NATURAL DISASTERS, INDUSTRIAL POLICY, AND INNOVATION: EVIDENCE FROM THE GREAT CHICAGO FIRE [*]

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Abstract

This paper examines whether, in response to natural disasters, industrial policy can shape innovation toward risk-mitigating technologies. We study the 1871 Chicago Fire and the consequent policy banning wooden construction. Using a synthetic control framework, we find that construction patenting and manufacturing in Chicago increased sharply, with positive spillovers into related sectors. To distinguish the effects of the Fire and the policy, we compare wood and non-wood construction, showing that gains were concentrated in non-wood construction. Additionally, we study the 1872 Boston Fire, where no regulations were implemented, and find no effect on patenting and a modest rise in manufacturing.

Keywords: Great Chicago Fire, Industrial Policy, Directed Innovation.

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INTRODUCTION

Natural disasters cause significant damage worldwide, and with ongoing climate change, these adverse effects are expected to intensify over the coming decades. Adaptation critically hinges on technical change. Directed innovation in US agriculture, for example, has offset 20% of the potential losses due to damaging climate trends since 1960 (Moscona and Sastry, 2023). Despite these prospective gains, economic theory indicates that market competition may lead to inefficiently low levels of innovation in areas that will generate new products or technologies in the future (Acemoglu, 2012, 2023).[1]

In this paper, we investigate whether public policy can address this inefficiency by guiding the innovation response to natural disasters and supporting technologies that mitigate their adverse effects. We examine how innovation and manufacturing responded to the 1871 Great Chicago Fire and to the subsequent legislation that prohibited wooden constructions within the city borders. We document a large increase in construction innovation and manufacturing, which generated positive knowledge spillovers into technologically related sectors. To distinguish between the effects of the fire and the construction policy, we contrast wood and non-wood construction and find that the gains are concentrated in the non-wood sector. Additionally, we examine the 1872 Great Boston Fire, where no construction regulations were enacted, and find no effects on construction innovation and modest gains in manufacturing. Our results suggest that public policy can be a powerful tool to direct technology in response to natural disasters, while also supporting economic growth.

Over the second half of the nineteenth century, Chicago witnessed momentous growth owing to its central location within the US railway network. This unregulated sprawl left it exposed to fire hazards. Estimates indicate that 100,000 people—out of a population of 300,000—were left homeless by the 1871 Fire, which caused approximately 200 million dollars in damages (5 billion 2010$), or 670$ per inhabitant (Smith, 2020). Following the Fire, the Chicago municipal authority passed, in 1874, an ordinance that prohibited the construction of wooden buildings within the city's borders. In the following decades, construction practices in Chicago introduced key innovations, including fireproof materials, iron frames, and the first skyscrapers. The "Great Rebuilding" attracted many architects and engineers, and Chicago emerged as the hub of innovative architecture (Condit, 1952).

To estimate the causal effects of the fire and the construction policy, we adopt a synthetic control

[1] Acemoglu (2012) uses electric and internal-combustion cars as an example. At time t, internal-combustion cars have higher quality and are thus preferred by consumers, but in $t' > t$, consumer tastes will change, and they will buy electric cars. Since private returns to innovation in internal combustion technology will be higher than in electric cars, market competition underprovides innovation in the "clean" technology.

approach, following Abadie and Vives-i Bastida (2022). The synthetic control method leverages information on untreated cities to construct a "synthetic" Chicago that serves as a counterfactual to estimate the treatment effects. Compared to the more traditional difference-in-differences estimator, the synthetic control method allows us to perform inference even if the treated group—Chicago—is small. In addition, it is historically plausible that Chicago was not on the same trend as other cities before the 1871 Fire, thus invalidating the identifying parallel trends assumption of the double differences estimator. The synthetic Chicago, however, closely mimics the real Chicago before the Fire, which suggests that it constitutes an appropriate policy counterfactual.[2]

We find that the 1871 Fire had a positive and large impact on construction-related innovation in Chicago. Ten years after the Fire, the number of construction patents issued to inventors living in the Chicago metropolitan area was approximately twice that of the synthetic control. This wedge widened over the following decades as construction-related innovation further increased. By 1900, 300 more construction patents were issued in Chicago relative to the synthetic control every year. To estimate the knowledge spillovers of the increased construction innovation, we measure the technological similarity between construction and other technology classes.[3] Patenting in Chicago increased relative to the synthetic control in classes technologically closer to construction, while we find modest and statistically insignificant effects on more distant sectors. These different patenting trajectories across sectors suggest that the response of innovation to the Fire is unlikely to be due to general economic growth spurred by the rebuilding of Chicago. If this were the case, we would observe similar increases in innovation across all technology classes, while we find a much stronger effect in innovation in construction-related sectors.

Turning to broader indicators of economic activity, we use output, number of establishments, fixed capital, and material and labor costs from manufacturing censuses, as digitized by Hornbeck and Rotemberg (2024). The 1871 Fire impressed a major upward shift on construction manufacturing in Cook County, where Chicago is located. Relative to the synthetic control, the number of construction establishments and their output increased fivefold within a decade of the Fire. Fixed capital, material, and labor costs also show substantial growth over the same period.

Finally, we examine the impact of the 1871 Fire on historical landmarks as an additional indicator of

[2] Within the historical urban economics literature, the synthetic control method has been recently applied by Becker, Heblich and Sturm (2021) to study how changes in public employment caused by the designation of Bonn as the capital of the German Federal Republic after World War 2 impacted private-sector economic activity.

[3] We adopt two measures of cross-sector technological similarity. First, we rank sectors by the share of patents we identify as construction-related. Second, we adopt a text-based similarity measure that leverages document embeddings (Mikolov, Sutskever, Chen, Corrado and Dean, 2013). The two approaches yield very similar results.

innovation in construction technology. We assemble a geo-referenced dataset covering the universe of sites listed in the National Register of Historic Places (Stutts, 2024). We compare the effect of the Fire on architectural landmarks to all other sites. As discussed in Section I, the "Great Rebuilding" ushered in an unprecedented agglomeration of architects and engineers in Chicago. We find that the number of architecturally relevant landmarks in Chicago more than doubled relative to the synthetic control by 1880 and further increased until 1900. The presence of these architectural sites, deemed worthy of preservation, arguably proxies for the architectural innovations developed in those years. By contrast, we find no statistically significant effects of the Fire on non-architectural landmarks.

How did the "industrial policy" intervention implemented by the Chicago municipality affect innovation and economic activity? We answer in two ways.

First, we contrast the impact of the 1871 Chicago Fire on wood-related and non-wood-related innovation and manufacturing. Since wood-related construction was forbidden within the city limits, the construction policy plausibly channeled the demand shock generated by the Fire into non-wood-related construction. Thus, one would expect that the Chicago Fire disproportionately affected innovation and manufacturing in non-wood construction. Our results corroborate this interpretation. Non-wood construction innovation largely contributes to the increase in overall construction innovation: by 1890, Chicago-based inventors obtained 90 more non-wood construction patents relative to the synthetic control, whereas the increase in wood-related patenting was about 70% smaller. The effects of the Chicago Fire on non-wood- *vis-à-vis* wood-related manufacturing indicators display similar heterogeneity. The number of non-wood construction establishments and their production value doubled in the ten years after the 1871 Fire. Fixed capital, material, and labor costs also display substantial increases. The effects on wood-related manufacturing construction are considerably smaller and statistically insignificant. The results hold when controlling for total employment, further suggesting that the increase in patenting and manufacturing is driven by the construction sector.

These patterns are consistent with our hypothesis that Chicago's construction policy channeled reconstruction efforts into non-wood construction, thus propelling innovation in that area. In hindsight, non-wood construction would become the predominant technology and vastly outpace wood construction. Non-wood buildings pose significantly fewer fire hazard concerns, permit denser agglomeration, and dominate contemporary urban landscapes.

Second, we examine the impact of the 1872 Boston Fire on construction innovation and manufacturing. In Boston, the Fire destroyed part of the central business district, causing 75 million dollars in damages (1,8 billion 2010$), approximately equivalent to 11% of the total real estate value of the city, or 300$ per inhabitant (Hornbeck and Keniston, 2017). Public opinion called for more restrictive legislation, similar to the one enacted in Chicago, but lobbying by real estate developers successfully opposed any initiative in this direction. These different institutional constraints resulted in vastly different reconstruction experiences. In Boston, post-Fire buildings largely resembled those that preceded them. Although the Boston and Chicago fires differed in proportions, they are still comparable in many dimensions. They were both severe, targeted the central business districts, and hit economically dynamic and growing cities. We thus view the 1872 Boston Fire as an instructive counterfactual, where no post-Fire construction policy is implemented.

