Technological Stickiness: Switching and Entry in the Long Transition from Water to Steam Power

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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. We leverage variation in US counties' waterpower potential, due to interacting water flow and elevation changes, which drove early mills' waterpower-use. Using newly digitized Census of Manufactures manuscripts for 1850-1880, we show that as steam costs declined, mill activity grew faster in low-waterpower counties. This growth was driven by steam-powered entrants, as waterpowered mills exited rather than adopt steam, suggesting technological lock-in. We estimate a dynamic model of firm entry and steam adoption, using geographic variation in waterpower potential to identify switching costs and to quantify the substantial delay in steam adoption from technological lock-in.

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Technological innovation drives economic growth, but the widespread adoption of new technology can be slow (David, 1990; Jovanovic and Rousseau, 2005; Comin and Hobijn, 2010). We focus on how early technological advantage can delay subsequent technological adoption over a long period, looking back to the era of American industry when mechanical power relied on local waterpower. The steam engine broke this substantive dependence of manufacturing on local geographic characteristics, and was a central technology to widespread industrialization.

We use geographic variation in local waterpower potential to explore how switching costs and firm entry interact to determine the magnitude and implications of technological lock-in. We document new facts about the transition from water to steam power, and estimate a structural model that rationalizes these facts and allows us to quantify the magnitude of forces that determined where and when steam power was adopted.

Waterwheels dotted the US countryside in the 19th century, with roughly one waterwheel or turbine in use for every 600 people (Rosenberg and Trajtenberg, 2004), as flour mills and lumber mills provided food and shelter to their local communities. We study technological adoption in these mills' transition from water to steam power. In 1850, only 10 percent of mills were powered by steam, a share which had increased to fifty percent by 1880.

Our main data source is establishment-level records that we digitized from the complete surviving manuscripts of the US Census of Manufactures in 1850, 1860, 1870, and 1880.[1] These records include data on power-use for every establishment, and we link mills over time based on their name, industry, and location. From the states with surviving establishment-level records, we construct a balanced panel of 722 counties, covering 80 thousand establishment-year observations.

We focus on lumber and flour mills because they were heavy users of mechanical power that relied initially on local waterpower availability. Most waterpowered establishments in 1850 were either lumber or flour mills (we abbreviate the official industry names of "flour and grist" to "flour" and of "lumber and sawing" to "lumber"). Flour was the largest industrial sector in the economy during our period, by revenue, and lumber was the largest by number of establishments. Combined, they accounted for around 20% of American manufacturing revenue at the start of our sample (United States Census Bureau, 1872).

The US used substantial waterpower throughout the eighteenth and nineteenth centuries, but waterpower sites were geographically dispersed and some counties had limited access to waterpower. Local waterpower potential depends on the interaction of water flow and ele-

[1]Samples of these manufacturing schedules were digitized by Atack (1976) and Bateman and Weiss (1981). 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 et al., 2023; Berger and Ostermeyer, 2023).

vation changes, and we link our manufacturing data with county-level waterpower potential using a hydrological model (McKay et al., 2012; Moore et al., 2019). There is substantial geographic dispersion in counties' waterpower potential even after controlling directly for river water volume and elevation changes. We further focus on the substantial residual variation after controlling for other local characteristics, such as access to navigable waterways, coal, and market access, that might otherwise impact local industrial activity (Fogel, 1964; Chandler, 1972).

We focus on local waterpower potential since it provides a plausibly exogenous cost-shifter to mills' initial waterpowered production. Lumber and flour mills sold primarily to local markets, unlike textile mills, so the power technology choices of lumber and flour millers were substantially influenced by local geography and we can consider milling in each county as a separate market. The fact that waterpower potential impacts power technology choices was noted 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).[2]

Relative to the literature, we study the influence of waterpower availability using more-comprehensive data and introduce a focus on the dynamics of producer technological lock-in: it was not just the *potential* for contemporaneous waterwheel use, but also *actual* prior use of waterwheels that slowed the adoption of steam power through technological lock-in. We can distinguish between these two forces by comparing the steam adoption decisions of entrants and incumbents who had previously invested in waterpower. Our setting highlights the role of switching costs for the diffusion of new technologies, illustrating how early advantages can directly discourage later adoption. As mill industries transitioned from water to steam power, eventually, steam brought mechanization to new industries and spurred broad productivity growth (Atack et al., 2008, 2019).

Steam power costs declined from 1850 to 1880, leading to increases in aggregate steam use in milling. We find these steam cost declines relatively benefited counties with less waterpower potential, which had faster growth in the number of mills and mill output. By the end of our sample, our estimated diffusion curve indicates that counties with higher waterpower potential had started to catch up. Many mills did switch from water to steam power, but the growth was driven mostly by steam powered entrants. This suggests a form of technological lock-in, observable only with our newly digitized Census data and linked establishment panel.

Steam power is the textbook example of a general purpose technology (Bresnahan and

[2]Duflo and Pande (2007); Lipscomb et al. (2013) and Severnini (2023) leverage geographic characteristics to understand how 20th century dams affect economic development.

Trajtenberg, 1995; Jovanovic and Rousseau, 2005), whose development was crucial for the Industrial Revolution (Ashton, 1948; Kuznets, 1967; Landes, 1969; Rostow, 1975). A defining feature of general purpose technologies is that they are useful across sectors, and we also find evidence of agglomeration spillovers (Stokey, 1984; Young, 1991; Irwin and Klenow, 1994; Greenstone et al., 2010). Many other sectors only mechanized with steam power, and lumber and flour mills were at the forefront of driving steam adoption in American manufacturing. We find that non-mill manufacturing establishments were more likely to adopt steam power when they were neighbors of mills, in places with less waterpower potential where mills were more likely to adopt steam power.

To quantify technological lock-in and explore counterfactual equilibrium technology transition dynamics, we develop and estimate a structural model of firm entry and steam adoption decisions (Rust et al., 1987). We use our estimated differences by county waterpower potential to identify parameters of the model, in addition to several new stylized facts about establishment-level patterns of water-use and steam adoption.

Using the model, we provide a quantitative mapping from regression coefficients and stylized facts to the costs and benefits in the technological adoption of steam power – a central technology to industrialization, and an illustrative case of prolonged technological transition. The market-level consequences from the diffusion of steam power are difficult to assess using only reduced-form micro-level regressions. The technology used by any particular mill depended on the choices made by their competitors, as well as potential entrants. The effect of a counterfactual policy to encourage technological transition, aimed at reducing switching frictions, depends on these equilibrium responses.

The model is also useful because 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. While we can model the diffusion curve directly, care must be taken interpreting the reduced-form regressions, as we estimate the effect of waterpower potential along the diffusion curve.

Firm power choices reflect a key economic force in our model: one technology had lower fixed costs and the other had lower marginal costs. In the data, steam-powered mills were larger than waterpowered mills, even within a county. 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.

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

distributions. Declining steam fixed costs is consistent with the history of steam engine use in rural US milling (Mayr, 1975; Hunter, 1985), which reflected a focus on low-cost practical innovation.

A central pattern that we try to rationalize in the model is that mill entrants were 2-3 times more likely to use steam power than incumbent waterpowered mills, despite incumbents being large establishments predisposed to benefit more from steam. There are two classes of explanations for this pattern.[3] Our explanation is there was a high cost of switching technologies. The leading alternative explanation is that 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.

The data supports switching costs as the explanation for incumbents' delayed adoption of steam power. Incumbent waterpower users did not experience faster productivity growth relative to successive generations of waterpowered entrants, suggesting little learning by doing. Qualitatively, high rates of learning-by-doing for waterpower would also be inconsistent with the longstanding use of water power in the US. We find that the frictions from switching from water to steam power were equal to about 5 months of revenue. Waterpowered incumbents were more likely to exit in counties with low water power, rather than adopt steam more like entrants, which also indicates that incumbents were more "stuck" with the old technology than content to remain in the old technology.

This raises questions about the sources of switching costs generating this technological lock-in. 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] Steam engines were more unfamiliar to rural America, however, compared to long-standing water wheels and turbines, which required an openness to new technology that was more prevalent among entrant mill owners than incumbents. Some of the switching cost reflects sunk investments in waterpower, which we estimate drives forty percent of the total switching cost.

There was substantial entry of new mills in this era, which might seemingly minimize the aggregate influence of technological lock-in, but while entrants werw forward-looking, they were still predisposed to use the old low-fixed-cost and high-marginal-cost technology when they started out young and small. These entrant firms become caught by switching costs in future periods. This pattern – that switching costs can matter even with substantial entry – is a general feature that decelerates the diffusion of new technologies that particularly benefit

[3]For related discussion of these classes of explanations, see Chari and Hopenhayn (1991); Bahk and Gort (1993); Irwin and Klenow (1994); Jovanovic and MacDonald (1994); Parente (1994) and Jovanovic and Nyarko (1996).

[4]Some waterpowered mills even used steam as an auxiliary power source (Hunter, 1985).

larger firms.

We use the model to estimate that steam would eventually reach 60% of mills by 1900, close to its steady-state, though our data stops in 1880.[5] We then use the model to estimate how waterpower potential and switching costs delayed and reduced adoption of steam power in lumber and flour mills, which were at the vanguard of adopting this general-purpose technology in American manufacturing.

Consistent with our reduced form fact, the model predicts that waterpower potential itself 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 switching costs, we estimate counterfactuals where we either completely remove switching frictions, or make them infinitely costly. We find that the presence of switching frictions substantively slowed steam adoption, as in their absence steam-use would have reached 50% of US mills 30 years earlier and been 20 percentage points greater in steady-state.[6]

Though switching costs slowed adoption, the possibility to switch was still important for aggregate switching from water to steam. In the counterfactual scenario where incumbents' face 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, despite substantial incumbent switching costs, because the entry of new firms was not a panacea for technological lock-in.

We also explore the role that entry can play in mitigating switching costs in driving the adoption of steam power. Steam adoption would have been slower if there had not been entry and exit, but we estimate that switching costs matter almost as much when there is entry/exit as when there is not entry/exit, suggesting that entry is not a panacea.

On net, we estimate that the switching costs were large enough that incumbent firms actually suffered 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 switching costs, the general equilibrium effects due to entry completely mitigate the direct benefits. However, in an alternative counterfactual with neither switching costs nor entry, incumbent firms would have been slightly better off.

Our establishment-level panel estimates complement a large literature studying long-run

[5] In 1900, electricity was not yet important for powering mills (Fenichel, 1966).

[6] Note that even in the absence of switching frictions, steam power would would not have reached its steady state level immediately, as the technology improved over time (Manuelli and Seshadri, 2014).

technology diffusion from a more aggregate perspective (Griliches, 1957; Gerschenkron, 1962; Jovanovic and Lach, 1989; Greenwood and Yorukoglu, 1997; Comin and Hobijn, 2010). The panel microdata allows us to directly measure plants changing their technologies, over an extended period of time. An important driver of steam adoption was the possibility for water users to switch, though the costs did deter some firms. This result places us between standard approaches of studying either infinite switching costs (Chari and Hopenhayn, 1991; Atkeson and Kehoe, 2007; Collard-Wexler and De Loecker, 2015) or no switching costs (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Beaudry et al., 2010; Miller et al., 2022). Our work complements research on inertia in other contexts, including consumer choice (Klemperer, 1995), occupational choice (Artuç et al., 2010), health care (Handel, 2013), and migration (Kennan and Walker, 2011). 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, Data Construction, and Stylized Facts

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). Local mills had a central role in the local economy: Mullin and Kotval (2021) notes 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." The carpentry and engineering skills required to build and maintain a watermill – including dams, wheels, and related machinery – were available in almost every community in the US. Hunter (1979, 1985) provides an overview of water and steam power in the 19th century, and we summarize a few key features of the context. See Appendix Figure A.2 for a diagram of a traditional gristmill.

The arrival of steam power provided a new source of mechanical power, particularly beneficial to places with less local waterpower potential (Rosenberg and Trajtenberg, 2004; Chernoff, 2021). These places had higher fixed costs for using water power, due to greater need for constructing dams and millponds and securing water rights.[7] By contrast, millers saw less early need for steam power when there was more local waterpower potential (Sharrer, 1982).

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-

[7] In places with less waterpower potential, mills can often use a dam to accumulate water and exploit less amenable sites. Swain (1888) reports the cost of water rights for 22 counties, which are negatively (though not significantly) correlated with our measure of waterpower potential.

power did not require a substantial transformation of mill operations. By contrast, some other technological innovations ushered in more wholesale changes in manufacturing operations, such as electricity, which does not use rotational power (Devine, 1983; David, 1990; Damron, 2023), factory cotton spinning (Juhász et al., 2023), automation (Feigenbaum and Gross, 2021), and information technologies (Brynjolfsson, 1993). The fundamental departure from steam power was in breaking the substantive dependence of mill activity on local geography and enabling mills to open in new places and expand beyond capacity constraints set by local waterpower availability.

American flour and lumber mills benefited from particular innovations in steam power through the 19th century, which enabled the expansion of steam use outside traditional manufacturing hubs. Textile manufacturing was agglomerated in major manufacturing centers, with substantial local waterpower capacity, whereas flour and lumber mills were needed locally throughout the country. Flour mills and lumber mills also required less horsepower than the large textile mills, so they could use smaller rivers and did not need large engine installations.

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. Incremental improvements in design and engineering increased system efficiency. 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. Through the early 19th century, subsequent improvements to Watt's engine increased efficiency, improving the insulation and valves and tinkering 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 lumber and flour mills throughout the US.

American lumber and flour mills focused on the practical alternative of "high-pressure" engines, patented and evangelized by Evans in the early 19th century, which did not use any 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. Watt resisted high pressure engines, partially due to this increased likelihood for explosions, but they became the dominant technology used in US mills and remained less popular in Britain where Watt had more influence. 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,

1880a).

In the second half of the 19th century, US mills began using "high-speed" engines that drew on earlier high-pressure boilers. Introduced by Porter and Allen in 1862, these high-speed engines were described contemporaneously as a "revolution in engineering" (*Scientific American*, 1870). High-speed engines were smaller and cheaper, though in early designs the parts needed to be made precisely to avoid the machine shaking dangerously and disintegrating. 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.3 for a diagram of the original Porter-Allen design.

This lower fixed cost of high-speed steam engines made them attractive to millers, though the Porter-Allen engine came without the declines in marginal costs associated with increases in the efficiency of Corliss-style steam engines. Over the second half of the 19th century, many engineers adapted and improved on the Porter-Allen design, which allowed mill owners to use steam power at steadily decreasing fixed costs. 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 who switched to steam power 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. Other switches came after fires destroyed waterpowered mills and the owners rebuilt a steam powered mill, consistent with partially non-salvageable fixed costs or other switching frictions (Hornbeck and Keniston, 2017; Huesler and Strobl, 2023).

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.

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.

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

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). 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.[8] We also exclude "seasonal" rivers that flow intermittently, which do not predict waterpower use (Appendix B).

We validate these estimates using historical records from the 1880 Census's "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 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

[8]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.

developed." For river segments covered in the historical Water Census, their flow rates are in close agreement with the modern data (Appendix Figure A.4).[9]

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.5). 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 Western sample areas (Atack et al., 1980).[10] 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 images of establishment-level manuscripts from the Census of Manufacturers in 1850, 1860, 1870, and 1880 (see Appendix Figure A.6 for example images, and Appendix Table A.4 for the coverage of manuscripts). We classify each establishment into one of 31 industries, following Hornbeck and Rotemberg (2022), using information on self-reported "name of business" and products the establishment produced.

we restrict our main analysis to counties with at least one mill in 1850 and non-missing data in each decade from 1850 to 1880. Our sample covers 722 counties, which include over 80 thousand lumber or flour mills from 1850-1880, and covers 87% of all steam-powered mills, and 90% of steam-generated sales, in the lumber and flour industries among counties with non-missing data. 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, 2022). We also use the total annual revenue for each establishment, which inform distributions of establishment sizes that are unavailable in more-aggregated data available previously. To allow for a new linked panel, 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).

[9]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 consided a river segment).

[10]Bleakley and Lin (2012) digitized the "summary tables" in the introduction of the reports; for our purposes, we digitized the "detailed tables."

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, 2022). 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, our microdata generally aligns closely with the tabulated county-level data (Appendix Figure A.7). 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" (Appendix Figure A.8). For county-industry cells above the Census tabulation threshold, our data aligns closely (Appendix Figure A.9). 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 et al., 2019), to study the transition of mechanical power from water to steam we focus on industries that had widely mechanized before steam arrived. Lumber and flour mills were the most mechanized sectors in 1850 (Figure 2). The other heavily-mechanized industry is textile mills, 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% were mechanized and used either water or steam power. Around 1% of mills used both water and steam power, which we classify as steam mills because they paid the fixed costs of steam and thereby benefited from the ability to scale relatively cheaply. Non-mechanized mills contributed little output share (Figure 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 (Hunter, 1979). Indeed, an important source of revenue for flour mills was grinding grain that customers brought themselves (Le Bris et al., 2019). Milling was dependent on local geographic endowments to generate power, but the material inputs for these mills were much less perishable (logs and whole grains) and were transported longer distances (Cronon, 2009).

Mill-specific Census schedules in 1880 asked for their installed horsepower, shown in Ap-

pendix Figure A.10: steam powered mills had slightly more horsepower than waterpowered mills, but most mills used between 10-50 horsepower. For context, Fenichel (1966) reports that, in 1880, the average steam engine had 39 horsepower and the average water wheel had 22 horsepower.

The spatial concentration of lumber and flour mills was particularly low (Appendix Figure A.11), consistent with them producing non-tradable output (Mian and Sufi, 2014).[11] Flour and lumber mills contrast with clothing and textile mills, whose output was more easily traded and so was much more concentrated geographically.[12] 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). Lumber milling remains diffused because cut lumber is prone to warping. In the 2021 County Business Patterns data, 98% of commuting zones had a lumber mill and 25% had a flour mill.

Mills had plenty of local competition. The median county/industry had 9 mills operating in a given year.[13] Over the whole sample, 94% of county/industries had multiple mills, and of those 53% had mills using both types of power, a share which increased over time as steam power became more prevalent.

