Appendix C), and when we hand-linked the mills we allowed for cross-industry links, but found very few. There were 483 mills that ever switched between lumber and flour.

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

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 1860. Our analysis looks to understand what factors affected steam adoption. In this section, we discuss the forces that encouraged steam adoption in lower-waterpower counties or, equivalently, what delayed and reduced the adoption of steam power and associated industrialization in higher-waterpower counties. In particular, 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.

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:

$$Y_{ic} = \beta LowerWaterpowerPotential_c + \gamma_i X_c + \alpha_i + \varepsilon_{ic}. \quad (1)$$

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, though also report estimates for each industry separately.

The estimated effect of $LowerWaterpowerPotential_c$ is conditional on industry fixed effects α_i and a set of county controls X_c, whose effects are allowed to vary by industry i. Our baseline X_c controls are: (1) total county water flow, summing over all river segments; (2) county ruggedness, defined as the standard deviation in county elevation;[18] (3) whether the county has navigable waterways, distance to the nearest navigable waterway, and county market access in 1850 (Hornbeck and Rotemberg, 2023); and (4) whether there are coal deposits in the county and the share of county area with coal deposits (Campbell, 1908). 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 (α_{it}) and allow the effects of the control variables to vary by year and industry ($\gamma_{it} X_c$).

[18] 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.

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 alternative 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 3 Panel B shows the residual waterpower potential of the counties in our sample after partialling out the baseline controls.[19]

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:

$$Y_{ict} = \beta_t LowerWaterpowerPotential_c + \gamma_{it} X_c + \alpha_i c + \alpha_i t + \varepsilon_{ict}. \tag{2}$$

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, 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 (α_{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 waterpower 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). Appendix D reports 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.

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

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 is informative about 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 counties-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). 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.[20]

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 (with a uniform kernel up to a cutoff and then zero thereafter). The standard errors are 1-2% lower for distance cutoffs of 200 to 400 miles, and 10-20% smaller for cutoffs of 800-1000 miles.

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.

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

[20]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.

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.7, 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. Since 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 in Panels B and C of Figure A.7.

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 benefits from lower waterpower availability and earlier steam adoption that we explore more directly.

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. Appendix Table A.2 shows that waterpower had roughly similar effects on the exit probabilities of steam and water incumbents.

Table 5 show 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 also 5 – 7 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). Water incumbents' lower steam use, combined with the increased exit of incumbents from Table 4, suggest that incumbent mills were subject to switching barriers.

II.C Spillover Impacts on Steam Adoption of Non-Mills

Lumber and flour milling were leading sectors for steam adoption, given their heavy reliance on mechanical power. As steam-use spread across sectors over the second half the nineteenth centuries, the broadening use of mechanical power helped spur industrialization. Indeed, steam power is the classic example of a general purpose technology (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005).

Early use of steam power in lumber and flour mills, across many parts of the country, may have encouraged nearby steam adoption in other sectors. Delayed steam adoption by mills, in places with more waterpower availability, may have then held back steam adoption in local manufacturing more broadly.

Qualitatively, it seems plausible that local mills' steam-use could have spillover impacts on other firms. 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. 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.

To estimate spillover effects in adoption of this general purpose technology, we examine the influence of neighbors (as in Foster and Rosenzweig, 1995; Conley and Udry, 2010; Juhász, Squicciarini and Voigtländer, 2023) and agglomeration spillovers (Marshall, 1920; Jaffe, Trajtenberg and Henderson, 1993; Black and Henderson, 1999; Glaeser, 1999; Greenstone, Hornbeck and Moretti, 2010; Carlino and Kerr, 2015). For this analysis of spillovers, we start with our mills – whose steam adoption was substantially influenced by local waterpower availability – and examine spillover impacts on steam adoption by neighboring non-mill manufacturing establishments in lower waterpower counties.

To measure mills' neighboring establishments, we take advantage of Census enumerators writing entries while traveling through an area. Nearby establishments are likely listed on the same manuscript page, similar to how neighbors are grouped together on pages of the Census of Population (Logan and Parman, 2017). We also define a sample of "non-neighbors"

in the county, who are not listed on the same page as a mill. When considering neighbors, we exclude all lumber and flour mills, as well as all non-mills whose owners also operate a mill. We also exclude 1880 for this analysis of spillovers, as most lumber and flour mills in 1880 were recorded on separate "special schedule" manuscripts and so we do not see their neighbors.

Steampowered mills are more likely to have steampowered neighbors, but this can reflect common factors encouraging both to use steam power (Manski, 1993). To identify spillover effects, we leverage our previous results, in which lumber and flour mills are more likely to use steam in lower waterpower counties. Our identification approach is to estimate how waterpower potential affects non-mills' steam adoption, through differences in mills' steam adoption but not directly affecting non-mills. Because there was little waterpower-use by non-mills (Figure 2), it is plausible that county waterpower availability does not directly affect non-mills' water-use and steam-use. We can explore this directly by estimating the relationship between waterpower potential and waterpower use in each sector (as in equation 1, allowing β to vary by sector). Appendix Figure A.13 reports, by industry, the impacts of lower county waterpower potential on the share of establishments using waterpower. Lumber and flour mills are the most responsive sectors, by far.

To estimate spillovers, we compare mill neighbors' steam adoption in counties with lower waterpower, relative to mill neighbors' steam adoption in counties with higher waterpower. We also estimate how waterpower potential affected steam adoption by establishments without mill neighbors, which could reflect direct effects of waterpower potential and potential spillover effects from mills to non-neighbors within the county. We extend our previous estimating Equation (1) to the establishment-level, and include industry-year fixed effects for 29 industries outside lumber and flour milling:

$$Y_{eict} = \beta LowerWaterpowerPotential_c + \gamma_{it} X_c + \alpha_{it} + \varepsilon_{eict}. \tag{3}$$

For establishment e, in industry i and county c and year t, the coefficient β reports the average increase in its likelihood of using steam power if its county has one standard deviation lower waterpower potential. The industry-year fixed effects (α_{it}) adjust for time-varying cross-industry differences in steampower use, and we include our baseline controls with standard errors clustered at the county level.

Table 6 reports that steam-use is 1.9 percentage points higher for neighbors of mills in counties with lower waterpower potential (Column 1). By contrast, there is less difference in steam-use among non-neighbors of mills (Column 2) and Column 3 reports the difference in these estimates for neighbors and non-neighbors (1.4 percentage points).

Panel B reports similar estimates, omitting industries whose steam-use may be more directly responsive to waterpower potential. For this, we omit all industries whose waterpower-use is at least as responsive as textiles to county waterpower potential (from Appendix Figure A.13): leather, paper, chemicals, iron & steel, brass & other metals, liquors, construction materials, wood products, and ship & boat building. The spillover estimates imply that having a mill neighbor in a county with one standard deviation less waterpower potential increases steam steam adoption by 25-33 percent.

For this spillover analysis, our assumption is that county waterpower potential does not directly affect steam-use in these other sectors (other than through affecting mills' steam-use). To explore this assumption, Appendix Table A.3 runs similar regressions for the *waterpower* use of neighbors. For the constrained set of sectors, in Panel B, county waterpower potential does not affect waterpower-use by mill neighbors or mill non-neighbors. For the full set of sectors, mill neighbors are less likely to use waterpower in lower waterpower counties, which may reflect these neighbors being in locations less suitable for waterpower-use and responding accordingly.

A potential concern is that mill neighbors' higher steam-use could reflect within-county heterogeneity in steam costs. Steam costs do not vary substantially with geography, which was a main advantage of steam, but perhaps mills chose places in lower waterpower counties where their neighbors would also be more likely to use steam even without spillover effects. One reason why we do not think that place-based advantages are driving our results is that they would generate a "diversion effect," as non-neighbors would be in places that were relatively less suitable for steam power and therefore less likely to use it. However, we find a mildly positive effect on non-neighbors in column 2 of Table 6.

One location advantage for steam power would be a short distance to a railroad station, which was a source of fuel. To explore the importance of this potential mechanism, we digitized historical maps of railroad station locations. There was variation across counties in their access to railroad stations, as some were relatively close and others were relatively far. Distance to railroad stations is additionally a potential source of lock-in, as in some counties the waterpower sites are close to stations, and in others they are far away (which possibly could lead to differences across water incumbents in the feasibility of using steam power). Nevertheless, Appendix Table A.4 shows that distance to railroad station is not a substantive source of variation in steam suitability, as it neither predicts predict steam-use nor water incumbents switching to steam (not does it predict a differential response of entrants versus incumbents).

The estimated spillover effect represents a large percent increase in steam-use across other sectors, catalyzing steam-use in the broader economy in places where lumber and flour mills

were less locked into waterpower. Our model in Section IV considers only lumber and flour mills, and counterfactual scenarios for growth in their steam-use, but these spillover effects imply that the speed of steam diffusion in milling also affected the broader economy through externalities that lumber and flour mills would not directly consider in their own technology adoption decisions.

II.D Robustness To Linkage Error and Alternative Factors Driving Steam Adoption

A potential alternative explanation for these cross-county results could be the nature of demand, as improvements in steam power made counties without waterpower potential more attractive for a variety of activities, which in turn could have effects on the demand for milling (Benhabib and Rustichini, 1993). Indeed, we find in Appendix Table A.5 Column 1 that counties with lower waterpower potential experienced faster population growth during this period, by 6-12 percent a decade. That said, we do not think population growth is driving steam adoption. First, Appendix Table A.5 Panel A shows that counties with lower waterpower potential were smaller in 1850, but Table 2 shows that they nevertheless had a higher share of mills using steam power. Second, Appendix Table A.5 Panel B shows that lower waterpower potential counties saw increases in milling activity even in per capita terms. Finally, the results in Table 4 are inconsistent with population growth driving our results. If the increased growth were driven by to more customers, it would be difficult to rationalize waterpower potential decreasing the survival of incumbents.

In Appendix D, we explore the robustness of our results to alternative measurements, features of the environment that may have had direct effects on steam adoption, and features that may have had a general effect on economic activity. Our results are broadly unaffected by these choices. We summarize our approach here, and defer detail to Appendix D. In Appendix Tables A.6, A.7, and A.8, we show our results are similar when studying only flour mills, which were the technologically less tradable good.

Waterpower potential was not randomly allocated across space, and in Appendix Tables A.9 and A.10 we consider how our results change when controlling for alternative local factors. In Appendix Table A.9 we include characteristics that could have driven the adoption of steam power, and in Appendix Table A.9 we include characteristics that more broadly could have driven growth.

Our primary focus is understanding how waterpower potential slowed the adoption of steam power. This is distinct from a large economic history literature studying the causes of steam power adoption (Crafts, 1977; Floud and McCloskey, 1981; Allen, 2009; Mokyr, 2016). In our main results, we always control for measures of local access to coal, given its

importance (Wrigley, 2010; Fernihough and O'Rourke, 2021; Reichardt, 2023). While we cannot do justice to the whole literature, in Appendix Table A.9 we show that our results are similar when we additionally control for other classic explanations, including alternative and more comprehensive measures of access to coal, as well as wages (Allen, 2009), access to banks (Jaremski, 2014), access to mechanics and engineers (Hanlon, 2022), and agricultural productivity (Ragnar, 1953).

In Appendix Table A.10 we show that our results are robust to controlling for additional features of the economic environment. First, we show our results are robust to removing some or all of our baseline controls, or changing our sample restrictions (such as requiring more milling activity in the initial period, dropping the counties with the most or least waterpower potential, or allowing for an unbalanced panel of counties). Our results are also robust to controlling for features important features of American geography at the time, including dummies for being in Appalachia or one of the 13 American colonies, controlling for longitude, time varying market access, being on the frontier (Bazzi, Fiszbein and Gebresilasse, 2020), having a portage site (Bleakley and Lin, 2012), and exposure to the civil war. Finally, we show that our results are robust to controlling for (potentially endogenous) features of economic activity, including dropping the largest cities, counties with "merchant mills" that exported their output, and measures of population, manufacturing output, and the share of workers in agriculture (Eckert and Peters, 2023).

Having established how waterpower potential slowed the adoption of steam power, we turn to explaining why. We start, in the next section, by describing how features of the environment help explain the nature of the costs and benefits of using and switching to steam power.

III Stylized Facts

Our view of the technological transition from water to steam is motivated by the following intuition, which we formalize in Section IV. Each technology was associated with marginal costs and fixed costs (which include initial purchase costs and overhead costs). Because neither technology was clearly more attractive to millers, throughout the 19th century, we presume that steam power was better on one cost dimension and waterpower was 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 are associated with 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 bigger 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.

III.A Costs and Benefits of Steam and Water

Figure 5 shows that steam-powered mills were larger than water-powered mills, on average. Given the Melitz (2003)-style logic discussed above, this suggests steam power has higher fixed costs and lower marginal costs than water power.

This interpretation requires some introspection, as steam engines likely had higher marginal costs in dollars, given expenditures for fuel and other supplies. Our interpretation is that our results reflect the difficulties in scaling waterpower-use. 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* costs. Many water-using incumbents did grow (Appendix Figure A.14), so waterpowered mills were not completely constrained, but expanding production further could require increasingly expensive modifications to their operations. Furthermore, waterpowered mills were constrained to be in very specific geographies, which may have made inputs more difficult to source and outputs more costly to sell relative to the more footloose steam-powered mills.

Figure 5 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 led to an increase 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 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.16 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.

Waterpower potential making waterpower use more attractive (as in Figure A.7 Panel B) implies that it 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 selection, larger steampowered mills). Figure 7 shows this was not the case (indeed, in most decades counties with high waterpower potential have more relatively small mills), so we model waterpower potential as lowering fixed costs of waterpower, consistent waterpower potential lowering the costs of water rights and of constructing dams and millponds.

Figure 5 also shows there was substantial overlap in the size distributions of steam and water powered mills, in every decade. This suggests there is a substantial idiosyncratic component to mills' technology adoption.

III.B Operating Costs

We calculate that 15-20% of mills survive from one decade to the next (Appendix Table A.11).[21] Our regression analysis estimates differences in survival rates, across counties with different waterpower potential, which would be generally attenuated by linkage error.

Firm exit implies that dynamic incentives are important, as only some firms will end up amortizing over long periods of time any fixed entry and technology adoption costs. Table 1 shows the share of each type of mill responsible for production. In any given Census year, most active mills entered over the course of the previous decade.

Appendix Figure A.15 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. We refer to "water incumbents" and "steam incumbents" as surviving firms who used that power technology in the previous decade, regardless of their technology in the current period.

III.C Barriers to Switching Technologies

Steam decisions of entrants are a useful contrast to those of incumbents, as entrant firms started with a clean slate. Figure 6 shows that entrants are four times more likely to use steam power than water incumbents.[22] The difference in adoption rates is slightly larger when conditioning on firm size (Appendix Table A.12). This suggests that there are barriers to switching from water to steam power. A fixed cost of switching technologies would cause

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

[22] There are a few firms that report switching from water to steam, but it is rare enough that we do not discuss them, though we do include those firms when we estimate the model in Section IV.

only the highest-productivity water incumbents to adopt steam, while relatively lower productivity entrants would use steam. Consistent with this logic, Appendix Figure A.17 shows that incumbents are larger than the entrants within each power technology. On average, incumbents are 24% larger when using water and 40% larger when using steam.

Switching costs are not infinite, however, as both entrants and incumbents were more likely to adopt steam power over time, consistent with technological improvements in steam power over time. From 1860 to 1880, steam adoption rates increased by sixty percent for both entrants and water incumbents, from a base rate of thirty percent for entrants and five percent for water incumbents (Figure 6).

III.C.1 Alternative Explanations

While the data patterns are consistent with fixed costs of switching technologies, we also we consider three alternative explanations for serial persistence in technology choices. A leading alternative explanation for low incumbent switching is learning-by-doing: incumbents could have freely switched technologies, but did not want to because incumbents had learned to use water power and, for them, it continued to dominate steam. Qualitatively, high rates of learning-by-doing for waterpower would be inconsistent with the longstanding use of water power in the US.

In the data, learning-by-doing would imply that water-using incumbents would experience fast growth, as they benefit both from general economic changes and learning. As a result, 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.18 shows that incumbents and successive generations of waterpowered entrants "grow" at a similar speed, consistent with no additional internal learning boost for water incumbents.

We think about switching costs as consisting of actual expenditures that the firm needs to pay. An alternative modeling approach is assuming a *productivity* cost from switching technologies (see, e.g., Parente and Prescott 1994). Qualitatively, productivity switching costs do not seem appropriate for this setting, as most of the day-to-day activities of a miller would be the same with either power source. In the data, Appendix Figure A.14 Panel (b) shows that switchers grow faster than the stayers, which suggests fixed costs of switching technologies (so the growth is partially driven by selection), and inconsistent with productivity losses from switching. Indeed, even though water incumbents were negatively selected (because they did not enter using steam power), those that switched to steam power were 5% larger than current steam entrants.

An alternative potential explanation for why incumbents rarely switch technologies is

permanent unobserved heterogeneity. In addition to Appendix Figure A.14, which directly provides evidence for the importance of switching costs, we can also compare directly the predictions of a model with "steam types" and "water types." Formally, methods for testing for the presence of first-order state dependence in binary sequences require observing agents for many periods (for instance, the approach of Chamberlain 1985 would require six observations per mill), and we observe mills for at most four census rounds. We therefore provide more suggestive evidence against the presence of "types" driving the relatively low switching rates.

First, inspired by Chay, Hoynes and Hyslop (1999), a simple test of state dependence is as follows. Consider the sample of mills who start with waterpower, end with steam power, and use steam power twice. These mills have the same initial and final conditions, in the spirit of Hotz and Miller (1993), and because they use steam power half of the time, they are relatively indifferent between technologies. If the driver of technological choice was purely persistent heterogeneity, with no scope for switching costs, these mills would be equally likely to use water for two periods and then steam for two periods as they would be to alternate between technologies. When switching is costly, the former pattern is more likely, and indeed in our data 90% of the relevant mills switch technologies once and then keep their new technology.

Chay, Hoynes and Hyslop (1999) also suggest a second test, which is that persistent types would predict that mill's past choices predict the future, conditional on the current technology. We find that, for current water users, having used water in the previous decade does not predict using water in the future, which again is inconsistent with the consequences of persistent types.

Third, qualitatively, historical accounts of mills discuss multiple instances of mills switching technologies after a fire destroyed their original structure (Appendix C). This is inconsistent with owners persistently preferring a particular technology, but consistent with sunk fixed costs or other barriers to switching (Hornbeck and Keniston, 2017; Huesler and Strobl, 2023).

Recap of Empirical Results Steam power offered lower effective marginal costs, at the cost of higher fixed costs, although those fixed costs declined over our sample period as steam technology improved. Both water and steam required fixed overhead costs, and millers had to pay a fixed cost to switch technologies. Potentially due to both direct effects, and these dynamic effects, counties with higher waterpower potential used relatively less steam power. We now turn to formally describing a parsimonious framework that fits the facts.

IV Quantitative Model of Steam Adoption with Switching Costs

It is difficult to interpret all of the estimates jointly – the stylized facts along with the 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. Furthermore, the quantitative model allows us to explore how switching costs and firm entry matter for overall steam adoption and growth.

We develop a quantitative model of technology adoption and firm entry in a composite milling sector. 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 fixed 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 cost of switching from water to steam power encourages 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 and 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 with elasticity ϵ. 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. For a price p_{jct} charged by firm j, that firm's quantity sold is: $y_{jct} = p_{jct}^{-\epsilon} P_{ct}^{\epsilon-\eta}$.

Firms produce using a constant-returns-to-scale technology in inputs x (labor, materials, and mill capital other than power source):

$$y_{jct} = \exp(\varphi_{jct} + \gamma_{jct} + \alpha_{R_{jct}} s_{ct}) x_{jct}. \tag{4}$$

We assume inputs x can be flexibly adjusted.

Firms' overall productivity is determined by their baseline productivity φ_{jct} and an additional $\gamma_{R_{jct}}$ from its 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.

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

$$p_{ct}(R,\varphi) = \frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma_R+\alpha_R s_{ct})}, \tag{5}$$

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

$$\pi_{ct}(R,\varphi) = \frac{1}{\epsilon}{P_{ct}}^{\epsilon-\eta}\left(\frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma_R+\alpha_R s_{ct})}\right)^{1-\epsilon}. \tag{7}$$

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, firms produce, and then the cycle starts again. For the initial stages, we consider the possible power states to be W, S, or E (for entrant). 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:

$$\mathbb{E}_{\varphi}\left[V_{ct}(E,\varphi)\right] \geq f^{e}, \tag{8}$$

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:

$$\varphi_{jt} = \pi\varphi_{jt-1} + \sigma\xi_{jt}, \tag{9}$$

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 its power source $R \in \{E,W,S\}$. Furthermore, each firm j pays an idiosyncratic cost $\nu^R_{jct}(0)$ if it continues its operation, and $\nu^R_{jct}(1)$ if it chooses to exit. Firms compare the

expected value from paying the operating cost to the value from exit:

$$V_{ct}(R,\varphi) = \max\{\mathbb{E}_{\varepsilon}\left[V^{o}_{ct}(R,\varphi)\right] - f^{R} - \nu^{R}_{jct}(0), \Omega^{R}_{ct} - \nu^{R}_{jct}(1)\}, \tag{10}$$

where $V^{o}_{ct}(R,\varphi)$ 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 costs, and expectations over future productivity (Rust et al., 1987). The value function for an establishment with power source R and productivity φ is:

$$V^{o}_{ct}(R,\varphi) = \max_{R' \in \{W,S\}} \{\pi_{ct}(R',\varphi) - c_{ct}(R,R') - \varepsilon_{jct}(R') + \delta \mathbb{E}_{\varphi'}\left[V_{ct+1}(R',\varphi')\right]\}. \tag{11}$$

$\pi_{ct}(R,\varphi)$ is the firm's static profit from Equation (7), 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 (9). 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 non-monetary reasons why some millers prefer waterpower as "greater cleanliness, less annoyance, and less area required." If the firm chooses to switch power sources, the firm pays a net cost $c_{ct}(R,R')$ to switch from power source R to power source R'. The firm then produces, charging the profit-maximizing price described in Equation (5).

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 also may induce other firms to enter, adopt steam, and compete for customers. The competitive pressure from the rich heterogeneity of firms (with different productivities and power sources) is fully summarized by the local price index P_{ct}. We study the local economies along their transition path as steam power becomes available.

Definition 1 (Dynamic Equilibrium)**.** An equilibrium of 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 $R'_{ct}(R,\varphi)$, such that taking the time path of steam costs $c_{ct}(S)$ as given:

1. Firms enter, exit, and adopt power sources to maximize expected discounted profits (Equations 8, 10, and 11).

2. Firms source inputs x to maximize flow profits period-by-period (Equation 7).

3. Output markets clear:

$$P_{ct}Y_{ct} = wX_{ct} + \Pi_{ct}, \tag{12}$$

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. We assume inputs are elastically supplied at price w.

4. The free entry condition holds:

$$\mathbb{E}_{\varphi}\left[V_{ct}(E,\varphi)\right] \leq f^{e}. \tag{13}$$

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.[23] 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.[24] In particular, steam power first becomes purchasable at a prohibitively high price in 1830, and its fixed adoption cost then monotonically declines until reaching its steady-state level in 1900.[25]

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 then a mature technology with horsepower per waterwheel largely stable over time (Rosenberg and Trajtenberg, 2004).

IV.E Comparative Statics

Before making parametric assumptions to estimate the model, this section describes the model's predictions for how access to waterpower mediates the economic impacts from the arrival of steam power. We defer formal arguments to Appendix E.

[23]The Census of Manufacturers was professionalized and comprehensive beginning in 1850 (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 (Treasury Department, 1838), and estimate the model to match steam diffusion from 1850 to 1880.

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

[25]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).

Prediction 1 (Higher water costs cause faster steam adoption, especially among entrants)**.** *Let $\mathbb{P}^E_{ct}(S)$ and $\mathbb{P}^I_{ct}(S)$ denote the shares of entrant and incumbent mills that use steam. Higher costs of water induce faster steam adoption, especially among entrants:*

$$\frac{d}{dc^W_c}\mathbb{P}^E_{ct}(S) > \frac{d}{dc^W_c}\mathbb{P}^I_{ct}(S) > 0 \tag{14}$$

Argument. 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 productivity. The *technology cost*, *selection*, *competition*, and *agglomeration* effects all lead to more steam use in places with higher water costs, which is what we find in Table 3.

Incumbents differ from entrants due to switching costs, which make their steam adoption decisions less responsive to the cost of waterpower (as we find in Table 5), especially when steam adoption is low (as in Figure 6).[26] □

Prediction 2 (Higher water costs cause faster growth, especially through entry)**.** *Let N_{ct} denote the total number of mills and N^E_{ct} the number of entrants. Higher costs of water induce faster growth of mills, especially of entrant mills:*

$$\frac{d}{dc^W_c}\Delta \log N^E_{ct} > \frac{d}{dc^W_c}\Delta \log N_{ct} > 0 \tag{15}$$

Argument. The arrival of steam affects the number of establishments by changing the operating values that determines entry and survival. Operating values are affected by the *technology cost*, *competition*, and *agglomeration* described in the proof of Prediction 1. Importantly, while the negative *competition* effect is shared among all establishments, the positive *technology cost* and *agglomeration* effects depend on steam adoption. Consequently, improvements in steam power increase operating values more when steam adoption rates are higher. Prediction 1 thus implies that operating values increase more in places with higher costs, especially by entrants. The overall growth from steam is also governed by the elasticity of demand for local milling η. □

Prediction 3 (Switching costs determine whether incumbents are crowded-out in counties with higher water costs)**.** *Let $\mathbb{S}_{ct}$ denote the survival rate of mills. It is unclear if higher*

[26]The first inequality in Equation (14) would not hold if the fixed costs of steam fell to so low values that all entrants everywhere would adopt steam. In this case, the only differences in steam adoption across space would come from incumbents. However, Figure 6 provides contrary evidence to this hypothetical case, showing that waterpower remained the popular power source among entrants in our data period.

costs of water hurt or help the survival of incumbent mills when steam arrives:

$$\frac{d}{dc_c^W}\mathbb{S}_{ct} \gtrless 0. \tag{16}$$

Incumbents are crowded out if switching costs are prohibitively high.