Using a synthetic control framework, we find that the 1872 Boston Fire had no statistically significant effect on construction innovation. While patenting in Boston increased towards the end of the century, construction-related patenting did not diverge from the synthetic control. On the other hand, we do find an effect on manufacturing output and material costs, still witnessing the post-Fire reconstruction–but these effects are more modest than in Chicago.

Altogether, the differences between wood and non-wood innovation and manufacturing, as well as the results of the 1872 Boston Fire suggest that construction policies implemented in Chicago might have played a key role in shaping the manufacturing and innovation dynamics it ignited. Thus, the Great Chicago Fire provides a unique natural experiment to examine how public policy can direct endogenous innovation responses to natural disasters and help mitigate their adverse effects. Our results reveal substantial scope for policy interventions to sustain resilience-enhancing innovation in the face of impending climate-related challenges.

Contributions to the Literature This paper contributes to three streams of literature. First, we contribute to the literature on the direction of innovation. Pioneering studies by Habakkuk (1962) and Schmookler (1966) and subsequent theoretical contributions by Acemoglu (2002, 2010) show that market size and relative factor prices shape the direction of innovation and have received vast empirical support (e.g., Popp, 2002; Hanlon, 2015; Andersson, Karadja and Prawitz, 2022; San, 2023). Recent papers document that innovation reacts to natural disasters using cross-country variation (Miao and Popp, 2014), as well as focusing on specific events, such as droughts (Moscona, 2021), climate change (Moscona and Sastry, 2023), and epidemics (Berkes, Coluccia, Dossi and Squicciarini, 2025). Our contribution here is twofold. First, we disentangle the effect of policy interventions from other, more general, post-Fire consequences and provide novel evidence that policy intervention can successfully direct the endogenous innovation response to natural disasters and mitigate their adverse consequences. Second, we show that technological change responds to the damages caused by urban fires, a growing concern amid contemporary global warming and overpopulation.

Second, we add to the growing literature on the economics of industrial policy (Juhász, Lane and

Rodrik, 2023; Bartelme, Costinot, Donaldson and Rodriguez-Clare, 2025). Recent papers study the efficacy of deliberate industrial policy interventions in sustaining industrialization in textiles (Juhász, 2018), shipbuilding (Kalouptsidi, 2018; Hanlon, 2020), heavy chemicals (Lane, 2025), among others, as well as their effects on regional development (Garin and Rothbaum, 2024; Incoronato and Lattanzio, 2024; Mitrunen, 2025). Additionally, the study of innovation policy has gathered considerable attention (Bloom, Van Reenen and Williams, 2019), particularly in terms of public R&D (e.g., Azoulay, Graff Zivin, Li and Sampat, 2019; Gross and Sampat, 2023; Moretti, Steinwender, Van Reenen and Warren, 2025). We inform this literature by building on Acemoglu (2012), who argues that market competition generally under-provides diversity in innovation. Our findings provide the first evidence that innovation policy can decrease excess conformity and increase the amount of diversity in technological change.

Third, we contribute to the literature on the economic effects of natural disasters. Existing papers adopt either a cross-country perspective (Dell, Jones and Olken, 2012; Cattaneo and Peri, 2016; Kocornik-Mina, McDermott, Michaels and Rauch, 2020) or focus on specific disasters, such as the 1871 Boston Fire (Hornbeck, 2012), the 1906 San Francisco Earthquake (Ager, Eriksson, Hansen and Lønstrup, 2020), the Dust Bowl (Hornbeck, 2012), the 1927 Mississippi Flood (Hornbeck and Naidu, 2014), and the 2009 Ketsana typhoon in Vietnam (Gröger and Zylberberg, 2016). In between these two approaches, Boustan, Kahn, Rhode and Yanguas (2020) construct a long series of natural disasters in the United States to employ within-country identifying variation. Strobl (2011) and Mahajan and Yang (2020) adopt a similar approach focusing on hurricanes, whereas Borgschulte, Molitor and Zou (2024) study wildfires. We present mixed evidence on the effects of natural disasters *per se*, while shedding light on the key role of policy intervention following such shocks.[4]

Outline of the Paper The rest of the paper is organized as follows. Section I presents a description of the Chicago and Boston fires. In Section II, we describe the data used in the analysis. Section III discusses the causal research design, and in Section IV, we present the main results on the effects of the 1871 Chicago Fire. Section V explores the underlying mechanisms and discusses the effect of the 1872 Boston Fire. Section VI concludes.

I HISTORICAL BACKGROUND

This section describes the events of the Great Chicago Fire of 1871, the construction policies that followed it, and their consequences on construction practices and technological advancements. Then, we present key information on the Great Boston Fire of 1872.

[4] On the one hand, the 1872 Boston Fire did not significantly impact innovation and economic activity. Conversely, the 1871 Chicago Fire had substantial positive effects on both variables.

I.A The Great Chicago Fire of 1871

The Fire started on October 8, 1871, and ravaged central Chicago for two days. Estimates indicate that hundreds of individuals died, and close to 100,000 people were left homeless following the conflagration (Smith, 2020). More than 16,000 buildings, worth approximately 200 million dollars (or 5 billion dollars at current prices), chiefly in the central business district, were destroyed.[5] The Fire devastated infrastructure, including water works, railroads, and private buildings, such as hotels and theaters.

Two factors, in particular, determined the devastating impact of the Fire. First, Chicago had been massively growing in the decade preceding the Fire through the construction of wooden slums which spread from the city's outskirts deep into the center (Rosen, 1986). Miller (1996) documents that the lack of regulatory oversight was instrumental in creating fire hazards in the central portion of the city. Second, the Fire Department proved ineffective in containing the Fire (Smith, 2020). Various alarms raised by the citizens failed to be communicated to the fire station. Firemen, who were badly equipped, faced logistical problems as the chaos in the streets obstructed their intervention.

I.B Construction Policy After the Fire

The pre-Fire growth of the city of Chicago was not accompanied by urban policy oversight. In 1871, only one piece of legislation prevented the construction of wooden buildings in a small area of the city center without affecting existing housing stock (Rosen, 1986). Soon after the 1871 Fire, a debate arose around the necessity to pass more stringent legislation on new constructions. Joseph Medill, elected in 1871 shortly after the Fire, enacted minor provisions affecting relatively small portions of the new immigrant neighborhoods. Only in 1874, after a second—minor—Fire threatened the center, the National Board of Fire Underwriters (now American Insurance Association), an organization established in 1866 by insurance companies to reduce fire losses and promote fire safety, successfully pushed for more comprehensive legislation to prevent further disasters (Critchell, 1909).

The first provisions enacted by the Medill administration shortly after the 1871 Fire allowed owners in each block to vote and decide to outlaw buildings made of inflammable materials. The ordinance issued after the 1874 fire, by contrast, prescribed that only bricks and non-combustible materials would be used in new buildings. Frame buildings, the predominant construction technology in Chicago, were prohibited except for very small units far from the city center. Warehouses and lumber yards were removed from all built-up areas within the limits of Chicago. Moreover, the fire department was reorganized and furnished with new equipment (Smith, 2020). The National Board of Fire Underwriters served as guarantor of the implementation of the legislation enacted by the municipal

[5] According to the 1870 census, the population of the inner Chicago area was approximately 300,000. The contemporary 200 million 1871$ figure equaled approximately 2.6% of the US GDP, which, today, would imply 700–800 billion 2010$ damages.

administration. While direct evidence on the enforcement of the ordinance is not available, the Board received a large number of requests to amend the law for specific wooden buildings, all of which were rejected by the Council (Mayer, Wade, Holt and Pyle, 1969).[6]

I.C Construction Practices and Innovations after the Fire

Despite initial fear that the new restrictive ordinance would hamper the city's redevelopment, rebuilding efforts were swift (Rosen, 1986). Compared to the pre-Fire buildings, the newly erected constructions had thicker walls, deeper foundations made of mortar and brick, often encapsulated elevators, and featured better fire escapes. They were also larger in area and taller, thus resulting in a larger internal space. The 1871 Fire ultimately ushered in substantial innovations in building technology and design, attracting many architects and engineers who would make Chicago a global hub for innovation in construction technology—a legacy that persists to this day (Wermiel, 1996).