I.D Data Linking

One contribution of our project is creating a linked panel of manufacturing establishments over time, allowing us to understand the forward-looking choices made by entrepreneurs. The manuscripts do not have a time-consistent identifier for each establishment, just as in the population censuses (Feigenbaum, 2016; Abramitzky et al., 2021), 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 an establishment to a different industry, we consider that a new establishment.[14] If the establishment's ownership changes entirely, with no clear link between previous and new owners, then we also consider that a new establishment. This is dictated by data availability, and also raises philosophical questions about what is an establishment. Our view is that mill owners were

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

[12] There were some cities in the early 19th century with "merchant mills" that carefully packed flour for export, especially to the Caribbean, but intranational trade in flour was rare (Kuhlmann, 1929; Cockriel et al., 2023).

[13] Because we aggregate counties to make consistent geographies, the number of operating mills per the actual administrative county/industry was slightly lower, 8.

[14] These "migrations" appear unusual for millers, based on historical society records (Appendix C).

sufficiently involved in the operation of the establishment that entire ownership changes are akin to closing its operation and selling its 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. We hand-linked all lumber and flour mills, across each decade. Two research assistants tried to find matches for each mill, and we reconciled any disagreements. In order to validate the hand-matches we trained a machine-learning algorithm to predict the matches, described in Appendix A.4. These predicted links also allow for additional analysis, allowing us to analyze robustness to different confidence thresholds (similar to the "roll-your-own" approach suggested by Ferrie 1996 for Population Census links). The matches are predictable: the ML model links are generally also made in the hand-links.

I.E Stylized Facts

Figure 7 shows steam power use from 1850 to 1880, in counties with average waterpower potential ("baseline") and counties with one standard deviation less potential ("low waterpower"). By 1850, a greater share of mills were using steam power in counties with less waterpower. This gap continued to grow through 1860. As steam power continued to improve, its use grew across higher-waterpower and lower-waterpower counties. This pattern motivates our analysis, seeking to understand what factors accelerated steam adoption in lower-waterpower counties or, alternatively, what delayed and reduced the adoption of steam power and associated industrialization.

We use our digitized Census data to document new stylized facts about these steam-powered and water-powered mills. Along with prior histories of water and steam power, these facts inform the model in Section IV. In particular, we infer variation in fixed costs and marginal costs from features of the firm size distribution across power source, decade, and county waterpower availability.

Figure 4 shows that steam-powered mills are larger than water-powered mills, on average. This suggests steam power has higher fixed costs and lower marginal costs than water power. The logic, in the spirit of Melitz (2003), is as follows. 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. Steam mills are then larger both because more-productive mills invest in steam power and because lower marginal costs encourage steam-powered mills to expand. While steam power mechanically requires fuel (coal, wood, or wood by-products from lumber mills), the difficulties in scaling waterpower effectively generate higher marginal

costs of waterpower.[15]

Over time, Figure 4 shows that the size distributions for steam and water powered mills converged. 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).

Figure 4 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 costs.

Appendix Figure A.12 shows the patterns of the size distributions of steam- and water-powered mills are similar when comparing within-counties (for counties with both types of mills). This implies that the convergence is not driven by steam power shifting activity to new locations that otherwise had mills of different sizes.

Appendix Table A.1 shows that 15-20% of mills survive, from one decade to the next.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 mills entered over the course of the previous decade.

Appendix Figure A.16 shows that surviving firms are larger than exiting firms, on average. 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.

Figure 5 shows that entrants are 3 times more likely to use steam power than water incumbents.This suggests switching frictions limit water incumbents' ability to use steam power. Switching frictions would cause only the highest-productivity water incumbents to adopt steam, while a greater share of entrants would use steam. Consistent with this logic, Appendix Figure A.14 shows that incumbents are larger than the entrants within each power technology.

[15]Consistent with this logic, Appendix Figure A.13 Panel A shows that the water incumbents who switch to steam are initially larger than those who stay with waterpower. Panel B shows that the switchers grow faster than the stayers, due to both selection and the direct effects of steam power.

Switching costs are not infinite, however, particularly as steam technology became increasingly attractive 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 precent for water incumbents (Figure 5).

Aside from switching costs, water incumbents may adopt steam less than entrants because of learning-by-doing in waterpower-use. Qualitatively, learning would seem to be a small effect because waterpower was a broadly well-known technology. Quantitatively, learning would imply that water incumbents who kept using water power would grow faster than the pace of general technological improvement. To test for this, 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.15 shows that entrants and incumbents "grow" at a similar speed, consistent with no additional internal learning boost for water incumbents.

In the next section, we report estimates that take more advantage of the geographic differences in local waterpower potential, which shifts local costs of waterpower adoption and the relative gains from steam.

II Estimating Differences by County Waterpower Potential

II.A Estimating Equations

To estimate cross-sectional effects of county waterpower potential on county outcomes, we estimate the following county-level regressions:

$$Y_c = \beta LowerWaterpower_c + \gamma X_c + \varepsilon_c. \tag{1}$$

We define $LowerWaterpower_c$ as a negative standardized measure of (log) county waterpower potential, so the coefficient β can be interpreted as the effect of having one standard deviation lower waterpower potential.

The estimated effect of $LowerWaterpower_c$ is conditional on a set of county controls X_c. Our baseline controls are: (1) total county water flow, summing over all river segments; (2) county ruggedness, defined as the standard deviation in county elevation;[16] (3) whether the county has navigable waterways, distance to the nearest navigable waterway, and county market access in 1850 (Hornbeck and Rotemberg, 2022); and (4) whether there are coal deposits in the county and the share of county area with coal deposits (Campbell, 1908). When we estimate pooled-cross sectional regressions, we additionally include year fixed effects, and estimate the effects of the controls separately for each year. Note that when we

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

estimate cross-sectional differences in 1850, this effectively captures the growth in steam use from Independence.

The key identifying variation comes from the interaction of river flow rates and fall heights. 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 water power and steam. 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 (Nunn and Puga, 2012), along with access to markets (Redding and Venables, 2004; Donaldson and Hornbeck, 2016) and access to coal.

Our main sample is a balanced panel of counties, from 1850 to 1880, restricting our analysis to counties with at least one lumber or flour mill in 1850. Figure 3 Panel B shows the residual waterpower potential of the counties in our sample after partialling out the baseline controls.[17]

To estimate changes over time in counties with lower waterpower potential, as steam technology improved, we estimate the following panel regressions:

$$Y_{ct} = \beta_t LowerWaterpower_c + \gamma_t X_c + \alpha_c + \gamma_t + \varepsilon_{ct}. \tag{2}$$

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, so rows labeled "From 1850 to 1860" include 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 fixed effects (α_c), year fixed effects (γ_t), and interact our baseline control variables with year dummies.

For these 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, ruggedness, navigable rivers and market access, coal deposits). Appendix X reports similar estimates without controls, with a subset of the baseline controls, or with additional controls to account for other factors that might be associated with differential steam adoption and mill activity across counties with different waterpower potential.

[17]The Appalachia region generally has higher waterpower potential and in A.3 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. This includes the number of lumber and flour mills and their annual sales, by power source, along with steam adoption rates. We also examine these outcomes separately for entrants and incumbents, which is informative about the role of switching costs 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 we for these outcomes estimate Equation 2 using OLS. Shares are undefined when there are no mills, so we omit the county if it has no mills in one of the relevant decades. For regressions considering the share of establishments using steam, we weight counties by their number of establishments 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 the elasticity with respect to waterpower potential. There are a few zeros in the sample, for counties 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.[18]

We report robust standard errors clustered by county. We also report standard errors that adjust for spatial correlation across counties, assuming that spatial correlation declines linearly up to an assumed distance cutoff and is zero thereafter (Conley, 1999). Mill activity serves largely local markets, though waterpower potential is more correlated across nearby counties, and we estimate standard errors that are XXX compared to our baseline estimates for distance cutoffs of 100, 200, and 300 miles.

II.B Waterpower Potential, Power-use, and Mill Growth

Table 2, Panel A, reports there were substantially fewer waterpowered mills in 1850 in counties with one standard deviation less waterpower potential. There is also less revenue in 1850 (Panel B), where coefficients of -1.4 and -1.1 correspond to 75% and 66% declines in the number of mills and revenue (Column 1). By contrast, the share of mills using steam power is 8.2 percentage points higher in lower waterpower counties in 1850 (Panel C).

[18]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.

Column 1 reports impacts of lower waterpower potential, controlling only for total water flow and ruggedness, so the identifying variation comes from the interaction of water flow and elevation changes. Water flow and ruggedness generally increase waterpower-use and decrease steam-use, if we omit waterpower potential from the specification (Column 2), but not when controlling for waterpower potential (Column 1). Columns 3 and 4 report similar estimates, including all baseline controls, and Column 3 reflects our primary specification.

We focus on this linear specification, as the estimated impacts of waterpower potential are roughly linear for the number of water mills in 1850 (Appendix Figure A.5) and later changes in the total number of mills A.20. To show the importance of using our geographically comprehensive measurement of waterpower potential, panel B of Appendix Figure A.5 shows a smaller estimated impact of waterpower potential on waterpower-use, when using only data available in the 1880 Water Census, because the Water Census selectively omitted places with lower waterpower potential and lower waterpower-use, naturally biasing estimates toward zero.

Waterpower potential making waterpower use more attractive implies that it lowers 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 6 shows this was not the case, so we model waterpower potential as lowering fixed costs of waterpower (consistent waterpower potential lowering the costs of securing water rights and constructing dams and millponds).

By 1850, steam-use had become more common in counties with lower waterpower potential (Table 2). From 1850 to 1860, steam use continued to grow faster in those counties (Table 3). From 1850 to 1860, the share of mills using steam power increased 6 percentage points more in counties with one standard deviation lower waterpower potential. There was no difference in relative changes from 1860 to 1870; and from 1870 to 1880 steam adoption began to catch up in higher waterpower potential counties by 3 percentage points. These regression estimates reflect the same pattern as Figure 7, which showed earlier steam adoption in lower waterpower potential counties and some subsequent catch-up in adoption as steam-use diffused further.

Table 3 also reports substantial growth in the total number of mills (column 2) and total revenue (column 3) in counties with less waterpower potential. The number of establishments increased by 26%, from 1850 to 1860. Growth was largest in this period, as steam use increased further, but also continued even as higher waterpower counties became later adopters of steam power by 1880. Continued growth from early adoption of steam is suggestive of agglomeration, which we later explore more directly.

Counties with lower waterpower potential also experienced faster population growth during this period by 6-12 percent a decade. Population growth is an endogenous outcome, but lower waterpower counties also experienced strong growth in mill activity on a per capita basis: Appendix Table A.2 shows that our estimates from Table 3 are smaller, though still substantial, when considering per capita growth in establishments and revenue.

Table 4 shows this growth in lower waterpower counties was driven by entrant firms. The entry rate was 38% higher in lower waterpower counties, from 1850 to 1860, while the firm survival rate was 21% lower. In each period, entrants crowded-out local incumbent firms, which exited at higher rates in lower waterpower counties despite the substantial overall growth in these counties.

Entrant firms also drove the greater adoption of steam power in lower waterpower potential counties. Table 5 reports that entrants were 17.4 percentage points more likely to be using steam power in lower waterpower counties relative to entrants in higher waterpower counties in 1860 (Column 1). The overall increase steam use in lower waterpower potential counties was then driven by: (1) more entrants in lower waterpower potential counties (Table 4); (2) entrants were more likely to adopt steam than water incumbents, in general (Figure 5); and (3) entrants were even more likely to adopt steam in lower waterpower counties (Table 5).

Lower waterpower also led water incumbents to be 6.8 percentage points more likely to switch to steam in 1860, 4.4 percentage points in 1870, and an insignificant 2.6 percentage points in 1880 (Table 5, Column 2). Still, steam choices of entrants were substantially more responsive than those of water incumbents (Column 3). Water incumbents' lower switching probabilities, combined with the increased exit of incumbents from Table 4, suggest that incumbent firms were subject to switching costs. Steam decisions of entrants are a useful contrast, as entrant firms started with a clean slate.

We show our results are robust to a wide variety of additional specification and control variables in Appendix Table A.3.

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

While our main analysis focuses on steam adoption by lumber and flour mills, who were early users of steam power despite delays from waterpower availability, steam-use also spread across sectors over the second half the nineteenth centuries. Steam power is the classic example of a general purpose technology, whose increasing use spurred industrialization.

A natural hypothesis is that early use of steam power in lumber and flour mills, across many parts of the country, encouraged nearby steam adoption in other sectors. Delayed steam adoption by some mills, due to higher waterpower availability, might have then held

back steam adoption in local manufacturing more broadly.

Qualitatively, it seems plausible that local steam-use could have spillover impacts on other firms. 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 explore spillover effects in adoption of this general purpose technology, and the importance of social learning, we study the role of neighbors as in Foster and Rosenzweig (1995); Conley and Udry (2010) and Juhász et al. (2023). 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," 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 spillover analysis, when most lumber and flour mills 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: lumber and flour mills are more likely to use steam in lower waterpower counties. We compare mill neighbors' steam adoption in counties with lower waterpower, relative to mill neighbors' steam adoption in counties with higher waterpower. We also study how waterpower potential affected steam use of factories without mills for neighbors, in order to measure direct effects of waterpower potential.

Because there was not much waterpower-use in non-mills (Figure 2), it is plausible that county waterpower availability does not directly affect non-mills' water use – and we can explore this directly by estimating equation 1, for each sector. Appendix Figure A.21 reports impacts of lower county waterpower potential on the share of establishments using waterpower. Lumber and flour are by far the most responsive sectors. For our spillovers regressions, we show robustness to excluding the other sectors whose waterpower use varies moderately with county waterpower potential (leather, paper, liquor and beverages, iron and steel, and textiles).

To measure spillovers, we extend our previous estimating equation 1 to the establishment-

level, and include industry-year fixed effects:

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

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 if its county has one standard deviation lower waterpower potential. We include industry-year fixed effects α_{it}, which adjust for time-varying cross-industry differences in steam shares, and include our baseline controls with standard errors clustered at the county level.

Table 6, Column 1, reports that steam-use is 1.4 percentage points higher for neighbors of mills in counties with lower waterpower potential. By contrast, there is little difference in steam-use of non-neighbors (Column 2), consistent with little direct effect of county waterpower potential on non-mills' use of waterpower. Column 3 reports the difference in these estimates.

Panel B reports estimates omitting sectors with the largest observed response of waterpower use to county waterpower potential. These estimates are fairly similar. While the model we describe in Section III considers only milling, it is important to keep in mind the speed of diffusion of steam power in milling affected the entire economy.

III Quantitative Model of Steam Adoption with Switching Costs

It is difficult to interpret the estimates jointly – the differences by waterpower potential and the stylized facts – with only economic intuition. One main purpose of the model is to collect and interpret the magnitudes of these different relationships. Further, using these estimates, we can explore how switching costs and firm entry matter for overall steam adoption.

We develop a quantitative model of technology adoption and firm entry in a composite milling sector, whose features are guided by the stylized facts and reduced-form effects of waterpower potential. In the model, firms face a dynamic choice of whether to adopt steam or waterpower technology. 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 fixed cost of adopting steam power is falling over time, which encourages firms to wait to adopt steam power, though the cost of switching from water to steam power encourages firms to enter using steam.

In Section III.A, we characterize the firm's static production problem taking the power choice and entry decision as given. In Section III.B, we characterize the firm's dynamic decisions over power adoption and entry. In Section III.C, we describe the driving force for technological transition: the improvement of steam power during American industrialization.

III.A Static Choices: Production and Demand

Each firm j in region c in year t maximizes its static profit by choosing its optimal level of inputs L 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. 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 L (labor, materials, and mill capital other than power source):

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

Firm Hicks-neutral productivity is determined by its 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.

Given power choices, by firm j and other local firms, firm j's price, output, and profits are:

$$p_{jct}(R) = \frac{\epsilon}{\epsilon - 1} \frac{w}{\exp(\varphi_{jct} + \gamma_{jct} + \alpha_{jct} s_{ct})}, \tag{5}$$

$$y_{jct}(R) = {P_{ct}}^{\epsilon-\eta} \left(\frac{\epsilon}{\epsilon - 1} \frac{w}{\exp(\varphi_{jct} + \gamma_{jct} + \alpha_{jct} s_{ct})} \right)^{-\epsilon}, \tag{6}$$

$$\pi_{jct}(R) = \frac{1}{\epsilon} {P_{ct}}^{\epsilon-\eta} \left(\frac{\epsilon}{\epsilon - 1} \frac{w}{\exp(\varphi_{jct} + \gamma_{jct} + \alpha_{jct} s_{ct})} \right)^{1-\epsilon}. \tag{7}$$

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

III.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 productivity and fixed operating cost. In Stage 4, surviving firms select their optimal power source. After these four stages, firms produce and then the cycle starts again. For the initial stages, we consider the possible power sources to be W, S, or E (for entrant), where E implies no ability to

produce and a need to purchase access to water or steam power.

Stage 1: Entry. A prospective firm enters in region l in year t if and only if its expected continuation value upon entry is greater than or equal to the fixed cost of entry:

$$\mathbb{E}_{\varphi}\left[V_{ct}(E,\varphi)\right] - f^{e} \geq 0, \tag{8}$$

where $V_{ct}(E,\varphi)$ is the continuation value for an entrant (who still needs to invest in either water or steam power to produce).

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. Firm j has to pay an operating cost $f^{R}+\nu^{R}_{jct}$, given its power source $R \in \{E,W,S\}$. The cost f^{R} is common across all firms of type R and the cost ν^{R}_{jct} is idiosyncratic. 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 and $\nu^{R}_{jct}(0)$ is idiosyncratic operating cost if the firm continues its operation. If instead the firm chooses to exit, it receives a resale value Ω^{R}_{ct} and pays an idiosyncratic closing cost $\nu^{R}_{jct}(1)$.