Argument. While aggregate growth is higher in places with higher water costs, the impact of water costs on the survival rate of incumbent mills is theoretically ambiguous. Higher water costs increase the option value of steam power (which raises survival) but intensify local competition from new entrants (which lowers survival). When switching costs are high, water incumbents cannot access steam power, and the negative competition effect will dominate. When switching costs are low, incumbents benefit from steam in places with high water costs, especially when entry is low. Table 4 reports that incumbents are crowded-out, on net, which suggests large switching costs. □

IV.F Parametric Assumptions

We make a series of parametric assumptions to take the model to the data. The first set are distributional assumptions about idiosyncratic firm characteristics. 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 parameter ρ:

$$\nu_{jct}^R(\text{OPERATE/EXIT}) \overset{\text{iid}}{\sim} GEV1(\rho_o^R) \tag{17}$$

$$\varepsilon_{jct}(R) \overset{\text{iid}}{\sim} GEV1(\rho). \tag{18}$$

The productivity innovations are drawn from a standard-normal distribution

$$\xi_{jt} \overset{\text{iid}}{\sim} \mathcal{N}(0,1), \tag{19}$$

which implies that entrants draw their productivities from the normal distribution

$$\varphi_{jct} \sim \mathcal{N}\left(0, \frac{\sigma^2}{(1-\pi)^2}\right). \tag{20}$$

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

$$\Omega_{ct}^R = \omega c_{ct}(R). \tag{21}$$

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

$$c_{ct}(R, R') = \begin{cases} 0 & \text{if } R = R' \\ c_{ct}(R') & \text{if } R = E \\ c_{ct}(R') + c(R, R') - \Omega_{ct}^{R} & \text{otherwise.} \end{cases} \tag{22}$$

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 the literal costs of retrofitting as well as other costs that make it difficult for enterprises to adopt new technologies (Holmes, Levine and Schmitz Jr, 2012; Atkin et al., 2017). Second, firms may sell their pre-existing technology, though due to partial irreversibility (if $\omega < 1$), the scrap value may not be equal to the purchase price of 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:

$$c_t(S) = c_S^{(floor)} + (c_S^{(origin)} - c_S^{(floor)}) \exp\left(-c_S^{(slope)}\,(t - T_0)\right), \tag{23}$$

where the cost at period T_0 is $c_{T_0}(S) = c_S^{(origin)}$, and $\lim_{t\to\infty} c_t(S) = c_S^{(floor)}$. 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 not over time.

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

$$\mathbb{E}_\nu[V_{ct}(R, \varphi)] = \rho_o^R \log\left[\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right) + \exp\left(\frac{\mathbb{E}_\varepsilon\left[V_{ct}^o(R, \varphi')\right] - f^R}{\rho_o^R}\right)\right], \tag{24}$$

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

$$\mathbb{E}_\varepsilon[V_{ct}^o(R, \varphi)] = \rho \log\left[\sum_{R' \in \{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R, R') + \pi_{ct}(R', \varphi) + \delta \mathbb{E}_{\varphi'}[V_{ct+1}(R', \varphi')]\right)\right]. \tag{25}$$

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

is:

$$\Pr_{ct}\left(\text{OPERATE/EXIT}|R,\varphi\right)=\frac{\exp\left(\frac{\Omega_{ct}^{R}}{\rho_{o}^{R}}\right)}{\exp\left(\frac{\Omega_{ct}^{R}}{\rho_{o}^{R}}\right)+\exp\left(\frac{\mathbb{E}_{\varepsilon}[V_{ct}^{o}(R,\varphi')]-f^{R}}{\rho_{o}^{R}}\right)}. \tag{26}$$

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

$$\Pr_{ct}\left(R'|R,\varphi\right)=\frac{\exp\left(\frac{1}{\rho}(-c_{ct}(R,R')+\pi_{ct}(R',\varphi)+\delta\mathbb{E}_{\varphi'}[V_{ct+1}(R',\varphi')])\right)}{\sum_{R''\in\{W,S\}}\exp\left(\frac{1}{\rho}(-c_{ct}(R,R'')+\pi_{ct}(R'',\varphi)+\delta\mathbb{E}_{\varphi'}[V_{ct+1}(R'',\varphi')])\right)}. \tag{27}$$

IV.G Solution Algorithms

The equilibrium of our 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 algorithm in the time path for the price index $\{P_{ct}\}_t$ and steam share $\{s_{ct}\}_t$, our two aggregate state variables. The convergence of our iterative algorithm is ensured by a congestion force due to competition in the product market.

IV.G.1 Existence and Uniqueness

Appendix F discuss the properties of our solution algorithm, including the existence and uniqueness of equilibrium. In brief, the convergence property of our iterative algorithm ensures the existence of an equilibrium. The congestion force behind the convergence property also tends to make the equilibrium unique. A strong steam agglomeration force (a high 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. In Section H.1, we provide simulations of the agglomeration force (value of α_S) needed to create multiple equilibria, given our estimated

values for the other parameters.

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 water power" 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 (after controlling for geographical and other local characteristics) as a cost-shifter for local firms' use of waterpower. In particular, the differences between the model counties corresponds to our reduced-form regression coefficients β_t in Equations (1)-(2). One feature of the model is that the transition to steam power had already started when comprehensive manufacturing census data started to be collected in 1850, as roughly 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.

In the model, firms choose to produce with either steam or waterpower, understanding that they face costs of switching out of their current technology and that their competitors are making similar choices. In Section V.A, we describe the key moments that we use to estimate the model, and how we calculate the moments in the data. In Section V.B, we describe our parameter estimates. In Section V.C, we describe how well the model fits the data. Our key in-sample test is to compare how the model does at predicting the diffusion pattern of steam power in the baseline and low-power counties, where the *only* modeled difference across the counties is the cost of adopting waterpower.

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 counties (e.g., 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 county. For each moment, we calculate the relevant outcome Y_{ct} within each county. We then predict Y_{ct} using our reduced-form specification in Equation (1). The moment we match

is then the predicted outcome for the average county:

$$\overline{Y}_t \equiv \mathbb{E}[Y_{ct}] = \hat{\gamma}_t' \mathbb{E}[X_{ct}], \tag{28}$$

where X_{ct} includes our baseline controls for ruggedness, total water flow, navigable rivers, initial market access, and access to coal deposits, and we use that *LowerWaterpowerPotential* is standardized around a mean of zero.

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 for each sector separately ($Y_{ct,\text{waterpower}}$ and $Y_{ct,\text{steam}}$), and then take the average (weighted by county revenue) to generate Y_{ct}.

While all of 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 elasticities between structural parameters and target moments, following Andrews, Gentzkow and Shapiro (2017).

Steam productivity. If steam is relatively more productive, so the steam productivity parameter γ is positive, steam adopters will have higher nominal sales in our model. We therefore use the log sales differential between steam adopters and water adopters within each county, as in Figure 5, to help estimate γ. The estimation of γ illustrates why all of the parameters need to be estimated jointly. The simple observed difference in sales between steam and water users also reflects selection, as more-productive mills are more likely to use steam power. We model this selection directly and account for it when estimating steam productivity jointly with the other parameters.

Power adoption costs. The additional fixed cost of using steam in year t, $c_t(S)$ - $c(W)$, leads fewer firms to invest in steam power relative to water, given the productivity advantage of steam power. We help estimate $c_t(S)$ using the share of establishments using steam in each county in that year, as in Figure 6. Increasing $c(W)$ makes operating less attractive, and is pinned down by the zero profit condition, given the other parameters in the model. In particular, a lower cost of water $c(W)$ increases the number of operating mills, especially in the initial steady state without steam power.

Dispersion of power adoption cost shocks. The parameter ρ determines the dispersion of the Gumbel distribution from which the idiosyncratic power switching cost ε is drawn. When ρ increases, ε becomes more heavy-tailed, leading to more overlap in sales size between firms that use different power sources. We therefore use the overlap coefficient of the log sales distribution between steam and water adopters within each county to help estimate

ρ, as in Figure A.15. The overlap coefficient of two distributions is the overlapping area of their histograms.[27]

While in the model we do not explicitly model sources of heterogeneity, we can use the linked Census of Population data to describe the relationship between owner characteristics and steam use. Appendix Table A.13 shows that immigrants, younger owners, and professional millers were more likely to use steam power, highlighting the importance of idiosyncratic talents.[28]

Power out-switching costs. Higher power out-switching costs lead *incumbents* to switch power technologies less often. To help estimate the additional costs that incumbents pay to adopt a technology (relative to entrants), we follow Equation (27) and use the (within-county) difference in adoption shares for entrants versus incumbents, as in Figure 6:

$$\log \frac{\Pr(R|R,\varphi)}{\Pr(R'|R,\varphi)} - \log \frac{\Pr(R|E,\varphi)}{\Pr(R'|E,\varphi)} = \frac{1}{\rho} \times \left(c(R,R') + (1-\omega^R) c_{ct}(R) \right), \tag{29}$$

Note that even in the absence of any retrofitting costs, incumbents would still switch technologies less than incumbents if scrapping values are low. In our benchmark estimates, we assume that investments are sunk and so $\omega = 0$. We discuss a counterfactual where the government subsidizes $\omega = .30$, following Kermani and Ma (2023)'s estimates in modern data.

Entry costs. Higher entry cost will result in a lower share of new entrants. As a result, we use each county's share of producers for each technology who are entrants to inform our estimates of f^e, as in Table 1.

Operating costs. In the model, given our assumptions on the dynamics of productivity, higher operating costs f^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.11, to help estimate f^R. We normalize the operating costs of entrants, f^E, to zero.

Dispersion of operating cost shocks. As the parameter ρ_o^R increases, so does the dispersion of the Gumbel distribution from which the idiosyncratic operating cost ν_{jct}^R(OPERATE/EXIT) is drawn, given current power source R. Higher dispersion means the exiting firms will have a similar size distribution to surviving firms, because the idiosyncratic draws become relatively more important. To help estimate ρ_o^R, we therefore measure the overlap coefficient

[27] In practice, we divide the histograms into 3 bins, where the two cut points are the median size of the water mills and the median size of the steam mills.

[28] McElheran et al. (2023) find that younger and growth-oriented owners are more likely to adopt artificial intelligence technologies.

of log sales between firms that survive to the next decade and those that exit within each county, as in Appendix Figure A.15.

Baseline productivity process. To help estimate the persistence parameter π for φ_{jt}, we estimate for each county the coefficient from regressing current log sales on lagged log sales at the establishment level, as in Appendix Table A.14. To help estimate the AR(1) dispersion parameter σ, we use the standard deviation of log sales within each county.

V.A.2 Across-County Moments

The "lower water power" county reflects the counterfactual outcomes that the baseline county would have had if its waterpower potential had been one standard deviation lower. We use our reduced-form regression equations (1)&(2) to estimate these counterfactual moments:

$$\widetilde{Y}_t \equiv \mathbb{E}[Y_{ct}|LowerWaterpowerPotential_c = 1, X_c = \mathbb{E}[X_{ct}]] = \hat{\beta}_t + \hat{\gamma}_t'\mathbb{E}[X_{ct}]. \tag{30}$$

The counterfactual moments for the "lower water power" county in Equation (30) are identified under the assumption that local waterpower potentials (after controlling for geographical and other local characteristics) act as cost-shifters for local firms' use of waterpower. In particular, comparing Equations (28) and (30), the difference in moments between the model counties exactly correspond to our reduced-form impacts of lower waterpower.

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

Costs of Waterpower. The additional fixed cost of waterpower in low waterpower potential places, $c_{LowerWaterpowerPotential}(W) - c_{Baseline}(W)$, lowers the attractiveness of using waterpower (see Prediction 1 of Section IV.E). We, therefore, use the relationship between waterpower potential and the share of mills using waterpower (as in Table 2) to help estimate it.

Demand elasticities. The elasticity of demand for milling η governs how local cost advantages affect total mill activity in the local economy. We identify η from the initial (1850) relationship between lower waterpower (increasing milling costs) and local milling activity.

Agglomeration. The other parameters of the model pin down how much more adoption of steam power there is in low waterpower potential places over time. Given η, this translates into a growth in output that may be less than in the data. To rationalize any difference between actual growth and what the model would otherwise predict, we allow for agglomeration (α_S) to increase the output boost from steam power. The key moment this relates to

is the impact of lower waterpower on economic growth, as in Table 3.

V.A.3 Estimation Procedure

We estimate our structural parameters jointly using a nested estimation procedure that reflects the distinction between "within county" and "across county" moments from Sections V.A.1 and V.A.2.

The outer loop searches for values of the additional cost of water $c_c(W)$ in the "lower waterpower" county, the level elasticity of demand η, and the steam agglomeration parameter α to match the differences in outcomes between the model counties. The inner loop uses a simulated annealing procedure to find the values of the remaining parameters that match our target moments within the baseline county.

V.B Estimation Results

Table 7 shows the targeted moments, and how well the model does at matching the data. For the most part, the standardized difference between the model and data is respectable: the moments for which the absolute difference is the largest are often ones where there is also uncertainty in the data.

Table 8 shows the estimated structural parameters, as well as related estimates from the literature for context. The historical literature does not generally have exactly comparable estimates for the same parameters, for this same setting, but for some parameters this gives some rough sense of plausible magnitudes.

The first panel shows power adoption costs as a function of 1830 revenue. The total switching cost of switching to steam power ($c^r(W, S)$) is equal to 0.38 years' worth of revenue, or about five months. The fixed cost of waterpower ($c(W)$) was around three months of revenue, so sunk water investments imply that owners effectively had to pay eight months of revenue to switch power sources. Eventually, the fixed cost of steam power was only slightly higher than the fixed cost of waterpower, so much of the continued use of waterpower was due to idiosyncratic shocks and switching costs. Waterpower potential dramatically lowered the fixed cost of investing in waterpower. The operating costs of steampower are larger than those of waterpower, consistent with the qualitative evidence that steam engines required more upkeep.

V.C Model Validation

To validate the model, we compare how the model does at predicting the diffusion pattern of steam power in the baseline and low-power counties, where the *only* modeled difference across the counties is a time-invariant cost of adopting waterpower. This time-invariant cost of adopting water will mechanically match the average difference in the share of plants using

waterpower between the baseline and "lower waterpower" county, so the validation of the model comes from matching the decade-to-decade pattern in adoption, as well as differences in other outcomes.

The validation results are in Figure 8. Panel A shows that the model closely matches the diffusion of steam in the data for counties with one-standard deviation less waterpower potential than the baseline. Lower waterpower places reached the value of the baseline steady state steam share around 20 years faster, and ultimately experienced an 10% higher steady state steam share.

VI Counterfactual Experiments

This section conducts counterfactual experiments to assess the general equilibrium impacts of the arrival of steam, given the model and parameter estimates from Section V. We use the model to quantify the complementarity between removing switching costs and entry/exit.

VI.A Switching Costs and Entry

The removal of switching costs leads to more incumbent use, but in equilibrium lowers switchers crowd out entrants, who were originally more likely to use steam power. In order to quantify the magnidtude of these forces for the overall diffusion of steam power, in Figure 9 we show counterfactuals from changing the environment. In aggregate, removing the barriers to switching raises the share of mills using steam. The economy would have reached the value of the baseline steady state steam share around 20 years faster, and ultimately experienced an 10% higher steady state steam share.[29] Much of this increase occurs at the start of the diffusion curve: the share of mills using steam would have counterfactually been double in 1850 in the absence of switching barriers.

Figure 9 also shows the effect on the steam share of removing entry/exit. Without entrants to speed up adoption, steam would only have reached its actual 1860 level by 1900. The extensive margin was crucial to the diffusion of steam: in a counterfactual with no entry or exit but also removing switching costs, steam would have diffused around 80% as quickly than in the baseline. While incumbents would have been more likely to switch, this effect would have been dominated by the prevention of steam entrants.

Table 9 reports the impact of the counterfactuals on aggregate milling output, relative to an environment where steam power had never been invented. At baseline, steam power increased the present discounted value of output by around 70% (150% in low waterpower places). This large effect masks distributional effects, as incumbents lose a little and the entrants benefited even more.

[29] Coincidentally, the effect of removing switching barriers on steam adoption is very similar than the effect of higher costs of waterpower.

Counterfactally removing water lock-in increases output by around a further 20 percentage points in both the baseline and low waterpower counties. Although the incumbents directly benefit from a lack of lock-in, this is overshadowed by the entrants also losing lock in: there is more entry in this counterfactual (since entrants now do not anticipate potentially paying the switching costs), and the entrants are more productive (since they can switch to steam power).

Entrants were crucial to the output benefits of steam power. Preventing entry would imply that the aggregate benefits of steam were only 1 % (2% in low waterpower counties), all mechanically accruing to incumbents. Switching costs are important but not the main driver of this result, as preventing entry while removing switching costs only raises the gains from steam power to around 2% (3% in low waterpower counties).

While incumbent switching on its own could not generate the output gains from the diffusion of steam power, it still was important. Figure 10 shows the counterfactual effects of introducing infinite switching barriers. We find that by 1900 steam penetration would only have been around half its observed value, with very slow diffusion. While we do find substantively important switching costs in our environment, a model which assumed prohibitive switching barriers would be missing a quantitatively important source of technology adoption.

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, some incumbents were resistant to change. Nevertheless, improvements in steam power meant that new places saw expansions in mechanized activity, and led the way to growth in a variety of sectors.

To understand the effect of steam power on milling, this paper makes several contributions. We compile previously undigitized panel microdata of manufacturing plants in the United States during the Second Industrial Revolution. We link the data to new estimates on the distribution of historical waterpower potential. This data effort allows us to uncover new facts about the diffusion of steam power.

Our first set of facts relates to understanding how waterpower potential slows the adoption of steam power. First, we provide systematic evidence consistent with Temin (1966)'s

hypothesis: in the data, places with higher waterpower potential adopted less steam power, and did so slower. In our model estimates, this is due to a substantially lower fixed cost of adopting waterpower.

In addition to the fact that water was statically cheaper, the pre-existing investments in waterpower also led to slower investments in steam power. We estimate moderate barriers to switching, which caused many incumbent mills to stay with waterpower. Specifically, incumbents who had previously used waterpower were around a third as likely as entrants to use steam power. Removing switching barriers would have doubled the penetration of steam power in 1850.

Our data also allows us to describe how steam power affected the production of mills. We find that steam mills were systematically larger than water powered ones in 1850, consistent with the historical view that steam was the high fixed cost and low marginal cost technology (Atack, 1979). Over time, the size distributions converged, which we rationalize with a falling fixed cost of steam power. This estimates are consistent with the historical narrative of the timing of the introduction of high speed steam engines and improved engineering, which led to lower fixed costs.

These features interact: the nature of steam power was that it was more attractive to more productive mills. Existing mills whose productivity increased after they had already invested in waterpower were therefore "stuck." It is not a first-order principle that new technologies are associated with high switching costs, high fixed costs, and low marginal costs, and this matters for their adoption. Outside of medical procedures, the technologies that Comin, Hobijn and Rovito (2006) document as having diffused the fastest are characterized by either having low switching costs (ATMS, credit card readers, and pesticides) or low fixed costs (Bessamer steel). We believe that systematically measuring the implications of switching costs and fixed costs across different technological revolutions would lead to interesting future work, and have important implications for understanding the diffusion of new technologies.

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Figure 1: Components of Theoretical Waterpower
(a) Flow Rates



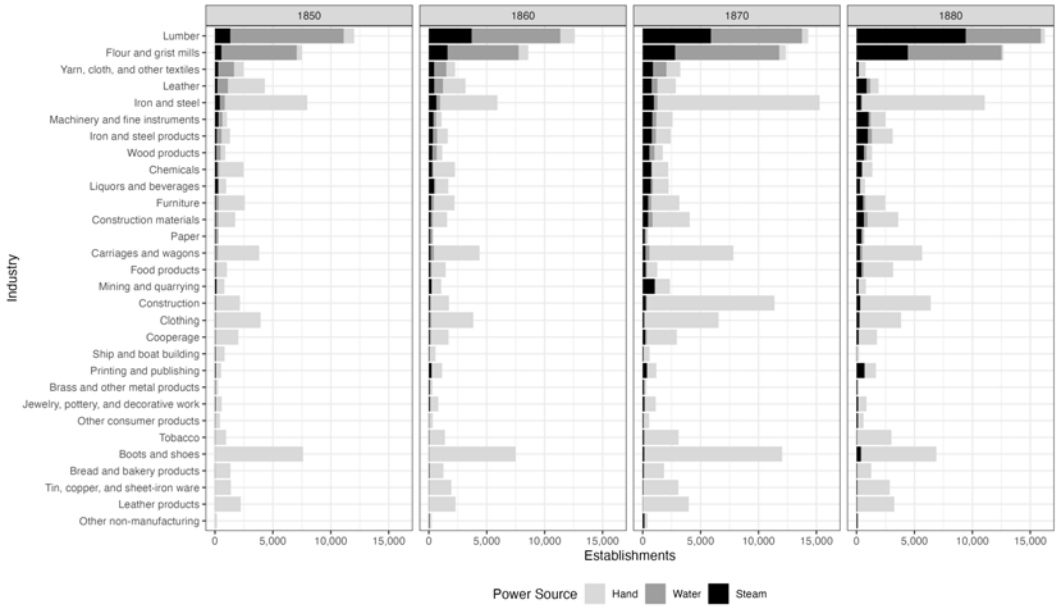
(b) Fall Heights



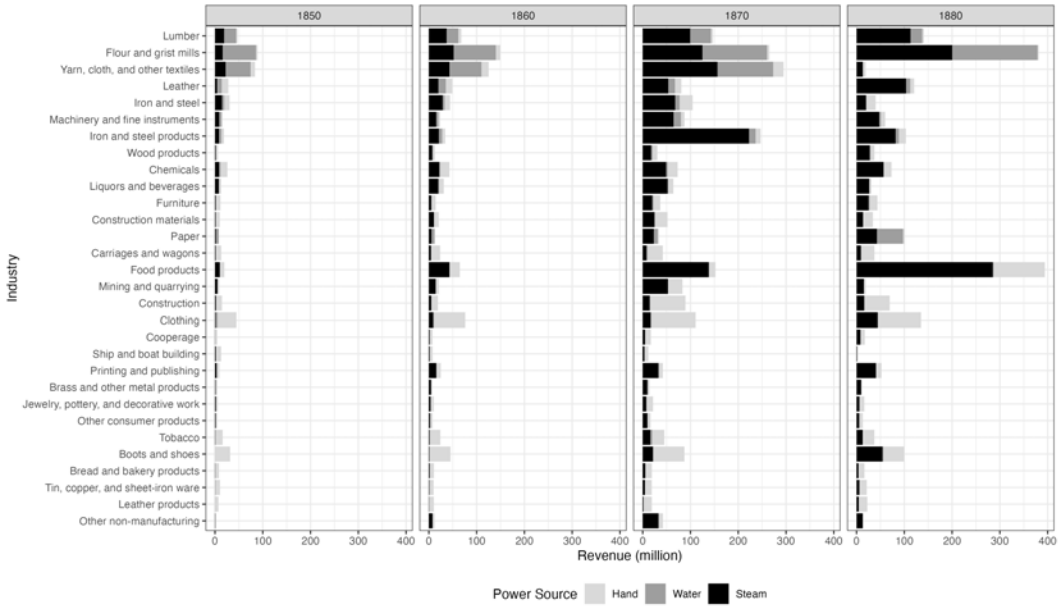
Notes: This figure plots the sources of waterpower potential in the United States. Panel A plots our measure of estimated historical flowrates (in cubic feet per second), Panel B shows elevation changes (in feet). Data from NHDPlusV2.

Figure 2: Power Use By Sector

(a) Establishments



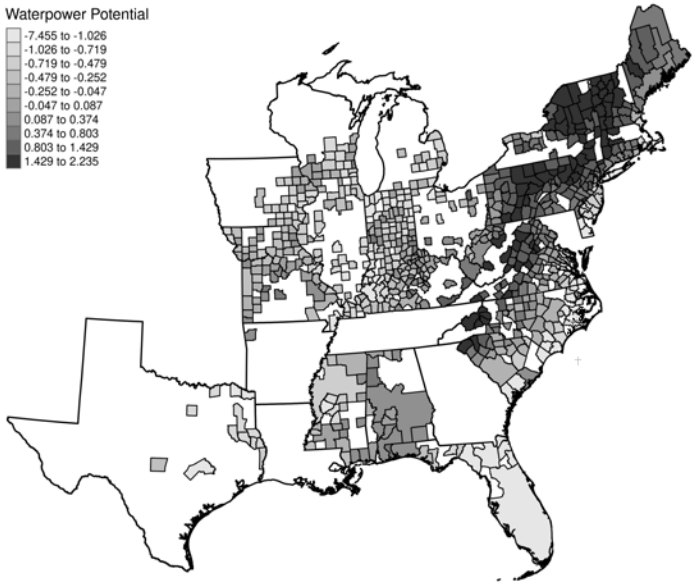
(b) Output



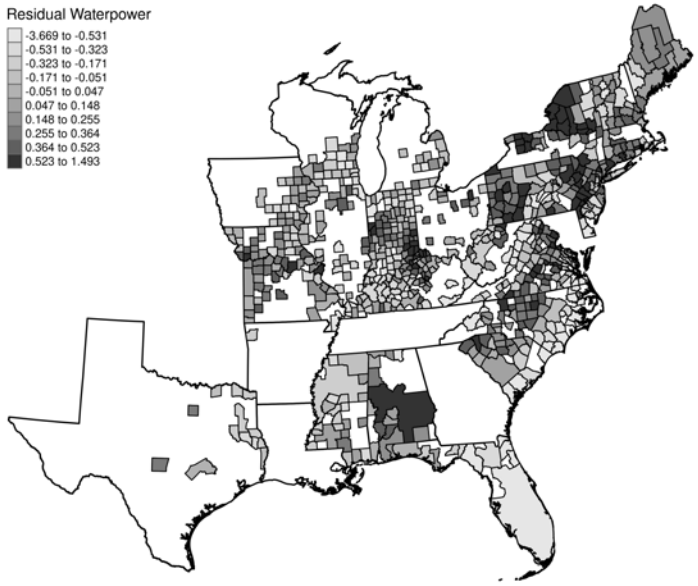
Notes: This figure plots the penetration of mechanization across industries in the United States, 1850-1880. Panel A plots the share of establishments in each sector using water, steam, or hand power, Panel B plots the share of output coming from each type of firm. Industries are sorted in decreasing order of the number of plants using either steam or water in 1850. Data from the 1850-1880 Census of Manufacturers.