The first breakthrough innovations were in fireproof construction. While fireproof techniques had been developed long before the Fire, their adoption and further advancement drastically accelerated after 1871. George H. Johnson, a designer who moved to Chicago in 1871, patented a hollow-tile system for fireproof floors (Sawislak, 1995). The application of terra-cotta tile to cover exposed iron parts became widespread. Being heat resistant, the tile remained intact in the heat of direct flames, thus providing a key step toward the design of fireproof buildings (Peters, 1991).

Under the ordinance's provisions, new constructions had to rely on an iron frame instead of a wooden inner structure. As land prices in the central business district area soared, developers sought to erect increasingly tall structures (Condit, 1952). Eventually, the first skyscrapers in history emerged in Chicago. In 1895, a writer in *Engineering News* cited in Randall (1949) reports that "The construction of enormously high office buildings [...] originated in Chicago, in its practical application, at least, and that city has at the present time buildings of steel skeleton type than have all other American cities together." The development of skyscrapers required substantial innovation in iron frames to reduce their weight and improve their stability. Additionally, the development of tall buildings promoted the fast adoption of the elevator.[7]

The "Great Rebuilding" attracted many architects, engineers, and designers. Historians refer to this newly formed community as the "Chicago School Architecture" (Fitch, 1948). The guiding principles of this heterogeneous movement–which embraced structural innovations such as steel-frame construction and improved wind resistance while also stressing the importance of spacious interiors and

[6]The requests appear in the Proceedings of the Common Council of the City of Chicago in 1874, 1875, and 1876.

[7]The Home Insurance Building, commonly considered the first skyscraper in the world due to its steel-framed structure, was inaugurated in Chicago in 1885. It had four elevators serving its ten floors.

abundant light (as in Holabird and Roche's 1889 Tacoma building design)–reverberated in European Modernism and contributed to making Chicago the global hub of innovative architecture (Condit, 1952).

I.D The Great Boston Fire of 1872

The Fire in Boston broke out on November 6, 1872. It centered in the wholesale business district and destroyed 776 buildings, causing approximately $75 million in damages, or 11% of the total assessed value of Boston real estate stock (Hornbeck and Keniston, 2017). Post-fire growth was fueled by strong private demand and resulted in growing land prices and capital inflows.

As in Chicago, public opinion called for stricter building regulations. Facing lobbying by powerful interest groups, however, the municipal authority could only enact weak building legislation, which was ultimately repealed in 1873 (Rosen, 1986).[8] Thus, unlike in Chicago, the reconstruction in Boston was not overseen by the municipal authority and was largely privately managed.

Partly because of the different policy constraints faced by developers in Boston and Chicago, post-fire buildings in Boston largely resembled those that preceded them. Fireproof techniques were applied to traditional materials, and the construction techniques remained largely unchanged. Rosen (1986) argues that this approach was rooted in the structural differences between the two cities. Boston had already undergone a rationalization of land use before the Fire, and consequently, its urban infrastructure was less amenable to dramatic improvement. As a result, Boston's post-fire reconstruction produced safer and better fireproofed buildings, yet largely unchanged in construction methods and architectural style.

II DATA

This section presents the data underlying the analysis and our procedures for compiling the final datasets. First, we present a new dataset of patents issued between 1853 and 1900. Then, we discuss how we use the manufacturing and population censuses and describe a newly compiled dataset of geo-coded historical US landmarks.

[8] In Chicago, landowners and industrialists were advocating for tighter regulations, whereas the less affluent feared that these regulations would force them out of the city center. On the other hand, in Boston, landowners advocated against tighter regulations because the city had already undergone extensive redevelopment before the fire (Rosen, 1986). These different positions partly explain the different provisions enacted in the two cities.

II.A Patent Data

We measure innovation activity using patents, in line with a long tradition in economics (Griliches, 1990). We collect the text of the universe of patents issued in the United States between 1853 and 1900 from Google Patents, following the approach of Moser and San (2020).[9] Using a state-of-the-art large language model (`GPT 4o-mini`), we extract, directly from the patent's text, data on the inventors' name, address, location, the filing and issuance date of the patent, and potential firm assignee. We augment this information with data on the patent CPC technology classes provided by Google Patents. Furthermore, using a commercial software (`Google Maps API`), we geo-code the addresses extracted from the patent documents to precise latitude and longitude coordinates.[10]

We identify construction-related patents using a simple dictionary-based approach. We label a patent as "construction" if it mentions at least five times one or more construction-related words (in a sample of 30 words). The list of construction-related words is provided in Table D.1. Thus, patents that the USPTO did not assign to the "Fixed Construction" technology class may still be classified as construction. We adopt a similar heuristic method to identify "wood-related" and "non-wood-related" construction patents. In particular, we label a patent as "wood-related" (resp. "non-wood-related") if: (i) it is a "construction" patent, and (ii) it mentions at least one wood-related (resp. non-wood-related) word within a pre-designed dictionary. On average, Table I shows that 22.9% of patents are flagged as related to construction. Of those, 11.7% are related to wood-related construction, while 22.3% are identified as non-wood-related construction patents.

To quantify the technological spillovers of the Chicago Fire on innovation outside of construction, we measure the technological similarity between construction-related and other patents by technology class. We propose two alternative procedures. First, we rank CPC classes by the share of patents in each class, which are also construction patents. Second, we employ the `doc2vec` document embedding model, a natural language processing technique (Mikolov et al., 2013). The model is trained on a 20% random sample of the universe of patents, allowing us to represent each patent as a real-valued vector. For each non-construction patent, we compute the average cosine similarity with all construction patents and take the average within each technology class. Thus, the ranking returns a technology class-level order of similarity between construction and non-construction patents. The two methods return the same ranking: as expected, patents in CPC class E ("Fixed Construction") technology class

[9] The United States Patent and Trademark Office (USPTO) was established in 1836. While data on patents issued before 1853 exist, patenting was rare and unusable for our empirical analysis.

[10] We compare our newly constructed data to Sarada, Andrews and Ziebarth (2019) and Petralia, Balland and Rigby (2016), which cover a partially overlapping time period but do not contain information on the text of patent applications. Our data coverage exceeds 90% of both datasets for the years when they overlap (see Appendix A for details).

are the most similar to the pool of construction patents, followed by classes G ("Physics") and B ("Performing Operations; Transports"). By contrast, patents in classes C ("Chemistry; Metallurgy"), H ("Electricity"), and A ("Human Necessities") are the least similar to construction patents.

Using the coordinates assigned to the location data extracted from patent documents, we assign patents to the locations listed in the Census Place Project (CPP), a directory of geo-coded locations listed in the US census (Berkes, Karger and Nencka, 2023). Specifically, we assign a patent to the closest CPP location provided that at least one of the inventors resides within 20 kilometers (12.4 miles).[11] The results are not sensitive to alternative thresholds between five and thirty kilometers.

II.B Manufacture Census

We use county-by-industry data from the 1860, 1870, and 1880 Censuses of Manufacturing digitized by Hornbeck and Rotemberg (2024). The data contain information on production value, number of establishments, value of fixed capital, and labor and material costs. Since more disaggregated data—e.g., at the city level—are not publicly available, the analysis is run at the county level. We thus assume that the Chicago Fire affects the entire Cook County (IL), where Chicago is located. Similarly, the Great Boston Fire impacted Suffolk County (MA), where Boston is located.[12] Since the data is at the decade level, we use 1880 as the only post-treatment period, whereas 1860 and 1870 constitute the pre-treatment window.

Table I lists selected statistics for the Manufacturing Census data. Counties have an average of ten establishments, although this figure conceals substantial heterogeneity. Cook County, where Chicago is located, and Suffolk County, where Boston is located, host more than 1,000 firms, placing them in the top percentile of the overall distribution. Other economic performance indicators, such as the total production value, display similar degrees of heterogeneity.

We consider the industries labeled as "construction," "construction materials," and "furniture" as related to construction manufacturing. Our baseline results remain unchanged if we only include the "construction" industry in the treatment group. In turn, we identify as wood-related industries those labeled as "carpentering," "lumber, planed," "lumber, sawed," "saw," "wood products, other," "wood, turned and carved," and "wooden ware." Finally, non-wood-related industries are "brick, stone, and tile," "lime and cement," and "marble and stone work."

[11] We assign patents with multiple inventors to each inventor's CPP location. Results remain unchanged if we assign equal shares to each inventor's location.

[12] This assumption is reasonable, for Chicago's and Boston's metropolitan areas account for more than 90% of the population of Cook and Suffolk Counties in 1870.