Stage 4: Choosing a Power Source. 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, for a given power technology R and productivity φ, is:

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

$\pi_{ct}(R,\varphi)$ is the firm's static profit from equation (7), δ is the discount factor, and $\mathbb{E}_{\varphi'}\left[V_{lt+1}(R',\varphi')\right]$ is the expected continuation value given changes in productivity from 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' in region l in year t.

III.C The Arrival of Steam

We assume that the only primitive difference across regions is the cost of waterpower. We also assume the economy was in a steady-state prior to the arrival of steam.

We model the arrival of steam power as an unexpected fall in its fixed adoption cost $c_t(E, S)$. When steam is introduced, and its price declines, mill activity in regions then endogenously responds differently due to differences in the cost of waterpower. We assume that water technology is comparatively unchanged over this time period, as it was a mature technology and horsepower per waterwheel was largely stable over time (Rosenberg and Trajtenberg, 2004).

The Census of Manufacturers was professionalized and comprehensive beginning in 1850 Atack and Bateman (1999), which is after the first introduction of steam power. We cannot use 1850 as the steady-state before steam power; instead, we start the model simulations in 1830, when there were few steam engines in use in milling (Treasury Department, 1838), and estimate the model to match steam diffusion from 1850 to 1880. We assume that steam power S becomes available at a prohibitively high cost in period T_0 (1830) and its fixed adoption cost monotonically declined until it reached its steady state price. We assume that firms have perfect foresight after period T_0.

III.D 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 D.

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:*

$$\frac{d}{dc^W_c}\mathbb{P}^E_{ct}(S) > \frac{d}{dc^W_c}\mathbb{P}^I_{ct}(S) > 0 \tag{12}$$

Argument. Higher costs of water affect steam adoption among incumbents by: (1) making steam power a comparably cheaper technology (a *technology costs* effect); (2) strengthening the selection of operating mills (a *productivity selection* effect); (3) weakening the competition in local product markets (a *competition* effect). All three effects lead to more steam use in places with higher water costs, which is what we find in Table 3 Panel A.

Incumbents differ from entrants due to switching frictions, which makes their steam adoption decision less responsive to the cost of waterpower (as we find in Table 5). If the fixed costs of steam fell to very low values (e.g., zero), then entrants everywhere would adopt steam at very high rates (e.g., 100%), so the only differences in steam adoption would come from incumbents. Table 5 reports large estimated differences in entrant adoption rates, however, which are consistent with steam power not being an obviously dominant technology across all counties during our sample period. □

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

$$\frac{d}{dc_c^W}\Delta \log N_{ct}^{E} > \frac{d}{dc_c^W}\Delta \log N_{ct} > 0 \tag{13}$$

Argument. The increase in steam-powered mills in places with higher water costs offsets higher exit of water-powered mills, so total establishments and total revenue grows faster in places with less waterpower due to greater entry (as in Tables 3). □

Prediction 3 (Switching costs determine whether incumbents are crowded-out in regions 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:*

$$\frac{d}{dc_c^W}\mathbb{S}_{ct} \gtrless 0 \tag{14}$$

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 raise survival rates) but intensifies local competition from new entrants (which lowers survival rates). When switching costs are high, water incumbents cannot access steam power and the negative competition effect will dominate. When switching costs are low, then incumbents benefit in places with high water costs. Table 4 reports that incumbents are crowded-out, on net, which suggests large switching costs. □

III.E Parametric Assumptions

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

$$\nu^R_{jct}(\text{OPERATE/EXIT}) \overset{\text{iid}}{\sim} GEV1(\rho^R_o) \tag{15}$$

$$\varepsilon_{jct}(R) \overset{\text{iid}}{\sim} GEV1(\rho). \tag{16}$$

The productivity innovations are drawn from a standard-normal distribution

$$\xi_{jt} \overset{\text{iid}}{\sim} \mathcal{N}(0,1), \tag{17}$$

which implies that entrants draw their productivities from the normal distribution

$$\varphi_{jct} \sim \mathcal{N}\left(0, \frac{\sigma^2}{(1-\pi)^2}\right). \tag{18}$$

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

$$\Omega^R_{ct} = \omega c_{ct}(R). \tag{19}$$

For a mill using technology R, the cost of technology R' can be decomposed into a switching friction, the resale value, and the cost of the new technology:

$$c_{ct}(R,R') = \begin{cases} 0 & \text{if } R = R' \\ c_{ct}(R') & \text{if } R = E \\ c^r(R,R') - \omega^R c_{ct}(R) + c_{ct}(R') & \text{otherwise.} \end{cases} \tag{20}$$

Mills keeping their existing technology do not pay any further costs. Mills purchasing technology R' have to pay a fixed cost $c_{ct}(R')$. Switchers face two additional forces. First, due to partial irreversibility (if $\omega < 1$), the returns to investing in a new technology are lower for incumbents, who have access to a power source whose full value they cannot recoup on the market (Bertola and Caballero, 1994; Ramey and Shapiro, 2001; Baley and Blanco, 2022). Second, incumbents face a switching friction to change power sources, $c^r(R,R')$, which captures the literal costs of retrofitting as well as other frictions that make it difficult for enterprises to adopt new technologies (Holmes et al., 2012; Atkin et al., 2017).

One potential source of switching frictions is location. Watermills were located on advantageous places along the river, which may not have been close to local demand or cheap access to fuel. Indeed, Appendix C discusses some examples of millers physically changing location (within a county) when switching from water to steam power.

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

$$c_t(S) = c_S^{(floor)} + (c_S^{(origin)} - c_S^{(floor)}) \exp\left(-c_S^{(slope)}\,(t - T_0)\right), \tag{21}$$

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 does not vary over time. The fixed cost of adopting waterpower is discretely higher in counties with low waterpower potential:

$$c_l(W) = c(W) + c_{\mathbb{1}\text{(Low Water Power)}}. \tag{22}$$

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

$$\mathbb{E}_\nu[V_{ct}(R,\varphi)] = \rho_o^R \log\left[\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right) + \exp\left(\frac{\mathbb{E}_\varepsilon\left[V_{ct}^o(R,\varphi')\right] - f^R}{\rho_o^R}\right)\right], \tag{23}$$

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

$$\mathbb{E}_\varepsilon[V_{ct}^o(R,\varphi)] = \rho \log\left[\sum_{R'\in\{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R,R') + \pi_{ct}(R',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{lt+1}(R',\varphi')]\right)\right]. \tag{24}$$

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

$$\Pr_{ct}\left(\text{OPERATE/EXIT}|R,\varphi\right) = \frac{\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right)}{\exp\left(\frac{\Omega_{ct}^R}{\rho_o^R}\right) + \exp\left(\frac{\mathbb{E}_\varepsilon[V_{ct}^o(R,\varphi')] - f^R}{\rho_o^R}\right)}. \tag{25}$$

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

$$\Pr_{ct}\left(R'|R,\varphi\right) = \frac{\exp\left(\frac{1}{\rho}(-c_{ct}(R,R') + \pi_{ct}(R',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{lt+1}(R',\varphi')])\right)}{\sum_{R''\in\{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R,R'') + \pi_{ct}(R'',\varphi) + \delta\mathbb{E}_{\varphi'}[V_{lt+1}(R'',\varphi')])\right)}. \tag{26}$$

IV Structural Estimation

In this section we describe the quantification of the model developed in Section III. In the model, we consider two regions, a baseline region with the average amount of waterpower in the United States, and a "low power" region with one standard deviation less waterpower.

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 IV.A we describe the key moments that we use to estimate the model, and in Section IV.A.1 we describe how we calculate the moments in the data. In Section IV.B we describe our parameter estimates. In Section IV.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 regions, where the *only* modeled difference across the regions is the cost of adopting waterpower.

IV.A Estimation Strategy

Our goal is to match the diffusion of waterpower for the baseline economy, which reflects the characteristics of the average county. In this section, we describe the set of structural parameters and the target moments used for estimation. Broadly, the moments that we target are a mix of estimates within and between counties, exploiting geographic variation in waterpower potential. We estimate the parameters simultaneously using the method of simulated moments (MSM).

IV.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 waterpower potential and the baseline controls:

$$Y_{ct} = \beta_t W_c + \Gamma_t' X_{ct} + U_{ct}, \tag{27}$$

where W_c is the waterpower potential of county c and X_{ct} includes ruggedness, total water flow, navigable rivers, and initial market access, as in Equation 2.

The moment we then match is the predicted outcome for the average county, $\overline{Y}_t$:

$$\overline{Y}_t \equiv \hat{\beta}_t \mathbb{E}[W_c] + \hat{\Gamma}_t' \mathbb{E}[X_{ct}]. \tag{28}$$

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 one of the moments, which we discuss below.

Steam productivity. If steam is more productive, so the steam productivity parameter γ_S 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 4, to help estimate γ. The estimation of γ exemplifies of 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 5. Similarly, increasing $c(W)$ makes operating less attractive, and is pinned down by the zero profit condition, given the other parameters in the model. $c(W)$ is estimated by the share of entrants who choose waterpower minus the (unobserved) share of entrants who decide not to operate.

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.16. The overlap coefficient of two distributions is the overlapping area of their histograms.[19]

Power out-switching costs. As with the power adoption 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 (26) and use the (within-county) difference in adoption shares for entrants versus incumbents, as in Figure 5:

[19]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.

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

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 Figure 5.

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.1, 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 doesthe 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 of log sales between firms that survive to the next decade and those that exit within each county, as in Figure A.16.

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 levelo help estimate the AR(1) dispersion parameter σ, we use the standard deviation of log sales within each county.

IV.A.2 Across-Region Moments

We match three moments that are generated by comparing low to high waterpower places.

Costs of Waterpower and Waterpower potential. The additional fixed cost of waterpower in low waterpower potential places, $c_{\mathbb{1}(\text{Low Water Power})}$, lowers the attractiveness of using waterpower. 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. To estimate ϵ and η, the elasticities of demand within milling and between milling and other sectors, we use measures of sales and other features of the model that predict the productivity advantages of steam. ϵ relates how model-predicted cost ad-

vantages between firms affect their local market shares in the product market. η relates how differences in model-predicted sectoral prices (given ϵ) leads to differences in total output across low and high waterpower places.

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 moment we use to that end is the relative growth rates of low and high waterpower potential places, as in Table 3.

IV.A.3 Connecting Model and Evidence

We aim to test how well our structural model can rationalize the observed empirical patterns across baseline and low waterpower regions based on the assumption that the only fundamental difference between the regions is the fixed costs of adopting water.

To this end, we estimate the counterfactual moments that the average economy would have had if its waterpower potential was one standard deviation lower than it actually was. Using equation (27), we can express this counterfactual moment as

$$\widetilde{Y}_t \equiv \mathbb{E}[Y_{ct}|W_c = \mathbb{E}[W_c] - 1, X_c = \mathbb{E}[X_{ct}]] = \beta_t(\mathbb{E}[W_c] - 1) + \Gamma_t'\mathbb{E}[X_{ct}], \tag{30}$$

which can be estimated consistently with $\hat{\beta}_t(\mathbb{E}[W_c] - 1) + \hat{\Gamma}_t{}'\mathbb{E}[X_{ct}]$.[20]

We proceed in three steps to calibrate the model and generate the model-predicted moments in regions with lower waterpower potential. First, we estimate the structural parameters using the structural moments of the baseline economy. Second, we calibrate the fixed cost of adopting water in the low waterpower county to exactly match the observed difference in adoption rates between low and baseline waterpower counties. The fixed cost of waterpower is the only parameter we allow to vary across regions in the model. Finally, we simulate the model using structural parameters obtained from step 1, except for the water adoption costs, which are obtained from the second step.

IV.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:

[20]The target can be expressed in a potential outcome framework as $\widetilde{Y}_t \equiv \mathbb{E}[Y_{ct}(1)]$, where $Y_{ct}(1)$ denotes the potential moment of county c in year t if its waterpower is one standard deviation lower than the average waterpower of the economy. It is identified under the assumption that the potential moments $\{Y_{ct}(1), Y_{ct}(0)\}$ are independent of waterpower potential W_c conditional on X_{ct}.

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 switching friction 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 those of waterpower, consistent with the qualitative evidence that steam engines required more upkeep.

IV.C Model Validation

In order to validate the model, we compare the model's predictions for the evolution of milling in the average county versus one with low watpower potential. While in the data it is possible that changes in waterpower are correlated with other features, in the model we add the estimated $c_{\mathbb{1}\,(\text{Low Water Power})}$ to the cost of adopting waterpower and leave all of the other estimated parameters the same. This will mechanically match the average difference in the share of plants using waterpower between the baseline and counterfactual "low waterpower" region, so the validation of the model comes from matching the decade-to-decade pattern in adoption, as well as differences in other outcomes.

The counterfactual results are in Figure 7. Panel A shows that the model closely matches the diffusion of steam in the data for regions with one-standard deviation less waterpower potential than the baseline.[21] Low 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.

V 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 IV. We use the

[21] It is worth noting that the gap between low and baseline places in the data is neither constant in levels nor in shares.

model to quantify the complementarity between removing switching costs and entry/exit.

V.A Switching Costs and Entry

For the diffusion of steam power, the removal of switching costs substitutes for entry and exit in equilibrium, as switchers crowd out entrants who could use the new technology. In order to quantify these forces, in Figure 8 we show counterfactuals from changing the environment. In aggregate, removing switching frictions 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.[22] Much of this increase is immediate: the share of mills using steam would have counterfactually been double in 1850 in the absence of switching frictions.

Figure 8 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 out 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.

Counterfacutally removing water lock-in increases output by around a further 20 percentage points in both the baseline and low waterpower regions. However, this is particularly bad for incumbents. 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 friction), 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 regions), 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 regions).

While incumbent switching on its own could not generate the output gains from the diffusion of steam power, it still was important. Figure 9 shows the counterfactual effects

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

of introducing infinite switching frictions. We find that by 1900 steam penetration would only have been around half its observed date, with very slow diffusion. While we do find substantively important switching costs in our environment, a model which assumed prohibitive switching frictions would be missing a quantitatively important source of technology adoption.

VI Discussion

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 substantive dependence mechanized power had 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 incumbent 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.

In order 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 switching frictions, 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 frictions 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 & 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 productive mills who had already invested in waterpower were therefore "stuck." It is not a first-order principle that this is the pattern for new technologies: others may instead have low fixed cost high and marginal costs. We believe 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

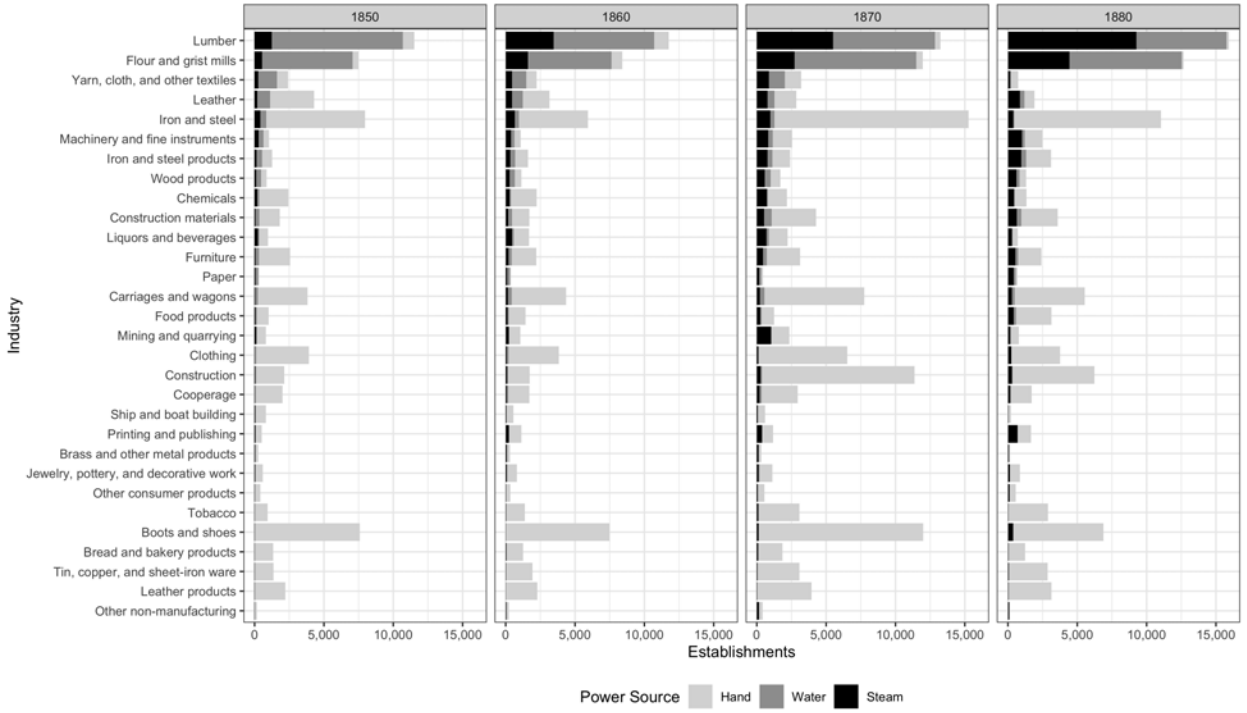
(a) Flow Rates

(b) Fall Heights

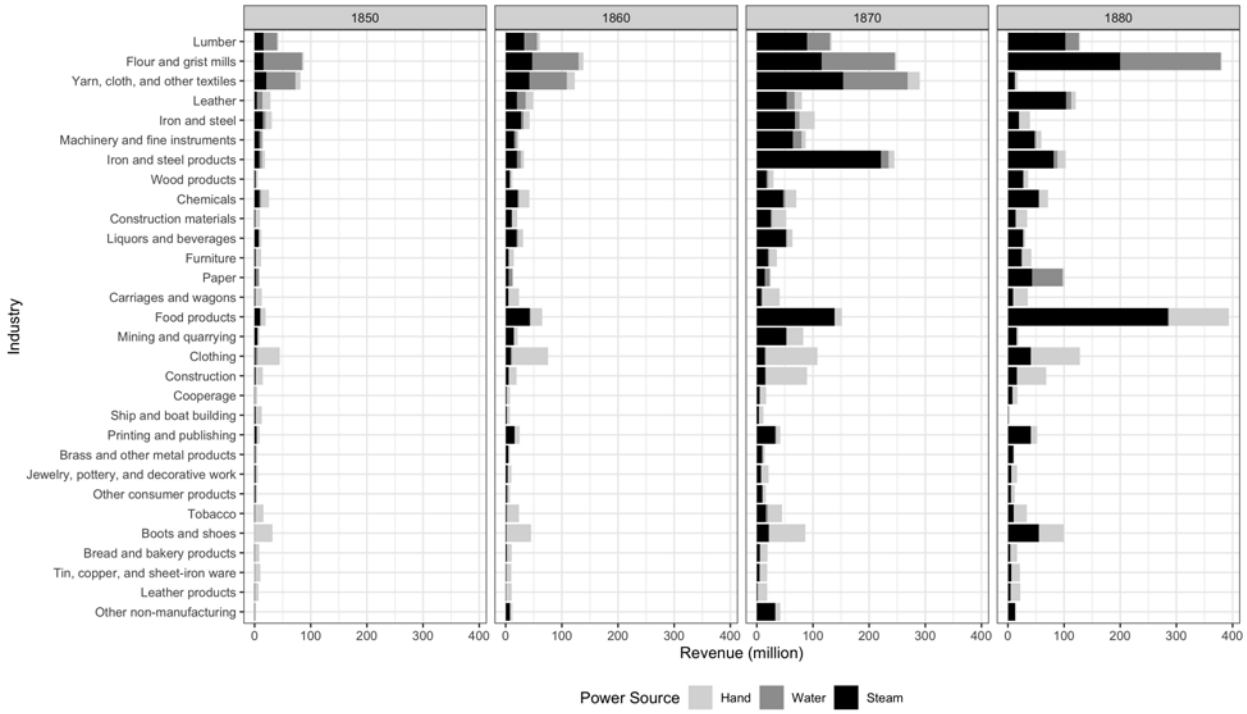
Notes: This figure plots the sources of waterpower potential in the United States. Panel A plots our measure of estimated historical flowrates (in cubic feet per second), Panel B shows elevation change (in feet). Data from NHDPlusV2.