Figure 3: County Waterpower Potentials

(a) Raw Waterpower Potential

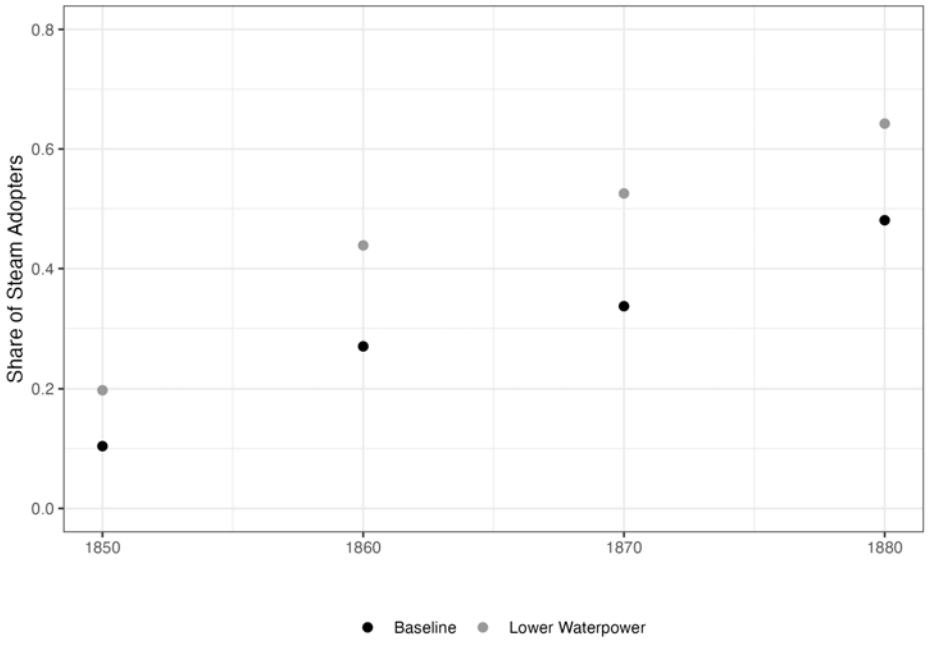


(b) Residual Waterpower Potential



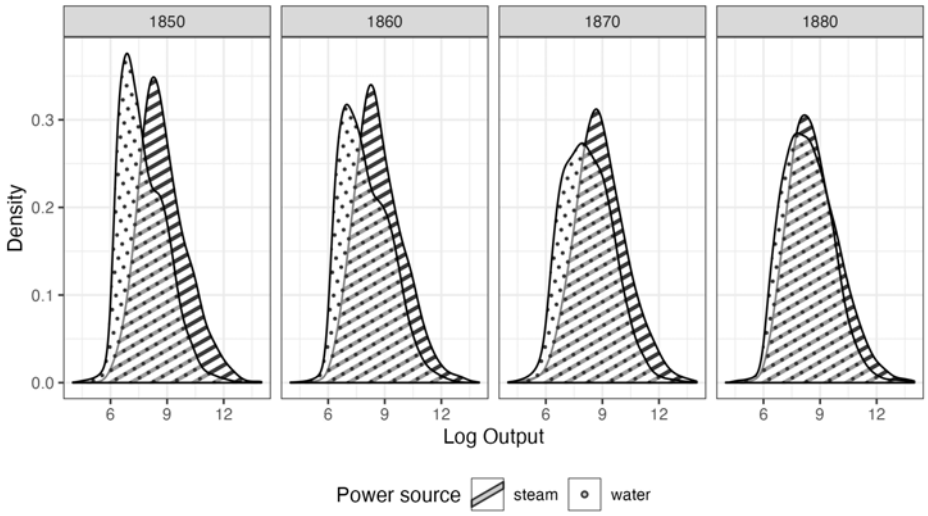
Notes: This figure plots waterpower potentials for the counties with at least one flour or lumber mill in 1850 (which is the main regression sample in the paper). Panel A plots raw waterpower potential: the sum across all rivers in the county of the flow rate times the fall height (times a gravitational constant). Panel B residualizes for the baseline controls described in the paper: total water flow and ruggedness in the county; an indicator for the presence of a navigable waterway as well as county market access in 1850; and a dummy for the presence of coal in the county, as well as the share of the county covered by coal deposits. Data from NHDPlusV2.

Figure 4: Steam Power Diffusion



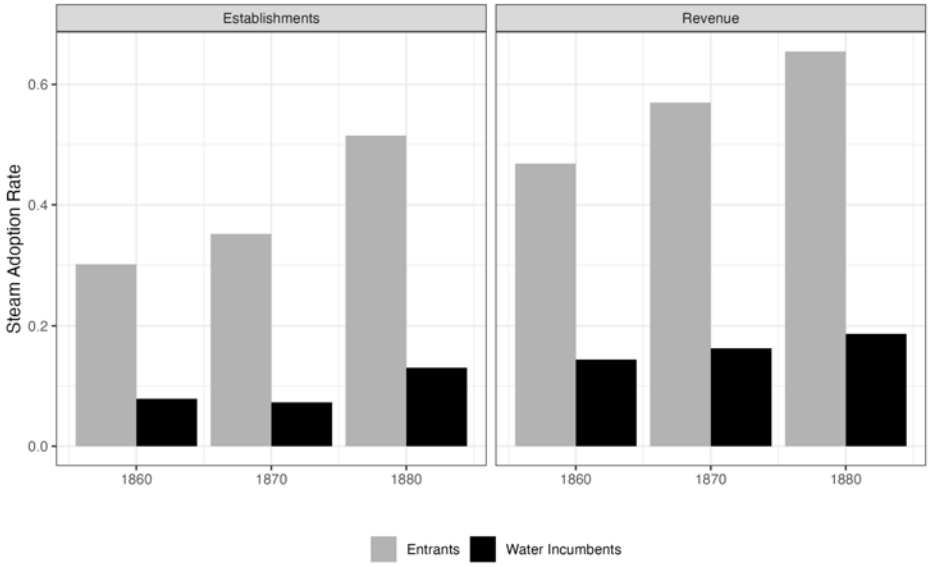
Notes: This figure plots the share of steam users in the average county ("baseline") and the typical county with one standard deviation less waterpower potential ("lower waterpower"), as described in text. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Figure 5: Mill Size by Power Source



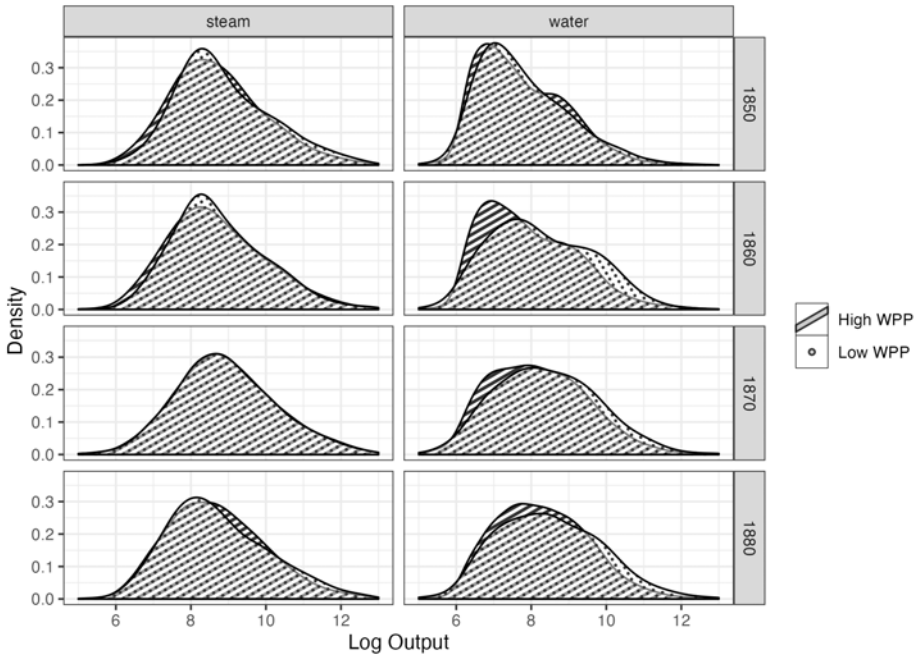
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water). The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers.

Figure 6: Power Sources for Entrants and Water Incumbents



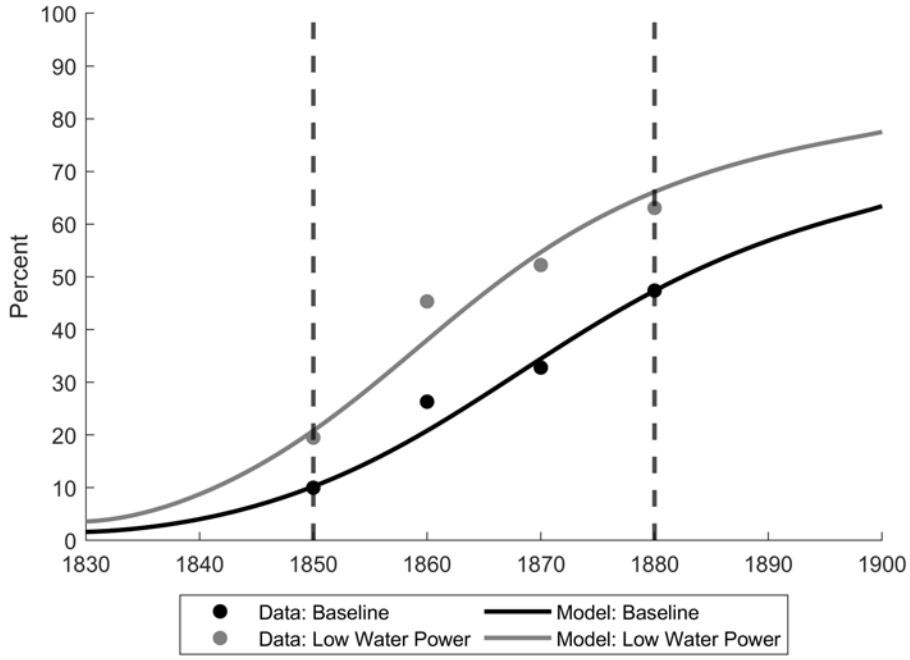
Notes: This figure plots the share of entrants and water incumbents (plants who used waterpower in the previous decade) currently using steam power. Panel A shows the share of establishments, Panel B weights by current output. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers.

Figure 7: Mill Size by Waterpower Potential



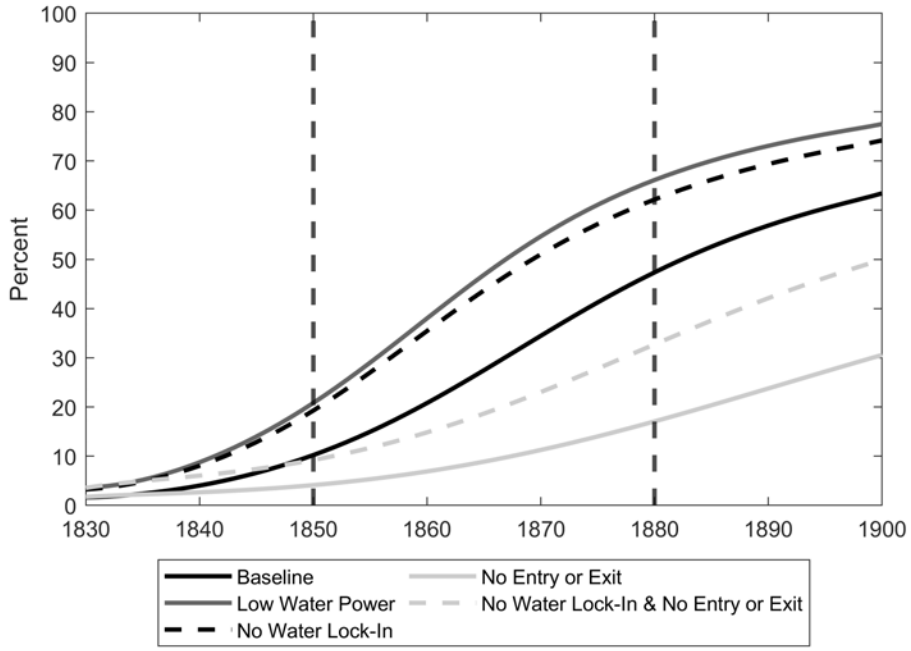
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water), separately by places above and below median waterpower potential. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Figure 8: Observed and Model Estimates for Steam Power Diffusion



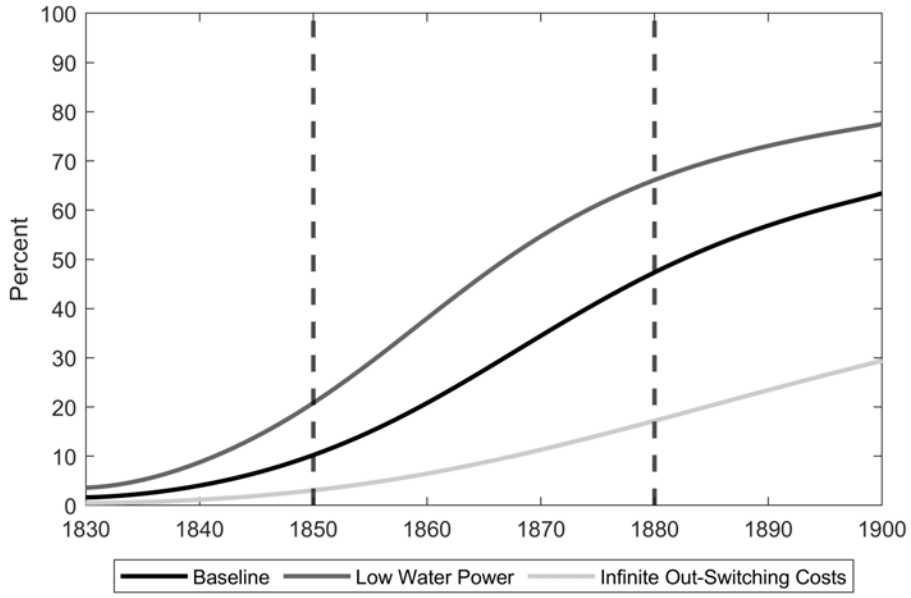
Notes: This figure plots the share of steam users in the average county and the typical county with one standard deviation less waterpower potential (in dots), as described in text. The lines are the model estimates for the diffusion of waterpower potential, where the only parameter difference underlying the dark gray line (baseline) and light gray line (low waterpower potential) is the fixed cost of waterpower adoption. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Figure 9: Counterfacutals for Steam Power Diffusion



Notes: This figure shows the model estimates for the share of mills adopting steam under various scenarios: using the actual parameters for baseline and low waterpower potential places (as in Figure 8), and then counterfactually: removing entry and exit, lowering the switching cost to steampower to zero, and both. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Figure 10: Counterfacutals Steam Power Diffusion With Infinite Switching Costs



Notes: This figure shows the model estimates for the share of mills adopting steam under various scenarios: using the actual parameters for baseline and low waterpower potential places (as in Figure 8), and counterfactually raising the switching cost to steampower to infinity. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table 1: Sources of Steam Power and Total Milling

	Share of Steam Milling			Share of Total Milling				
	Entrants (1)	Steam Incumbents (2)	Water Incumbents (3)	Steam Entrants (4)	Water Entrants (5)	Steam Incumbents (6)	Water Incumbents (Switchers) (7)	Water Incumbents (Stayers) (8)
Panel A. Establishments								
1850-1860	0.90	0.04	0.06	0.24	0.56	0.01	0.01	0.17
1860-1870	0.91	0.07	0.03	0.30	0.56	0.03	0.01	0.11
1870-1880	0.85	0.11	0.04	0.41	0.38	0.06	0.02	0.13
Panel B. Revenue								
1850-1860	0.87	0.08	0.06	0.37	0.42	0.03	0.02	0.15
1860-1870	0.85	0.12	0.03	0.47	0.36	0.07	0.02	0.09
1870-1880	0.78	0.17	0.06	0.47	0.25	0.10	0.03	0.15

Notes: This table shows, in columns 1—3, the share of steam-using mills who are entrants, steam incumbents, or water incumbents. Columns 4—8 show the share of total production coming from steam and water entrants, steam incumbents, or water incumbents (distinguishing between those who stayed with waterpower and those that switched to steam). Panel A reports the share of total milling establishments, Panel B reports the share of total milling revenue. The sample is counties with at least one mill in 1850. Data from the 1850-1880 Census of Manufacturers.

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

	All Mills (1)	Lumber Only (2)	Flour Only (3)
Panel A. Number of Waterpowered Mills			
Lower Waterpower	-1.089	-1.297	-0.783
	(0.131)	(0.173)	(0.111)
Panel B. Total Revenue of Waterpowered Mills			
Lower Waterpower	-1.189	-1.132	-1.209
	(0.251)	(0.239)	(0.305)
Panel C. Steam Share of Mills			
Lower Waterpower	0.095	0.114	0.057
	(0.015)	(0.017)	(0.016)
Panel D. Steam Share of Revenue			
Lower Waterpower	0.130	0.161	0.068
	(0.022)	(0.027)	(0.024)
Panel E. Total Number of Mills			
Lower Waterpower	-0.965	-1.104	-0.745
	(0.122)	(0.160)	(0.107)
Panel F. Total Revenue of Mills			
Lower Waterpower	-0.591	-0.362	-0.727
	(0.388)	(0.414)	(0.409)
# Counties	722	637	604

Notes: This table shows the relationship between 1850 milling activity and waterpower potential. 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. Column 1 pools all mills, Column 2 includes only lumber mills and Column 3 includes only flour mills. Panels A, B, E, and F use (pseudo) Poisson maximum likelihood estimation. Panels C and D weight counties by their number of mills. Each observation is a county-industry in 1850, and the sample is all county-industries with at least one mill in 1850. All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

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

	Steam Share of Mills (1)	Total Mills (2)	Total Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.059	0.227	0.200
	(0.020)	(0.058)	(0.051)
# Counties	664	722	722
From 1860 to 1870	0.034	0.125	0.104
	(0.012)	(0.051)	(0.080)
# Counties	650	722	722
From 1870 to 1880	-0.016	0.135	0.138
	(0.015)	(0.036)	(0.077)
# Counties	696	722	722

Notes: This table shows the relationship between waterpower potential and milling growth from 1850-1880. The outcome in column 1 is the share of mills using steam power, in column 2 the outcome is the total number of mills, and in column 3 the outcome is total milling revenue. Each row corresponds to a different regression, using only data from the indicated years. The sample is all counties with at least one mill in 1850. Column 1 reports OLS results for the counties that have at least one mill in both decades (since there needs to be at least one mill for the steam share to be defined), and is weighted by the number of mills in the county in 1850. Columns 2 and 3 report (pseudo) Poisson maximum likelihood estimates for the balanced panel (including the zeroes). "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers 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	0.328	-0.220	0.548
	(0.070)	(0.068)	(0.090)
# Counties	722	722	
In 1870	0.175	-0.215	0.390
	(0.061)	(0.070)	(0.098)
# Counties	722	722	
In 1880	0.205	-0.140	0.345
	(0.044)	(0.042)	(0.062)
# Counties	722	722	

Notes: This table shows the elasticity of entry and survival with respect to waterpower potential from 1860-1880. Column 1 shows results for entry, and column 2 for incumbent survival. Column 3 reports the difference. Each row corresponds to a different regression, using only data from the indicated year. The sample is all county-industries with at least one mill in 1850, and we report (pseudo) Poisson maximum likelihood estimates. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table 5: Steam Adoption of Entrants and Water Incumbents, by County Waterpower Potential

	From Entrants (1)	From Water Incumbents (2)	Difference (1) − (2) (3)
Adoption in Lower Waterpower Counties:			
In 1860	0.163	0.048	0.115
	(0.025)	(0.023)	(0.023)
# Counties	658	424	
In 1870	0.187	0.053	0.134
	(0.024)	(0.019)	(0.027)
# Counties	702	398	
In 1880	0.163	0.071	0.092
	(0.026)	(0.031)	(0.031)
# Counties	709	466	

Notes: This table shows the relationship between waterpower potential and the steam use of entrant and incumbent mills from 1860-1880. 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 a different regression, using only data from the indicated year. The sample is all county-industries with at least one mill in 1850 and at least one current entrant (in column 1) or incumbent (in column 2). "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits, and are weighted by the number of mills in the county in 1850. Each observation is a county-industry-decade, and we weight by the number of mills in 1850. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table 6: Spillovers of Steam: Mills' Neighbors

	Neighbor of Mill (1)	Neighbor of Non-mill (2)	Difference (1) − (2) (3)
Panel A. All Non-mills			
Lower Waterpower	0.019	0.005	0.014
	(0.004)	(0.003)	(0.005)
# Establishments	98,448	99,276	
Panel B. Excluding Water Users			
Lower Waterpower	0.016	0.006	0.010
	(0.004)	(0.002)	(0.004)
# Establishments	73,183	77,433	

Notes: This table shows the how mills affected their neighbors' steam use. The outcome in columns 1 and 2 is the share of establishments using steam power, where column 1 limits the sample to non-mill establishments whose census enumeration is on the same page as a mill, and column 2 limits the sample to non-mill establishments without a mill on their page. Column 3 reports the difference. Panel A includes all non-mill establishments, Panel B limits the sample to industries that are not responsive to waterpower in Appendix Figure A.13: we drop leather, paper, chemicals, iron & steel, brass & other metals, liquors, construction materials, wood products, ship & boat building, and textiles. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include industry-decade fixed effects in addition to the baseline controls (total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits). Standard errors are clustered by county. Data from the 1850-1880 Census of Manufacturers.

Table 7: Targeted Moments

Parameter (1)	**Moment** (2)	**Year** (3)	**Model** (4)	**Data** (5)	**Std. Diff.** (6)
	Baseline				
$c_t(S)$	Steam Adoption Rate	1850	0.102	0.100 [0.260]	0.006
$c_t(S)$	Steam Adoption Rate	1860	0.206	0.263 [0.685]	-0.083
$c_t(S)$	Steam Adoption Rate	1870	0.342	0.328 [1.065]	0.013
$c_t(S)$	Steam Adoption Rate	1880	0.471	0.474 [1.108]	-0.003
$c(W,S)$	Water Choice Differentials: Water Incumbents vs. Entrants	1850-1880	0.703	0.731 [1.483]	-0.019
$c(S,W)$	Steam Choice Differentials: Steam Incumbents vs. Entrants	1850-1880	1.053	0.969 [1.346]	0.062
ρ	Log Sales Overlap Shares (Between Steam and Water Users)	1850-1880	0.553	0.654 [0.391]	-0.259
γ	Log Sales Differential Between Steam and Water Users	1850-1870	1.103	0.702 [2.247]	0.178
Π	Log Sales Autocorrelation	1850-1880	0.467	0.514 [1.287]	-0.037
Σ	Log Sales Standard Deviation	1850-1880	1.154	1.167 [0.858]	-0.016
f^e	Water Entry Rate	1850-1880	0.823	0.743 [0.309]	0.260
f^e	Steam Entry Rate	1850-1880	0.879	0.816 [0.400]	0.158
f^W	Water Exit Rate	1850-1880	0.703	0.770 [0.274]	-0.245
f^S	Steam Exit Rate	1850-1880	0.851	0.795 [0.259]	0.213
ρ_o	Log Sales Overlap Shares (Between Survivors and Exiters)	1850-1880	0.871	0.792 [0.532]	0.148
	Baseline vs. Low Water Power: Differences				
$c_{\mathbb{1}(\text{Low Water Power})}$	Steam Adoption Rate	1850	0.107	0.095 (0.013)	0.906
$c_{\mathbb{1}(\text{Low Water Power})}$	Steam Adoption Rate	1860	0.174	0.190 (0.027)	-0.612
$c_{\mathbb{1}(\text{Low Water Power})}$	Steam Adoption Rate	1870	0.205	0.195 (0.022)	0.480
$c_{\mathbb{1}(\text{Low Water Power})}$	Steam Adoption Rate	1880	0.191	0.157 (0.026)	1.330
η	Log Total Output	1850	-0.969	-0.962 (0.201)	-0.034
η	Log Total Output	1860	-0.747	-0.602 (0.182)	-0.797
η	Log Total Output	1870	-0.569	-0.225 (0.362)	-0.949
η	Log Total Output	1880	-0.428	-0.189 (0.311)	-0.769

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 in-sample estimate of the moment from the model, column 5 the data estimate (and its standard deviation in brackets), and column 6 the standerdized difference.

Table 8: Parameter Estimates

Parameter (1)	Description (2)	Value (3)	Literature (4)
	Power Adoption Costs (Unit of 1830 Average Firm Sales)		
$c^r(W,S)$	Out-switching costs from water	0.3803	≈ 0.052 (Atack, 1979)
$c^r(S,W)$	Out-switching costs from steam	0.8744	≈ 0.042 (Atack, 1979)
$c(w)$	Water purchasing price	0.2692	
$c_{\mathbb{1}(\text{Low Water Power})}$	Low water region's relative water purchasing price	0.2345	$\approx$ 0.029 (Swain, 1888); 0.011-0.040 (Atack, Bateman and Weiss, 1980)
$c_S^{(floor)}$	Steam purchasing price (floor) minus water purchasing price	0.0428	≈ -0.071 (Atack, 1979)
$c_S^{(origin)}$	Steam purchasing price (origin) minus water purchasing price	2.7468	≈ 0.065 (Atack, 1979)
	Power Adoption Costs		
$c_S^{(slope)}$	Steam purchasing price (slope)	0.0199	0.067 (Atack, 1979)
$\rho/c_S^{(origin)}$	Relative dispersion in power costs	0.1533	1.295 (Humlum, 2022)
	Productivity (Elasticities)		
γ	Steam productivity premium	0.0596	≤ 0.035 (Crafts, 2004); 0.07-0.09 (Atack, Bateman and Margo, 2008); 0.229 (Chernoff, 2021)
Π	Autocorrelation in baseline productivities	0.9779	0.9675 (Bachmann and Bayer, 2014); 0.962 (Coşar, Guner and Tybout, 2016); 0.983 (Schaal, 2017); 0.90 (Ottonello and Winberry, 2020); 0.93 (Humlum, 2022)
Σ	Dispersion in baseline productivities	0.2116	0.21 (Foster, Haltiwanger and Syverson, 2008); 0.0905 (Bachmann and Bayer, 2014); 0.137 (Coşar, Guner and Tybout, 2016); 0.533 (Schaal, 2017); 0.08 (Carvalho and Grassi, 2019); 0.03 (Ottonello and Winberry, 2020); 0.28 (Humlum, 2022)
	Demand (Elasticities)		
ϵ	Firm output	3.9733	4 (Bloom, 2009); 4 (Asker, Collard-Wexler and De Loecker, 2014); 6.667 (Coşar, Guner and Tybout, 2016); 11 (Sedláček and Sterk, 2017); 2.9 (Acemoglu et al., 2018); 4.25 (Felbermayr, Impullitti and Prat, 2018); 3 (Buera et al., 2021)
η	Local output	2.8645	
α_W	Steam agglomeration of water users	0.0000	
α_S	Steam agglomeration of steam users	0.0437	
	Entry and Operating Costs (Unit of 1830 Average Firm Sales)		
f^e	Entry costs	0.0012	0.15 (Eaton, Kortum and Kramarz, 2011); 0.15-0.42 (Bartelsman, Haltiwanger and Scarpetta, 2013); ≈ 0.015 (Coşar, Guner and Tybout, 2016); 0 (Carvalho and Grassi, 2019); 0.006-0.133 (Buera et al., 2021)
f^W	Operating cost for incumbent water user	0.0007	0.021-0.036 (Bloom, 2009); 0.00065-0.00825 (Edmond, Midrigan and Xu, 2015); $\approx$ 0.008 (Coşar, Guner and Tybout, 2016); 0.005-0.022 (Ulyssea, 2018)
f^S	Operating cost for incumbent steam user	0.1792	0.021-0.036 (Bloom, 2009); 0.00065-0.00825 (Edmond, Midrigan and Xu, 2015); $\approx$ 0.008 (Coşar, Guner and Tybout, 2016); 0.005-0.022 (Ulyssea, 2018)
	Entry and Operating Costs		
ρ_o^E/f^E	Relative dispersion in operating costs of entrants	0.0926	
ρ_o^W/f^W	Relative dispersion in operating costs of water users	47.9596	
ρ_o^S/f^S	Relative dispersion in operating costs of steam users	0.0976	

Notes: This table shows the structural estimates for the parameters of the model.