II.C Population Census

We use individual-level data from decennial population censuses and location data from the CPP (Ruggles, Fitch, Goeken, Hacker, Nelson, Roberts, Schouweiler and Sobek, 2021; Berkes et al., 2023). The CPP assigns precise latitude and longitude coordinates to the large majority of individuals in the population census, which lacks standardized and comprehensive location data beyond the county of residence. We use these two sources to produce two distinct datasets.

First, we tabulate data from the 1870 population census at the CPP-location level. For each location, we compute a set of demographic characteristics listed in Table I (Panels B–D). Among those, we choose the set of variables we use to construct the synthetic control units, as discussed in detail in the next section.

Second, we construct an individual-level dataset from the 1870 and 1880 censuses. We consider the universe of the working-age population—i.e., above 15 years old—with a valid occupational response. We identify as a construction worker any individual listing an occupation where at least 50% of the employed are listed in the "Construction" industry in the federal census. Among those, "Carpenters" are identified as wood-related construction workers, whereas we assign "Brickmasons, stonemasons, and tile setters," "Cement and concrete finishers," and "Plasterers" to non-wood-related construction. On average, 1.9% of the workforce is employed in construction, 1.1% is employed in wood-related construction jobs, and 0.3% is assigned to non-wood-related construction occupations.

II.D Historical Landmarks

To assess the cultural and architectural legacy of the Chicago Fire, we assemble data on significant buildings erected in the metropolitan areas in our sample between 1850 and 1900. We start from places listed in the "National Register of Historic Places" (Stutts, 2024). The National Register is the United States' official list of historically significant places. It was established under the 1966 National Historic Preservation Act and is currently maintained by the National Park Service. The Register records buildings, districts, sites, and, more generally, places deemed worthy of preservation.

The Register lists 99,199 sites.[13] It indicates the state, county, and city where each entry is located, along with the type of record (e.g., "district" or "building"), the area of significance (e.g., "architecture" or "industry"), and other information less relevant for the analysis. We first geo-code each entry and assign it to the closest metropolitan area within 20 kilometers (12.4 miles). We successfully geo-coded 98% of the Register. We find that 24,673 sites (24.8% of the sample) are assigned to a metropolitan area in our sample. Second, we augment the dataset with information on the construc-

[13] We accessed the Register in October 2024, when the last update was dated August 2024.

tion year of the landmarks. To do so, we individually search for each entry on Wikipedia and parse the text to retrieve the construction year. We correctly impute a construction year to approximately 80% of the entries.

The final sample of historical landmarks erected in one of the metropolitan areas in the sample, along with information on their construction year, comprises 19,110 entries. In the analysis, we concentrate on the subset of 5,907 landmarks erected between 1850 and 1900. Additionally, we focus on 3,792 "buildings" entries, thus discarding residual observations listed as "district," "site," and "object." Moreover, we distinguish units based on their area of significance: "architecture" and all others.

II.E Construction of the Samples

The first sample we construct is a city-level yearly panel dataset with data on innovation activity between 1853 and 1900. The data covers the largest *metropolitan areas* in the United States in 1870. To construct a metropolitan area, we first extract all CPP locations with at least 20,000 individuals in the 1870 census.[14] There are 84 such places, each corresponding to a major city. Then, we map all other minor towns to the closest city with a population above 20,000, provided their distance does not exceed 20 kilometers (12.4 miles).[15] The results remain qualitatively unchanged for thresholds between 5 and 30 kilometers. The resulting dataset thus comprises 84 "metropolitan areas" which include a single major town above 20,000 inhabitants and all other minor towns within 20 kilometers from its center.[16] For each metropolitan area, we tabulate demographic characteristics from the 1870 census—the last census before the Fires—and compute the number of patents issued in each metropolitan area between 1853 and 1900. Figure I displays the geographic distribution of all metropolitan areas thus constructed.

The second sample is constructed at the county level and comprises all counties where our metropolitan areas are located. There are 76 such counties. The difference between the number of counties (76) and metropolitan areas (84) is due to the fact that some counties encompass more than one metropolitan area. These data are available at a decennial frequency between 1860 and 1880. For each county, we observe data from the Census of Manufactures and information extracted from the 1870 population census and mapped onto 1870 county borders. Data from the 1860 and 1880 Census of Manufactures

[14] Our results remain robust when we apply alternative population thresholds between 5,000 and 50,000 to construct the donor metropolitan area pool. We focus on relatively large cities primarily because the synthetic control approach applies a zero weight to small towns when constructing the synthetic control, as they are too different from the treated cities.

[15] Figure C.2 provides a graphical description of the agglutination procedure that forms the "Chicago" metropolitan area within Cook County (IL).

[16] The full list of cities above 20,000 inhabitants, as well as all minor cities within their metropolitan areas, is provided in Table D.2.

are cross-walked to county borders in 1870, following the methodology described by Eckert, Gvirtz, Liang and Peters (2020). We observe the number of establishments, production value, fixed capital, material costs, and labor costs in construction, wood-related manufacturing, and non-wood-related manufacturing.

Third, we complement the individual-level data extracted from the 1870 and 1880 population censuses with the intergenerational links produced by Abramitzky, Boustan, Eriksson, Pérez and Rashid (2020). We link the 1870 entries to their records from the 1880 census so that, for each individual, we observe a set of fixed individual characteristics and time-varying outcomes—specifically their industry and occupation—at two points in time, 1870 and 1880. Because we seek to measure how the Chicago and Boston fires affected the probability of taking jobs in construction, we restrict the sample to include individuals between 16 and 70 years old with a valid occupational response in either census, who were not working in construction-related occupations in 1870.

III RESEARCH DESIGN

Our empirical analysis seeks to evaluate the impact of the 1871 Fire on innovation and manufacturing activities. The key challenge to disentangle its effects is that other correlated shocks in Chicago may affect the variables of interest. A natural approach would thus be to compare Chicago with other cities in a difference-in-differences setting. This strategy, however, relies on the hypothesis that without the Fire, Chicago and the other cities would have followed similar trajectories. This parallel trends assumption is unlikely to be verified. Before the Fire, Chicago was the fastest-growing large city in the United States and a central hub of the expanding railway network (Miller, 1996). It thus seems plausible that Chicago was not on the same trend as other cities before 1871. Additionally, inference in the double differences framework would be infeasible since we only have a single treated unit.

To circumvent this issue and construct an appropriate counterfactual for post-Fire Chicago, we adopt the synthetic control method (Abadie and Gardeazabal, 2003; Abadie, Diamond and Hainmueller, 2010). The core idea of synthetic controls is to employ information on treated and control units to construct a "synthetic" control that "resembles" the treated unit and can serve as a counterfactual. The estimated causal effect is, thus, the difference between the treated and synthetic control outcome values after the treatment period.

Formally, suppose we observe $j \in \{1, \ldots, J+1\}$ units over time $t \in \{1, \ldots, T\}$. In our analysis, j denotes a metropolitan area or a county, and t is a year or a decade. Suppose $j = 1$ denotes Chicago. Let Y_{jt}^N be the potential outcome of city j in year t absent the Fire, and let Y_{jt}^I be the observed outcome of city j in all post-Fire periods $t = 1871, \ldots, T$. Finally, let Y_{jt} denote the observed outcome. Since, all

$j \neq 1$ are untreated cities, $Y_{jt}^N = Y_{jt}$ for all t. The estimand is thus $\tau_t \equiv Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N$, i.e., the treatment effect of the Fire on Chicago. A synthetic control estimator approximates the counterfactual and unobserved term Y_{1t}^N with a weighted average of the outcome of all untreated units so that the estimator reads out as follows:

$$\hat{\tau}_t = Y_{1t} - \sum_{j=2}^{J+1} \omega_j Y_{jt}, \tag{1}$$

where the weights $\omega_j \in \{\omega_{j'}\}_{j'=2}^{J+1}$ capture the contribution of each "donor" unit to the estimate of the counterfactual. To compute the weights, the standard approach is to maximize the pre-treatment similarity between the treated and the control units. Formally, let $\mathbf{X}_j = (X_{1j}, \ldots, X_{kj})'$ be a vector of pre-treatment characteristics of unit j, and let $\mathbf{X}_0 = [\mathbf{X}_2, \ldots, \mathbf{X}_{J+1}]$ collect all such characteristics across donor units. The vector $\mathbf{X}_j$ includes both time-invariant characteristics and pre-intervention values of the outcome variable. Following Abadie and Vives-i Bastida (2022), a simple data-driven approach to find the weighting scheme $\Omega = (\omega_2^*, \ldots, \omega_{J+1}^*)'$ is to minimize the following expression:

$$||\mathbf{X}_1 - \mathbf{X}_0\Omega|| = \left[\sum_{h=1}^{k} \nu_h \left(X_{h1} - \omega_2 X_{h2} - \cdots - \omega_{J+1} X_{hJ+1}\right)^2\right]^{1/2}, \tag{2}$$

where the non-negative weights $\{\nu_h\}_{h=1}^k$ can be used either to standardize the predictors or to reflect their importance for the in-sample fit. In our application, following Abadie et al. (2010), we simply standardize the predictors.