Figure 2: Power Use By Sector

(a) Establishments



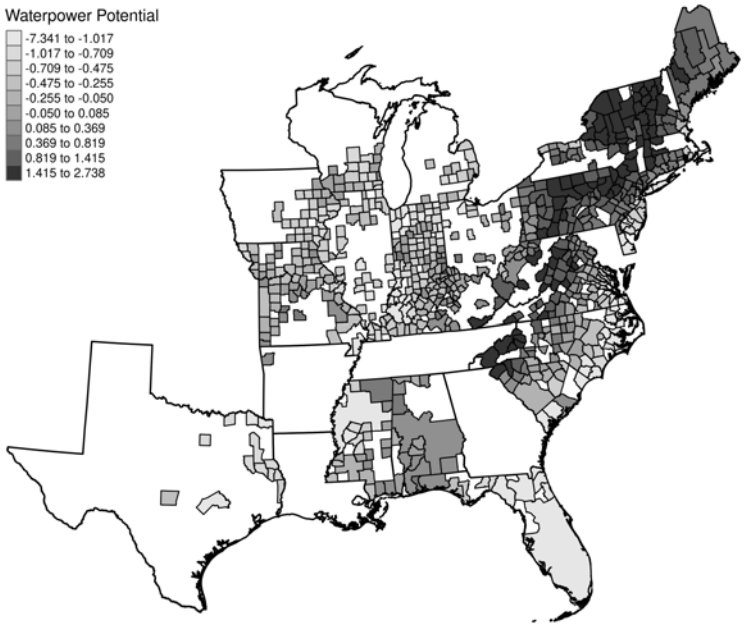
(b) Output



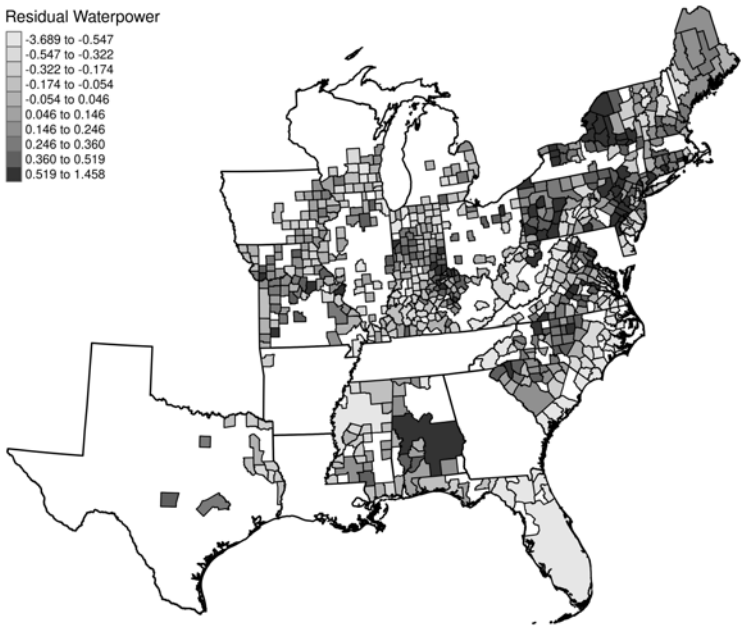
Notes: This figure plots the penetration of mechanization across industries in the United States, 1850-1880. Panel A plots the share of establishments in each sector using water, steam, or hand power, Panel B plots the share of output coming from each type of firm. Industries are sorted in decreasing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

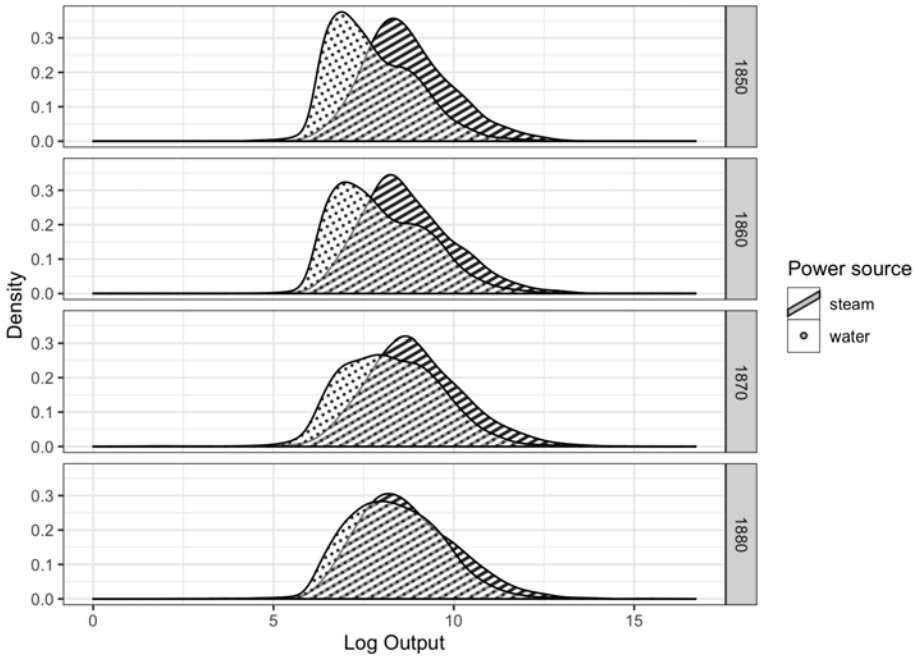


(b) Residual Waterpower Potential



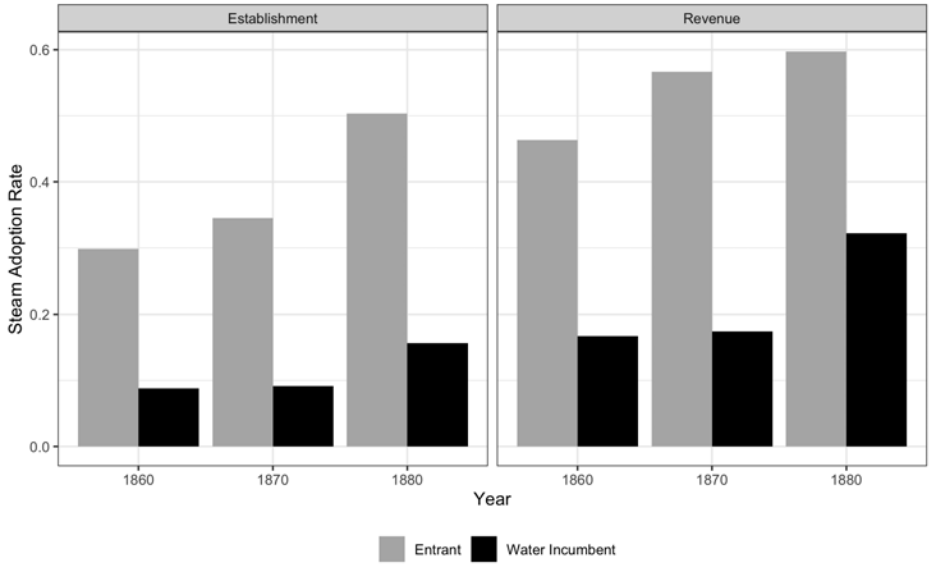
Notes: This figure plots waterpower potential for the counties with a flour or lumber mill in 1850 (which is the regression sample in the paper). Panel A plots raw Waterpower potential, the sum across all rivers in the county of the flow rate times the fall height (times a gravitational constant). Panel 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: Mill Size by Power Source



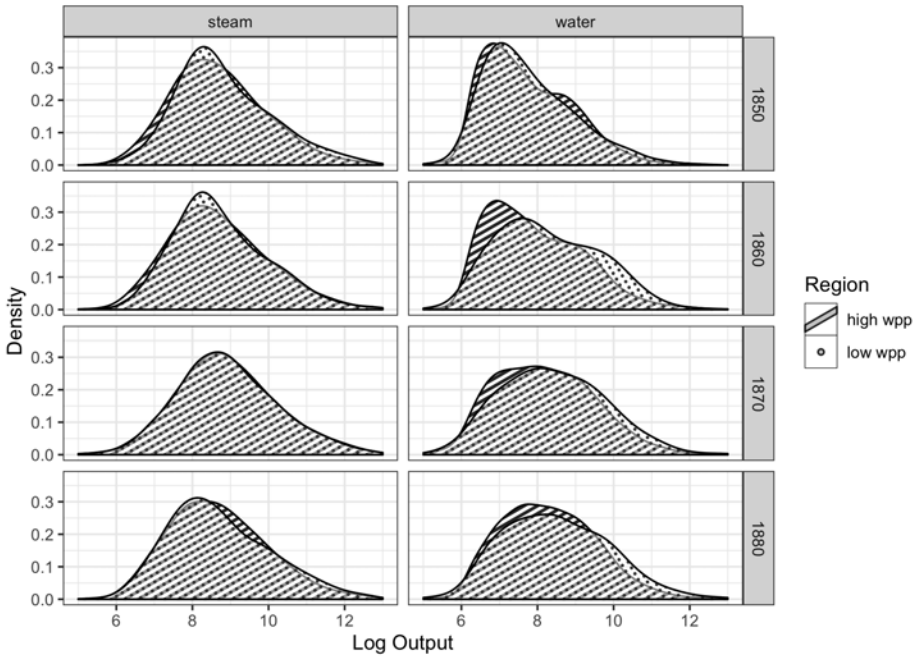
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water). The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880 Census of Manufacturers.

Figure 5: Power Sources for Entrants and Water Incumbents



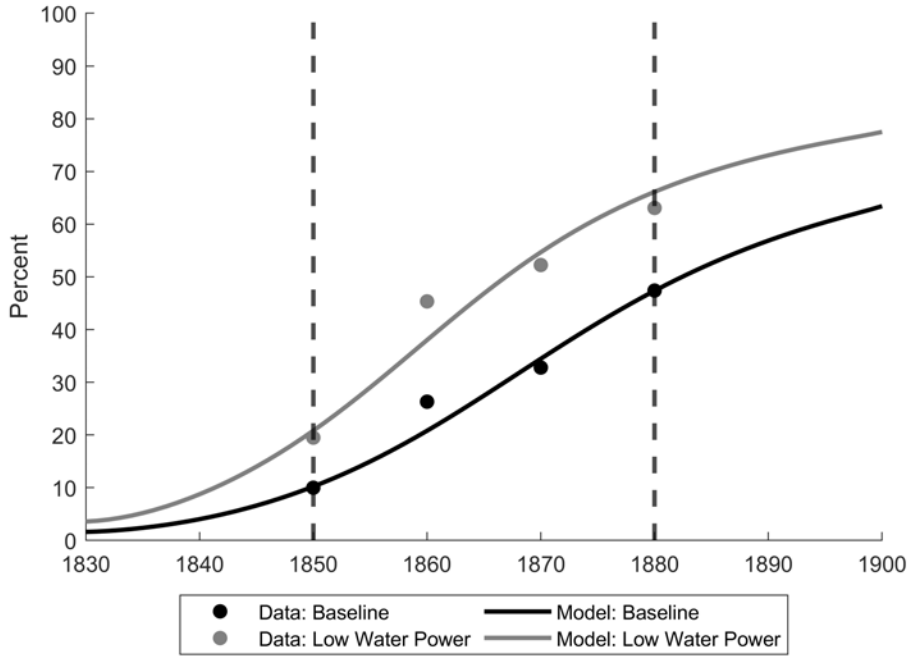
Notes: This figure plots the share of entrants and water incumbents (plants who used waterpower in the previous decade) currently using steam power. Panel A shows the share of establishments, Panel B weights by current output. The sample is all counties in the baseline sample (those that had at least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

Figure 6: Mill Size by Waterpower Potential



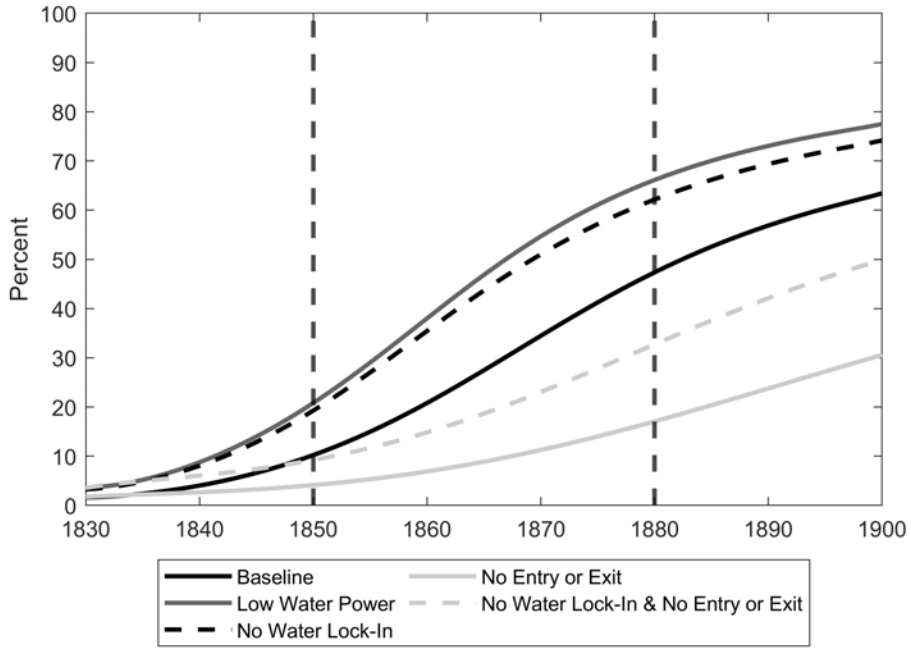
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water), separately by places above and below median waterpower potential. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1850-1880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

Figure 7: Observered and Model Estimates for Steam Power Diffusion



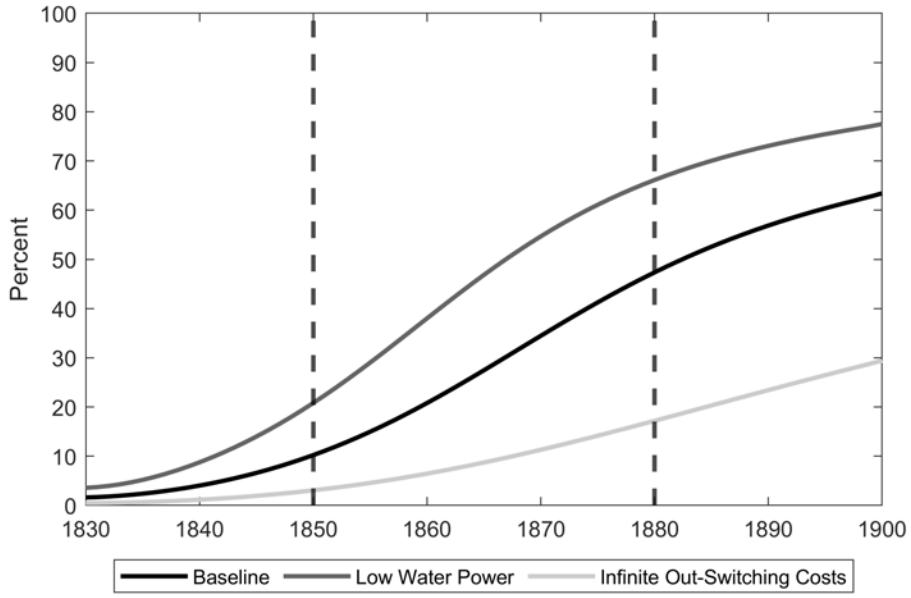
Notes: This figure plots the share of steam users in the average county and the typical county with one standard deviation less waterpower potential (in dots), as described in text. The lines are the model estimates for the diffusion of waterpower potential, where (for the parameters) the only difference between 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 8: 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 7), 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 9: 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 7), 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 Manufacturing			Share of Total Manufacturing				
	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	0.89	0.05	0.07	0.23	0.55	0.02	0.02	0.18
1860-1870	0.88	0.08	0.04	0.29	0.55	0.03	0.01	0.12
1870-1880	0.84	0.11	0.05	0.40	0.39	0.06	0.02	0.12
Panel B. Revenue								
1850-1860	0.86	0.07	0.08	0.36	0.42	0.03	0.03	0.16
1860-1870	0.83	0.12	0.04	0.45	0.35	0.07	0.02	0.10
1870-1880	0.76	0.16	0.08	0.45	0.30	0.10	0.05	0.10

Notes: This table shows, in the left Panel, the share of steam-using mills who are entrants, steam incumbents, or water incumbents. The right panel shows the share of total production coming from steam and water entrants, steam incumbents, or water incumbent stayers and switchers. The sample is counties with at least one mill in 1850. Data from the 1850-1880 Census of Manufacturers.