Table 9: The Impact of Steam on Output 1830-1900 (PDV)

	Baseline	No Water Lock-In	No Entry or Exit	No Water Lock-In & No Entry or Exit
			Baseline	
Total	72.8	91.6	1.3	2.0
Incumbents	-4.4	-6.3	1.3	2.0
Entrants	88.8	109.6	0.0	0.0
			Low Water Power	
Total	151.3	169.8	2.3	3.2
Incumbents	-10.4	-12.7	2.3	3.2
Entrants	174.3	193.1	0.0	0.0

Notes: This table reports the percentage change of the present discounted value of output relative to the counterfactual in which steam purchasing price had not decreased over time. "No Water Lock-In" refers to the counterfactual in which the out-switching costs from water are zero. "No Entry or Exit" refers to the counterfactual in which establishments could neither enter or exit the region. Incumbents refer to the establishments that had been active since 1829 or earlier. Entrants refer to the establishments that entered the region in 1830 or later.

A Data Appendix

A.1 Industry Manufacturing Data

We have digitized establishment-level manufacturing data for 1850, 1860, 1870, and 1880 from the original published manuscripts of the Census of Manufactures. We are very grateful to Jeremy Atack who provided us with many manuscripts, the rest of the manuscripts were located in a variety of state, non-profit, and university archives. Most of the manuscripts were already available on microfilm, the rest we took pictures of ourselves or were able to acquire pictures from archive staff. Our data include some manuscripts that had not been found during the construction of the previously-digitized samples described in Atack and Bateman (1999), including Rhode Island and Nevada. Delle Donne (1973) describes the enumeration of the Census.

Before 1880, the enumeration of the Census was done in person by U.S. Marshals, and all firms received the same questionnaire (though it changed slightly over time). In 1880, the Census of Manufactures was split into broadly three parts. Many industries maintained the regular schedule. Many important sectors, listed below, were given "special agent" schedules, which involved both sector-specific forms as well as specially trained enumerators: manufactures of cotton, wool and worsted goods, and 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. All of the "special agent" manuscripts are believed to be lost (Delle Donne, 1973).

Finally, some sectors were given "special schedules" with sector-specific questions, but without also getting special enumerators. In addition to "Lumber and Saw Mills" and "Flouring and Grist Mills," the manufacturing sectors with their own schedules were agricultural implements, paper mills, boots and shoes, leather, brick and tile, cheese and butter, and slaughtering and meat packing. The additional sector-specific questions include questions such as the "number of runs of stone" in flour and if a lumber mill does its own logging.

The 1860 Census instructions to enumerators discuss the data collection guidelines in useful detail. Prior to 1850, there are greater concerns about the comprehensiveness of the data collection and the Census data collection was professionalized in 1850 (Atack and Bateman, 1999). As with the population records, all of the 1890 Census manuscripts were lost.

In addition to establishment count, our main variables of interest, from the manufacturing data, are:

Manufacturing Revenue. Products were valued at the factory gate, excluding transportation 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*).

Power Source. Many mills report their power source, and the kind of power 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," though in milling the former two were by far the most common). Part of the reason why we drop the non-mechanized mills is that we are worried about measurement error. For instance, we checked in historical records for several suspiciously-large "non-mechanized" mills, and found that several were in fact mechanized. Since we cannot systematically correct these non-mechanized mills' recorded power-use, we drop them from the main analysis. the Census additionally asked all establishments for their number of horsepower used. The one exception is that some mills use "steam" or "water" in their industry name (e.g. "steam mill") but then do not report steam or water as their power source (normally only reporting "horse.") For those mills, we assume that "horse" means horsepower, and that they used the named power source.

Industry. In all years, the general schedule Census asked firms to report the type of business that they were in, along with (other than in 1880) the products that they made. Most flour mills and lumber mills were surveyed on the special schedules in 1880, but some (2%) were instead recorded in the general schedule, we include those firms in our analysis unless the mill was also surveyed in the special schedule. We describe our processing of the industry strings below.

Location. In addition to the county, information on the closest post office is available for over 90% of establishments in 1860, 1870, and in the 1880 general schedules. Post office is rarely recorded on the 1850 manuscripts and 1880 special schedules, and, consistent with our assumption that firms surveyed on the same page are nearby, firms with the same post office are surveyed together.

A.2 Digitization and Processing of the Census

In order to analyze the data, we worked with Digital Divide Data to double-enter and reconcile manuscript images. In total, there were 64,447 manuscript images with manufacturing firms on them, where 27,102 sheets were from 1880. The average sheet had 10 firms on it. Appendix Table A.1 shows the coverage rates for what we were able to find and digitize (outside of the special agent schedules for 1880 that were lost). On the whole, we were able to enter almost every survey that was collected. In our data files, we keep track of each establishment's decade, state, county, page, and the row that it came from, this allows us to do our neighbors analysis in Section II.C.

To help clean the data, we received assistance from many diligent undergraduates (mostly from the University of Chicago), graduate students, and full time research professionals. In addition the team randomly checking many of the entries (on the whole, we found a very low error rate), we had one additional source 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 the sum of the total material value for a given firm. We also digitized these values, and compared the entered total with the sum of the relevant responses. Consistent with our verification of the data in general, the most common sources for the discrepancy 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 (such as output to employment) seemed unusually high, 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.

Unlike for the numeric values, we found no systematic way to verify any of the strings besides going through them one-by-one. We manually processed the strings for product names, material inputs, and self-reported industry, and searched the power strings for relevant information such as "water" and "steam." The overall goal was to correct misspellings & British spellings, expand abbreviations and assign strings to broader categories. To clean industries, we relied additionally on the product strings.

The data report many self-reported industries in each decade, with some small variations, which we group together for our analysis. Following Hornbeck and Rotemberg (2023), we homogenized industry names into 31 categories, additionally using reported information on products when needed. In our analysis, we focus on flour and lumber milling, which were relatively straightforward to classify since they had unique outputs.[30]

Some values from string variables were entered in the wrong places, which we manually corrected, as we did when numeric variables were entered in a string column. Especially for strings, there were some entries where the data processing team could not read part or all of a cell and and marked it with a question mark. We looked at those ourselves, and were rarely able read them either.

The census considered an enterprise one establishment even if it contained multiple locations within the same Census subdivision, if they were for the "same concern, and all engaged in the same manufacture." There were also some lines in the Census that were associated

[30]To give a sense of the raw data, there were 1,591 distinct industry strings in the original manuscripts that we associate with either the lumber or flour industries, including "grist," "flower mill," "wood & lumber," "steam saw mills," and "mills" (whose industry we could only identify because of their products).

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. So, for instance, when we consider the revenue of E E Locke & Co, we only consider the revenue of the mill, not of the distillery. This is particularly relevant for the mills in the period that produced both cut lumber and flour, we classify those as separate mills in our analysis. This approach follows contemporaneous 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." 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 essentially referring to single-establishment "firms."

A.3 County Borders

It is important for us to understand exactly where each plant was located (instead of probabilistically placing it in all of the potentially relevant counties after administrative borders changed), in order to consider the panel. As a result, we group together counties that had overlapping geographies, in order to create time-consistent borders.

Our baseline boundaries start with 1850 borders. Issues arise when an 1860-1880 fips code overlaps with multiple 1850 counties. To overcome this issue, we first crosswalk the county boundaries across 1850-1880, and group 1850 counties so that every county in 1860-1880 corresponds to a unique grouped 1850 cell. Our approach is, in the first step, for a given 1850 county, assign the same id for all of its overlapped (overlapping by at least 5% of the area) 1860-1880 counties. Then for a given 1860/1870/1880 county, we assign the same id for all of its overlapped 1850 counties (overlapping by at least 10% of the area).

There are two counties who both in the manuscripts and the tabulated data that have more than 10 firms in an initial decade, in the subsequent decade have no firms, and then have more than 10 firms. Worried about enumeration error (or the manuscripts being lost contemporaneously), we drop these counties. This is in the spirit of Allcott, Collard-Wexler and O'Connell (2016), who similarly drop firms who are very different from both adjacent observations.

A.4 Creating a Panel of Mills

For our analysis, we study if a mill existed in the previous decade, and, if so, its size and power choice. To link mills over time, we compared every mill in a decade to every plausible match in the subsequent decade, and matched if the name was close. For the whole census, we matched on name and location, but did not force establishments to be in the same industry in every

decade. However, because millers rarely switched, and working in a different manufacturing sector is effectively part of the outside option for the model, for this project we consider these switches "exits."

In order to guide the hand-links at scale, we first matched a few counties ourselves, comparing every mill to every single manufacturing establishment in the subsequent decade. We then trained a machine learning algorithm on those matches, and so when we did the hand-linking at scale we only showed the team potential matches with a relatively high linking probability. Roughly, we included all candidates with over a 9% linking probability. However, for firms with many potential links we only sent the top twenty, and for firms with few potential links we sent the top 5, as long as their linking probabilities were above 5%. In practice, the links with a low match probability were rarely hand-chosen as an actual match. For the analysis in the paper, we then retrained the model on the full set of matches. Below, we describe our approach in detail.

A.4.1 Hand-linking Procedure

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

To make the matches, we considered each establishment's names, industry classifications (including self-reported values 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 handlinking sheet was completed by two people, and assigned to a third person to reconcile any discrepancies. For each 1860 establishment, we sort all 1870 candidates by Jaro-Winkler (JW) name similarity and by whether or not their broad industries match to increase the likelihood that links are at the top of each block of names.

Broadly, there were two types of matches in the data. "Direct" matches are matches where the name of the establishments in both years appears to be identical. 'Ownership transfer" matches are matches where part of the name is identical, but some other part has different, implying a partial change in ownership. In practice, this second category thus contains anything ranging from incorporations, partnership formation, or newer members taking on the family business.[31]

[31] 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."

A.4.2 Model Specification

From hand-linking establishments, we noticed in the data that there were broadly four categories for how the establishment's name was reported (though it was not a formal rule, and the way names were written down varied across time and space). 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 orders.

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 of partnership and expanded partnership reported two or more names of the proprietors; limited partnerships reported one or more people's names followed by *& co.*

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

Often, when searching the historical record, there are mills that fall into many of these categories (For instance, sole owners in the Census could own a mill that had an understood name, often the name of the waterway).

Unlike male names in the Census of Population, establishment names change commonly due to ownership transfers or investment. For example, we often see examples of sole proprietorships that were expanded into a family business, or business with several owners have a slightly different set of owners in the next decade. Even for establishments with a single owner across time, the order of the first and last name might change, as might which name got reported as an initial in the Census.

The observation on the way names were recorded motivates us to build two separate linking models, one matching the owners' names, and the other matching the established names as a whole (we are also grateful to conversations with Jeremy Atack, who also suggested this approach). Effectively, we use two random forest models to predict establishment pairs by tracking the owners and company as a whole, respectively.[32] Both linking models predict

[32]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 provides the most reliable output in false positive and negative rates, and the empirical distribution of

establishment pairs to be either a same-owner match, an ownership transfer match, or not a match, and we describe our approach below.

Name Classifier To let the owner-linking model tracks owners successfully, we build a name classifier to categorize establishments by their types, extract the name of the owners and identify the name order. The names of establishments owned by sole proprietors, families, partners, or expanded partner contain the names of their owners; however, names were sometimes initialized and did not follow specific first-last name orders. We collect a list of company tokens that identify establishments with impersonal names, that we do not use in first model that links owners. The list includes the names of the location, such as state and county names, and also tokens related to their product or business, such as wine, tanning, manufacturing, lumber, etc. For establishments without any 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 with the location of comma and ampersand. 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.") Next, we standardized common nicknames and abbreviations to their original names (e.g., Wm to William; Geo to George.) We then determine the name order using the first and last name frequency in the 1880 census of the population. When both name tokens can be first or last names, instead of guessing with the frequency, we keep both orders and find both of them in the next period.

Owner Linking Model The owner-linking model predicts links based on three sets of information, establishment name, industry, and post office, which provide the information that linkers use to determine a link. We create several sets of variables for each of the first, middle, and last names: JW string distance, whether the token is initialized, and whether the initial matches. These variables, by their nature, often contain missing values that are incompatible with the random forest model. In these cases, we fill in the median of the variable and flag missing with an indicator. Another set of crucial variables is the industries. We use our stratified industry classification based on the raw industry string to create matching indicators for broad and detailed industries. We also create a measure of industry distance based on the stratified industry classification and similarity in their material kinds. In addition, post offices, despite being available only in 1860, 1870, and 1880 general schedules, provide a finer location than the county boundary. We incorporate the JW string distance of post offices and an indicator for missing values in the model.

For establishments with multiple owners, the model predicts matches at the establishment-

predicted probability does not concentrate on the two ends, leaving room for setting the probability threshold and leveraging false positive and negative errors.

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. The process mimics how human makes links: a firm matches when one owner is the same, even if other owners are different.

Company Linking Model Similar to the owner-linking model, the company-linking model depends on the establishment name, industry, and post office. The company-linking model has a similar approach to the latter two sets of variables; however, instead of extracting the owner information from the establishment names, it treats the full string of established names as a whole and looks for establishments with similar names. Besides the full name JW string distance, we also measure the string distance after extracting business and location tokens and the minimum token-wise distance. The extracted name distance measures the name similarity unrelated to the business itself, which helps us negate false establishments with close full string distance due to the common token, e.g., "Eagle Mill" and "James Mill." Per token string distance similarly measures the closest distance between non-business tokens among all token pairs.

A.4.3 Model prediction reconciliation and hand-linking

After the two models make predictions separately, we reconcile their predictions by taking the maximum of the predicted probability. We then select all pairs with a linking probability above 9% as our set of potential matches that we use as a basis for hand-linking the panel.

Specifically, we worked with Digital Data Divide to hand link the Census. We traveled to Kenya to help train their team in person, who also had experience working on linking individuals in the Census of Population for Hornbeck and Keniston (2023). We sent the list of all potential matches (though not the estimated linking probabilities), sending them establishment name, industry, post office, and products produced when available. Two members of the team (separately) found the best match (if any) for each establishment, with a third member reconciling any disagreements. After they sent us back links, we manually rechecked with them unlikely matches and non-matches. Specifically, we asked (different) members of the Digital Data Divide team if they agreed with links that were made but for which the algorithm predicted link probability was below .09, and links that were not made but that the algorithm thought had a linking probability of .4. For the most part, this reconciliation tended to agree with the matches: the "unlikely" hand-linked matches looked reasonable, and on second look the potential algorithm matches were likely to be accepted.

Given the final, complete, hand-linked data, we re-estimate the model, in order to create model-predicted links. In particular, we set a threshold of .4, and consider an establishment

an entrant if it has no links in the previous period that high. To eliminate multiple links, we prune connections for each pair of years A and B by first keeping the likeliest year B link for every unique year A establishment, then applying the same strategy backward for every unique year B establishment. A small percentage of our data remains with tying matches, mostly adjacent establishments in the same industry with the same owners. In these cases, we randomly select one of the establishments to break the ties to guarantee our panel data have no multiple links. The output data after the above steps form the baseline panel links.

A.4.4 Linking to the Census of Population

Taking all active milling establishments in our sample in 1850, 1860, and 1870, we construct an owner-name dataset analogous to the owner-linking model setup, where we attempt to link each probable name ordering of every owner of a firm. We attempt to link owners to demographic and household information using the complete 1850, 1860, and 1870 Censuses of Population. We used a similar procedure to hand-link individuals as we did manufacturing firms. Specifically, for each owner-name, we took the top 20 potential matches from individuals who, in the same census year and county, had a readable name, were over 18, and had a matching first initial or first name Jaro-Winkler distance less than .3, and had a last name JW-distance less than .3. On the rare cases were there were too many potential matches, we trimmed the list to 20 names, using the most close strings as well as preferring to match individuals with milling-adjacent occupations.

The list of potential matches was sent to Digital Data Divide, again with two team members selecting any best match, and a third member reconciling all disagreements. Team members were able to compare owner name to census names, as well as the firm industry to the 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. From here, we collapse to the firm level, such that each mill is paired with the following transformations of census variables: the average age of the owners, a dummy for the presence of any immigrant owner, and a dummy for the presence of any miller. Age is stated in the census, an immigrant is any person with a reported birthplace not in the US, and miller is determined by having a self-reported occupation associated with milling. In most cases, there is only one unique linked name among any of the owners for a given firm, so these collapses and match selections were often from lists of one observation. This dataset of firms matched to their owners' census characteristics was

then used for analysis.

B Measuring Water Power Potentials and Other Local Information

This section primarily describes how we measure the waterpower potentials of rivers in the United States. We will first describe the data source used. Then, we define our baseline theoretical waterpower in Section B.2. Next, we discuss in Section B.3 our criteria for sample restrictions to exclude the rivers whose waterpowers are considered less useful. Section B.4 illustrates how we aggregate the flowline-level waterpower to the county, especially for those that cross a county boundary. Finally, Section B.5 describes the other county-level information used in the paper.

B.1 The NHDPlusV2 Data

National Hydrography Dataset Plus is a national geospatial surface water framework that geospatial analysts and modelers use to support water resources applications. It is developed and maintained by the U.S. EPA in partnership with the U.S. Geological Survey (USGS).

This project uses NHDPlus Version 2 (NHDPlusV2), which was released in 2012 as an update of the previous version (NHDPlusV1) in 2006 (McKay et al., 2012).[33] 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 the waterpower potentials at the "flowline" or "segment" level (the basic unit of the NHD linear surface-water network) and aggregate them up to the county. A flowline is a path through a waterbody in the network.

We use the two types of flowline 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) is a feature that represents a flow-path through a waterbody in the surface water network. As the surface of a river is by nature a two-dimensional object (with surface area), 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.

[33] The latest version is NHDPlus High Resolution (NHDPlus HR), which is at a higher resolution (1:24,000-scale or better) (Moore et al., 2019). We decided not to use that more detailed version mainly because it does not (yet) include monthly streamflow estimates as does the previous version, NHDPlusV2. Furthermore, the medium resolution of the NHDPlusV2 is sufficient given we geolocate mills at 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):

$$\text{TheoreticalWaterPower}_r = \underbrace{\text{FlowRate}_r}_{\substack{\text{Cubic Feet}\\ \text{Per Second}}} \times \underbrace{\text{FallHeight}_r}_{\text{Feet}} \times^{\substack{\text{Gravitational}\\ \text{Constant}}}, \tag{31}$$

where the gravitational constant roughly equals 0.1134 when the theoretical water-power is measured in horsepower.

Intuitively, the theoretical waterpower available from a body of flowing water is proportional to the force and its falling height. As the force of flowing water is induced by gravity, it is proportional to the mass or volume of the water. The greater the flow rate and the larger the falling height, the greater the theoretical waterpower.

Flow Rate The NHDPlusV2 product uses the Enhanced Unit Runoff Method (EROM), a five-step procedure, to estimate mean monthly flow rates of rivers:

1. A unit runoff based on a flow-balance model, taking into account precipitation, potential evapotranspiration, evapotranspiration, and soil moisture.
2. Adjust for excessive evapotranspiration.
3. Adjust in a log-log regression estimated using "reference gauge".
4. Adjust for flow transfers, withdrawals, and augmentations.
5. Gage-adjustment based on actual observed flow at the gauge.

It is worth highlighting the importance, for our purposes, of adjusting for flow transfers, withdrawals, and augmentations. The model predicts waterpower potential in the absence of the various interventions built by Americans since the 20th century, reflecting the average patterns observed by contemporaneous millers.

Fall Height The NHDPlusV2 product provides the maximum and minimum elevation values for each flowline. Following the hydrology literature that estimates the potential hydropower, we take the difference along a flowline to approximate the falling height (or hydraulic head) for the river segment.

B.3 Practicable Waterpower

On its own, theoretical waterpower potential does not reflect the opportunities for power, because many sources of waterpower were infeasible, for instance because they were too large.

For example, as discussed in Section I, it would be impractical to exploit the waterpower of the lower Mississippi river. As discussed in the Water Census (1880):

There is a sharp distinction to be made between ***theoretical*** *and* ***actually available*** *waterpower.*

In this Section, we discuss two reasons why potential waterpower wasn't practicable: river width and seasonality.

B.3.1 River Width

More broadly, we exclude the very large rivers that were be exceedingly costly to build a dam around. They might also tend to be used for water navigation and transportation purposes.[34] For this, we obtain information about the top width of rivers for the NHD segments from the National Water Model (NWM), which is developed by NOAA (2016).[35]

We sort rivers into bins (in percentiles) by their top width T and exclude the rivers above a certain cutoff before calculating county waterpower potentials from the remaining rivers. We then run the baseline regression of Table 2: the relationship between waterpower potential and the number of water mills in 1850. We then see how that relationship evolves for different maximum widths x. Appendix Figure A.19 plots the coefficient on negative waterpower by each upper bound X. There is a clear sharp decline in the relationship for very wide rivers, around the 95th percentile. For our measures of waterpower potential, we correspondingly exclude rivers that are wider than the 95th percentile (roughly 92 feet).

To get a sense of how large the cutoff is, we plot in Appendix Figure A.20 the distribution of top width for the Stream Rivers and Artificial Paths, respectively. The blue dashed line indicates the cutoff of 92 feet. The Artificial Paths are generally wider than the Stream Rivers, and the restriction mostly excludes the widest Artificial Paths, including most of the the lower Mississippi River network.

We also drop Niagara Falls from our analysis, because during our sample the only mill that used it for power opened during the late 1870s, because water-wheels were "inadequate" for the magnitude of the falls (Adams, 1927).

B.3.2 Seasonality

Besides the average flow rate, the seasonality of flows is also important from a perspective of water adoption because it determines the duration in which a watermill can be active throughout the year.

The NHDPlusV2 product included an indicator for whether a Stream River is "perennial"

[34]The transportation use of large rivers could crowd out waterpower for manufacturing, as millers had to provide rights of way.

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

(that have a steady water flow throughout the year) or "intermittent" (with variable water flow in different seasons). However, there is no such indicator for the Artificial Paths. We thus use the hydrological characteristics to infer the features of intermittent rivers. In particular, we show that variations in monthly flow rates are the most important feature of intermittent rivers. We then use these inferred features to classify all rivers in the United States, including the Artificial Paths.

There are a few benefits of using the given indicator for intermittent or perennial rivers instead of defining our own seasonality measure. First, the USGS/EPA might observe or use more information than we do from the NHDPlusV2 when making the indicator. Second, with their knowledge of hydrology, they are likely better at classifying rivers into intermittent or perennial. We thus treat the intermittent/perennial distinction given by USGS as a sufficient statistic for seasonality.

Having classified all rivers by their flow seasonality, we calculate the waterpower potentials coming from intermittent, perennial, or both. We find that the intermittent rivers are not as correlated with water adoption as perennial rivers, shown in Appendix Table A.15.

In our analysis, we use only the perennial rivers to generate waterpower potentials, deferring questions of seasonality and power use to future research.

B.4 Aggregating to County

Having constructed the "practicable" waterpower potentials by rivers across the US, we aggregate them up to the county level to be comparable with the Census microdata. One issue is that the definition of a flowline does not necessarily correspond to administrative borders. Therefore, for any flowline that intersects a county boundary, we split it into multiple segments, each of which is entirely within a county border. We allocate the waterpower associated with that flowline in proportion to the share of its length inside each of the counties. We then aggregate the waterpower potentials of the river segments in a county by summing them up.

For our baseline estimates, we use the average flow rate over the three lowest months of the year, as historical accounts argued this was a key determinant of the feasibility of waterpower (Census Bureau, 1883). In Appendix Table A.15, we show our results are similar if we use the average over all tweleve months.

B.5 Other County Level Controls

In addition to the NHDPlusV2, which provides us with our main variation on ruggedness and flow rates, we use a variety of other county-level information in the paper, as part of our baseline controls, for measuring heterogeneity, and for robustness analysis. In this subsection, we describe those variables.

Water Census We digitized the "detailed" tables, and calculated county waterpower potential in the same way as in the NHDPlusV2, discussed above. We also used the data in order to get information on the price of water rights, via Swain (1888).

Population Data on populations, as well as occupations, comes from the U.S. Census Haines (2010), with the microdata accessed through the NBER.

Market Access Our maps of navigable waterways comes from Fogel (1964). The GIS maps of navigable waterways, as well as GIS maps of the railway network, comes from Atack et al. (2010) and Donaldson and Hornbeck (2016). For controlling for the distance to the nearest navigable waterway, we calculate the log of the average distance to nearest navigable river for each county in GIS. We additionally digitized, from the original maps, the detailed locations of railroad stations.

Market access is approximated as:

$$MA_c = \sum_{d \neq c} (\tau_{cd})^{-\theta} L_d. \tag{32}$$

The market access of any county is the distance-weighted sum of the population to other counties, where the iceberg trade costs τ are raised to the power of the trade elasticity, and we use $\theta = 3.05$ following Hornbeck and Rotemberg (2023). We control for the log of market access, as is standard.

Coal We digitized maps of coal deposit locations from Campbell (1908), a survey run by the United States Geological Survey.

Soil Quality We use data on crop suitability from the Global Agro-Ecological Zones project of the Food and Agriculture Organization, using the measures appropriate for 19th century farming shared by Rusanov (2021).

Portage Following Bleakley and Lin (2012), we digitized information on the location of actual and potential portage sites from Semple (1903) and Fenneman (1946). We also included the historic location of portage sites along the Ohio, the Missouri, and the Mississippi rivers collected by Bleakley and Lin (2012).