Abadie et al. (2010) prove that the magnitude of the bias $E[\tau_t - \hat{\tau}_t]$ is bounded and that it increases in (i) the ratio between transitory shocks and the number of pre-intervention periods, (ii) the number of units in the donor pool, and (iii) the number of potential unobserved factors. Abadie and Vives-i Bastida (2022) highlight, among other suggestions, that (i) a long pre-intervention time series is crucial to assess the capacity of the synthetic control to reproduce the trajectory of the treated unit, (ii) a sensible choice of co-variates is fundamental to ensure minimize the impact of unobserved correlated shocks, (iii) pre-intervention fit of the synthetic control is crucial for credible causal inference, and (iv) out-of-sample validation of the synthetic control is useful to validate it against over-fitting. In our application, we closely follow these recommendations.

We apply the synthetic control methodology to estimate the impact of the Great Chicago (and Boston) Fires on various outcomes. The level of observation is either a metropolitan area or a county. The sample includes 84 metropolitan areas—Chicago, Boston, and 82 untreated cities—or the counties where these cities are located. Units are observed either at a yearly or decennial frequency, depending on data constraints, as we explained in Section II. Throughout the analyses, we use the same set of balancing variables. These are the pre-treatment outcome variables, as well as population, the share of men, the share of literate, the share of Blacks, and the employment shares by occupation and industry in 1870. We choose these variables to ensure that the synthetic control reproduces Chicago's—and Boston's—demographic and occupational composition. All balancing variables are constructed from the population census except for the pre-treatment outcome values. Table D.3 reports the non-zero weights that determine the influence of each donor city in the synthetic control unit. We exclude Boston and Chicago from the set of donor cities when constructing the synthetic control for Chicago and Boston, respectively.

In the spirit of the synthetic control approach, Table II compares observed characteristics in 1870 in Chicago (column 1), other cities (columns 2–4), and the synthetic Chicago (columns 5–7).[17] As expected, Chicago is substantially different from the average US city: it is richer, presents a larger share of Whites, and has a higher share of foreign-born. It also differs in terms of the occupational structure—most notably, it displays a higher share of skilled manufacturing workers—and industry composition—with lower shares of agricultural and textile workers and more trade and transportation workers. These differences reflect historical evidence depicting Chicago as a transportation hub within the expanding railway network. Differences between Chicago and the synthetic control are much less pronounced, often statistically insignificant, and always considerably smaller in magnitude compared to the crude average of untreated cities. Overall, Table II provides evidence supporting the validity of the synthetic control research design. In the remainder of the paper, we evaluate the goodness-of-fit of the synthetic unit for the various outcomes of interest.

In robustness checks, we employ the synthetic difference-in-differences (SDiD) method developed by Arkhangelsky, Athey, Hirshberg, Imbens and Wager (2021). The SDiD estimator nests the intuition of standard difference-in-differences (DiD) and synthetic control frameworks to obtain an estimator that outperforms both in terms of bias mitigation and efficiency. The SDiD estimator can be thought of as a local difference-in-differences estimator, which assigns larger weights to control units that resemble the treated unit(s) along a set of specified characteristics. We compute bootstrap standard errors to assess the statistical significance of the estimates. Appendix B.II provides the analytical details on the SDiD framework.

IV MAIN RESULTS

This section presents the main results of the paper. We organize it into four parts. First, we explore the effect of the Chicago Fire on innovation in construction. Then, we look at how the effects of

[17] To construct the synthetic Chicago, we use the weights obtained by applying the synthetic control approach on construction patenting, as in Section IV.A. The balancing variables thus comprise the baseline covariates constructed from the census, as well as the lagged values of construction patenting. Table D.4 replicates the balance table for Boston.

construction innovation spilled over into innovative activities in other industries. Third, we explore the broader consequences of the Fire on the manufacturing sector. Finally, using data on historically significant landmarks, we document the historical and cultural legacy of the Fire.

IV.A The Great Chicago Fire and Innovations in Construction Technology

The central objective of this paper is to understand how innovation responded to the 1871 Fire shock, trying to shed light on the role of policy interventions. To quantify this effect, we first focus on construction-related technological change, as measured by patents. In particular, we implement a synthetic control design that leverages yearly information on construction-related patenting for each metropolitan area.

Figure II reports the baseline estimates. In Figure IIa, we display the number of construction-related patents in Chicago (solid red line) and the synthetic control (dashed grey line). The dashed black line marks the timing of the 1871 Fire. Trends in construction-related innovation in the actual and synthetic Chicago units are remarkably similar before 1871. This pattern is a direct consequence of the synthetic control method, which constructs the counterfactual to mimic the pre-intervention trends in the treated unit. After the Fire, however, trends in the treated and control units diverge sharply. Construction-related innovation in Chicago began to increase three to four years after the Fire, exhibiting substantial growth in the following decades. Innovation in the synthetic control unit displays only moderate increases. Quantitatively, the treated and control units both produced approximately 20 construction-related patents in 1870. Fifteen years later, this Figure increased to almost 300 patents in Chicago and 80 in the synthetic control. The remarkable and growing divergence indicates that the Fire had a positive and large effect on construction innovation in Chicago.

Figure IIb reproduces the same graph by reporting the difference in construction-related patents between Chicago and synthetic Chicago. As previously noted, the two units are on the same trend before the Fire and drastically diverge after 1871 and, especially, after 1874. This seemingly "lagged" response may reflect at least three factors. First, the timing depends on the year when each patent is *issued*. Ideally, the filing year would be more appropriate to reflect the supply-side response of inventors to the Fire. However, this information is missing from many patent documents before the 1880s. The delay between the filing and granting year is thus one factor influencing the seemingly lagged response of construction innovation to the Fire. Second, the construction policy that prohibited new wooden buildings was promulgated in 1874 after a second, minor fire threatened the city center. Third, the reconstruction activity was halted by the bankruptcy of Jay Cooke and Company, a major local bank, and the 1873 national downturn, which limited capital inflows (Miller, 1996). The timing of the divergence between Chicago and synthetic Chicago is thus consistent with the nature of the data and the historical circumstances.

In Figure IIc, we report the results of a standard analysis to facilitate inference using the synthetic control estimates. Specifically, we assign the treatment status to each of the 84 metropolitan areas in the sample and compute the difference between construction-related patenting in that city and its associated synthetic control. This difference is an estimate of the treatment effect for Chicago, as shown in equation (1), whereas other cities constitute "placebo" units. The underlying intuition is that we want to gauge the probability that the estimated impact of the Fire in Chicago was random. The Figure highlights the estimates for Chicago in red, while all other metropolitan areas are shown in gray. The Figure shows that the treatment response in Chicago far exceeds all other cities. To put it differently, if we pretended that the 1871 Fire had happened in any other city, we would never estimate a response of construction-related innovation as big as it is in Chicago.

One final way to evaluate the impact of the Great Chicago Fire on construction-related innovation is to look at the distribution of the pre-post Fire root mean squared prediction error (RMSPE) ratios across metropolitan areas.[18] Intuitively, the ratio between post- and pre-intervention RMSPE quantifies the quality of the fit of the synthetic control after the treatment compared to the quality of the fit before the intervention. Figure IId reports the distribution of the post-to-pre-intervention RMSPE ratios across metropolitan areas. Chicago is highlighted in red. The post-to-pre-Fire RMSPE ratio in Chicago stands out compared to all 83 other cities. If we were to assign the Great Chicago Fire to each city, the probability of observing a post-to-pre-Fire RMSPE as large as Chicago's would be $1/84 \approx 0.01$.