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

	(1)	(2)	(3)	(4)
Panel A. Number of Waterpowered Mills				
Lower Waterpower	-1.398		-1.257	
	(0.099)		(0.122)	
Total Water Flow	-0.256	0.350	-0.196	0.329
	(0.075)	(0.089)	(0.077)	(0.068)
Ruggedness	-0.419	0.296	-0.322	0.335
	(0.078)	(0.081)	(0.077)	(0.072)
Panel B. Total Revenue				
Lower Waterpower	-1.108		-0.869	
	(0.164)		(0.232)	
Total Water Flow	-0.344	0.123	-0.219	0.132
	(0.102)	(0.084)	(0.108)	(0.064)
Ruggedness	-0.562	0.088	-0.388	0.145
	(0.088)	(0.089)	(0.114)	(0.084)
Panel C. Steam Share of Establishments				
Lower Waterpower	0.082		0.084	
	(0.012)		(0.012)	
Total Water Flow	-0.014	-0.056	-0.008	-0.049
	(0.016)	(0.012)	(0.014)	(0.010)
Ruggedness	0.004	-0.039	0.007	-0.038
	(0.007)	(0.007)	(0.008)	(0.007)
Baseline Controls	No	No	Yes	Yes
# Counties	718	718	718	718

Notes: This table shows the relationship between 1850 milling and flow rates, fall heights, and waterpower potential. Panel A shows the number of mills using water, Panel B shows the total number of mills, and Panel C shows the share of mills using steam power. The sample is all counties with at least one mill in 1850, and Panels A and B using (pseudo) Poisson maximum likelihood estimation. "Lower Waterpower" is the negative standardized measure of county waterpower potential (as described in the text). Regressions whose outcome is the share of firms using steam are weighted by the number of mills in the county in 1850. Each observation is a county in 1850. 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 Establishments (1)	Total Establishments (2)	Total Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.061	0.263	0.161
	(0.016)	(0.067)	(0.050)
# Counties	676	718	718
From 1860 to 1870	0.004	0.160	0.147
	(0.012)	(0.048)	(0.081)
# Counties	675	718	718
From 1870 to 1880	-0.029	0.136	0.080
	(0.016)	(0.033)	(0.099)
# Counties	711	718	718

Notes: This table shows the relationship between waterpower potential and milling growth from 1850-1880. Column 1 shows the share of mills using steam power, where Panel A shows the share of establishments using steam, and Panel B shows the share of output coming from steam powered mills. Column 2 shows results for total milling activity, where Panel A reports total milling establishments and Panel B reports total output. The sample is all counties with at least one mill in 1850. Column 1 reports OLS results for the unbalanced panel (since a county needs at least one mill for the share to be defined), column 2 reports (pseudo) Poisson maximum likelihood estimates for the balanced panel. "Lower Waterpower" is the 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. Regressions whose outcome is the share of firms using steam are weighted by the number of mills in the county in 1850. Each observation is a county/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	0.382	-0.208	0.590
	(0.095)	(0.071)	(0.104)
# Counties	718	718	
In 1870	0.217	-0.177	0.395
	(0.065)	(0.057)	(0.081)
# Counties	718	718	
In 1880	0.196	-0.143	0.338
	(0.045)	(0.041)	(0.062)
# Counties	718	718	

Notes: This table shows the relationship between waterpower potential and growth of entrant and incumbent mills from 1860-1880. Column 1 shows results for entrants and column 2 for incumbents. Panel A shows the number of establishments, and Panel B total output. The sample is all counties with at least one mill in 1850, and we report (pseudo) Poisson maximum likelihood estimates for the balanced panel. "Lower Waterpower" is the 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/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	0.174	0.068	0.106
	(0.019)	(0.022)	(0.023)
# Counties	673	428	
In 1870	0.170	0.044	0.126
	(0.022)	(0.027)	(0.031)
# Counties	713	415	
In 1880	0.132	0.026	0.106
	(0.024)	(0.027)	(0.028)
# Counties	713	493	

Notes: This table shows the relationship between waterpower potential and growth of entrant and incumbent mills from 1850-1880. Column 1 shows results for entrants, column 2 for incumbents, and column 3 reports the difference. Panel A shows the share of establishments using steam power, and Panel B weights by output. The sample is all counties with at least one mill. "Lower Waterpower" is the 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. Regressions whose outcome is the share of firms using steam are weighted by the number of mills in the county in 1850. Each observation is a county/decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table 6: Spillovers of Steam: Mills' Neighbors

	Neighbor of		Difference
	Mill	Non-mill	(1) − (2)
	(1)	(2)	(3)
Panel A. All Non-mills			
Lower Waterpower	0.014	0.002	0.012
	(0.005)	(0.004)	(0.007)
# Establishments	89,002	93,911	
Panel B. Excluding Water Users			
Lower Waterpower	0.016	0.004	0.012
	(0.005)	(0.003)	(0.006)
# Establishments	76,939	86,096	

Notes: This table shows the how mills affected their neighbors' steam use. Column (1) limits the sample to factories (outside of milling) who have a neighbor who is a mill. We report how the steam share of mill-neighbors relates to waterpower potential. Column 2 instead limits the sample to factories without a mill for a neighbor, again showing the effect of waterpower potential on the steam use of those firms. Column 3 reports the difference in the coefficients. Panel (B) further limits the sample by not including factories in the following industries: leather, paper, liquor and beverages, and textiles. All regressions include industry/year fixed effects in addition to the baseline controls, and 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	≈ 0.029 (Swain, 1888); 0.011-0.040 (Atack et al., 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 et al., 2008); 0.229 (Chernoff, 2021)
Π	Autocorrelation in baseline productivities	0.9779	0.9675 (Bachmann and Bayer, 2014); 0.962 (Coşar et al., 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 et al., 2008); 0.0905 (Bachmann and Bayer, 2014); 0.137 (Coşar et al., 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 et al., 2014); 6.667 (Coşar et al., 2016); 11 (Sedláček and Sterk, 2017); 2.9 (Acemoglu et al., 2018); 4.25 (Felbermayr et al., 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 et al., 2011); 0.15-0.42 (Bartelsman et al., 2013); ≈ 0.015 (Coşar et al., 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 et al., 2015); ≈ 0.008 (Coşar et al., 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 et al., 2015); ≈ 0.008 (Coşar et al., 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. Many microfilms were provided by Jeremy Atack, for which we are very grateful, 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 samples described in Atack and Bateman (1999), including Rhode Island and Nevada. Delle Donne (1973) describes the enumeration of the data.

The enumeration of the Census before 1880 was done in person by U.S. Marshals, and all firms received the same questionnaire. 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).

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

Manufacturing Revenue. These 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 1860a).

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). In 1870 and 1880, the Census additionally asked all factories for their number of horsepower used.

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.

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. 27,102 sheets were from 1880. The average sheet had 10 firms on it. Appendix Table A.4 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 (2022), we homogenized industry names into 31 categories, additionally using reported information on products. In our analysis, we focus on flour and lumber milling, which were relatively straightforward to classify since they had unique outputs.

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 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. Specifically, there were some 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 and activity is recorded where it takes place, not at headquarters, so this refers to single-establishment "firms."

A.3 County Borders

Unlike in population-level regressions, 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) .

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 factories 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 a switch an "exit."

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 linking probability of at least 9% (in practice, we ended up matching very few of those). 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 createe 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 factory'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.[23]

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, corperations 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

[23]In our replication files, we denote direct matches as "y", ownership transfer matches as "o", and non-matches as "n".

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 motivates us to build two separate linking models, one matching the owners' names, and the other matching the established names as a whole. Effectively, we use two random forest models to predict establishment pairs by tracking the owners and company as a whole, respectively.[24] Both linking models predict 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

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

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-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 potential matches with a linking probability above 9%, and use those pairs as a basis for hand-linking the panel.

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.

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).[25] 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 particurally 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.

[25] 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 gages".
4. Adjust for flow transfers, withdrawals, and augmentations.
5. Gage-adjustment based on actual observed flow at the gage.

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 contemporeanous 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.[26] 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).[27]

We sort rivers into bins (in percentiles) by their top width T and exclude the rivers above a certain cutoff before calculating the resulting county waterpower potential. 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. Figure A.19 plots the F-stat of the regression against the exclusion cutoff X. There is a clear sharp decline in the relationship for very wide reviers. 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 Figure A.1 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 only mill used it for power, 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"

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

[27]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. 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 CMF 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.

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:

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

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 (2022). We control for the log of market access, as is standard.

Coal & Resource Regions We digitized maps of coal deposit locations from Campbell (1908), a survey run by the United States Geological Survey. We additionally used information from the USGS on resource regions (Seaber et al., 1987). A third of counties have a coal deposit, conditional on having coal an average of half of the county is on a deposit.

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.[28] We were unable to find records for many mills, and for many of the remainder 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

[28]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.

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:

Emery (1883) describes an (unnamed) water factory 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 factory 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 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).

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 inhereted 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. It is very possible that the switch from water to steam of the mill occurred because of the total destruction by the fire, though 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 Orff's mill exclusively used steam power.

The Pheonix 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). e 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 Comparative Statics

In this section, we describe in more detail the comparative statics of Section III.D.

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. Formally, the adoption of steam among incumbents satisfies:

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

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

Note that, from the viewpoint of a mill of productivity φ and existing power source R, the impact of the regional environment (lt-subscripts) on its adoption of steam power is summarized by the cost of water (entering c_{ct} through Equation (20)) and the local price index (entering π_{ct} through Equation (7)).

Higher costs of water power affect steam adoption among incumbents in Equation (34) through three channels, all of which lead to more steam use:

1. *Technology costs:* Consider a mill of productivity φ facing a local price index $\{P_{ct}\}_t$. Higher water costs c^W_l make steam power a more appealing choice of technology. Math-

ematically, c_l^W enters the LHS of the inequality in Equation (34), thus increasing steam adoption rates, ceteris paribus.

2. *Selection:* Consider a region with price index $\{P_{ct}\}_t$. First, because higher water costs lower the operating value $V_{ct}^o(R,\varphi)$ in Equation (11), mills have to be of higher productivity φ in low-water regions to overcome the fixed operating costs R in Equation (10). Second, because of the complementarity between productivity and steam power in Equation (4), productive firms will adopt more steam. Taken together, this selection on productivity implies that mills in low-water regions will use more steam power.

3. *Competition*: High water costs increase the local price index $\{P_{ct}\}_t$ when firms are free to enter markets.[29] The lower local competition will increase the baseline profits of any mill of productivity φ, assuming that the elasticity of substitution between varieties ϵ is higher than the elasticity of substitution between sectors η; see (7). Because of the complementarity between baseline profits and steam-use, this local competition effect implies that mills in low-water regions will use more steam power.

Following Equation (11), steam adoption among incumbents and entrants differ due to switching frictions and partial irreversibility, both of which tend to make the steam adoption decision of incumbents less responsive to the cost of waterpower:

1. *Switching frictions* lower steam adoption rates among incumbents who use water power. These incumbents will also be less responsive to waterpower costs in their decisions to adopt steam power if

$$\frac{\partial}{\partial c^r(W,S)}\frac{d}{dc_c^W}\mathbb{P}_{ct}(S|W,\varphi) < 0 \tag{35}$$

where $\mathbb{P}_{ct}(S|R,\varphi)$ is the steam adoption rate among mills with existing power R and productivity φ.

For example, assuming idiosyncratic adoption cost shocks are drawn from a Gumbel distribution as in Section III.E, the steam adoption policy function satisfies

$$\log\frac{\mathbb{P}_{ct}(S|R,\varphi)}{1-\mathbb{P}_{ct}(S|R,\varphi)} = c_{ct}(S,R) - c_{ct}(R,R) + \pi_{ct}(S,\varphi) - \pi_{ct}(R,\varphi) \tag{36}$$

$$+ \beta\mathbb{E}_{\varphi'}\left[V_{lt+1}(S,\varphi') - V_{lt+1}(R,\varphi')\right] \tag{37}$$

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

Focusing on the instantaneous effect in Equation (36), we see that Equation (35) holds when $\mathbb{P}_{ct}(S|R,\varphi) \leq \frac{1}{2}$. Hence, comparing incumbents and entrants, the steam adoption decisions of incumbents are less responsive to the cost of waterpower as long as the steam entrant adoption rate $\mathbb{E}_{\varphi}[\mathbb{P}_{ct}(S|E,\varphi)]$ is less than $\frac{1}{2}$. Figure 5 shows that this condition holds in our data period.

2. *Partial irreversibility* makes incumbents want to stick to their existing water powers. These incumbents will also be less responsive to waterpower costs in their decisions to adopt steam power if

$$\frac{\partial}{\partial \omega^W}\frac{d}{dc_c^W}\mathbb{P}_{ct}(S|R,\varphi) < 0 \tag{38}$$

Similarly, given the specification in Section III.E, Equation (38) holds if the entrant steam adoption rate is less than $\frac{1}{2}$, which Figure 5 shows holds in our data period.

□

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

$$\frac{d}{dc_c^W}\Delta \log N_{ct}^E > \frac{d}{dc_c^W}\Delta \log N_{ct} > 0 \tag{39}$$

Argument. First, higher water costs make steam power a more valuable technology in Equation (11), boosting the value of operation in low-water regions when steam arrives. Hence, the growth of firms will be larger in low-water regions when steam arrives. Second, because water incumbents face switching frictions and partial irreversibilities, they will tend to adopt less steam power. Consequently, their operating values in Equation (11) – and thus their survival rates – increase less than for entrant when steam arrives. □

Prediction 3 (Unclear if incumbents of crowded out in regions 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:*

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

Argument. Examining the value of operating in Equation (11), higher water costs increase the option value of steam power but also intensify the local competition from new entrants.

The positive option value effect will dominate the competition effect when power switching costs are low. For example, in the extreme case where incumbents face no switching frictions or irreversibilities, incumbents and entrants access steam power similarly, and their operating values are similarly affected by the arrival of steam. However, when switching costs rise, water incumbents do not benefit from steam arrival, and the negative competition effect will dominate the option value effect. For example, in the extreme case where incumbents face infinite switching frictions, incumbents cannot access steam power, and their operating values are only affected by the negative competition effect. Taken together, these arguments shows that the impact of water costs on incumbent survival is theoretically ambiguous and depends crucially on the power switching cost. □

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Figure A.1: Distribution of river top width by SR/AP