C Qualitative Evidence from Historical Society Records

For a random subset of mills, we searched in historical society records (and other documents, when possible) to help us understand the qualitative history of switching, to motive the assumptions of our model why water incumbents faced higher costs of steam power than entrants.[36] We were unable to find records for many mills, and for many of the remainder

[36]We also include examples that we found while reading secondary sources. We are particularly grateful to David Kirchenbauer and Tony Li for outstanding assistance finding historical sources.

the qualitative information was limited, though it was useful to verify that most millers never changed locations (and we were also able to verify the information in the Census on when a mill switched to steampower). Here we provide a few examples of millers (in alphabetical order), for whom we were able to find more information, to provide color on the push and pull factors behind switching to steam power:[37]

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.

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 steam mill was not finished 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 in 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 side bank of a stream in Kenduskeag, Maine , and Moses Hodson owned a waterwpower mill west bank of that same stream (Hubbard, 1861). After a lawsuit, it was determined that while Garland had the senior water rights for using two stones of grist mill, 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, already a prominent miller exploiting the high waterpower availability in Baltimore, built a steam powered mill there in 1813, but did not operate it for very long, as it became clear that in Baltimore it was "too costly to operate for milling flour" relative to water, at least 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 owner (Frederick Graue) had to construct a dam in order to create a three foot fall. In order to expand, Graue spent three years retrofitting his mill for steam use (including with the help of a visiting millwright).

[37]We provide one additional example in Appendix Figure A.8.

The Hardesty Brothers inherited a profitable grist mill in Canal Dover, Ohio from their father after his death 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, 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, it is a location with excellent access to waterpower. Knight converted the mill to run on steam power, 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.

S. B. Lewis & Eichelberger operated the Miami mills in Dearbon, Indiana until 1852, when the canal was damaged by floods (Shaw, 1915). It was believed that the canal would never be repaired, and so they retrofitted their mill to use steam power. Eventually the canal was indeed repaired, and they used both water and steam power.

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 switch from water to steam of the mill occurred because of the total destruction by the fire. 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 that used only waterpower in 1870 and used only steam power in 1880, in Columbus, Wisconsin (Jones, 1914). He purchased and came into possession of his mill in 1849, which was already the busiest mill in Central Wisconsin. The wait for grist work was often weeks. Manning switched to steam power in order 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 exclusively used steam power.

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 in 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 of Tookany Creek, in Montgomery County, Pennsylvania Rothschild (1976). The family operated the mill for a 100 years, when 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). We do not know the exact timing, but the mill used waterpower in 1850 and steam power in 1860, without changing location. During that time period, dams were abolished within city limits.

D Alternative Specifications

In this section, we describe in more detail the robustness specifications mentioned in Section II.D. Across the tables, the first row corresponds to our main estimates, to facilitate comparison.

Appendix Table A.9 focuses on the role of factors that might have directly influenced steam adoption. Because these controls tend to be more county-specific, this table shows for the main aggregated outcomes of the paper: steam share and water mills in 1850, as well as the growth of total mills and growth in steam use from 1850 to 1860, 1860 to 1870, and 1870 to 1880. Row 2 controls separately for deposits of the four main types of coal (Campbell, 1908): lignite, subbituminous, bituminous, and anthracite (listed in increasing amounts of carbon content). Row 3 controls for a cubic polynomial in the share of the county covered by coal, instead of the baseline linear specification. Row 4 controls for the cost of getting coal to the county, given the location of coal deposits at the 1850 transportation network. Row 5 controls for 1850 wages, measured for the mills in our sample. Row 6 controls for banks in 1850, shared by Jaremski (2014). Row 7 controls for the the number of engineers, the number of mechanics, and their (combined) employment share in the 1850 Census of Population in the county. Rows 7 and 8 consider suitability for the primary inputs, with row 7 controlling for agronomic suitability for wheat from the FAO (shared by Rusanov 2021) and Row 8 controls for the share of the county covered by woodland (from Hornbeck 2010).

Appendix Table A.10 focuses on the role of factors that might broadly affected local county growth. Like Appendix Table A.9, this table shows for the main aggregated outcomes of the paper: steam share and water mills in 1850, as well as the growth of total mills and

growth in steam use from 1850 to 1860, 1860 to 1870, and 1870 to 1880. Rows 2–4 show our results are not driven by our choice of baseline controls, with row 2 removing controls for access to markets (market access, navigable waterways, and distance to waterways), row 3 removing controls for local access to coal, and row 4 removing both. While our baseline sample requires at least one mill in 1850, this leads to the inclusion of very small counties with little industrial activity. Limiting the sample to more active counties (in row 5, at least 3 1850 mills, in row 6 at least 5) does not substantively change the results. Our results are not driven by the waterpower extremes, as shown in row 7 (dropping the 5% of counties with the most waterpower potential) and row 8 (the 5% smallest potentials). Row 9 includes the unbalanced panel of counties, including the counties that ever have a mill. Rows 10–15 control for measures of American expansion and development. Row 10 controls for state fixed effects (which does lower the results somewhat, though they mostly remain significant). Givem the general westward expansion, row 11 controls for a dummy for the 13 original colonies, row 12 controls for being in Appalachia, and row 13 controls for a polynomial in longitude. Row 14 controls for civil war battles and casualties and row 15 controls for time varying market access, both from Hornbeck and Rotemberg (2023). Row 16 drops the 20 largest cities in the country from the analysis, since many cities imported flour from neighboring areas. Similarly, row 17 instead drops counties described as having merchant mills producing flour for export in Kuhlmann (1929). Row 18 controls for portage sites from Bleakley and Lin (2012). Conceptually, there are two differences between waterpower potential and portage. First, portage sites are only located on navigable rivers, while some waterpower comes from rivers that are not navigable. Second, portage is basically an indicator for ruggedness. For instance, the Falls of Ohio by Louisville, Kentucky are 26 feet, whereas St. Anthony Falls in Minnapolis, Minnesota is twice as high. Both were portage sites, but the latter was more useful for mechanized power. It is also worth noting that Bleakley and Lin (2012) argue that "portage was already shrinking in importance for local economies as early as 1850" (though its persistent effects remained). Row 19 controls for being on the frontier (Bazzi, Fiszbein and Gebresilasse, 2020). Row 20 controls for 1850 popultion, while row 21 controls for 1850 output. Finally, Row 22 controls for agricultural share, since Eckert and Peters (2023) argue that there was general structural convergence during the period.

E Comparative Statics

This section describes in more detail the comparative statics of Section IV.E. We focus our analysis on the policy functions that govern our predictions for how the costs of waterpower mediate the impacts of steam. We then support these analytical insights with numerical simulations that take into account the equilibrium links between firms' decisions about entry,

exit, and power adoption.[38]

Prediction 1 (Higher water costs cause faster steam adoption, especially among entrants)**.** *Let $\mathbb{P}^E_{ct}(S)$ and $\mathbb{P}^I_{ct}(S)$ denote the shares of entrant and incumbent mills that use steam. Higher costs of water induce faster steam adoption, especially among entrants:*

$$\frac{d}{dc^W_c}\mathbb{P}^E_{ct}(S) > \frac{d}{dc^W_c}\mathbb{P}^I_{ct}(S) > 0 \tag{33}$$

Argument. Figure A.1 illustrates how higher costs of water power cause faster steam adoption and that the faster adoption is especially true for entrants when incumbents face power-switching costs.

The adoption of steam among incumbents satisfies:

$$\mathbb{P}^I_{ct}(S) = \int\int \mathbf{1}\begin{bmatrix} -c_{ct}(R,S) + \pi_{ct}(S,\varphi) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(S,\varphi')] + \varepsilon(S) \\ \geq -c_{ct}(R,W) + \pi_{ct}(W,\varphi) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(W,\varphi')] + \varepsilon(W) \end{bmatrix} dF_\epsilon(\varepsilon)dF^I_{ct}(R,\varphi) \tag{34}$$

where F_ϵ is the CDF of idiosyncratic power adoption costs and $F^I_{ct}(R,\varphi)$ is the cumulative distribution of survival firms over power sources and productivities.

Equation (34) shows that the regional environment (c-subscripts) affects steam power adoption among incumbents by changing the cost of water $c_c(W)$, the profit gain from steam $\pi_{ct}(S,\varphi) - \pi_{ct}(W,\varphi)$, the continuation value gain of steam $V_{ct+1}(S,\varphi') - V_{ct+1}(W,\varphi')$, and the selection of operating firms $F^I_{ct}(R,\varphi)$.

Higher costs of water power affect steam adoption among incumbents through five channels, all of which lead to more steam use:

1. *Technology costs:* Higher water costs $c_c(W)$ make steam power a more appealing choice of technology. Mathematically, $c_c(W)$ enters the LHS of the inequality in Equation (34), thus increasing steam adoption rates, ceteris paribus.

2. *Selection:* The argument proceeds in two steps. First, because higher water costs lower the operating value $V^o_{ct}(R,\varphi)$ in Equation (11), mills have to be of higher productivity φ to overcome the fixed operating costs f^R in Equation (10). Second, because of the profit complementarity between productivity and steam power (that is, $\frac{\partial\pi_{ct}(S,\varphi)}{\partial\varphi} \geq \frac{\partial\pi_{ct}(W,\varphi)}{\partial\varphi}$ when $\pi_{ct}(S,\varphi) \geq \pi_{ct}(W,\varphi)$ in Equation (7)), productive firms will adopt more steam.

[38]The equilibrium of our economy is a complicated fixed point. The economy features heterogeneous firms that make forward-looking decisions about entry, exit, and power adoption, and the decisions are interlinked through the competition of firms in local product markets.

Taken together, this selection on productivity implies that mills in regions with higher water costs will use more steam power.

3. *Competition*: High water costs increase the local price index P_{ct} when firms are free to enter markets.[39] The lower local competition will increase the profit gains of steam power adoption when (i) the elasticity of substitution between varieties ϵ is higher than the elasticity of substitution between sectors η, and (ii) steam power generates higher profits than water power. That is, $\frac{\partial \pi_{ct}(S,\varphi)}{\partial P_{ct}} \geq \frac{\partial \pi_{ct}(W,\varphi)}{\partial P_{ct}}$ when $\epsilon \geq \eta$ and $\pi_{ct}(S,\varphi) \geq \pi_{ct}(W,\varphi)$ in Equation (7).

4. *Agglomeration*: A higher local steam share s_{ct} increases the profit gains from steam power when steam features positive production externalities $\alpha_S \geq 0$. This agglomeration channel reinforces the other effects of water costs on steam power adoption.

5. *Continuation values*: The continuation value gain from steam may be decomposed into the present-discounted profits gains from steam and changed option values:

$$\underbrace{\mathbb{E}_{\varphi'}[V_{ct+1}(S,\varphi') - V_{ct+1}(W,\varphi')]}_{\text{Continuation value gain}} = \underbrace{\sum_{\tau=1} \delta^{\tau-1} \mathbb{E}[\pi_{ct+\tau}(S,\varphi_{t+\tau}) - \pi_{ct+\tau}(W,\varphi_{t+\tau})|\varphi_t]}_{\text{Present-discounted profit gain}} + \underbrace{\mathbb{E}_{\varphi'}[O_{ct+1}(S,\varphi') - O_{ct+1}(W,\varphi')]}_{\text{Option value gain}}$$

The *present-discounted profit gain* from steam is larger in places with higher water costs, reflecting the *competition* and *agglomeration* effects described above.

The *option value gain* reflects the changed values of exit (Equation (10)) and power switching (Equation (11)). These option values attenuate the *technology cost* and *profit gain* effects mentioned above: If firms can either switch to steam later or recoup a share ω of their water costs when exiting or switching, higher water costs increase the option value of water power. However, because firms discount the future ($\delta < 1$) and exiting/switching firms may only recover parts of their water investment ($\omega < 1$), the changed option values will only partially remedy the effects on *technology costs* and *profit gains* described above.

Next, compare entrants and water incumbents. Following Equation (11), entrants are more prone to adopting steam when power switching is costly $c(W,S) > 0$. Whether entrants

[39] By contradiction, consider two regions with different water costs $c_{c'}^W > c_c^W$ but same price indices $P_{c'} = P_c$. Because water costs lower the value of entry in Equation (8), entry would either need to decrease in region c' or increase in region l. Since the entry of mills lowers the price index, region c' will have a higher price index $P_{c'} > P_c$.

are also more responsive to the cost of waterpower depends on whether more entrants than incumbents are on the margin of steam adoption. This, in turn, depends on whether the distribution of idiosyncratic adoption cost differences $\epsilon(W) - \epsilon(S)$ has more density around the indifference thresholds of entrants or incumbents:

$$-(c_{ct}(E,S) - c_{ct}(E,W)) + (\pi_{ct}(S,\varphi) - \pi_{ct}(W,\varphi)) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(S,\varphi') - V_{ct+1}(W,\varphi')] \tag{35}$$

or

$$-(c_{ct}(W,S) - c_{ct}(W,W)) + (\pi_{ct}(S,\varphi) - \pi_{ct}(W,\varphi)) + \delta\mathbb{E}_{\varphi'}[V_{ct+1}(S,\varphi') - V_{ct+1}(W,\varphi')] \tag{36}$$

For example, if the CDF of idiosyncratic cost differences $\epsilon(W) - \epsilon(S) \sim G$ is S-shaped, entrants are more responsive to the cost of waterpower when their steam adoption rates are below the inflection point of G. Furthermore, because $\epsilon(W)$ and $\epsilon(S)$ are drawn i.i.d. from the same distribution F_ϵ, the inflection point of G occurs at 0.5. Consistent with this condition, Figure 6 shows that steam adoption rates of entrants was below 50% in our data period. □

Prediction 2 (Higher water costs cause faster economic growth, especially through entry)**.** *Let N_{ct} denote the total number of mills and N^E_{ct} the number of entrants. Higher costs of water induce faster growth of mills, especially among entrants:*

$$\frac{d}{dc^W_c}\Delta\log N^E_{ct} > \frac{d}{dc^W_c}\Delta\log N_{ct} > 0 \tag{37}$$

Argument. Figure A.2 illustrates how higher water costs cause faster economic growth. The effect is especially true for entrants when incumbents face high power-switching costs. The arrival of steam affects the number of establishments by increasing operating values in Equation (11), which induces entry (Equation (8)) and survival (Equation (10)). Applying the envelope theorem, the effect of steam costs on operating values is

$$\frac{\partial V^o_{ct}(R,\varphi)}{\partial c_t(S)} = \underbrace{\frac{\partial \pi_{ct}(R,\varphi)}{\partial c_t(S)}}_{\text{Profits}} - \underbrace{\Pr_{ct}(S|R,\varphi)}_{\text{Technology costs}} + \underbrace{\delta\sum_{R'}\Pr_{ct}(R'|R,\varphi)\mathbb{E}_{\varphi'}\left[\frac{\partial V_{ct+1}(R',\varphi')}{\partial c_t(S)}\right]}_{\text{Continuation values}} \tag{38}$$

with

$$\underbrace{\frac{\partial \pi_{ct}(R,\varphi)}{\partial c_t(S)}}_{\text{Profits}} = [\underbrace{(\epsilon-\eta)\frac{\partial \log P_{ct}}{\partial c_t(S)}}_{\text{Competition}} + \underbrace{(\epsilon-1)\alpha_R\frac{\partial s_{ct}}{\partial c_t(S)}}_{\text{Agglomeration}}]\pi_{ct}(R,\varphi) \tag{39}$$

Equations (38)-(39) show that cheaper steam costs affect operating values through the *technology cost*, *agglomeration*, *competition*, and *continuation value* channels described in the proof of Prediction 1. While the negative *competition* effect is shared among all establishments, the positive *technology cost* and *agglomeration* effects depend on steam adoption. Consequently, improvements in steam power will tend to increase operating values more when steam adoption rates are high.[40] We combine this insight with Prediction 1 to infer how steam power affects operating values in places with low versus high costs of waterpower.

Consider first entrants. Prediction 1 shows that entrants adopt more steam in places with higher water costs. Following the argument above, the value of entry tends to increase more in places with higher water costs.

Next, compare entrants to incumbents. Prediction 1 shows that the steam adoption of entrants is more responsive to the cost of water power. Following the argument above, operating values increase more for entrants (relative to incumbents) in places with higher water costs.

Finally, consider total establishments. Prediction 1 shows that steam adoption rates are higher in places with higher water costs. Following the argument above, operating values increase more in places with higher water costs. The higher operating values boost total mill activity as long as local demand for milling has some elasticity ($\eta > 0$). □

Prediction 3 (Switching costs determine whether incumbents are crowded-out in counties with higher water costs)**.** *Let $\mathbb{S}_{ct}$ denote the survival rate of mills. It is unclear if higher costs of water hurt or help the survival of incumbent mills when steam arrives:*

$$\frac{d}{dc_c^W}\mathbb{S}_{ct} \gtrless 0. \tag{40}$$

Incumbents are crowded out if switching costs are prohibitively high.

Argument. Figure A.3 illustrates how the impact of water costs on incumbent survival is theoretically ambiguous and depends crucially on the power switching costs. Prediction 2 shows that steam affects the survival of mills through a *technology cost*, an *agglomeration*, and a *competition* effect. While the negative *competition* effect is shared among all mills, the positive *technology cost* and *agglomeration* effects depend on steam adoption. Furthermore,

[40]The impact of steam arrival on *continuation values* generally depends on the entire path of falling steam costs. Equation ((38)) considers a one-off drop in steam costs. In this case, continuation values are only affected by how the adoption of steam power in year t affects future profits. In particular, more steam adoption in year t increases *competition* and *steam agglomeration* in subsequent periods. Again, while the negative competition effect is shared among all establishments, the positive agglomeration is only enjoyed by firms using steam power. Hence, the *continuation value* effect is also more positive when steam adoption rates are higher.

the strength of the *competition* effect depends on the amount of entry induced by steam power.

For example, if switching costs are prohibitively high, incumbents are only exposed to the negative *competition* effect of steam power. In this case, steam power will hurt the survival of incumbent mills. By contrast, if switching costs are low and steam induces minimal entry (i.e., few firms are on the margin of entry, e.g., because entry costs are high), the positive *technology cost* and *agglomeration* effects will tend to dominate so that steam boosts the survival of incumbent mills.

Taken together, these arguments show that the impact of steam on the survival of incumbent mills is theoretically ambiguous and depends crucially on the power switching cost. □

F Solution Algorithms

F.1 Dynamic Programming

The expected operating values $\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)]$ is 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 (8)-(11) are only determined by contemporaneous features of the economy.

The expected operating values satisfy the Bellman equation:

$$\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)] = \mathbb{E}_\varepsilon \max_{R'} \left\{ \begin{array}{l} \pi_{ct}(R,\varphi) - c_{ct}(R,R') - \varepsilon_{jct}(R) \\ + \delta \mathbb{E}_{(\varphi'|\varphi)} \mathbb{E}_\nu \max \left\{ \mathbb{E}_\varepsilon \left[V^o_{ct+1}(R',\varphi') \right] - f^{R'} - \nu^{R'}_{jct}(0), \Omega^{R'}_{ct} - \nu^{R'}_{jct}(1) \right\} \end{array} \right\} \tag{41}$$

Equation (41) involves two maximization steps over distributions of idiosyncratic cost shocks (for adoption ϵ and operation/exit ν, respectively). The parametric assumptions in Section IV.F greatly simplify these steps. In particular, when the cost shocks follow Gumbel distributions, Equation (41) simplifies to:

$$\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)] = \rho \log \left[\sum_{R'} \exp \left\{ \frac{1}{\rho} \left(\pi_{ct}(R,\varphi) - c_{ct}(R,R') + \delta \mathbb{E}_{(\varphi'|\varphi)} \rho_o \log \left[\exp \left(\frac{\mathbb{E}_\varepsilon \left[V^o_{ct+1}(R',\varphi') \right] - f^{R'}}{\rho_o} \right) + \exp \left(\frac{\Omega^{R'}_{ct}}{\rho_o} \right) \right] \right) \right\} \right], \tag{42}$$

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

F.1.1 Steady State

Equation (42) 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 may solve for the unique fixed point $\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)]$ by iterating on Equation (42) 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 (42) 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 $F^{(0)}_{ct}(R,\varphi)$ and entrants $M^{(0)}_{ct}$. For each iteration $(i) = 0, 1, 2, ..., :$

2. Solve for the expected operating values $\mathbb{E}_\varepsilon[V^{o(i)}_{ct}(R,\varphi)]$ by iterating on the contraction mapping in Equation (42).

3. Simulate the mass of operating firms:

   - Given $F^{(i)}_{ct}$ and $M^{(i)}_{ct}$, use the policy functions for exit and power adoption (Equations (10)-(11)) to simulate the firm mass $F^{(NEW)}_{ct}(R,\varphi)$.

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 (10) 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:

$$\mathcal{E}^{(i)} = \frac{d\log \mathbb{E}_\varphi\left[V_{ct}^{(i)}(E,\varphi)\right]}{d\log M_{ct}^{(i)}}. \tag{43}$$

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

$$M_{ct}^{(NEW)} = \exp\left(\log M_{ct}^{(i)} + h\left(\frac{1}{\mathcal{E}^{(i)}}\right)\left(\log f^e - \log EV_{ct}^{(i)}\right)\right), \tag{44}$$

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

$$M_{ct}^{(i+1)} = \lambda M_{ct}^{(NEW)} + (1-\lambda)M_{ct}^{(i)} \tag{45}$$

$$F_{ct}^{(i+1)}(R,\varphi) = \lambda F_{ct}^{(NEW)}(R,\varphi) + (1-\lambda)F_{ct}^{(i)}(R,\varphi), \tag{46}$$

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, from the comparative statics in Section IV.E, 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:

$$M_{ct}(\xi) = \exp\left(\log M_{cT_0} + \left(\frac{t-T_0}{T_1-T_0}\right)^{\xi}(\log M_{cT_1} - \log M_{cT_0})\right) \quad t \in [T_0, T_1], \tag{47}$$

   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:

$$Y_{ct}^{(0)} = Y_{cT_0} + \frac{t-T_0}{T_1-T_0}(Y_{cT_1} - Y_{cT_0}) \quad \text{for} \quad Y_{ct} \in \{P_{ct}, F_{ct}(R,\varphi)\}, \tag{48}$$

   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 (42) 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 (10)-(11)) to simulate the firm mass $\{F_{ct}^{(NEW)}(R,\varphi)\}_t$.

5. Calculate the new price index:

$$P_{ct}^{(NEW)} = \left[\int p_{ct}^{(i)}(R,\varphi)^{1-\epsilon} dF_{ct}^{(NEW)}(R,\varphi)\right]^{\frac{1}{1-\epsilon}}. \tag{49}$$

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

$$F_{ct}^{(i+1)}(R,\varphi) = \lambda F_{ct}^{(NEW)}(R,\varphi) + (1-\lambda)F_{ct}^{(i)}(R,\varphi) \tag{50}$$

$$P_{ct}^{(i+1)} = \lambda P_{ct}^{(NEW)} + (1-\lambda)P_{ct}^{(i)}, \tag{51}$$

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 (8)) along the transition path:

$$\Delta(\xi) = \min_{\xi' \in \{\xi^{(1)},..,\xi^{(J)}\}} \sum_{t=T_0}^{T_1} \left| \mathbb{E}_\varphi \left[V_{ct}(E,\varphi) | \xi = \xi' \right] - f^e \right|. \tag{52}$$

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 (13) 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 (7)) 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 described, 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

The structural parameters are jointly estimated as follows:

1. For the baseline region (representing the average county), we begin with an educated guess of each parameter's value. We use these initial parameter values to simulate the initial and terminal equilibria as well as the transition path (using the solution algorithms described in Section F.2).

2. Holding region-level elasticity of demand η and steam agglomeration parameter α constant, we calibrate the other parameters to match the within-county moments of the baseline county using a simulated annealing algorithm from their initial values.[41] Sec-

[41] We provide a brief description of the simulated annealing algorithm below.

tion V.A.1 provides a discussion of the selection of within-county moments.

3. Conditional on all other calibrated parameter values, we search for values of η and α to match the simulated moments and the empirical targets, including the across-county moments listed in Section V.A.2. This search requires the simulation of the "lower waterpower" county as well.

4. We repeat Steps 2-3 until the simulated moments match the empirical targets (within and across counties).

For step 2, the simulated annealing algorithm for the parameters other than η and α could be summarized as follows:

1. Denote the vector of parameter values (excluding η and α that are assumed to be constant) at the i'-th iteration by $X^{(i')}$, where $X^{(0)}$ is the vector of initial parameter values.

2. For $i' = 0, 1, 2, \cdots$, select K random vectors from a small neighborhood of $X^{(i')}$, where $K = 12$ by default. Simulate the economy with each of these random vectors of parameter values. Keep the one whose simulated moments are the closest to the empirical targets. Denote this optimal vector by $X^{(NEW)}$.

3. Denote the discrepancy between the simulated moments and the empirical targets by $L(X^{(NEW)})$ for $X^{(NEW)}$ or by $L(X^{(i')})$ for $X^{(i')}$. If $L(X^{(NEW)}) < L(X^{(i')})$, then $X^{(i'+1)} = X^{(NEW)}$. If $L(X^{(NEW)}) \geq L(X^{(i')})$, $X^{(i'+1)} = X^{(NEW)}$ with a probability of $\exp(2(i'+1)(L(X^{(i')}) - L(X^{(NEW)})))$ or $X^{(i'+1)} = X^{(i')}$ with a probability of $1 - \exp(2(i'+1)(L(X^{(i')}) - L(X^{(NEW)})))$.

4. Repeat steps 2-3 for 1000 iterations. Return the vector of parameter values $X^{(i_0)}$, where $i_0 = \text{argmin}_{i'=0}^{1000} L(X^{(i')})$.

G.2 Robustness to Panel Linking Error

Our conclusions about switching costs and the incidence of steam power on entrants vs. incumbents hinge on the validity of our panel links. In this section, we use our estimated structural model to simulate the consequences of measurement error in the panel links. In particular, we take our model-simulated data and scramble the transitions of establishments. We simulate both false negatives (i.e., misclassifying incumbents as entrants) and false positives (i.e., misclassifying entrants as incumbents) and examine how these panel linking errors affect our key estimates for how steam power impacts entrants and incumbents.

In Tables A.17 and A.18, we reproduce our estimate for how access to waterpower mediates the impact of steam on entrants and incumbents. The "Data" column reproduces our empirical estimates of the impact of lower waterpower on entrants and incumbents from Tables 4 and 5. The "Model" column reports the corresponding moments, simulated from our estimated structural model. The "FN Error Rates" columns calculate the same moments with increasing rates of false-negative, and the "FP Error Rates" columns calculate the moments with increasing rates of false-positive panel links.

The overarching conclusion from Tables A.17 and A.18 is that our key estimates for how steam power impacts entrants and incumbents are remarkably robust to measurement error in our panel links. The robustness partly reflects that the error rates are not correlated with the cost of waterpower (our instrument).