Patents vary extensively in terms of their economic significance. The standard practice to account for this heterogeneity is to look at citations. This approach is infeasible in historical settings because the inclusion of citations to prior art became compulsory only after World War II (Andrews, 2021). To address this limitation, we adopt the novelty measure developed by Kelly, Papanikolaou, Seru and Taddy (2021), which measures novelty as the excess text similarity of each patent with future patents relative to previous patents. In Figure C.3, we repeat the analysis focusing on patents in the top 20% of the novelty measure distribution. Figure C.3a focuses on construction patents and indicates that high-impact construction innovation in Chicago sharply diverged from the synthetic control after 1871. This pattern indicates that the positive effect of the Fire on construction innovation is not driven

[18] Abadie et al. (2010) define $R_j(t_1, t_2)$ to be the mean squared prediction error for unit j between two periods $0 \leq \cdots \leq t_1 \leq t_2 \leq T$ as

$$R_j(t_1, t_2) \equiv \left[\frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \left(Y_{jt} - \hat{Y}_{jt}^N \right)^2 \right]^{1/2},$$

where $\hat{Y}_{jt}^N$ is the outcome of the synthetic control as defined in the second term of equation (1). Then, the ratio of post-to-pre-intervention RMSPE for unit j is given by $r_j = R_j(T_0 + 1, T)/(1 + R_j(1, T_0))$.

by low-quality innovation.

In Figure C.4, we report the event-study synthetic difference-in-differences estimated effects of the Great Chicago Fire on construction innovation. We find no statistically significant difference in construction patenting before 1871 between Chicago and the synthetic control group. After 1871, and particularly after the 1874 municipality ordinance, the SDiD estimates replicate the synthetic control treatment effects, indicating a large and growing wedge in construction patenting in Chicago relative to the synthetic control.

Altogether, these results suggest that the Fire triggered an increase in construction-related innovation as a response to both the need for reconstruction in conjunction with policies pushing for the use of fireproof and innovative designs and materials.

IV.B Knowledge Spillovers

The previous analysis provides strong evidence that the 1871 Fire propelled a self-sustaining wave of innovation in construction in Chicago that spanned at least three decades after the Fire. In this section, we examine how the boom in construction innovation spilled over to other fields depending on their technological similarity to construction. This exercise is informative along two dimensions. First, it allows us to gauge the relevance of knowledge spillovers in sustaining subsequent innovation. Second, we can use fields other than construction to construct a "within-Chicago" counterfactual. It is, in fact, possible to interpret the estimated increase in construction-related innovation after 1871 as a collateral consequence of unusual economic growth spurred by the Fire. By comparing the pattern of innovation activity across sectors within Chicago, one can net out the aggregate impact of the Fire and disentangle its effect on construction.

Our text-based measure of "construction" patents does not exploit technology class information. Thus, construction patents are scattered across CPC technology classes. Our main measure of technology-class-level similarity to construction is the share of patents in a given CPC technology class flagged as "construction" by the text-based algorithm. Then, we rank classes according to this share and divide them into terciles such that the bottom tercile comprises classes with the least share of construction patents, and the top one collects those with the largest share. As a robustness exercise, we also compute the average text-based similarity between non-construction and construction patents by CPC technology class using a document embedding model, which produces the same ranking as the main classifier.

Following the previous analysis, we estimate the treatment effects of the Fire, using as the outcome variable the number of non-construction patents by tercile of similarity with construction patents.

Figure III reports the results of this exercise by showing the difference between the number of patents in Chicago and those in the synthetic control. The solid line reports the estimates for patents in the technology classes in the top tercile of similarity with construction patents, the dashed line refers to the mid tercile, and the dotted line displays the estimates for the bottom tercile of least similar technology classes. In all cases, the synthetic control closely follows patenting activity in Chicago before the Fire, indicating that it plausibly constitutes a good counterfactual for what would have happened in Chicago after 1871 if the Fire had not happened.

However, the trajectories sharply diverge after 1871. The number of non-construction patents belonging to technology classes most similar to construction patents sharply increased over the two decades following the Fire. By contrast, innovation in the middle and bottom terciles displayed a much more modest increase in the mid-1880s, and there is no evidence of further growth after that. Figure III thus documents considerable knowledge spillovers of innovation in construction onto more similar technology classes and limited evidence that these spillovers benefited more distant fields in the technology space.

Showing different trajectories of patenting across terciles of similarity to construction innovation, this exercise suggests that the response of construction innovation to the Fire is unlikely to be due to general economic growth spurred by the rebuilding of Chicago. If this were the case, one would expect similar increases in innovation in other technology classes. Looking at the universe of non-construction patents would not provide a convincing placebo because knowledge spillovers (in sectors technologically closer to construction) would contaminate the aggregate response of non-construction innovation to the Fire. Figure III, instead, clearly indicates that patenting in technologies distant from construction did not significantly increase after the Fire.[19]

IV.C The Impact of the Fire on Construction Manufacturing

Patents provide a direct way to quantify the economic response to the Great Chicago Fire at a high time frequency. In this section, we examine the broader economic implications, focusing on the manufacturing sector.[20] Specifically, we compute the total number of establishments, the value of production,

[19] To corroborate our interpretation of patenting dynamics after 1871 as reflecting the effects of the Fire and not only increasing population, in Table D.5, we normalize patenting activity in construction by total employment. We do not use this as the baseline metric because (i) employment is only available at decennial census frequency, and (ii) the resulting series displays considerable volatility. Despite these caveats, Figure C.5a in Figure C.5 clearly displays that construction innovation per capita increased after 1871 in Chicago relative to the synthetic control.

[20] The two main disadvantages relative to the previous analysis are: (i) manufacturing data are from decennial censuses, as opposed to yearly data from patents, and (ii) they are county-level tabulations instead of the city-level data constructed from patents.

the value of installed fixed capital, and labor and material costs of establishments based in one of the 76 counties where the original 84 metropolitan areas are located.

Table III reports the results. Each county is observed in 1860, 1870, and 1880. The 1880 census is thus the only post-Fire observation. Each row reports the difference between the column variable in Cook County, IL—where Chicago is located—and the synthetic Cook County. As in the city-level analysis, the synthetic control closely matches trends in each outcome variable before 1880. In particular, the difference between Cook County and the synthetic control never exceeds 1% of the value of the pre-treatment outcome in Cook County except for labor costs in 1860 (column 5), where the difference is approximately 7% of the pre-Fire average. Even when the unit of analysis is less granular, the synthetic control approach allows us to construct a credible counterfactual for the treated unit.[21]

Construction manufacturing in Cook County increases after the Fire compared to the counterfactual in all specifications. The estimate is sizable: relative to the synthetic control, the number of firms in construction increases by four times relative to the pre-treatment value (column 1), production value increases six-fold (column 2), the value of fixed capital by four times (column 3), and the cost of materials and labor respectively increase by nine (column 4) and four times (column 5). It is plausible that we find these large effects because the outcomes are measured in 1880, when the "Great Rebuilding" was in full swing. This notwithstanding, the shift towards a more construction-centered production structure appears unequivocal.

Figure C.6 reports the distribution of ratios of post-to-pre RMSPE ratios in the 76 counties and highlights the value for Cook County in red. For all outcome variables except labor costs, the estimated impact of the Fire on construction manufacturing stands out sharply. There is a 1% probability of observing a post-to-pre RMSPE ratio as large as Cook County's when assigning the Fire at random across counties when looking at production value, fixed capital, and material costs, and a 5% probability when looking at the number of establishments.

How does the effect of the Fire on construction compare to other manufacturing sectors? In Figure C.7, we report the estimated treatment effect—i.e., the difference between Chicago and the synthetic control—across the various outcomes compiled from the manufacturing census and industries. Our estimates imply that construction manufacturing was the fastest or second-fastest-growing sector after the Fire. Only food production outpaced construction in terms of production value, largely owing to Chicago's position within the US railway network and growing grain exports (e.g. Heblich, Redding and Zylberberg, 2025). Besides food processing, however, construction manufacturing dis-

[21] This finding is not surprising and, as noted by Abadie and Vives-i Bastida (2022), synthetic control methods work best when the level of aggregation of the outcome variable reduces high-frequency volatility.

plays the largest growth across the five indicators of economic activity. This pattern corroborates our hypothesis that the Fire reshaped the structure of economic activity over the years of the "Great Rebuilding." Additionally, in Panel A of Table D.5, we report the estimated effects when normalizing the outcomes by total employment over time and find qualitatively similar effects, thus confirming that the patterns we uncover are unlikely to be entirely explained by the growing population in Chicago.