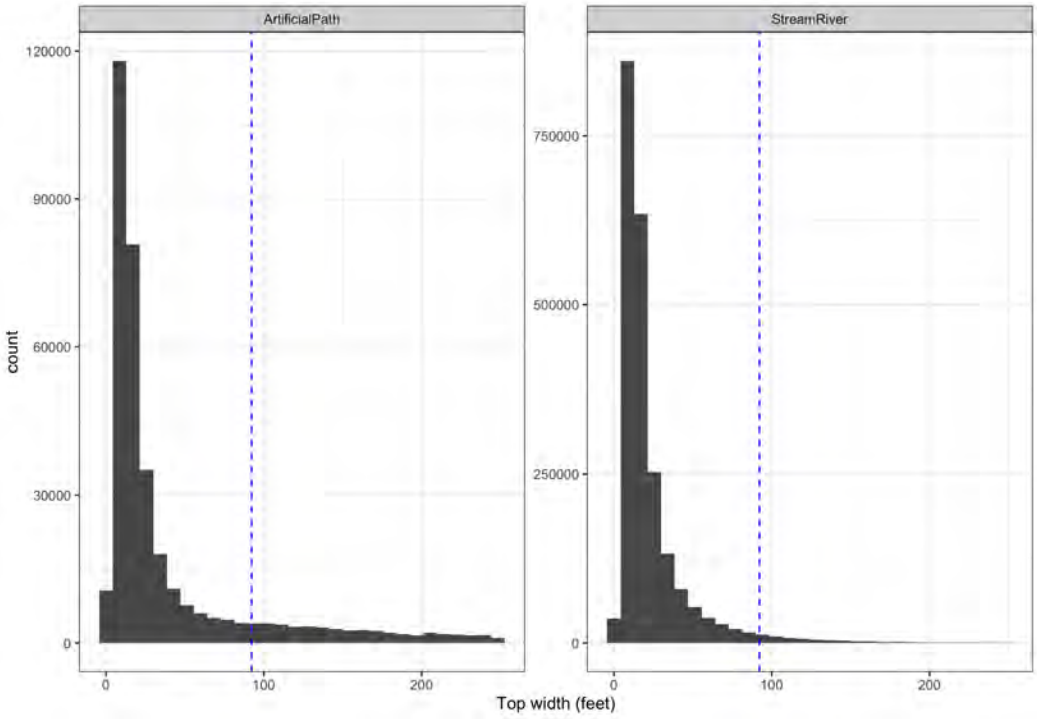
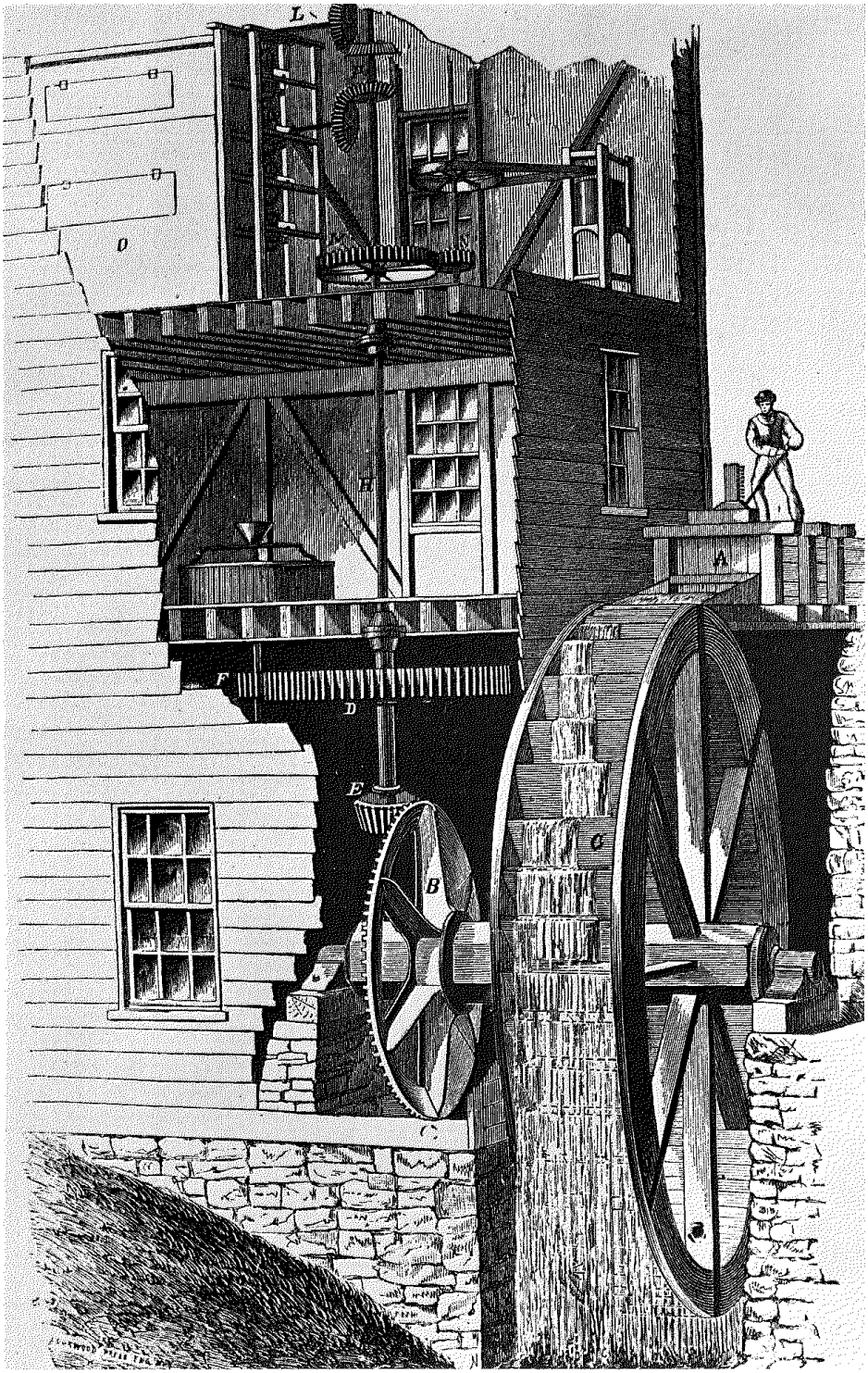
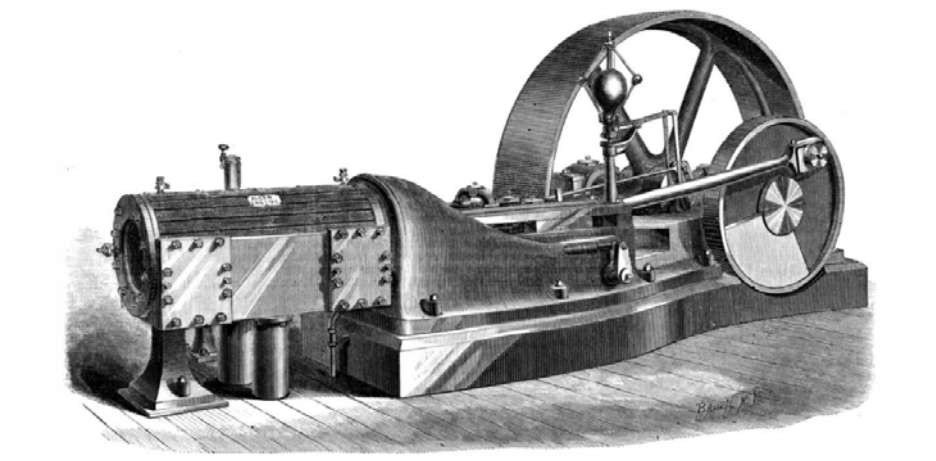


Figure A.2: Gristmill Diagram



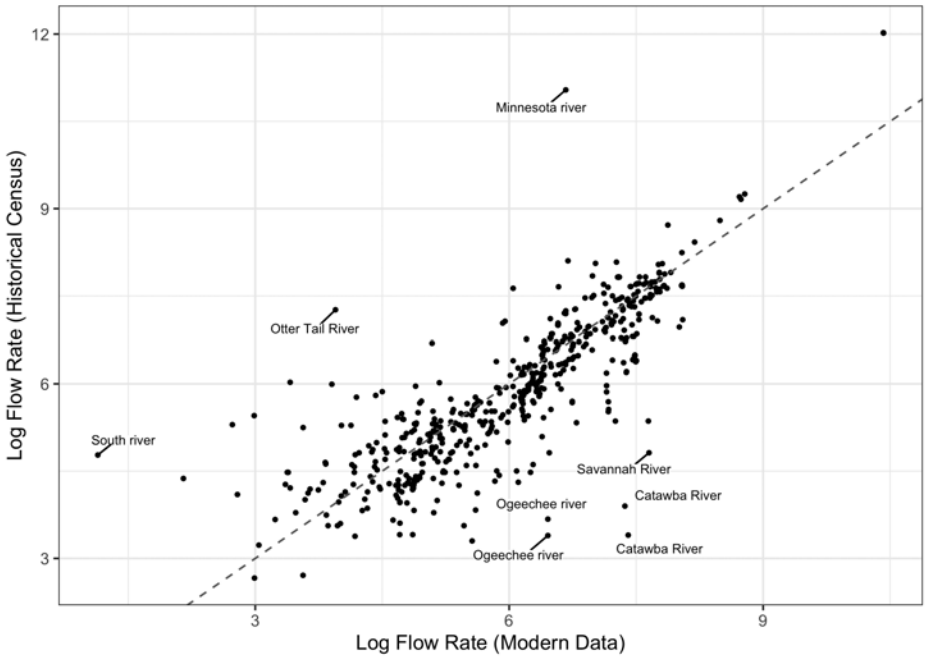
Notes: A diagram of gristmill. (A) is the sluice gate, (b) is the crown wheel attached to a shafty waterwheel, which transmits the power to (E), a small bevel wheel on the upright shaft. A spur wheel (D) is placed on the up right shaft, which works into the pinion (F) on the spindle, which drives the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

Figure A.3: The Porter-Allen Engine



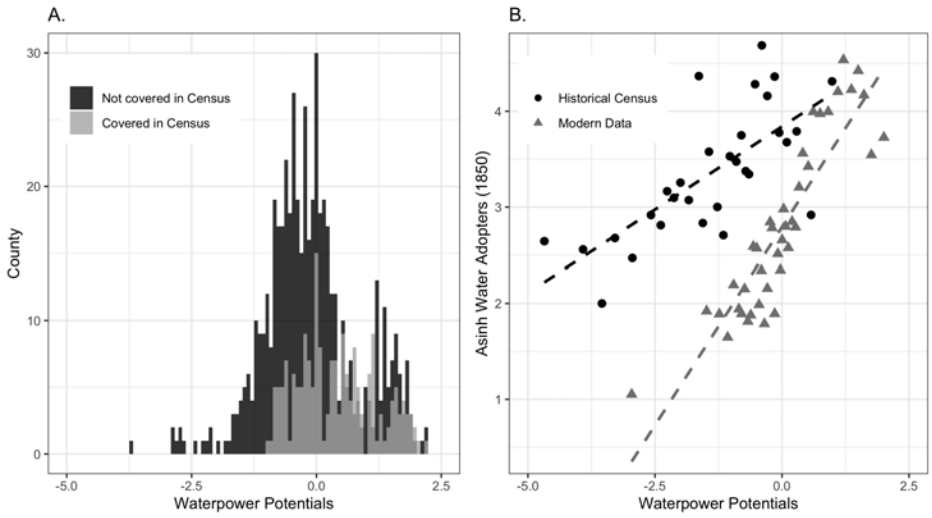
Notes: A diagram of the Porter-Allen Engine, from *Scientific American* (1870).

Figure A.4: Segment Flow Rates in Water Census compared to NHD Data



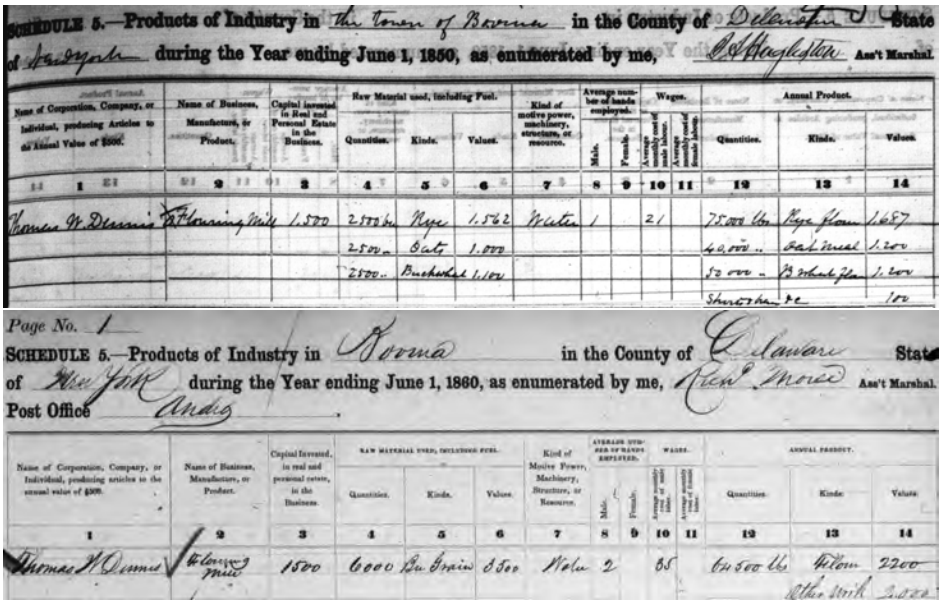
Notes: This figure plots waterpower potential for the river segments that we were able to identify both in the National Hydrography Dataset Plus (NHDPlus) as well as in the Water Census. Each point represents one segment. Data from NHDPlusV2 and Census Bureau (1883).

Figure A.5: The Water Census compared to NHDPlusV2



Notes: Panel A plots the distribution of country waterpower potential in the Water Census Data (light gray) and only in NHDPlusV2 (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. Data from NHDPlusV2, Census Bureau (1883), and the 1850-1880 Census of Manufacturers. All counties are included in Panel B.

Figure A.6: Example Census Image: Dennis "Flouring Mill"



SCHEDULE 5.—Products of Industry in the Town of Bovina in the County of Delaware State of New York during the Year ending June 1, 1850, as enumerated by me, D. D. Bayleston Ass't Marshal.

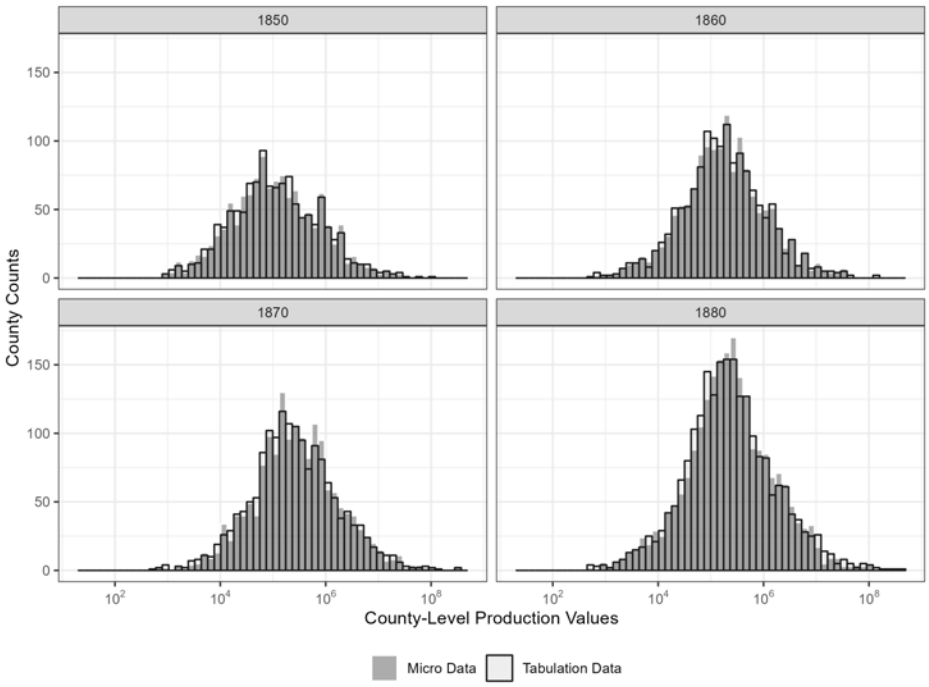
Name of Corporation, Company, or Individual, producing Articles to an Annual Value of $500.	Name of Business, Manufacture, or Product.	Capital invested in Real and Personal Estate in the Business.	Raw Material used, including Fuel.			Kind of motive power, machinery, structure, or resource.	Average number 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
Thomas W. Dennis	Flouring Mill	1,500	2500 bu	Rye	1,562	Water	1		21		7500 lbs	Rye flour	1687
			2500 "	Oats	1,000						40,000 "	Oat meal	1,200
			2500 "	Buckwheat	1,100						52,000 "	Buckwheat flour	1,300
												Shingles &c	100

Page No. 1

SCHEDULE 5.—Products of Industry in Bovina in the County of Delaware State of New York during the Year ending June 1, 1860, as enumerated by me, Rich'd Moore Ass't Marshal.
Post Office Andes.

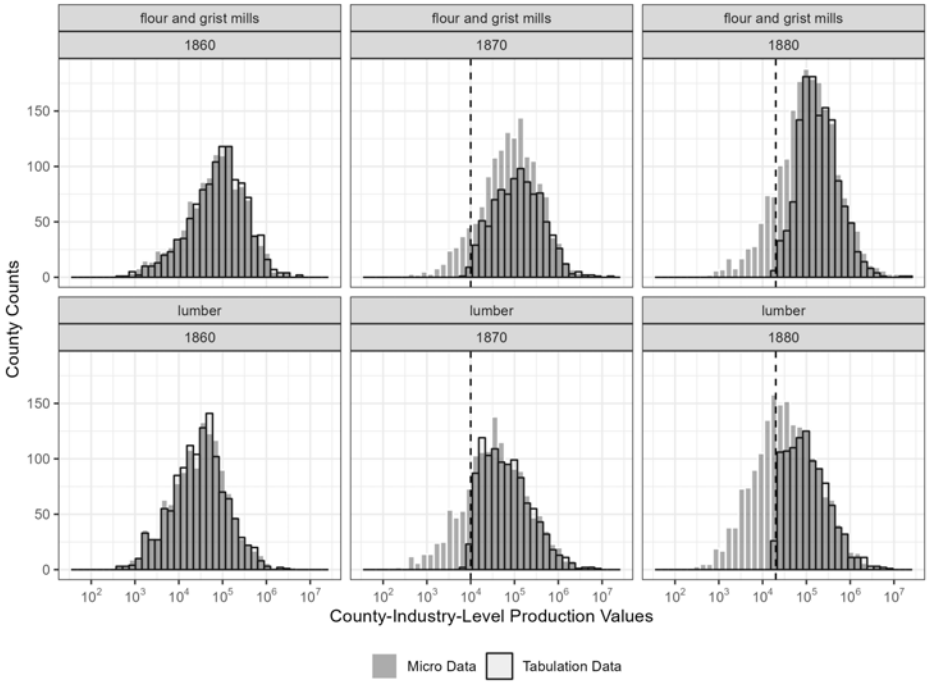
Name of Corporation, Company, or Individual, producing articles to the annual value of $500.	Name of Business, Manufacture, or Product.	Capital Invested, in real and personal estate, in the Business.	Raw Material used, including Fuel.			Kind of Motive Power, Machinery, Structure, or Resource.	Average 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
Thomas W Dennis	Flouring mill	1500	6000	Bu Grain	8500	Water	2		65		64500 lbs	Flour	2200
												Chop feed	2000

Figure A.7: County-Level Production Values in Microdata and County/Industry Tabulations



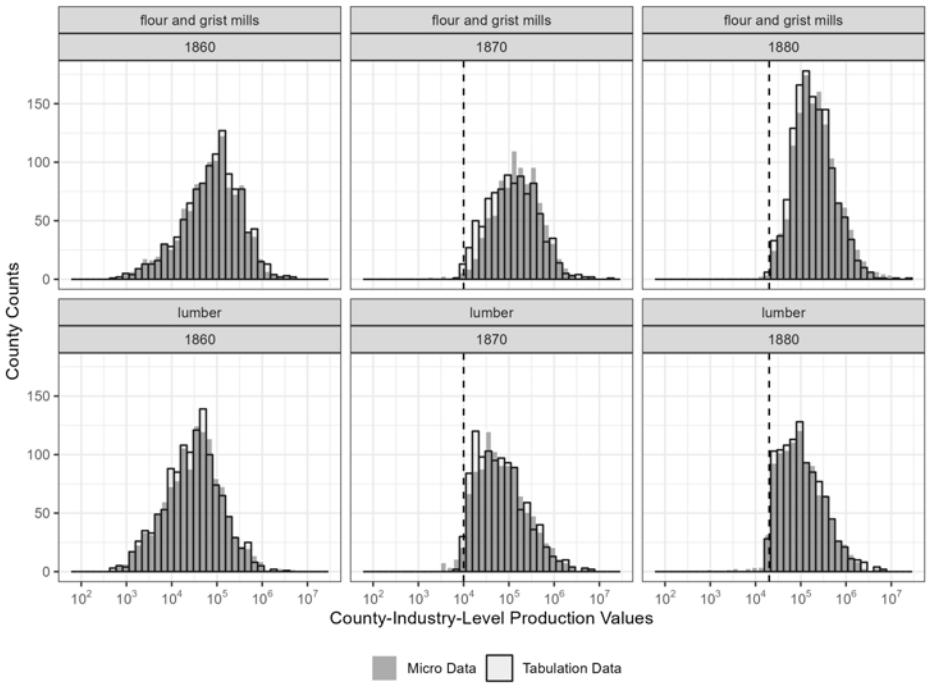
Notes: This figure shows the distribution of total manufacturing output by county in our digitized Census of Manufacturers data and the county-industry reports contemporaneously tabulated by the Census. Data from the 1850-1880 Census of Manufacturers, and the sample is all counties with surviving manuscripts.