H Counterfactual Experiments

H.1 Multiple Equilibria

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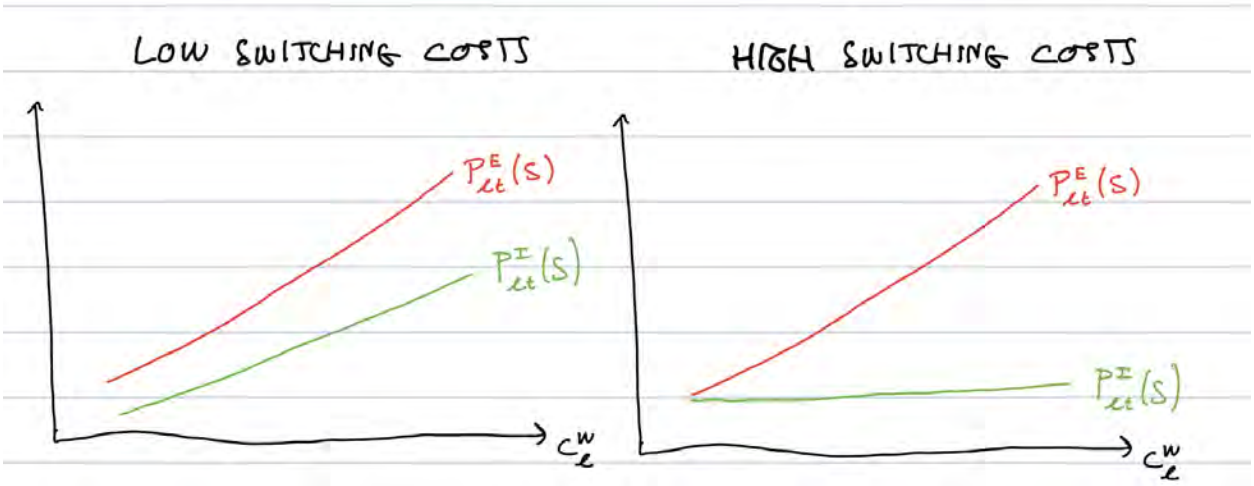
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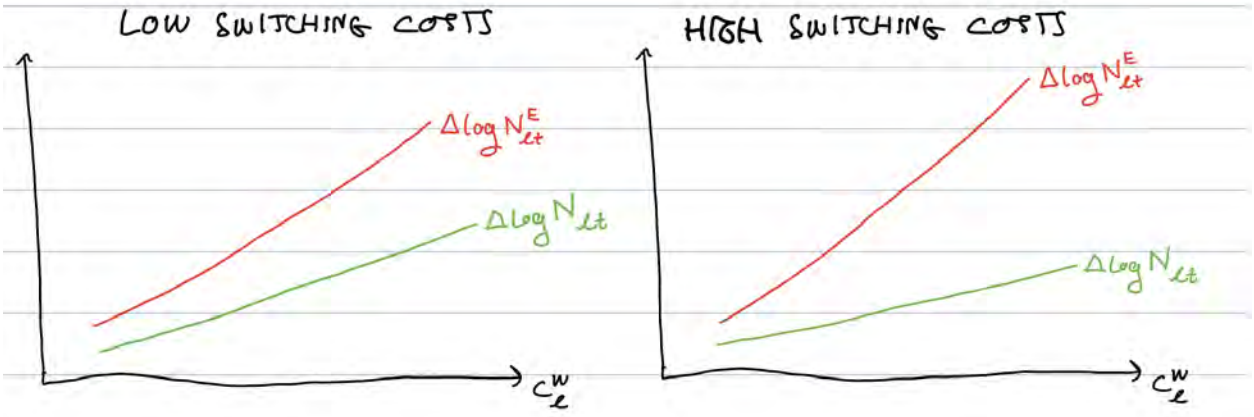
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Figure A.1: Water Costs and Steam Adoption



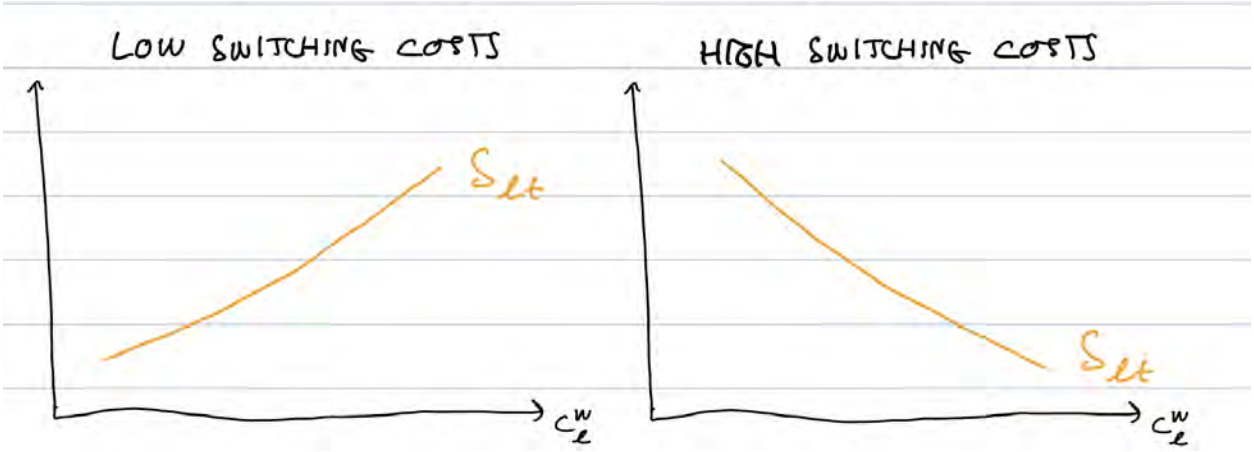
Notes: This figure shows the steam use rates among entrants and incumbent mills for varying levels of water buying costs c_l^W. "Low switching costs" correspond to a power-switching cost that is 1/10 of the baseline value estimated in Section V. "High switching costs" correspond to a power-switching cost that is 10 times the baseline value. The remaining parameter values are kept at their baseline levels.

Figure A.2: Water Costs and Economic Growth



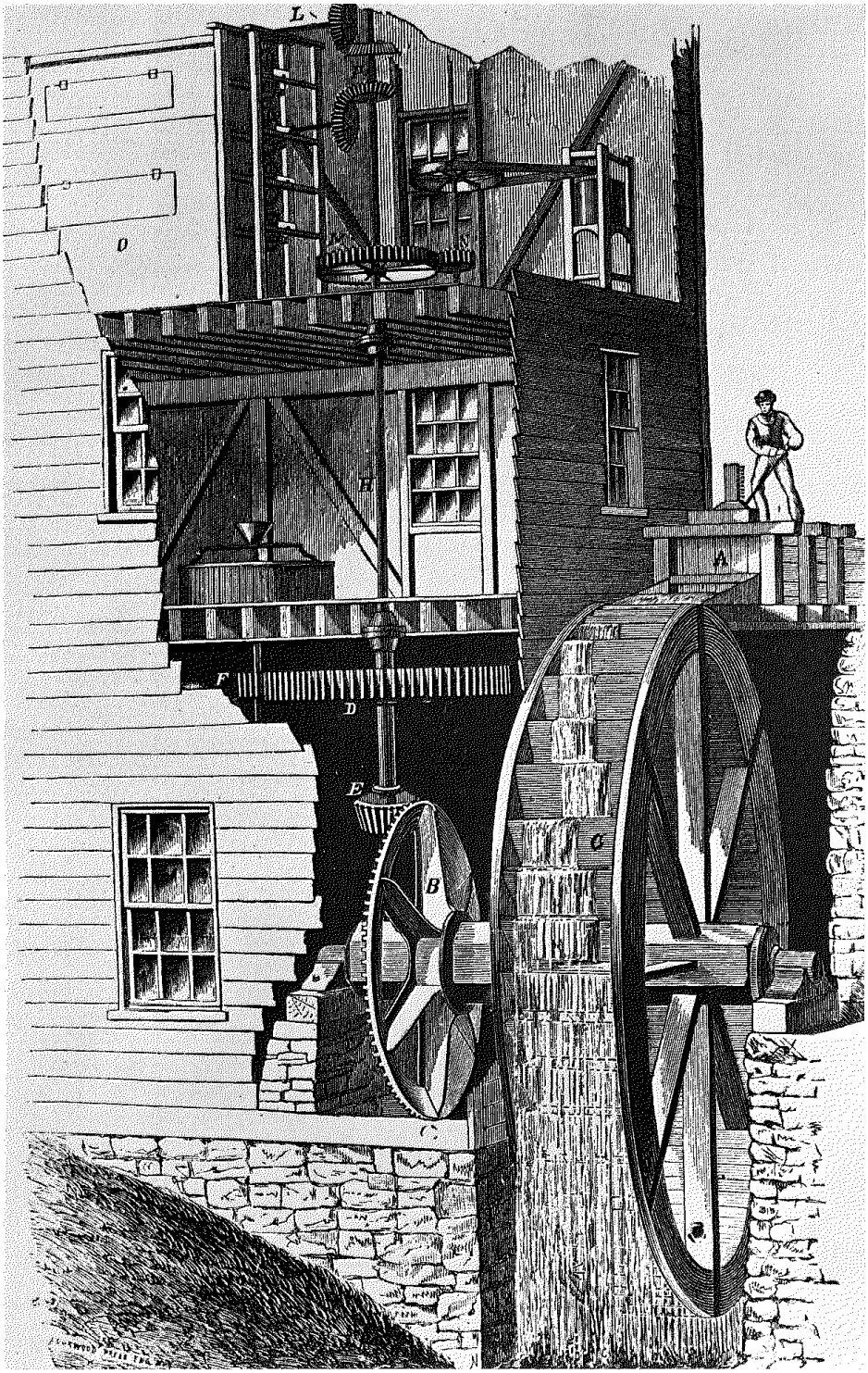
Notes: This figure shows the growth among entrants and incumbent mills for varying levels of water buying costs c_l^W. "Low switching costs" correspond to a power-switching cost that is 1/10 of the baseline value estimated in Section V. "High switching costs" correspond to a power-switching cost that is 10 times the baseline value. The remaining parameter values are kept at their baseline levels.

Figure A.3: Water Costs and the Survival of Mills



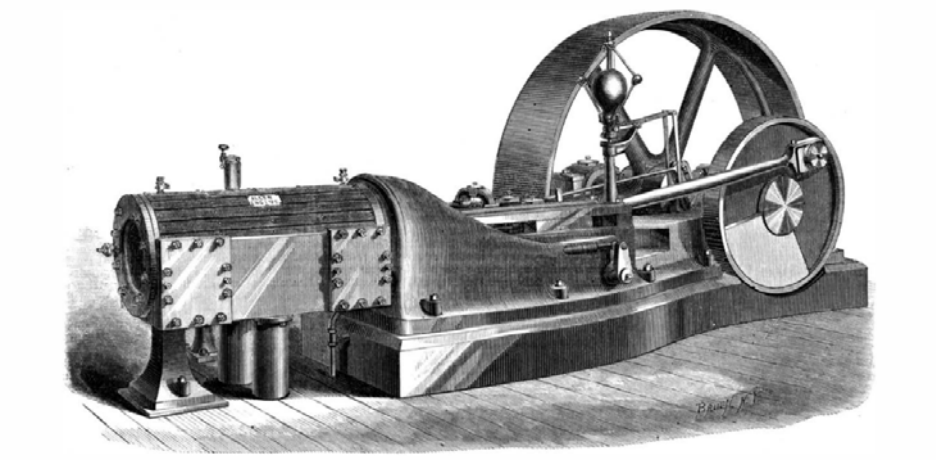
Notes: This figure shows the survival rate among incumbent mills for varying levels of water buying costs c_l^W. "Low switching costs" correspond to a power-switching cost that is 1/10 of the baseline value estimated in Section V. "High switching costs" correspond to a power-switching cost that is 10 times the baseline value. The remaining parameter values are kept at their baseline levels.

Figure A.4: Gristmill Diagram



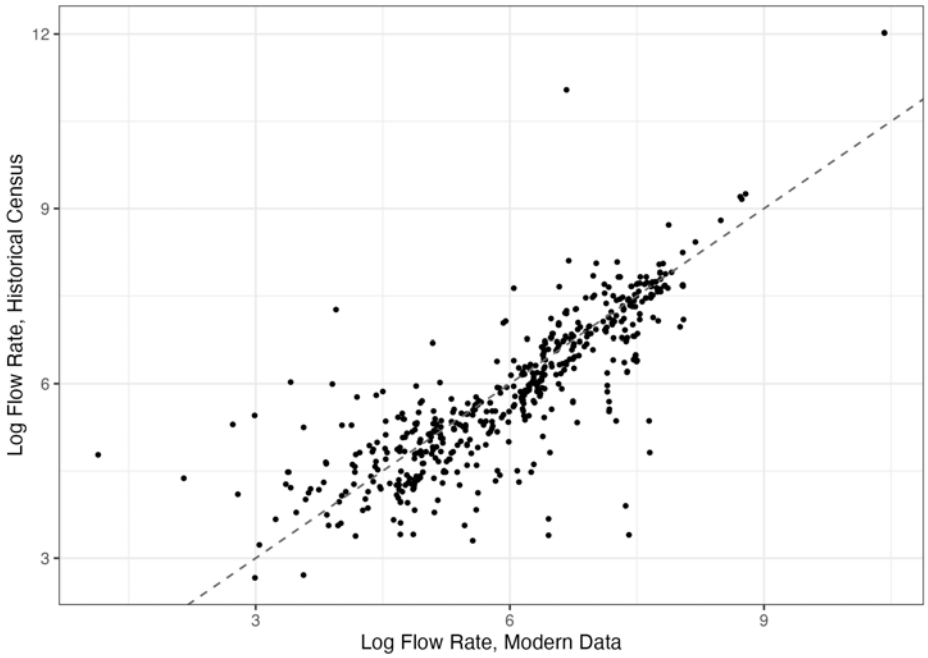
Notes: A diagram of gristmill. (A) is the sluice gate, (B) is the crown wheel attached to a shafty waterwheel (C), which transmits the power to (E), a small bevel wheel on the upright shaft. A spur wheel (D) is placed on the up right shaft, which works into the pinion (F) on the spindle, which drives the stone. Image and description from Zimiles and Zimiles (1973), page 13.

Figure A.5: The Porter-Allen Engine



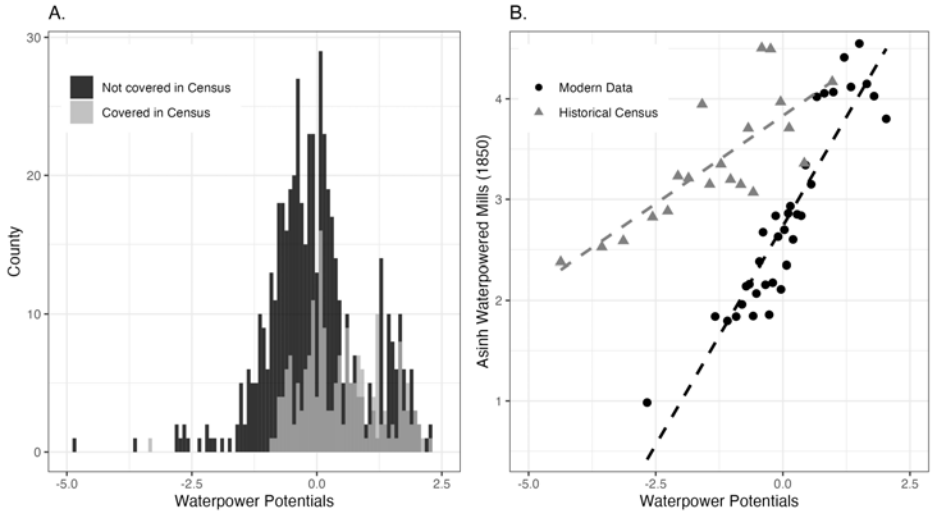
Notes: A diagram of the Porter-Allen Engine, from *Scientific American* (1870).

Figure A.6: Segment Flow Rates in Water Census compared to NHD Data



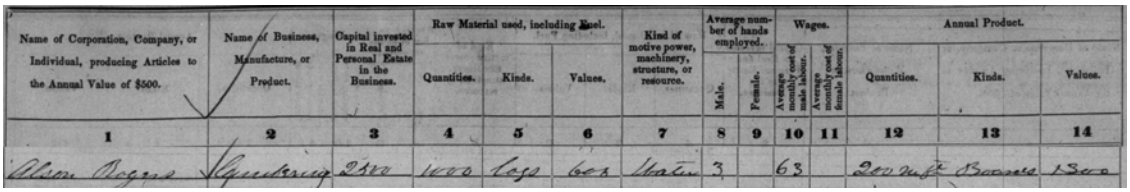
Notes: This figure plots waterpower potential for the river segments that we were able to identify both in the National Hydrography Dataset Plus (NHDPlus) as well as in the Water Census. Each point represents one segment. Data from NHDPlusV2 and Census Bureau (1883).

Figure A.7: The Water Census compared to NHDPlusV2



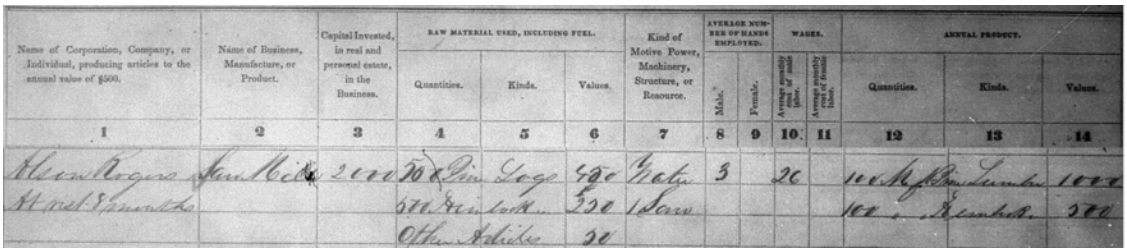
Notes: Panel A plots the distribution of country waterpower potential for counties covered in the Water Census (light gray) and counties not covered (dark gray). Panel B plots the raw relationship between the number of waterpowered mills in 1850 and waterpower potential in the NHDPlus data and the Water Census data. Panel C plots the raw relationship between the growth in the number mills between 1850 and 1880 and waterpower potential in the NHDPlus data and the Water Census data. Data from NHDPlusV2, Census Bureau (1883), and the 1850-1880 Census of Manufacturers. All counties with available data are included in Panels B and C.

Figure A.8: Example Census Images: The Rogers' Lumber Mill
(a) 1850



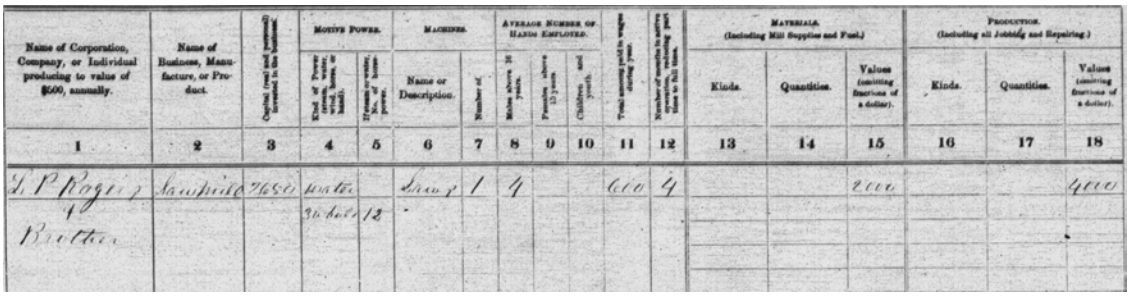
Name of Corporation, Company, or Individual, producing Articles to the Annual Value of $500.	Name of Business, Manufacture, or Product.	Capital invested in Real and Personal Estate in the Business.	Raw Material used, including Fuel.			Kind of motive power, machinery, structure, or resource.	Average number of hands employed.		Wages.		Annual Product.		
			Quantities.	Kinds.	Values.		Male.	Female.	Average monthly cost of male labour.	Average monthly cost of female labour.	Quantities.	Kinds.	Values.
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Alson Rogers	Squibrig	2500	1000	Logs	600	Water	3		63		200 M ft	Boards	1300

(b) 1860



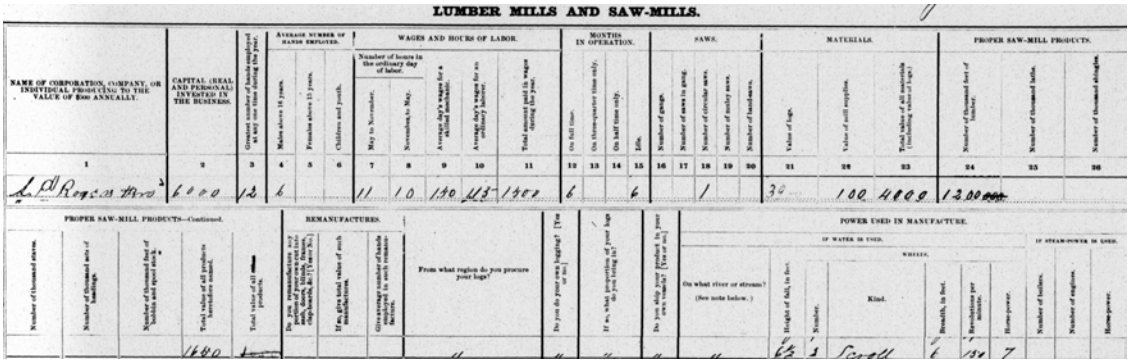
Name of Corporation, Company, or Individual, producing articles to the annual value of $500.	Name of Business, Manufacture, or Product.	Capital Invested, in real and personal estate, in the Business.	RAW MATERIAL USED, INCLUDING FUEL.			Kind of Motive Power, Machinery, Structure, or Resource.	AVERAGE NUMBER OF HANDS EMPLOYED.		WAGES.		ANNUAL PRODUCT.		
			Quantities.	Kinds.	Values.		Male.	Female.	Average monthly cost of male labor.	Average monthly cost of female labor.	Quantities.	Kinds.	Values.
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Alson Rogers	Lumber	2000	500	Pine Logs	400	Water	3		26		100 M ft	Lumber	1000
			500	Pine Logs	250	Steam					100 "	Lumber	300
				Other Articles	30								

(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.		MACHINES.		AVERAGE NUMBER OF HANDS EMPLOYED.			Total amount paid in wages during year.	Number of months in active operation during part of which mills were in full time.	MATERIALS. (Including Mill Supplies and Fuel.)			PRODUCTION. (Including all Jobbing and Repairing.)		
			Kind of Power (steam, water, wind, horse, or hand).	H'rsepr. or water, No. of horse-power.	Name or Description.	Number of.	Males above 16 years.	Females above 15 years.	Children and youth.			Kinds.	Quantities.	Values (omitting fractions of a dollar).	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	Sawmill	7650	water		Saws	1	4			600	4			2000			4000
Burton			30 H.P.	12													

(d) 1880



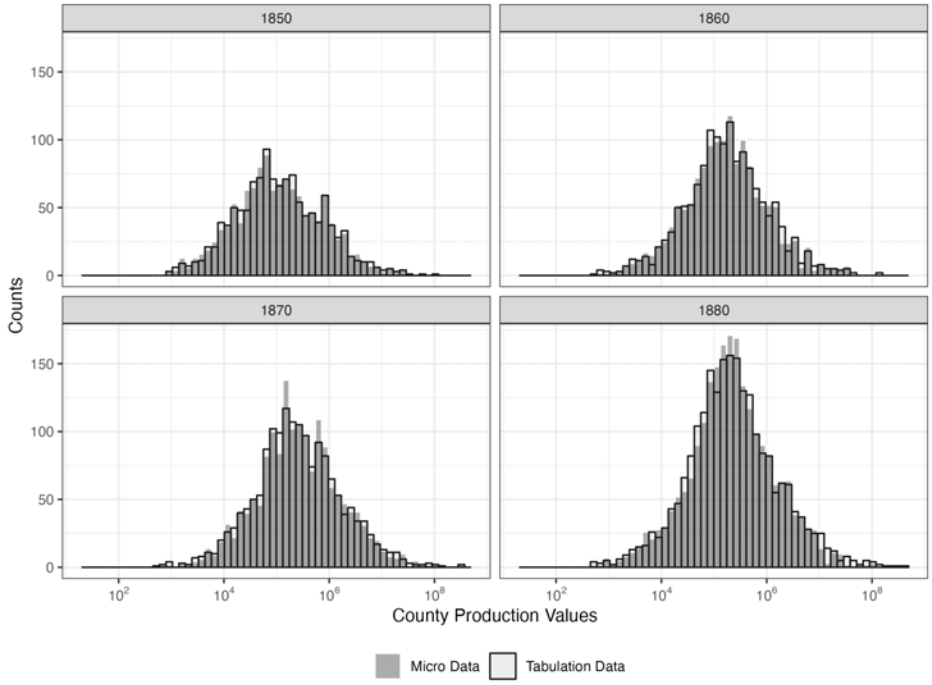
LUMBER MILLS AND SAW-MILLS.