Finally, in Figure C.8, we replicate the synthetic control results using the SDiD approach. The results remain quantitatively unchanged using this alternative estimator. Importantly, we can leverage the event-study estimates to compare treated and control units before 1871. As we fail to estimate statistically significant differences between the two groups, we conclude that the SDiD estimates corroborate the empirical plausibility of the parallel trends assumption.

IV.D A Quantitative Analysis of the Cultural Legacy of the Fire

We conclude our analysis of the effects of the 1871 Great Chicago Fire by studying its cultural legacy. We measure the cultural impact of the Fire using comprehensive data on historical buildings listed in the National Register of Historic Places. We compute each metropolitan area's total number of sites by construction year. We view landmarks as a measure of the economically relevant innovations in construction practices and technologies. The National Register aims to list all places deemed worthy of preservation due to their cultural importance. Hence, a count of sites indicates the cultural legacy of the Fire and its impact on architecture. As we discussed in Section I, there is vast qualitative evidence that the Fire was a crucial agglomeration factor for architects and designers who ultimately formed the first Chicago School of Architecture (Wermiel, 1996).

We report the results in Table IV. Since landmark construction is relatively rare, we group years at the decade level. For each metropolitan area, we thus observe two pre-Fire periods (1851–1860 and 1861–1870) and three post-intervention decades (1871–1880, 1881–1890, and 1891–1900). Column (1) reports the estimates for the overall number of historic landmarks; column (2) restricts the sample to entries listed because of their architectural significance; column (3) excludes all sites listed because of their architectural significance.[22] As in the previous Table, we display the difference between Chicago and the synthetic control unit. Across all specifications, synthetic Chicago accurately matches the pattern of the outcome variable observed in Chicago.

We find a sizable increase in the number of listed buildings in Chicago after the Fire relative to

[22] A single entry may be associated with more than one area of significance. In the outcome variable, whose results are displayed in column (2), we look at sites listed solely due to architectural significance. Analogously, in column (3), we exclude all entries where architecture appears as an area of significance. For this reason, the total number of landmarks included in the outcomes in columns (2) and (3) is generally lower than that in column (1).

the counterfactual. The total number of landmark buildings almost doubles relative to the pre-Fire Chicago average in the 1871–1880 decade, doubles again in the following decade, and by the end of the analysis sample, the increase is almost six-fold. However, the picture is very different when contrasting architecture and non-architecture sites. The increase in historical landmarks is driven by the growth of architectural landmarks relative to the pre-Fire average. By the end of the sample, architecture-related historical buildings listed in the Register are almost ten times as many as before the Fire in Chicago, relative to the synthetic control. By contrast, the number of non-architecture-related sites barely doubles over the same sample period. This sharp difference echoes the historical evidence indicating that the Fire was a decisive factor in making Chicago the center of US architecture throughout the second half of the century. Provided that culturally relevant heritage sites partly reflect innovations in construction technology and techniques, these patterns provide evidence that the pace of construction innovation in Chicago greatly accelerated after the 1871 Fire.

The synthetic difference-in-differences estimates displayed in Figure C.9 confirm the quantitative implications of the synthetic control results and provide empirical support for the plausibility of the parallel trends assumption.

Our results provide strong evidence that the Great Chicago Fire fostered construction manufacturing and technological advancements. These patterns are consistent with historical narratives documenting the swiftness of the "Great Rebuilding" of the city over the following decade. At the same time, however, they also indicate that these effects were not short-lived, as they shaped economic activity in the area well into the twentieth century. Chicago did not die out of economic distress following the Fire. Instead, it grew to be the second-largest city in the United States. Our results thus indicate that economic responses to adverse natural disasters may reverse their adverse effects into opportunities for growth. In the next section, we explore the role of the "industrial policy" intervention in shaping the magnitude and characteristics of such a large response.

V MECHANISMS

This section examines potential mechanisms that may explain the results presented thus far. We begin by studying the effects of the Chicago Fire on wood- and non-wood-related construction innovation to try to isolate the impact of construction policies from the effects of the Fire as such. Second, we explore the employment dynamics in Chicago before and after the Fire using longitudinal linked census data. Finally, we use the 1872 Great Boston Fire as a laboratory to study the effects of urban fires in the absence of significant construction policy interventions.

V.A Non-Wood and Wood Construction Innovation after the Fires

We begin by studying how the innovation response to the 1871 Chicago Fire was influenced by the policy that forbade the construction of wooden buildings within the city perimeter. To do so, we apply the synthetic control framework to non-wood and wood construction patenting activity. The historical literature suggests that the policy played a key role in shifting economic activity toward non-wood construction (see Section I.B). Figure IV displays the difference between non-wood (Figure IVa) and wood (Figure IVb) patenting in Chicago and the synthetic control (in red) and when assigning the treatment status to each of the 83 remaining metropolitan areas (in gray). The synthetic control mimics trends in non-wood and wood construction innovation in most cities in the pre-fire period, suggesting that synthetic control units provide an adequate counterfactual.

In both panels, the red line stands out, indicating that wood-related and non-wood-related innovation in Chicago increased relative to the counterfactual and that such an increase is larger than in other cities. However, the effect's size starkly differs between the two graphs. In particular, by 1890, Chicago had produced 90 more patents in non-wood construction innovation relative to the counterfactual, whereas the difference in wood-related innovation was one-third of this figure. To put this difference in perspective, our estimates imply that approximately 25% of the increase in construction innovation in Chicago after the 1871 Fire consists of non-wood construction innovation, and less than 7% is due to wood-related construction technologies.[23]

This large difference is consistent with our hypothesis that the policy intervention enacted by the Board of Fire in 1874 to forbid wooden constructions within the city perimeter shifted the demand for new buildings onto non-wood constructions. This sharp demand shock ushered in momentous innovation in non-wood construction, ultimately contributing to the overall increase in construction innovation.[24]

In Figure C.3b and Figure C.3c, we confirm that the effect of the Fire on wood- and non-wood-related innovation is not driven by economically irrelevant innovation. We consider patents in the top 20% of the novelty distribution, using the measure developed by Kelly et al. (2021), and find that the baseline divergence between Chicago and the synthetic control documented with the entire patent corpus is qualitatively unchanged on this restricted sample of more novel innovations.

Figure C.10 replicates the results using the synthetic difference-in-differences estimator for non-wood (Figure C.10a) and wood (Figure C.10b) innovation. We find no statistically significant differences be-

[23] The remaining 68% of the increase is in construction patents that are not explicitly wood- or non-wood- construction patents.

[24] In line with this interpretation, we find similar patterns in non-wood and wood construction innovation when we normalize both series by total employment (see Figure C.5b–Figure C.5c).

tween non-wood and wood innovation in Chicago and the control group before 1871. After 1871, and especially after 1874, non-wood and wood innovation increased in Chicago. As with the synthetic control estimates, however, the increase in non-wood innovation is considerably larger—roughly double—than that in wood innovation. The post-Fire treatment effects are, in both cases, statistically significant beyond the 1% level.

V.B Non-Wood and Wood Construction Manufacturing after the Fires

Following the logic of the previous section, we now turn to the effects of the 1871 Fire on manufacturing in wood and non-wood construction. Since innovation and broader economic activity should co-move, we expect innovation in non-wood construction manufacturing to increase.

Table V reports the county-level estimates obtained using decennial data from the Census of Manufactures for Chicago. The Tables report the difference between various indicators of economic performance in Cook County, IL, and in the synthetic control unit. The synthetic control units closely match the pre-treatment outcome values of the treated county (1860 and 1870), hence providing evidence in support of the identification assumption. The estimates confirm our conjectures. The number of establishments operating in non-wood construction, their production value, and their wage bill doubled over the decade following the 1871 Fire. The value of fixed capital and the cost of materials employed increases by 50% over the same sample period. In Figure C.11, we report the associated distribution of post-to-pre-intervention RMSPE and confirm that Cook County appears, in most cases, as a clear outlier. We find similar patterns when we normalize non-wood manufacturing by total employment (see Panel B in Table D.5). The synthetic difference-in-differences estimates of the effect of the Chicago Fire on non-wood manufacturing in Cook County are displayed in Figure C.12. It confirms the baseline results.

In Table D.6, we replicate the previous exercise, looking at wood-related construction manufacturing. In this case, however, the synthetic control procedure does not produce a control unit that adequately matches the pre-treatment trends in the outcome. The absence of an appropriate counterfactual invalidates any causal inference. However, in all specifications, Cook County exhibits a large upswing in wood construction manufacturing after the 1871 Fire. If anything, these patterns indicate declining economic activity in wood-related manufacturing. It is worth noting, however, that neither of these comparisons bears causal validity because, over the 1860 and 1870 pre-treatment periods, treatment and control groups are on different trends.