Figure A.8: Unmatched County-Level Production Values in Microdata and County/Industry Tabulations, Flour and Lumber Mills



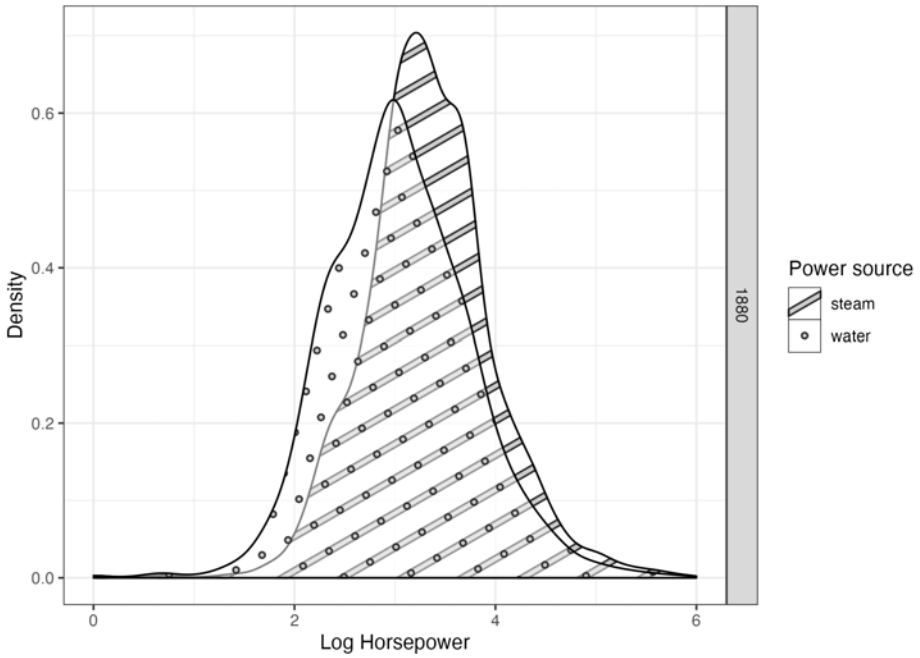
Notes: This figure shows the distribution of total flour milling + lumber milling out by county in our digitized Census of Manufacturers data and the county-industry reports contemporaneously tabulated by the Census. Data from the 1850-1880 Census of Manufacturers, and the sample is all counties with surviving manuscripts, including counties without tabluations for the relevant industries. The vertical lines corresponds to the *de jure* minimum value of total output that was supposed to be tabulated in the Census.

Figure A.9: Matched County-Level Production Values in Microdata and County/Industry Tabulations, Flour and Lumber Mills



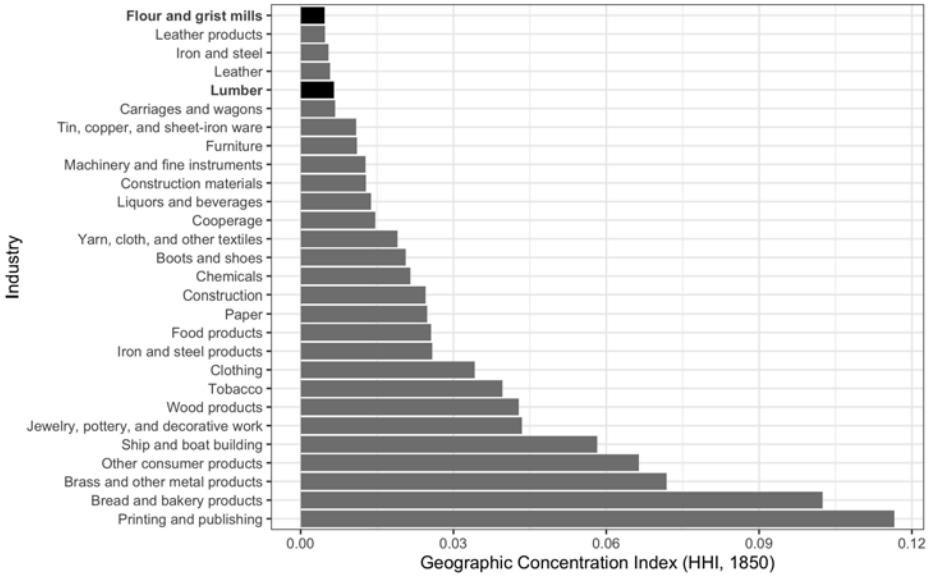
Notes: This figure shows the distribution of total flour or lumber milling by county in our digitized Census of Manufacturers data and the county-industry reports contemporaneously tabulated by the Census. Data from the 1850-1880 Census of Manufacturers, and the sample is all counties with surviving manuscripts & available tabluations for the relevant industries. The vertical lines corresponds to the *de jure* minimum value of total output that was supposed to be tabulated in the Census.

Figure A.10: Total Horsepower Installed, by Power Source



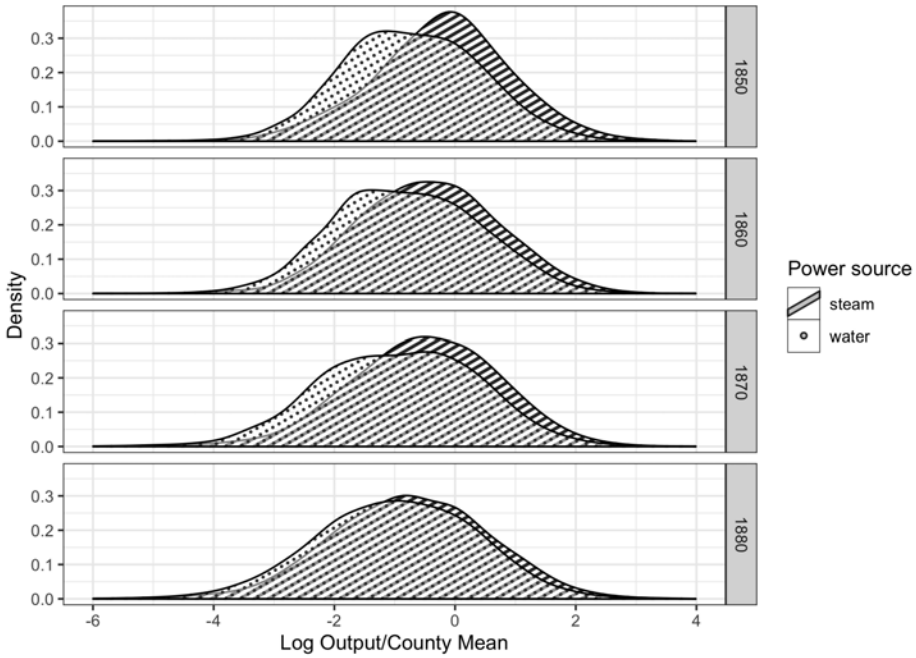
Notes: This figure shows the distribution of horsepower installed for flour mills and lumber mills in 1800. Data from the 1880 Census of Manufacturers.

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.

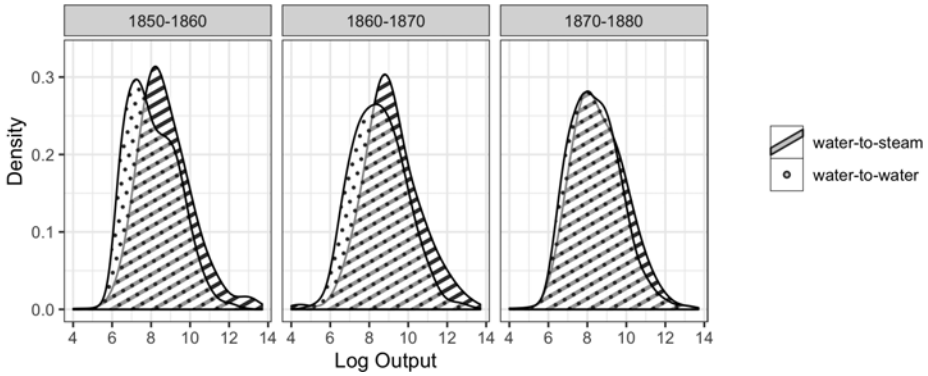
Figure A.12: Mill Size by Power Source, Within-County



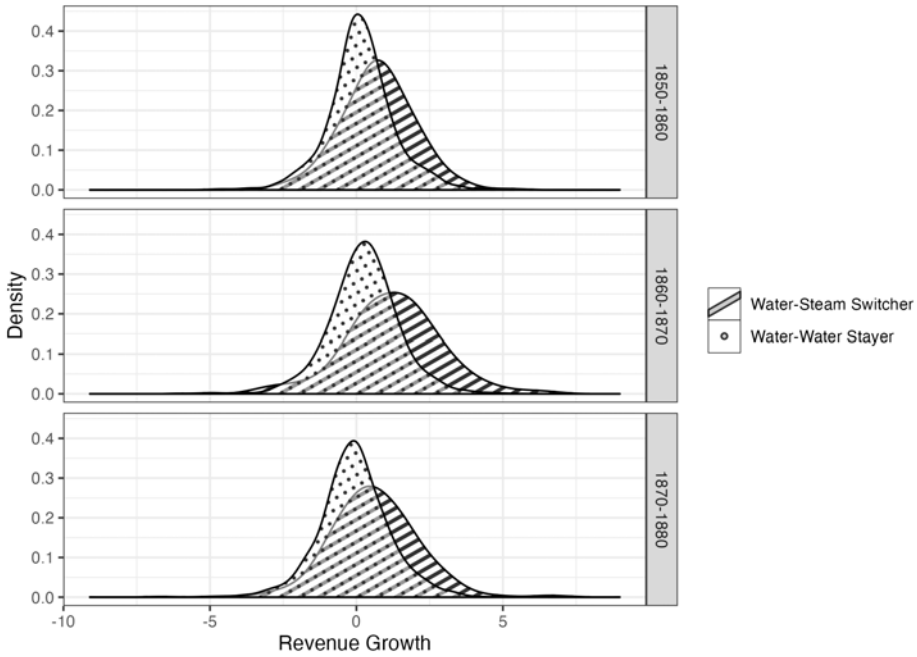
Notes: This figure plots the distribution of mill revenues in each decade for each type of power source (steam or water). For each plant, we first divide their revenue by the average revenue in their county/industry. The sample is all counties in the baseline sample (those that had at least one mill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

Figure A.13: Mill Size by Switching Choice

(a) Mill Size by Future Switching Choice

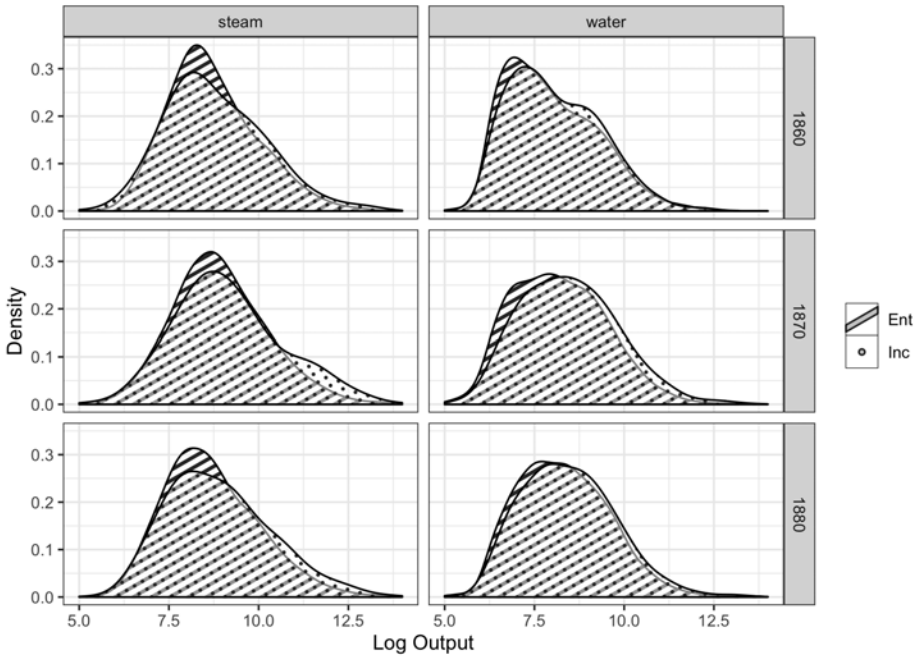


(b) Mill Size by Past Switching Choice



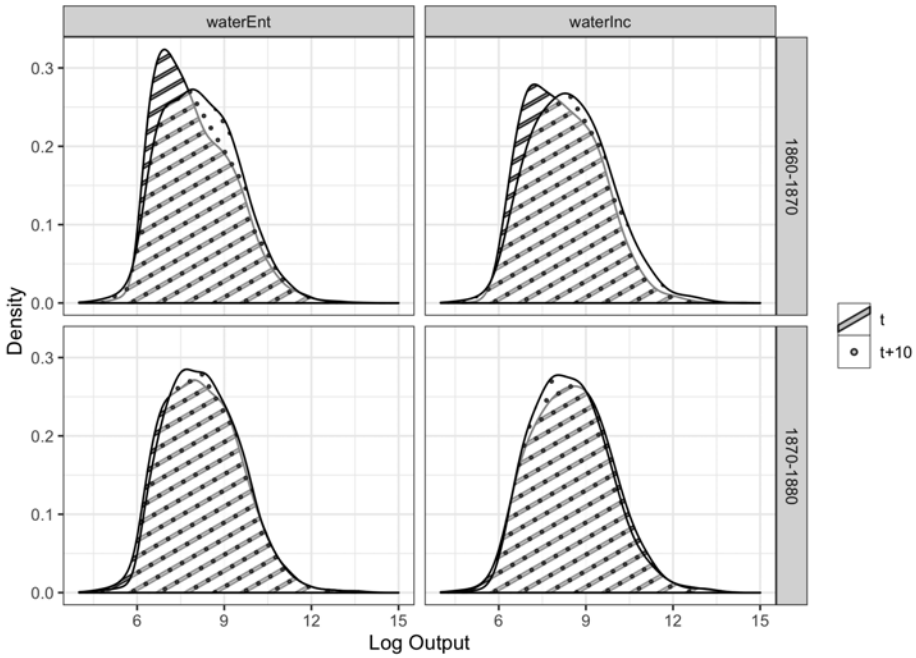
Notes: Panel A plots the distribution of mill revenues for water incumbents in the initial period, as a function of if they subsequently switch (water-to-steam) or stay with their current power source (water-to-water). Panel B plots the distribution of mill revenues for water incumbents, comparing those who switched 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.14: Mill Size by Entrant/Incumbent, by Power Source



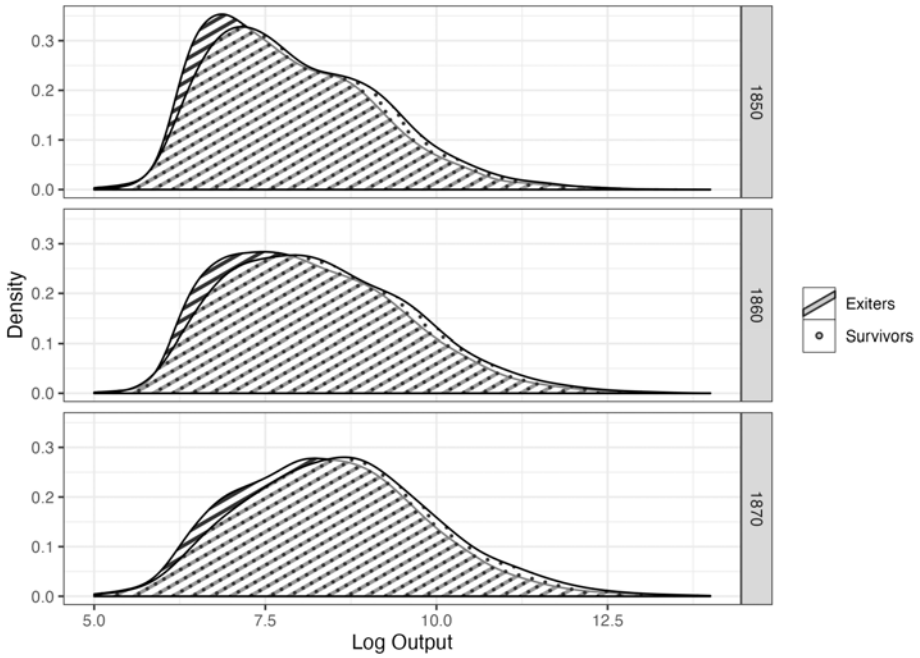
Notes: This figure plots the distribution of mill revenues for all mills, as a function of (a) if the mill is an entrant or an incumbent and (b) the current power souce. We cannot include 1850, as we do not know which plants are incumbents. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1860-1880 Census of Manufacturers.