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.			WAGES AND HOURS OF LABOR.				MONTHS IN OPERATION.				SAWS.				MATERIALS.			PROPER SAW-MILL PRODUCTS.		
			Males above 16 years.	Females above 15 years.	Children and youth.	Number of hours in the ordinary day of labor.		Average day's wages for a skilled mechanic.	Average day's wages for an ordinary laborer.	Total amount paid in wages during the year.	On full time.	On three-quarter time only.	On half time only.	Idle.	Number of gangs.	Number of saws in gang.	Number of circular saws.	Number of muley saws.	Number of band-saws.	Value of logs.	Value of mill supplies.	Total value of all materials (including value of logs).	Number of thousand feet of lumber.	Number of thousand laths.	Number of thousand shingles.
						May to November.	November to May.																		
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
L. P. Rogers & Bro.	6000	12	6			11	10	1.50	1.25	1400	6			6		1				30	100	4000	1200000		

PROPER SAW-MILL PRODUCTS—Continued.				REMANUFACTURES.			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.								
Number of thousand cords.	Number of thousand sets of bandings.	Number of thousand feet of bobbin and spool stock.	Total value of all products included under.	Total value of all products.	Do you remanufacture any of the products of your mills (as, for example, boards, planed, dressed, or sawed, into sash, doors, blinds, boxes, &c.)?	If so, give total value of such manufactures.	Give average number of hands employed in such remanufactures.				On what river or stream? (See note below.)	IF WATER IS USED.				IF STEAM-POWER IS USED.			
												WHEELS.							
												Height of fall, in feet.	Number.	Kind.	Breadth, in feet.	Revolutions per minute.	Horse-power.	Number of boilers.	Number of engines.	Horse-power.
			1680									63	1	Scroll	6	134	7			

Notes: This figure shows the images for the Rogers' Mill in the Census of Manufacturers. 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 Census image) and Burton took over the business. Source: Schenck and Rann (1887), Census of Manufacturers 1850-1880, Census of Population

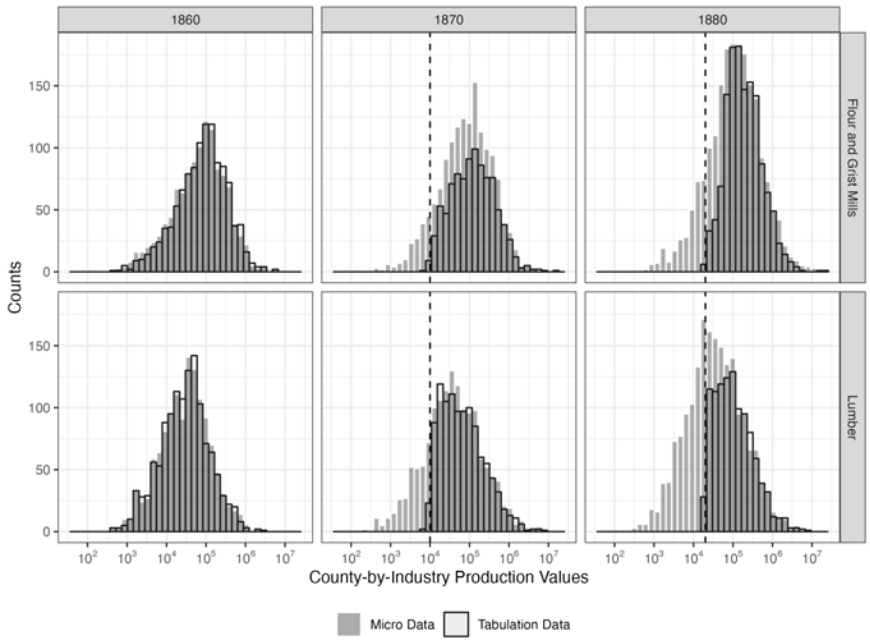
Figure A.9: County-Level Production Values in Microdata and County-Industry Tabulations



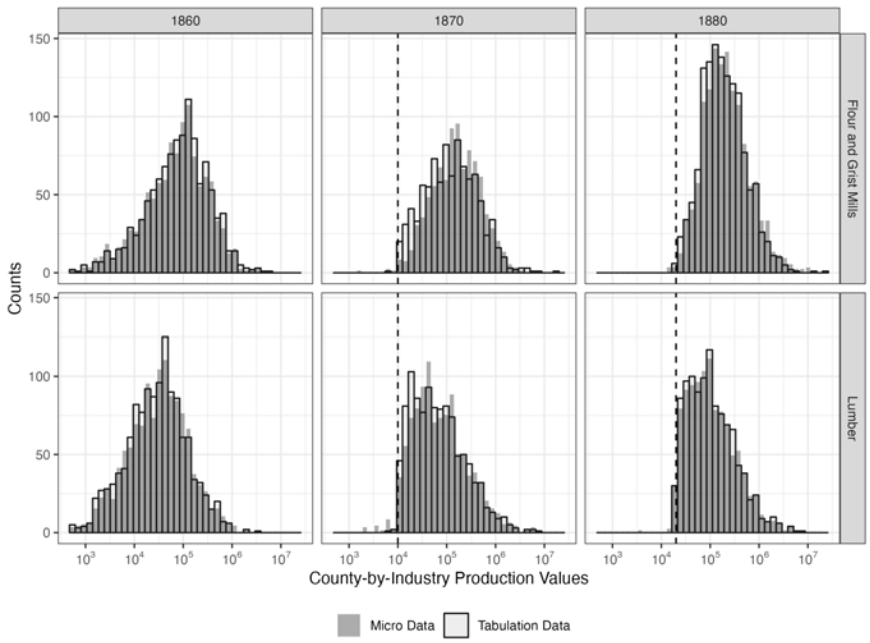
Notes: This figure shows the distribution of total recorded manufacturing output by county in our digitized Census of Manufacturers data and the county-industry reports contemporaneously tabulated by the Census. Data from the 1850-1880 Census of Manufacturers, and the sample is all counties with surviving manuscripts.

Figure A.10: Unmatched County-Level Production Values in Microdata and County-Industry Tabulations, Flour and Lumber Mills

(a) All County-Industries

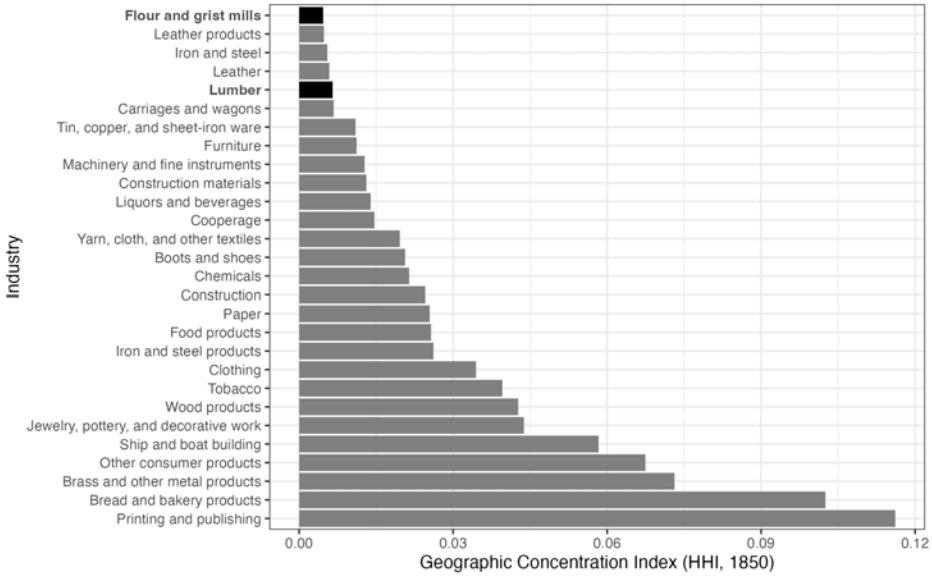


(b) Matched County-Industries



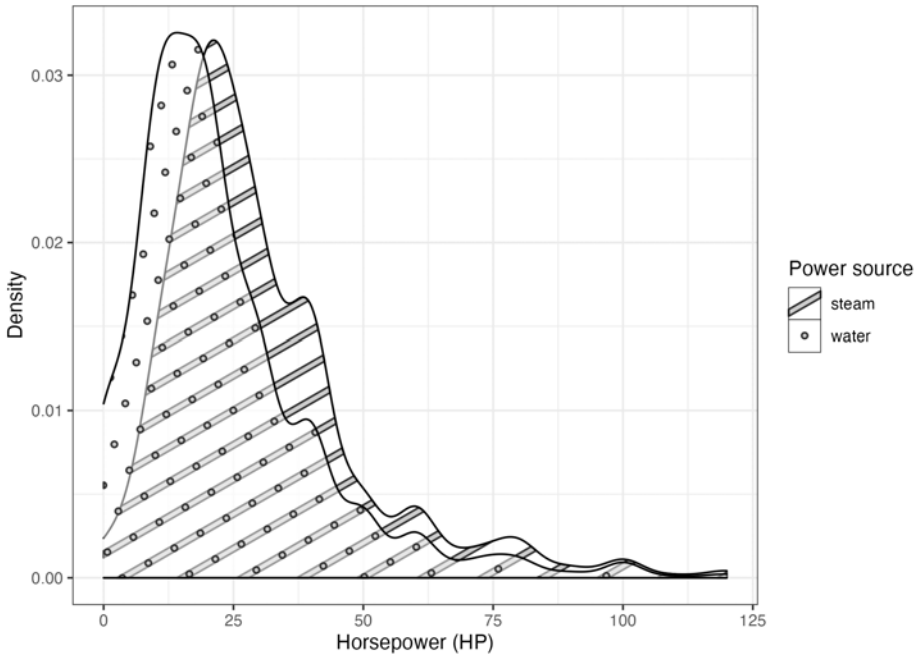
Notes: This figure shows the distribution of total flour milling and lumber milling by county as measured in our digitized Census of Manufacturers data and the county-industry reports contemporaneously tabulated by the Census. Panel A reports values for all county-industries with data in either source, Panel B reports values only for county-industries for which we have data from both sources. The Census had a *de jure* minimum value of total output for reporting county-industry values in 1870 and 1880, which correspond to the vertical lines. Data from the 1850-1880 Census of Manufacturers.

Figure A.11: Geographic Concentration of Activity, by Industry



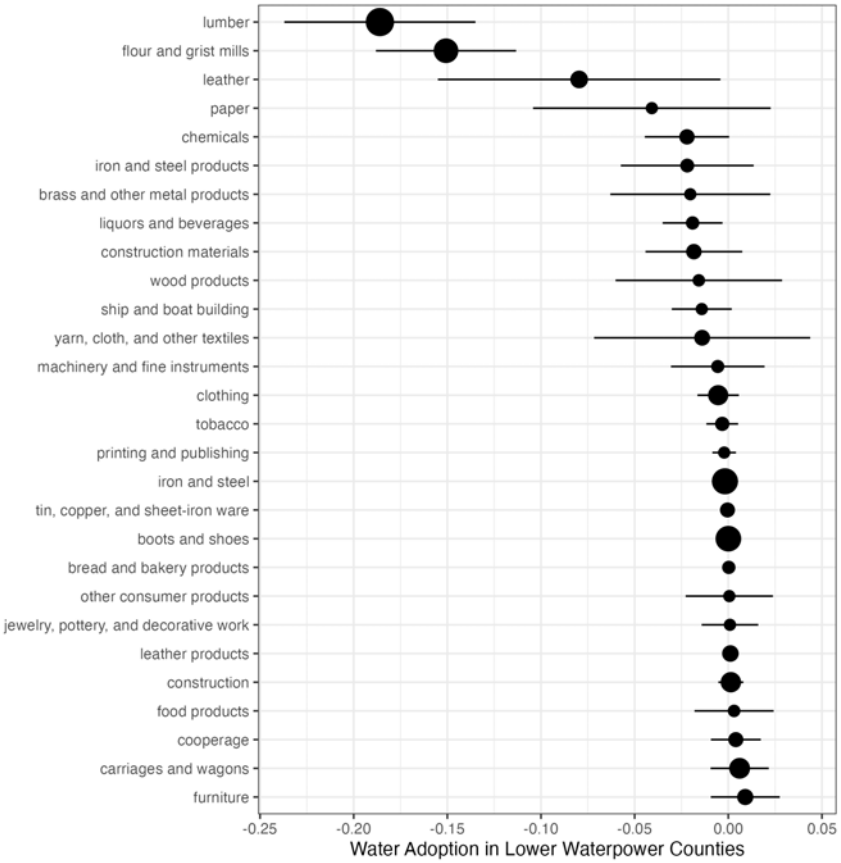
Notes: This figure shows, for each sector, the Herfindahl–Hirschman index of output across counties, sorted in increasing order. Data from the 1850-1880 Census of Manufacturers.

Figure A.12: Total Horsepower Installed, by Power Source



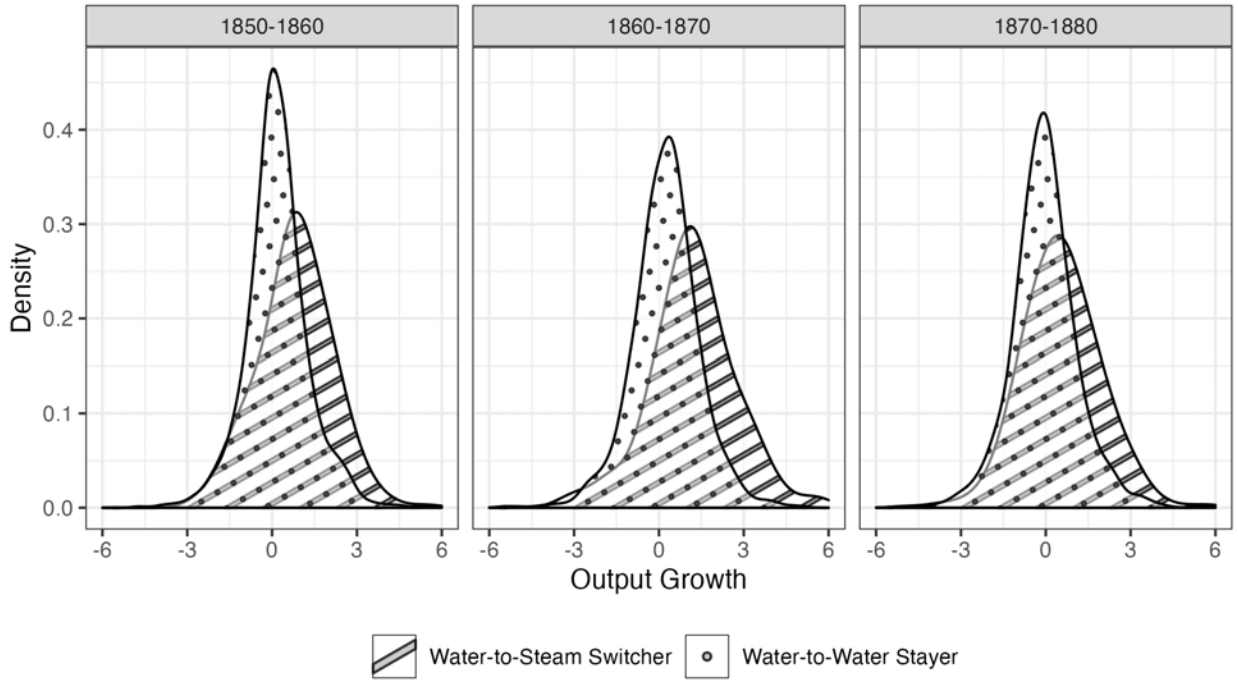
Notes: This figure shows the distribution of horsepower installed for flour mills and lumber mills in 1870 and 1880, pooled across industries and decades. Data from the 1870 and 1880 Census of Manufacturers.

Figure A.13: Waterpower Potential and Water Mills by Industry



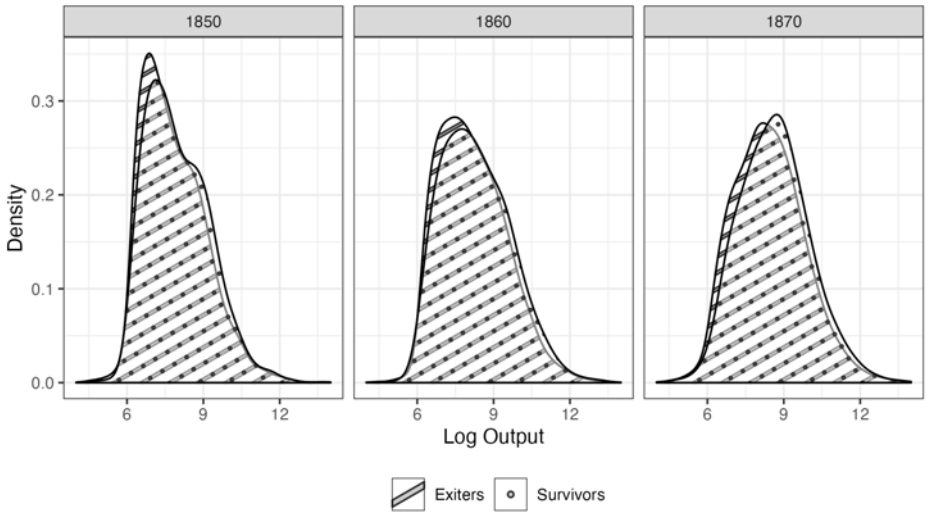
Notes: The figure plots the elasticity of waterpowered mills with respect to waterpower potential (β from Equation 1) for each industry separately. We pool data from 1850-1870 (and correspondingly include year fixed effects and interact the baseline controls by year). Standard errors are clustered by county. Data from the 1850-1880 Census of Manufacturers.

Figure A.14: Mill Growth by Switching Choice



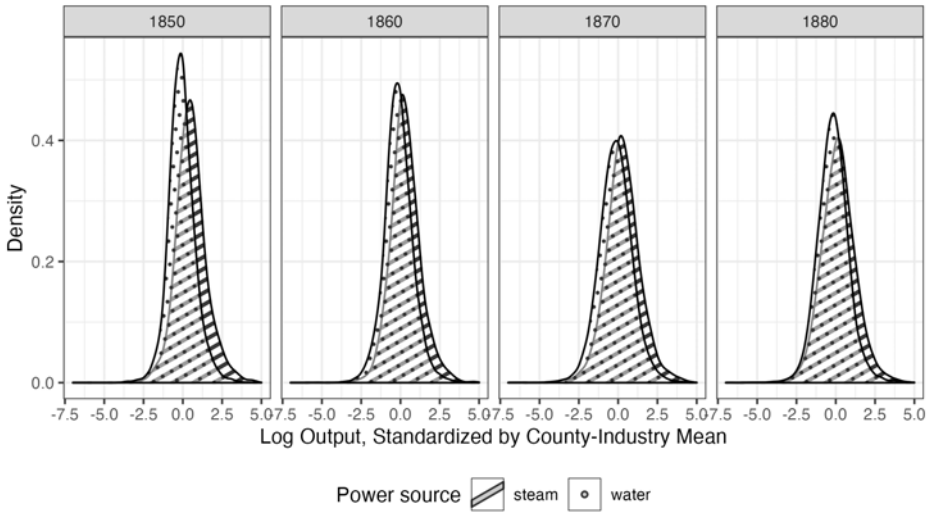
Notes: This figure plots the growth rates for water incumbents by decade, comparing those who switched to steam to those who stayed with waterpower. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers.

Figure A.15: Mill Size For Exiters and Survivors



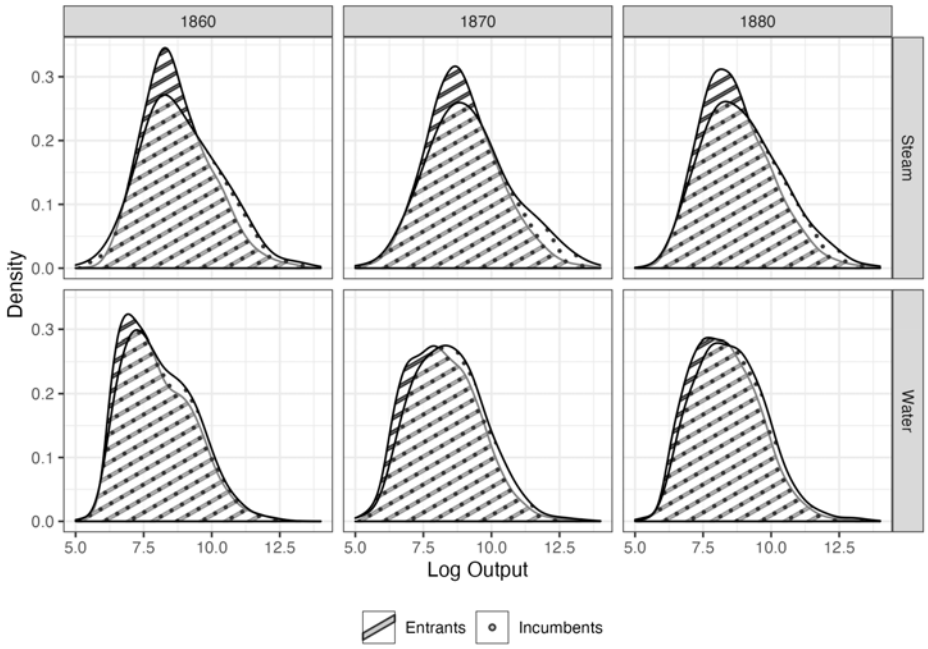
Notes: This figure plots the distribution of mill revenues by decade, comparing those that close in the subsequent decade to those that survive. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1870 Census of Manufacturers.

Figure A.16: Mill Size by Power Source, Within-County



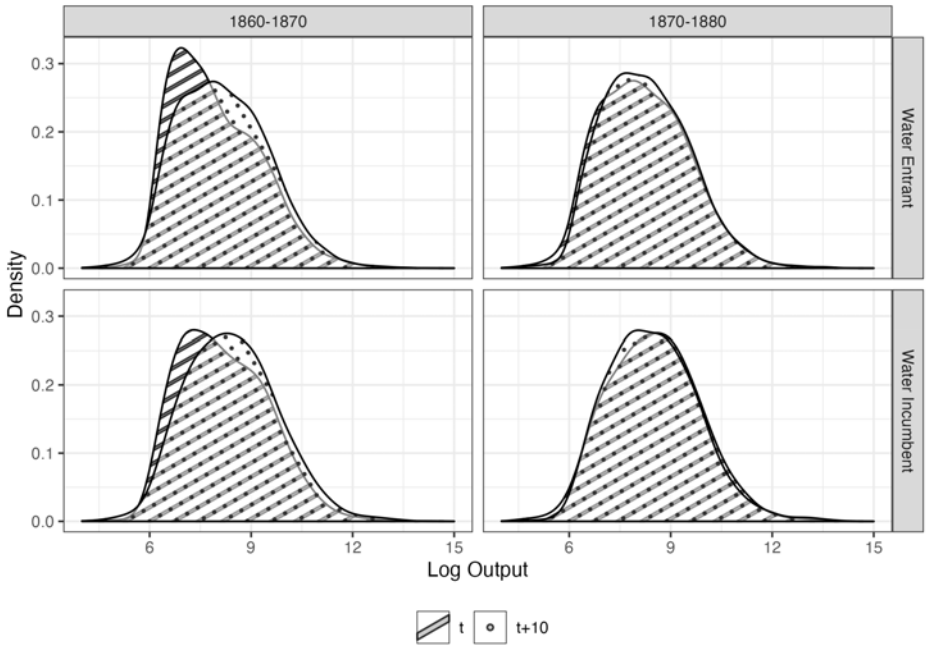
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water). For each plant, we standardize their revenue by county-industry. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers.

Figure A.17: Mill Size for Entrants and Incumbents, by Power Source



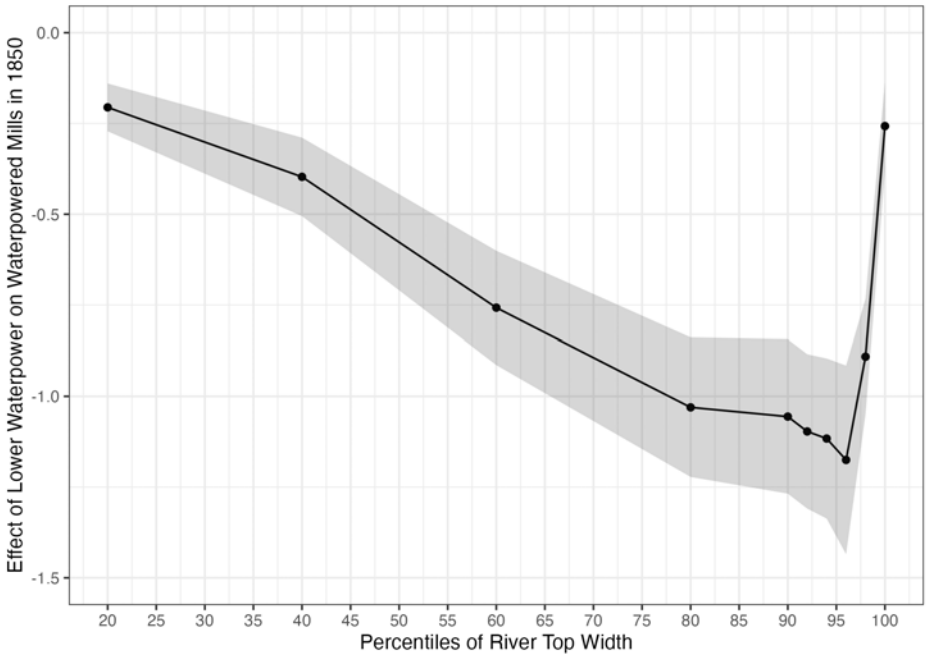
Notes: This figure plots the distribution of mill revenues by decade, comparing entrants to incumbents by power source. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1860-1880 Census of Manufacturers.

Figure A.18: Mill Growth For Incumbents verses Successive Generations of Entrants



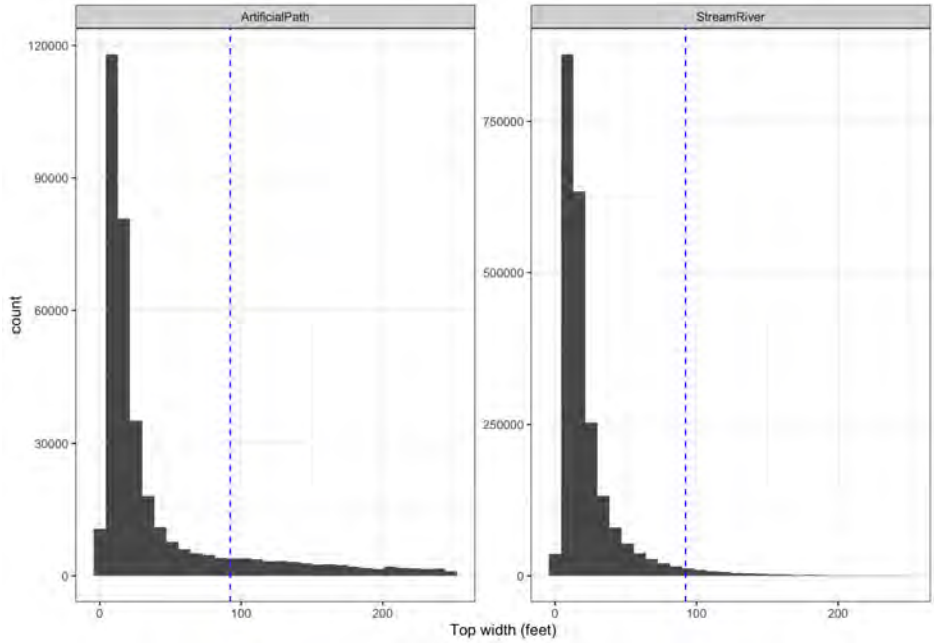
Notes: This figure plots the distribution of mill revenues for all water mills, by decade. The top panel shows the size distributions of water entrants in t and $t + 10$. The bottom panel shows the size distributions of the water incumbents (who do not subsequently switch to steam power) in t and $t + 10$. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1860-1880 Census of Manufacturers.

Figure A.19: Effect Size of Lower Waterpower vs. Percentiles of River Width



Notes: We sort rivers into bins (in percentiles) by their widthand exclude the rivers above a certain cutoff before calculating county waterpower potentials. We then run a regression of (negative) waterpower potential on the number of waterpowered mills in 1850 and plot the resulting coefficients. Data from NHDPlusV2 and the the 1850 Census of Manufacturers.

Figure A.20: Distribution of River Widths



Notes: This figure plots the distribution of widths of the Stream Rivers and Artificial Paths in the United States, along with the cutoff width above which we assume in our regressions that waterpower is impractical (from Appendix Figure A.19). Data from 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	-	-	-	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. 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	-0.240	-0.269	0.029
	(0.074)	(0.169)	(0.179)
# Counties	722	722	
In 1870	-0.246	-0.062	-0.184
	(0.070)	(0.095)	(0.115)
# Counties	722	722	
In 1880	-0.196	-0.150	-0.046
	(0.057)	(0.073)	(0.092)
# Counties	722	722	

Notes: This table shows the elasticity of survival with respect to waterpower potential from 1860-1880. Column 1 shows results for waterpowered mills, and column 2 for steam powered ones. Column 3 reports the difference. Each row corresponds to different regressions, using only data from the indicated year. The sample is all county-industries with at least one mill in 1850, and we report (pseudo) Poisson maximum likelihood estimates. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1860-1880 Census of Manufacturers and NHDPlusV2.

Table A.3: Spillovers of Water: Mills' Neighbors

	Neighbor of Mill (1)	Neighbor of Non-mill (2)	Difference (1) − (2) (3)
Panel A. All Non-mills			
Lower Waterpower	-0.026	-0.001	-0.025
	(0.011)	(0.004)	(0.009)
# Establishments	98,448	99,276	
Panel B. Excluding Water Users			
Lower Waterpower	-0.007	-0.001	-0.006
	(0.006)	(0.002)	(0.005)
# Establishments	73,183	77,433	

Notes: This table shows the relationship between mills and their neighbors' water use. The analysis is identical to that in Table 6, but the outcome is *water*power instead of *steam*power. The outcome in columns 1 and 2 is the share of establishments using waterpower, where column 1 limits the sample to non-mill establishments whose census enumeration is on the same page as a mill, and column 2 limits the sample to non-mill establishments without a mill on their page. Column 3 reports the difference. Panel A includes all non-mill establishments, Panel B limits the sample to industries that are not responsive to waterpower in Appendix Figure A.13: we drop leather, paper, chemicals, iron & steel, brass & other metals, liquors, construction materials, wood products, ship & boat building, and textiles. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include industry-decade fixed effects in addition to the baseline controls (total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits). Standard errors are clustered by county. Data from the 1850-1880 Census of Manufacturers.

Table A.4: Switching Rates of Water Incumbents, by Distance to Railroad Station

	From Entrants (1)	From Water Incumbents (2)	Difference (1) − (2) (3)
Lower Waterpower	0.171	0.058	0.113
	(0.022)	(0.017)	(0.018)
Log Distance, WPP-to-RR Station	-0.021	-0.031	0.009
	(0.045)	(0.033)	(0.047)
Log Distance, to RR Station	0.019	0.015	0.004
	(0.049)	(0.035)	(0.052)
# Counties	720	541	

Notes: This table shows the relationship between waterpower potential, railroad station placement, and the steam use of entrant and incumbent mills from 1860-1880. 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 all county-industries with at least one mill in 1850 and at least one current entrant (in column 1) or incumbent (in column 2). "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). "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. All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Regressions are weighted by the number of mills in the county in 1850. Each observation is a county-industry-decade, and we weight by the number of mills in 1850. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.5: Per Capita Manufacturing Growth and Steam Diffusion by Waterpower

	Log Population (1)	Mills Per Capita (2)	Revenue Per Capita (3)
Difference in Lower Waterpower Counties:			
In 1850	-0.251	-0.605	-0.515
	(0.128)	(0.082)	(0.122)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.084	0.125	0.202
	(0.023)	(0.073)	(0.112)
# Counties	722	722	722
From 1860 to 1870	0.038	0.034	-0.023
	(0.017)	(0.073)	(0.082)
# Counties	722	722	722
From 1870 to 1880	0.039	0.105	0.137
	(0.011)	(0.050)	(0.108)
# Counties	722	722	722

Notes: This table shows the relationship between waterpower potential and milling per capita. 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. The sample is all counties with at least one mill in 1850. Column 1 reports OLS estimates, and columns 2-3 report (pseudo) Poisson maximum likelihood estimates. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.6: Steam Diffusion and *Flour* Mill Growth, by County Waterpower Potential

	Steam Share of Mills (1)	Total Mills (2)	Total Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.023	0.109	0.140
	(0.019)	(0.070)	(0.065)
# Counties	543	604	604
From 1860 to 1870	0.041	0.203	0.133
	(0.019)	(0.071)	(0.079)
# Counties	538	604	604
From 1870 to 1880	0.011	0.131	0.165
	(0.016)	(0.040)	(0.105)
# Counties	588	604	604

Notes: This table shows the relationship between waterpower potential and milling growth from 1850-1880, limiting the sample to flour mills. The outcome in column 1 is the share of mills using steam power, in column 2 the outcome is the total number of mills, and in column 3 the outcome is total milling revenue. Each row corresponds to a different regression, using only data from the indicated years. The sample is all counties with at least one mill in 1850. Column 1 reports OLS results for the counties that have at least one mill in both decades (since there needs to be at least one mill for the steam share to be defined), and is weighted by the number of mills in the county in 1850. Columns 2 and 3 report (pseudo) Poisson maximum likelihood estimates for the balanced panel (including the zeroes). "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.7: *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	0.175	-0.128	0.303
	(0.084)	(0.092)	(0.118)
# Counties	604	604	
In 1870	0.244	-0.079	0.322
	(0.081)	(0.070)	(0.103)
# Counties	604	604	
In 1880	0.222	-0.201	0.423
	(0.048)	(0.063)	(0.084)
# Counties	604	604	

Notes: This table shows the elasticity of entry and survival with respect to waterpower potential from 1860-1880, limiting the sample to flour mills. Column 1 shows results for entry, and column 2 for incumbent survival. Column 3 reports the difference. Each row corresponds to a different regression, using only data from the indicated year. The sample is all county-industries with at least one mill in 1850, and we report (pseudo) Poisson maximum likelihood estimates. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits. Each observation is a county-industry-decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.8: Steam Adoption of Entrants and Water *Flour* Mills, by County Waterpower Potential

	From Entrants (1)	From Water Incumbents (2)	Difference (1) − (2) (3)
Adoption in Lower Waterpower Counties:			
In 1860	0.098	0.027	0.071
	(0.028)	(0.032)	(0.036)
# Counties	536	342	
In 1870	0.113	0.057	0.057
	(0.024)	(0.027)	(0.037)
# Counties	589	341	
In 1880	0.136	0.054	0.083
	(0.028)	(0.025)	(0.030)
# Counties	593	431	

Notes: This table shows the relationship between waterpower potential and the steam use of entrant and incumbent mills from 1860-1880, limiting the sample to flour mills. 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 a different regression, using only data from the indicated year. The sample is all county-industries with at least one mill in 1850 and at least one current entrant (in column 1) or incumbent (in column 2). "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits, and are weighted by the number of mills in the county in 1850. Each observation is a county-industry-decade, and we weight by the number of mills in 1850. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.9: Robustness to Alternative Drivers of Steam Use

	Water Establishments	Steam Share	Growth in Total Establishments			Steam Diffusion		
	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	-1.088	0.095	0.225	0.125	0.136	0.059	0.034	-0.016
	(0.131)	(0.015)	(0.058)	(0.051)	(0.036)	(0.020)	(0.012)	(0.015)
2. Each type of coal separately	-1.088	0.095	0.225	0.124	0.136	0.059	0.034	-0.016
	(0.131)	(0.015)	(0.058)	(0.051)	(0.036)	(0.020)	(0.012)	(0.015)
3. Square and cubic in coal shares in county	-1.081	0.092	0.210	0.139	0.137	0.059	0.031	-0.012
	(0.131)	(0.015)	(0.057)	(0.053)	(0.035)	(0.020)	(0.012)	(0.014)
4. Market access to coal	-1.077	0.095	0.227	0.121	0.136	0.057	0.034	-0.016
	(0.128)	(0.015)	(0.057)	(0.052)	(0.036)	(0.019)	(0.012)	(0.015)
5. 1850 local wages in milling	-1.078	0.098	0.226	0.127	0.130	0.057	0.032	-0.015
	(0.131)	(0.014)	(0.059)	(0.052)	(0.036)	(0.020)	(0.011)	(0.015)
6. 1850 access to banks	-1.058	0.076	0.226	0.156	0.131	0.061	0.037	-0.007
	(0.136)	(0.016)	(0.065)	(0.051)	(0.040)	(0.019)	(0.012)	(0.014)
7. 1850 engineers and mechanics	-1.081	0.093	0.232	0.130	0.142	0.066	0.036	-0.011
	(0.128)	(0.014)	(0.060)	(0.051)	(0.038)	(0.018)	(0.012)	(0.013)
8. FAO suitability for wheat	-1.096	0.095	0.214	0.137	0.135	0.057	0.033	-0.016
	(0.131)	(0.015)	(0.058)	(0.053)	(0.036)	(0.019)	(0.012)	(0.015)
9. 1870 share of woodland	-1.033	0.101	0.194	0.113	0.140	0.048	0.030	-0.022
	(0.131)	(0.014)	(0.062)	(0.051)	(0.037)	(0.018)	(0.012)	(0.015)

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. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits (unless otherwise specified). Each observation is a county/decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.10: Robustness to Alternative Drivers of County Growth

		Water Establishments	Steam Share	Growth in Total Establishments			Steam Diffusion		
		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	-1.088	0.095	0.225	0.125	0.136	0.059	0.034	-0.016
		(0.131)	(0.015)	(0.058)	(0.051)	(0.036)	(0.020)	(0.012)	(0.015)
2.	No controls for MA/navigable rivers	-1.287	0.085	0.281	0.139	0.152	0.069	0.033	-0.021
		(0.138)	(0.016)	(0.061)	(0.051)	(0.035)	(0.019)	(0.011)	(0.015)
3.	No controls for coal	-1.091	0.101	0.234	0.129	0.138	0.065	0.036	-0.013
		(0.126)	(0.015)	(0.060)	(0.051)	(0.035)	(0.022)	(0.013)	(0.017)
4.	No extra controls	-1.300	0.090	0.293	0.142	0.156	0.078	0.034	-0.019
		(0.134)	(0.016)	(0.062)	(0.051)	(0.035)	(0.021)	(0.012)	(0.016)
5.	At least 3 mills in 1850	-0.970	0.087	0.179	0.118	0.112	0.060	0.038	-0.019
		(0.132)	(0.016)	(0.060)	(0.057)	(0.041)	(0.020)	(0.012)	(0.015)
6.	At least 5 mills in 1850	-0.875	0.080	0.158	0.117	0.106	0.060	0.045	-0.020
		(0.135)	(0.016)	(0.064)	(0.062)	(0.044)	(0.022)	(0.013)	(0.017)
7.	Exclude 5% largest WPP counties	-1.083	0.085	0.236	0.135	0.139	0.077	0.045	-0.012
		(0.134)	(0.016)	(0.068)	(0.059)	(0.042)	(0.018)	(0.012)	(0.015)
8.	Exclude 5% smallest WPP counties	-1.206	0.094	0.234	0.119	0.168	0.046	0.029	-0.019
		(0.136)	(0.016)	(0.064)	(0.056)	(0.037)	(0.022)	(0.014)	(0.016)
9.	Unbalanced panel	-1.202	0.095	0.289	0.122	0.153	0.059	0.034	-0.016
		(0.134)	(0.015)	(0.061)	(0.049)	(0.034)	(0.020)	(0.012)	(0.015)
10.	State fixed effects	-0.456	0.085	0.139	0.133	0.077	0.013	0.021	-0.014
		(0.105)	(0.016)	(0.071)	(0.063)	(0.041)	(0.015)	(0.013)	(0.018)
11.	13 American colonies	-0.841	0.074	0.172	0.103	0.126	0.033	0.028	-0.008
		(0.126)	(0.016)	(0.058)	(0.051)	(0.037)	(0.019)	(0.013)	(0.016)
12.	Appalachia	-1.069	0.095	0.226	0.124	0.138	0.058	0.034	-0.016
		(0.130)	(0.015)	(0.058)	(0.051)	(0.035)	(0.019)	(0.012)	(0.015)
13.	Longitude	-0.812	0.072	0.165	0.141	0.121	0.014	0.022	-0.018
		(0.120)	(0.016)	(0.060)	(0.056)	(0.036)	(0.014)	(0.012)	(0.015)
14.	Civil war battles and casualties	-1.079	0.093	0.231	0.120	0.127	0.052	0.037	-0.016
		(0.132)	(0.015)	(0.059)	(0.051)	(0.035)	(0.019)	(0.012)	(0.015)
15.	Time-varying market access	-1.074	0.095	0.220	0.121	0.140	0.057	0.036	-0.014
		(0.127)	(0.015)	(0.056)	(0.051)	(0.034)	(0.019)	(0.012)	(0.014)
16.	Exclude largest 20 cities in 1850-1880	-1.080	0.091	0.227	0.133	0.141	0.076	0.042	-0.012
		(0.131)	(0.015)	(0.067)	(0.057)	(0.043)	(0.018)	(0.012)	(0.014)
17.	Exclude merchant mill cities	-1.040	0.099	0.219	0.115	0.139	0.055	0.033	-0.016
		(0.127)	(0.015)	(0.060)	(0.053)	(0.037)	(0.020)	(0.013)	(0.016)
18.	Portage sites	-1.096	0.097	0.224	0.125	0.136	0.059	0.033	-0.016
		(0.131)	(0.014)	(0.058)	(0.051)	(0.036)	(0.020)	(0.012)	(0.015)
19.	Frontier	-1.080	0.096	0.221	0.123	0.138	0.057	0.035	-0.016
		(0.131)	(0.015)	(0.058)	(0.051)	(0.036)	(0.020)	(0.012)	(0.015)
20.	1850 population	-0.821	0.097	0.201	0.129	0.127	0.050	0.032	-0.015
		(0.103)	(0.015)	(0.059)	(0.052)	(0.037)	(0.019)	(0.012)	(0.015)
21.	1850 total MFG output	-0.766	0.105	0.152	0.107	0.111	0.031	0.026	-0.023
		(0.108)	(0.015)	(0.064)	(0.051)	(0.040)	(0.016)	(0.012)	(0.015)
22.	1850 agricultural share	-1.070	0.099	0.220	0.115	0.137	0.057	0.032	-0.018
		(0.129)	(0.014)	(0.059)	(0.049)	(0.036)	(0.018)	(0.011)	(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. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the county covered by coal deposits (unless otherwise specified). Each observation is a county/decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.11: Survival Rates

	Survival Rate By Initial Power Source		
	All	Water	Steam
	(1)	(2)	(3)
From 1850 to 1860	0.202	0.209	0.138
From 1860 to 1870	0.195	0.217	0.135
From 1870 to 1880	0.237	0.260	0.191

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. Data from the 1850-1880 Census of Manufacturers.

Table A.12: Incumbency, Size, and Steam Use

	Steam Adoption		
	(1)	(2)	(3)
Water Incumbent	-0.188		-0.192
	(0.009)		(0.009)
Log Revenue		0.086	0.087
		(0.004)	(0.004)
# Mill-Years	66,111	66,111	66,111

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. Standard errors clustered by county. The sample is all counties with at least one mill in 1850. All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, the share of the county covered by coal deposits, and waterpower potential, all interacted with year. Data from the 1860-1880 Census of Manufacturers and NHDPlusV2.

Table A.13: Steam Use and Characteristics of the Owner

	Mean Value	Uses Steam			
	(1)	(2)	(3)	(4)	(5)
Immigrant	0.066	0.071			0.070
	[0.247]	(0.009)			(0.009)
Age, in years	44.1		-0.0016		-0.0014
	[13.1]		(0.0002)		(0.0002)
Professional Miller	0.384			0.027	0.022
	[0.486]			(0.005)	(0.005)
Number of Mills	19,555	19,555	19,555	19,555	19,555
Mean of Dependent Variable		0.142	0.142	0.142	0.142

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 controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, the share of the county covered by coal deposits, and waterpower potential, interacted with year. Each observation is a mill-decade. Standard errors clustered by county. Data from the 1850-1870 Census of Manufacturers, the 1850-1870 Census of Population and NHDPlusV2.

Table A.14: Persistence of Productivity

	Log Revenue, Current (1)
Log Revenue, Last Decade	0.407
	(0.017)
# Mills	9,537

Notes: This table shows the relationship between current log sales (as the dependant variable) and lagged log sales (the independent variable). All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, the share of the county covered by coal deposits, and waterpower potential, all interacted with year. Each observation is a plant in a decade. Standard errors clustered by county. Data from the 1860-1880 Census of Manufacturers and NHDPlusV2.

Table A.15: Lumber and Flour Mill Activity in 1850, by County Waterpower Potential, by Different River Classifications

	Baseline (1)	12-Month Average (2)	Intermittent River (3)
Panel A. Number of Waterpowered Mills			
Lower Waterpower	-1.089	-0.571	0.032
	(0.131)	(0.101)	(0.034)
Panel B. Total Revenue of Waterpowered Mills			
Lower Waterpower	-1.189	-0.718	0.034
	(0.251)	(0.166)	(0.056)
Panel C. Steam Share of Mills			
Lower Waterpower	0.095	0.056	-0.004
	(0.015)	(0.014)	(0.003)
Panel D. Steam Share of Revenue			
Lower Waterpower	0.130	0.059	-0.007
	(0.022)	(0.021)	(0.004)
Panel E. Total Number of Mills			
Lower Waterpower	-0.965	-0.488	0.027
	(0.122)	(0.092)	(0.033)
Panel F. Total Revenue of Mills			
Lower Waterpower	-0.591	-0.228	0.026
	(0.388)	(0.244)	(0.047)
# Counties	722	722	722

Notes: This table shows the relationship between 1850 milling activity and waterpower potential. 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. Each observation is a county-industry in 1850, and the sample is all county-industries with at least one mill in 1850. All regressions include controls for total county water flow, county ruggedness, whether the county has navigable waterways, county market access in 1850, a dummy for the presence of coal in the county, and the share of the

Table A.16: Sensitivity of Simulated Moments to Structural Parameters

Moment	Year	$c_S^{(floor)}$	$c_S^{(slope)}$	$c_S^{(origin)}$	$c^o(W)$	$c^o(S)$	ρ	γ	Π	Σ	f^e	f^W	f^S	ρ_o
Steam Adoption Rate	1850	-2.954	1.916	-10.805	-0.916	0.788	2.749	1.069	19.599	0.890	0.569	0.004	-1.105	-0.047
Steam Adoption Rate	1860	-1.749	1.670	-6.327	-0.782	0.628	1.762	0.824	16.786	0.664	0.446	0.004	-0.964	0.101
Steam Adoption Rate	1870	-1.013	1.278	-3.601	-0.655	0.483	1.152	0.623	14.133	0.491	0.348	0.003	-0.815	0.159
Steam Adoption Rate	1880	-0.593	0.920	-2.051	-0.548	0.375	0.793	0.479	11.953	0.370	0.279	0.002	-0.690	0.171
Water Choice Differentials: Water Incumbents vs. Entrants	1850-1880	0.400	-0.360	1.523	2.360	-0.145	-2.674	-0.164	-20.470	-0.204	-0.411	-0.007	0.544	-1.208
Steam Choice Differentials: Steam Incumbents vs. Entrants	1850-1880	-0.639	0.616	-2.314	0.242	3.677	-3.172	0.080	10.847	-0.131	0.189	0.002	0.028	0.423
Log Sales Overlap Shares Between Steam and Water Users	1850-1880	-0.006	-0.014	-1.855	0.007	0.028	0.111	-0.099	-2.069	1.633	-0.120	0.001	1.972	0.287
Log Sales Differential Between Steam and Water Users	1850-1870	-0.085	0.091	-0.351	-0.060	-0.015	-0.139	0.403	7.449	0.890	0.169	-0.002	0.123	-0.467
Log Sales Autocorrelation	1850-1870	-0.314	0.355	-1.115	-0.065	0.235	0.094	0.105	10.010	0.015	-0.133	-0.002	0.026	0.136
Log Sales Standard Deviation	1850-1880	-0.157	0.207	-0.539	-0.016	0.019	0.040	0.051	10.305	1.149	-0.177	-0.001	0.026	0.001
Water Entry Rate	1850-1880	-0.136	0.192	-0.470	-0.089	0.093	0.126	0.076	-2.949	0.167	-0.040	0.001	-0.034	0.187
Steam Entry Rate	1850-1880	-0.026	0.090	-0.067	0.059	-0.034	-0.005	0.025	-4.574	0.124	-0.087	0.000	0.050	0.084
Water Exit Rate	1850-1880	-0.133	0.146	-0.474	-0.089	0.040	0.172	0.055	-5.236	0.275	-0.066	0.001	0.020	0.263
Steam Exit Rate	1850-1880	-0.238	0.246	-0.831	-0.029	0.324	-0.048	0.005	-7.545	0.279	-0.143	0.001	0.233	0.183
Log Sales Overlap Shares Between Survivors and Exiters	1850-1880	-0.058	0.058	-0.211	-0.009	0.092	1.102	0.024	-0.575	1.149	0.040	-0.001	0.098	1.035

Notes: This table shows the sensitivity of the estimates to model parameters.

Table A.17: Differences Between Baseline and "Low Water" Regions: Contribution to Growth by Entrants and Water Incumbents

				FN Error Rates			FP Error Rates		
Moment	**Year**	**Model**	**Data**	**5%**	**25%**	**90%**	**5%**	**25%**	**90%**
Growth Entrant Establishments	1850-1860	0.295	0.295	0.296	0.299	0.306	0.295	0.295	0.295
			(0.070)						
	1860-1870	0.218	0.232	0.218	0.220	0.223	0.218	0.218	0.218
			(0.076)						
	1870-1880	0.157	0.124	0.158	0.159	0.162	0.157	0.157	0.157
			(0.061)						
Growth Water Incumbent Establishments	1850-1860	0.320	-0.384	0.320	0.320	0.320	0.297	0.263	0.242
			(0.118)						
	1860-1870	0.151	-0.442	0.151	0.151	0.151	0.146	0.132	0.122
			(0.119)						
	1870-1880	0.087	-0.579	0.087	0.087	0.087	0.077	0.059	0.048
			(0.109)						
Growth Steam Incumbent Establishments	1850-1860	0.242	0.118	0.242	0.242	0.242	0.219	0.184	0.163
			(0.114)						
	1860-1870	0.167	0.305	0.167	0.167	0.167	0.161	0.147	0.137
			(0.128)						
	1870-1880	0.117	0.247	0.117	0.117	0.117	0.107	0.089	0.078
			(0.055)						
Growth Entrant Output	1850-1860	0.197	0.179	0.198	0.200	0.207	0.197	0.197	0.197
			(0.097)						
	1860-1870	0.139	0.243	0.139	0.141	0.144	0.139	0.139	0.139
			(0.079)						
	1870-1880	0.095	0.123	0.096	0.097	0.100	0.095	0.095	0.095
			(0.114)						
Growth Water Incumbent Output	1850-1860	0.235	-0.609	0.235	0.235	0.235	0.201	0.161	0.142
			(0.150)						
	1860-1870	0.089	-0.906	0.089	0.089	0.089	0.075	0.054	0.042
			(0.150)						
	1870-1880	0.039	-0.489	0.039	0.039	0.039	0.019	-0.004	-0.014
			(0.235)						
Growth Steam Incumbent Output	1850-1860	0.155	0.058	0.155	0.155	0.155	0.117	0.079	0.062
			(0.132)						
	1860-1870	0.072	0.476	0.072	0.072	0.072	0.068	0.060	0.055
			(0.211)						
	1870-1880	0.040	0.124	0.040	0.040	0.040	0.034	0.022	0.014
			(0.158)						

Notes: The "Model" column reports the simulation results from the structural estimation. The "Data" column reports the reduced-form estimates from the CMF data. Standard errors are reported in parentheses. FN refers to the false negative of labeling incumbents as entrants. FP refers to the false positive of labeling entrants as incumbents. The top three panels report the growth rates of the number of entrants, water incumbents or steam incumbents over a given 10-year period. The bottom two panels report the growth rates of the output produced by entrants, water incumbents or steam incumbents over a given 10-year period.

Table A.18: Differences Between Baseline and "Low Water" Regions: Steam Adoption Rates by Entrants and Water Incumbents

				FN Error Rates			FP Error Rates		
Moment	**Year**	**Model**	**Data**	**5%**	**25%**	**50%**	**5%**	**25%**	**50%**
Entrant-to-Steam Establishment Switching Rate	1850-1860	0.165	0.195	0.165	0.165	0.165	0.165	0.165	0.165
			(0.032)						
	1860-1870	0.188	0.196	0.188	0.188	0.189	0.188	0.188	0.188
			(0.026)						
	1870-1880	0.187	0.162	0.187	0.187	0.188	0.187	0.187	0.187
			(0.029)						
Water-to-Steam Establishment Switching Rate	1850-1860	0.104	0.048	0.104	0.104	0.104	0.131	0.154	0.162
			(0.018)						
	1860-1870	0.143	0.085	0.143	0.143	0.143	0.166	0.182	0.186
			(0.026)						
	1870-1880	0.160	0.089	0.160	0.160	0.160	0.176	0.185	0.186
			(0.047)						
Entrant-to-Steam Output Switching Rate	1850-1860	0.183	0.205	0.184	0.184	0.185	0.183	0.183	0.183
			(0.032)						
	1860-1870	0.182	0.212	0.182	0.182	0.184	0.182	0.182	0.182
			(0.023)						
	1870-1880	0.162	0.183	0.162	0.162	0.162	0.162	0.162	0.162
			(0.026)						
Water-to-Steam Output Switching Rate	1850-1860	0.159	0.046	0.159	0.159	0.159	0.177	0.184	0.184
			(0.016)						
	1860-1870	0.185	0.032	0.185	0.185	0.185	0.190	0.187	0.183
			(0.027)						
	1870-1880	0.178	0.085	0.178	0.178	0.178	0.174	0.167	0.164
			(0.049)						

Notes: The "Model" column reports the simulation results from the structural estimation. The "Data" column reports the reduced-form estimates from the CMF data. Standard errors are reported in parentheses. FN refers to the false negative of labeling incumbents as entrants. FP refers to the false positive of labeling entrants as incumbents. Each value in the top two panels refers to the share of entrants or water incumbents in year $t-10$ that switched to use steam in year t. In contrast, each value in the bottom two panels refers to the same switching rate but instead using output shares in year $t-10$.