Figure A.15: Mill Growth For Entrant/Incumbent Watermills



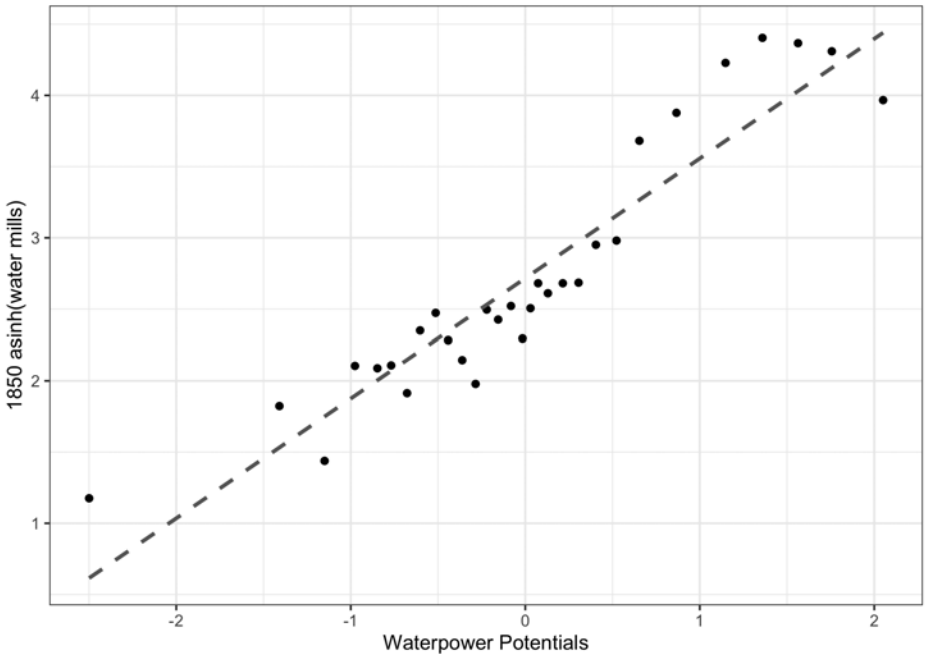
Notes: This figure plots the distribution of mill revenues for all water mills. The left panel shows the size distribution of water entrants in $t-1$ and t (where we can only identify entrant status starting in 1860). The right panel shows the size distribution of the non-switching survivors in $t-1$ and t. 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.16: Mill Size For Exiters and Survivors



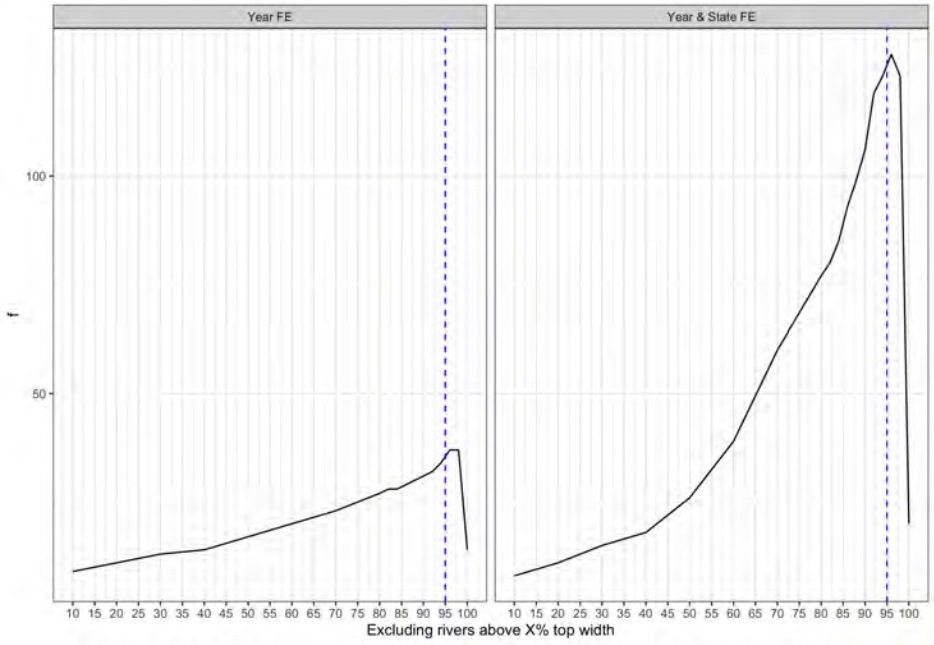
Notes: This figure plots the distribution of mill revenues for all mills, by decade. The two categories are mills that close in the subsequent decade, and those that survive. The sample is all counties in the baseline sample (those that had at least one mill in 1850). Data from the 1860-1880 Census of Manufacturers.

Figure A.17: Waterpower Potential and Water Mills, 1850



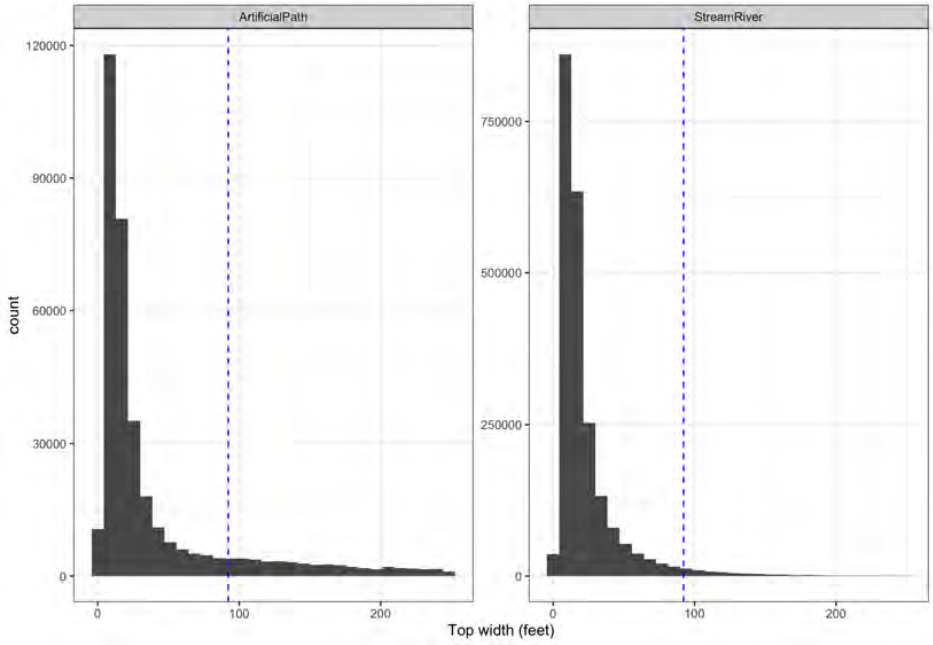
Notes: Panel A plots the raw relationship between the number of waterpowered mills in 1850 and waterpower potential. Panel B plots the raw relationship between the growth in the number of waterpowered mills and waterpower potential. Data from the 1850-1880 Census of Manufacturers.

Figure A.18: F-stats in the y-axis vs. quantiles of river size in the x-axis



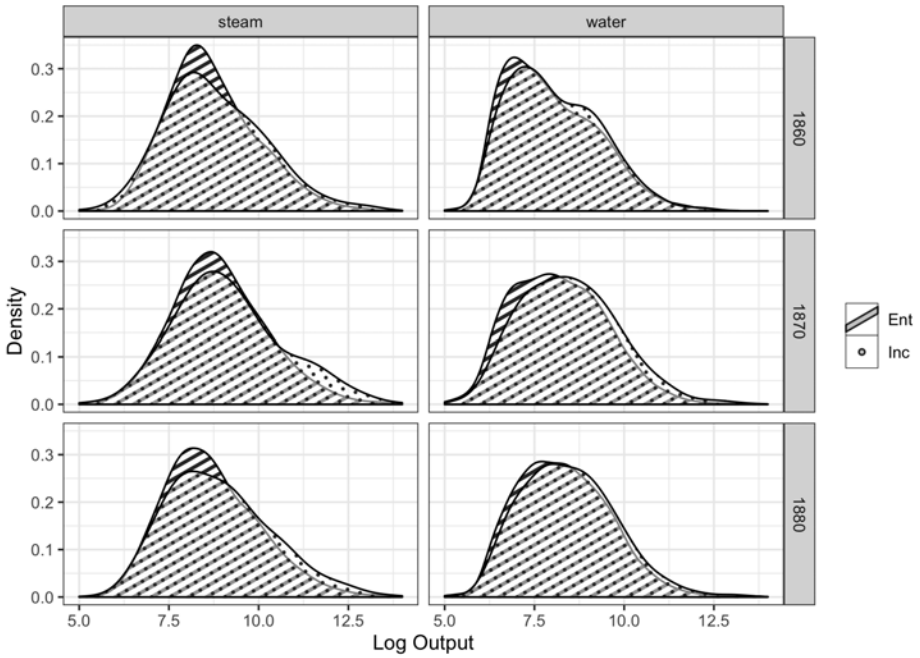
Notes: We sort rivers into bins (in percentiles) by their top width T and exclude the rivers above a certain cutoff before calculating the resulting waterpower potentials. A first-stage regression (on waterpowered mills in 1850) is run for each set of exclusions to obtain an F-statistic to guide our final cutoff. Data from NHDPlusV2 and the the 1850-1880 Census of Manufacturers.

Figure A.19: Distribution of river top width by SR/AP



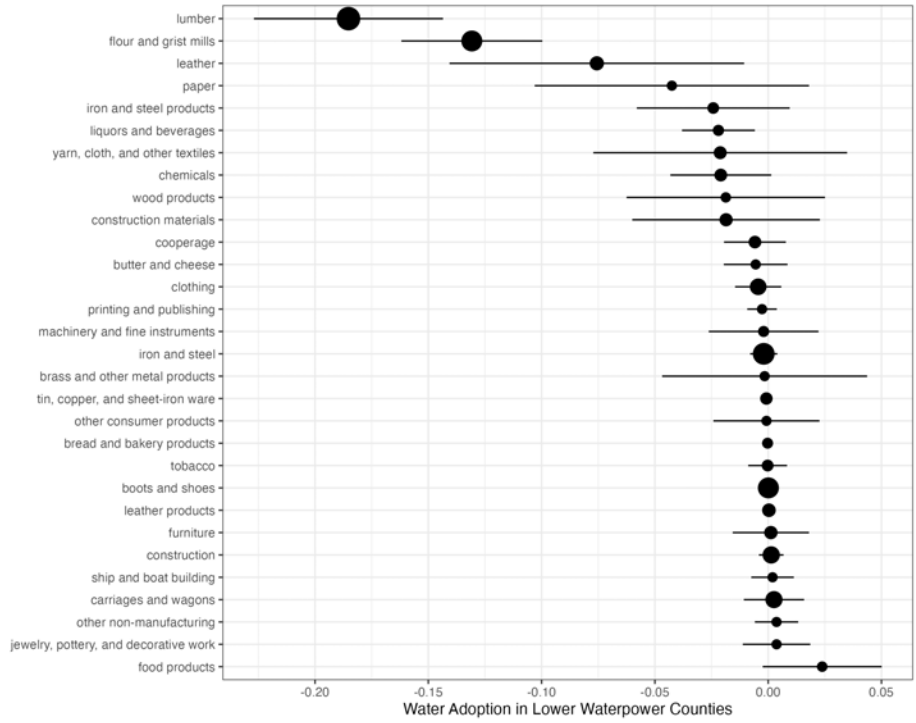
Notes: This figure plots the distibution of widths of the Stream Rivers and Artificial Paths in the United States, along with the cutoff width above which we assume in our regressions that waterpower is impractical. Data from NHDPlusV2.

Figure A.20: Growth in the Number of Mills, 1850-1880, by Waterpower Potential



Notes: This figure plots a binscatter of the relationship between waterpower potential and the growth in the total number of flour mills and lumber mills from 1850-1880. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Figure A.21: Waterpower Potential and Water Mills by Industry



Notes: The figure plots coefficients of running Equation 1 for each industry one at a time. The coefficient corresponds to the elasticity of waterpowered factories in the sector with respect to waterpower potential. We pool data from 1850-1870 (and correspondingly include year fixed effects and interact the controls by year). Standard errors are clustered by county. Data from the 1850-1880 Census of Manufacturers.

Table A.1: Survival Rates

	Survival Rate By Initial Power Source		
	All	Water	Steam
1850-1860	0.217	0.223	0.163
1860-1870	0.212	0.229	0.165
1870-1880	0.240	0.256	0.207

Notes: This table shows the measured survival rate in each decade of all, steam, and water mills. We denote a mill as surving if we can find a record for it in the subsequent Census. Data from the 1850-1880 Census of Manufacturers.

Table A.2: Per Capita Manufacturing Growth and Steam Diffusion by Waterpower

	Population (1)	Establishments Per Capita (2)	Revenue Per Capita (3)
LowerWaterPower×1860	0.066	0.262	0.270
	(0.016)	(0.085)	(0.110)
LowerWaterPower×1870	0.083	0.323	0.298
	(0.036)	(0.090)	(0.123)
LowerWaterPower×1880	0.126	0.400	0.336
	(0.048)	(0.094)	(0.133)
Number of Counties	722	722	722
County-Year Obs.	2,888	2,888	2,888

Notes: This table shows the relationship between waterpower potential and per capita milling growth from 1850-1880. Column 1 shows the population, Column 2 establishments per capita, and column 3 revenue per capita. The sample is all counties with at least one mill in 1850. All columns report (pseudo) Poisson maximum likelihood estimates for the balanced panel. "Lower Waterpower" is the 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/decade. Standard errors clustered by county. Data from the 1850-1880 Census of Manufacturers and NHDPlusV2.

Table A.3: Manufacturing Growth and Steam Diffusion by Waterpower

	Estimated Impact of LowerWater on:					
	Establishment growth			Steam diffusion		
	50-60	50-70	50-80	50-60	50-70	50-80
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline specification	0.299	0.447	0.593	0.090	0.091	0.065
	(0.069)	(0.069)	(0.079)	(0.019)	(0.019)	(0.025)
Restrict to counties with ≥ 3 mills in 1850	0.264	0.395	0.519	0.090	0.099	0.064
	(0.074)	(0.075)	(0.076)	(0.019)	(0.019)	(0.026)
Restrict to counties with ≥ 5 mills in 1850	0.224	0.365	0.479	0.088	0.100	0.063
	(0.071)	(0.066)	(0.069)	(0.018)	(0.019)	(0.028)
Restrict to counties with ≥ 1 mill 1850-1880	0.323	0.456	0.606	0.090	0.091	0.065
	(0.067)	(0.070)	(0.080)	(0.019)	(0.019)	(0.025)
Exclude largest 20 cities in 1850-1880	0.292	0.444	0.610	0.105	0.114	0.098
	(0.077)	(0.076)	(0.088)	(0.021)	(0.027)	(0.040)
Control for 1850 agri. employment share	0.266	0.396	0.537	0.082	0.079	0.049
	(0.069)	(0.069)	(0.071)	(0.015)	(0.016)	(0.020)
Control for precipitation and temperature	0.238	0.363	0.489	0.059	0.064	0.029
	(0.079)	(0.098)	(0.103)	(0.026)	(0.026)	(0.031)
Control for all resource regions	0.276	0.421	0.537	0.066	0.055	0.029
	(0.056)	(0.073)	(0.092)	(0.024)	(0.019)	(0.022)
Control for all resource subregions	0.246	0.371	0.502	0.054	0.046	0.027
	(0.073)	(0.098)	(0.118)	(0.027)	(0.029)	(0.039)
Control for longitude and Atlantic coastline	0.202	0.357	0.462	0.029	0.034	0.018
	(0.065)	(0.077)	(0.097)	(0.020)	(0.018)	(0.030)
Control for the 13 American colonies	0.227	0.368	0.498	0.059	0.044	0.028
	(0.071)	(0.076)	(0.097)	(0.018)	(0.018)	(0.022)
Control for State fixed effects	0.126	0.243	0.343	0.039	0.031	0.016
	(0.067)	(0.071)	(0.084)	(0.018)	(0.014)	(0.021)
Control for 1850 population	0.277	0.417	0.559	0.078	0.079	0.049
	(0.068)	(0.069)	(0.077)	(0.016)	(0.019)	(0.028)
Control for 1850 output	0.198	0.313	0.443	0.066	0.063	0.031
	(0.069)	(0.067)	(0.074)	(0.016)	(0.016)	(0.025)
Control for time-varing market access	0.272	0.431	0.564	0.078	0.082	0.051
	(0.071)	(0.073)	(0.083)	(0.018)	(0.017)	(0.024)
Control for 1870 acres of woodland	0.301	0.449	0.596	0.091	0.093	0.066
	(0.068)	(0.069)	(0.078)	(0.019)	(0.019)	(0.025)
Control for 1850 access to banks	0.274	0.436	0.587	0.086	0.093	0.071
	(0.073)	(0.075)	(0.087)	(0.019)	(0.018)	(0.030)
Control for 1850 machine producers/engineers	0.247	0.402	0.541	0.082	0.076	0.047
	(0.068)	(0.067)	(0.073)	(0.016)	(0.019)	(0.028)
Control for coal resources	0.281	0.423	0.560	0.076	0.074	0.047
	(0.067)	(0.075)	(0.086)	(0.020)	(0.018)	(0.020)

Notes: This table shows the relationship between waterpower potential and milling growth from 1850-1880, the same outcomes as Table 3 but with alternative controls, as described in the text. "Lower Waterpower" is the 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.4: Coverage Rates

State	1850	1860	1870	1880	State	1850	1860	1870	1880
AL	✓	✓	✓	✓	MT	-	-	✓	✓
AR	✓	✓	✓	✓	NE	-	✓	✓	✓
CA	✓	✓	✓	✓	NV	-	-	✓	✓
CO	-	-	✓	✓	NH	✓	✓	✓	✓
CT	✓	✓	✓	✓	NJ	✓	✓	✓	✓
DE	✓	✓	✓	✓	NY	✓	✓	82.3%	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	-	-	-	✓	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. Checkmarks indicate that we have complete coverage.