V.C Employment Dynamics after the 1871 Fire: Evidence from Linked Individual-Level Data

In this section, we leverage the granularity of the census data to measure employment transitions into construction, wood-, and non-wood-related construction in Chicago. We construct employment from decennial population censuses and link individuals between the 1870 and the 1880 waves using state-of-the-art algorithms developed by Abramitzky et al. (2020). Because we look at individuals in the labor force, we exclude those without a valid occupational response from the sample. Our guiding question is thus to understand whether individuals living in Chicago at the time of the Fire were more likely to take up construction jobs and, more specifically, whether these jobs are more likely to be in non-wood *vis-à-vis* wood construction.

We estimate variations on the following difference-in-differences specification:

$$y_{it} = \alpha_{c(i)} + \beta_t + X_i'\Gamma + \delta \times [I(c(i) = \text{Chicago}) \times I(t = 1880)] + \varepsilon_{it}, \tag{3}$$

where i denotes an individual, $t \in \{1870, 1880\}$ denotes a census wave, and $\alpha_{c(i)}$ and β_t are city and census-wave fixed effects. The term X_i collects a set of individual-level controls—race, birth year, literacy, migration status, and broad occupational category—measured in 1870.[25] The explanatory variable of interest is the treatment defined as the interaction between a dummy equal to one for individuals residing in Chicago either in 1870 or in 1880 ($I(c(i) = \text{Chicago})$) and a post-Fire dummy variable ($I(t = 1880)$). Standard errors are clustered at the city level. We employ three dependent variables: construction employment, wood-related construction employment, and non-wood-related construction employment.

Under a standard parallel trends assumption, the difference-in-differences coefficient $\hat{\delta}$ captures the causal effect of living in Chicago after the 1871 Fire on the probability of working in construction. Since we observe individuals only twice and census data are available at a decennial frequency, we cannot rule out that the estimates partly reflect shocks other than the Fire occurring in Chicago that influence the outcome variables. We thus view this exercise as providing descriptive, but not necessarily causal, evidence on the labor market effects of the Fire.

Columns (1–3) of Table VI report the results. In column (1), the dependent variable is an indicator equal to one if the individual works in construction in 1880 and zero otherwise; in column (2), we restrict the attention to non-wood-related construction occupations; in column (3), we only consider wood-related construction jobs. Our estimates indicate that treated individuals are 2.1% more likely to work in construction in 1880. This shift is large in magnitude as it corresponds to approximately

[25] Results are robust to controlling for individual fixed effects (α_i).

100% of the mean. This large effect is plausibly consistent with urban reconstruction in the aftermath of the destructive effects of the 1871 Fire. Contemporary observers labeled the swift reconstruction as the "Great Rebuilding" (Miller, 1996). In column (2), we show that treated individuals were approximately 0.26% more likely to work in non-wood-related construction, implying that the share of individuals employed in non-wood construction in Chicago doubled relative to the mean. By comparison, in column (3), we find that while wood-related construction employment increased by 0.6% after the Fire, this effect corresponds to a 50% increase relative to the mean. These findings echo evidence from the Census of Manufactures, indicating that construction manufacturing activity in Chicago increased after the Fire and that such an increase was primarily (though not exclusively) driven by non-wood-related industries.

The heterogeneous response of wood and non-wood construction to the 1871 Fire documented using individual micro-data, is thus consistent with more aggregate—yet more solidly causal—city- and county-level evidence and indicates that the booming construction industry in Chicago after the Fire was predominantly dominated by non-wood construction firms, as envisioned by the 1874 municipal ordinance.

V.D The Impact of the 1872 Great Boston Fire on Construction Innovation and Manufacturing

A possible explanation for the pattern of construction manufacturing in Chicago after the Fire is that it reflects a more general economic upswing impressed by the demand shock originating from the rebuilding effort–rather than the effect of the industrial policies implemented. We already saw that this explanation is unlikely: first, the heterogeneous responses of innovation to the 1871 Fire depended on the relative similarity to construction innovation within the technology space (Section IV.B); second, the Fire had a much stronger impact on non-wood (rather than wood) innovation and manufacturing (Section V.B). Another approach to gauge this hypothesis is to contrast the case of Chicago with Boston, which also experienced a destructive fire in 1872. While the Boston and Chicago fires differed in proportions, both caused massive damage and required extensive reconstruction efforts, resulting in large temporary economic booms (Miller, 2000; Hornbeck and Keniston, 2017). Importantly, a key difference between the two contexts is that while Chicago experienced the introduction of comprehensive provisions, prohibiting the use of wood and combustible materials in new buildings, this was not the case in Boston (see details in Section I).

In Figure C.13, we display average plot-level land values in Chicago and Boston. Both fires targeted central parts of both cities, where land values, indicated by the red line, were on average higher than in the rest of the city, as shown by the gray line. In both cities, land values in areas exposed to the fire increased more than in unaffected areas. This comparison suggests that we can cautiously look at the Boston fire as a plausible counterfactual for the Chicago fire in the absence of construction policy interventions.

We begin by looking at construction innovation in Boston after 1872. Figure V replicates Figure IIc, using 1872 as the treatment year. Boston is displayed in red, and all other cities—except Chicago—are displayed in gray. The Figure reports the difference between the number of construction-related patents in each treated city and the associated synthetic control. In Boston, these estimates reflect the treatment effect of the 1872 Fire, whereas all other cities are "placebos." As in the case of Chicago, the synthetic control closely mimics Boston—and almost all other metropolitan areas—before 1872. However, unlike Chicago, Boston does not display any significant increase in construction-related innovation after the Fire. The difference between Boston and its synthetic control is not different from most other metropolitan areas throughout the sample period. It thus seems implausible that the increase in construction innovation observed in Chicago is entirely explained by a general economic upswing following the Fire. If that were the case, it would be natural to expect a similar pattern in Boston. The synthetic difference-in-differences estimates confirm these patterns. Appendix Figure Figure C.4b shows no significant response of construction innovation in Boston after the 1872 Fire. The statistically insignificant difference between Boston—or Suffolk County—and the control group lends credibility to the identifying parallel trends assumption.

In Panel A of Table VII, we look at the response of construction manufacturing in Suffolk County, MA—where Boston is located—compared to the synthetic control counterfactual. As expected, we find a response of manufacturing in the post-Fire period, with production value and material costs increasing by approximately 50% of their pre-Fire values.[26] On the other hand, in Boston, we do not find a post-Fire response of non-wood construction manufacturing (see Panel B of Table VII). The point estimates are considerably smaller than in Chicago, negative (with the exception of fixed capital, which may take more time to adjust), and not statistically significant. This pattern further supports our argument: Boston did not see the implementation of policies fostering the construction of non-wood buildings and did not see innovation and manufacturing in this sector.[27]

Finally, in columns (4–6) of Table VI, we estimate the difference-in-differences specification (3) using Boston, as opposed to Chicago, as the cross-sectional treatment variable (i.e., $I(c(i) = \text{Boston})$). We find that the probability of working in construction after the 1872 Fire in Boston increased by approximately 1.5%. This effect is roughly 70% as large as the increase in construction manufacturing we estimate in Chicago. This finding echoes historical and quantitative evidence indicating that

[26] We find no detectable response in terms of the number of establishments, labor costs, and fixed capital.

[27] As for wood construction manufacturing, the synthetic control in the pre-Fire period does not allow us to draw causal implications (see Table D.7).

the reconstruction efforts in Boston were substantial (Hornbeck and Keniston, 2017). In turn, neither non-wood (column 5) nor wood-related (column 6) construction employment displayed a statistically significant response to the 1872 Fire, unlike in Chicago. Our results thus strongly suggest that the construction policy enacted by the Chicago municipal authority was key in shifting economic activity toward non-wood construction activity. These exercises indicate that the impact of the 1872 Great Boston Fire was, at best, modest compared to the 1871 Great Chicago Fire.

Altogether, these results suggest that it is unlikely that urban fires inherently fuel local economic growth by generating demand shocks for reconstruction. On the other hand, they suggest that the construction policy enacted in Chicago in response to the 1871 fire was key in supporting innovation, manufacturing employment, and, ultimately, contributing to long-term economic growth.

VI CONCLUSIONS

Climate change is among civilization's most pressing challenges. Worsening climate conditions are impacting the frequency and severity of natural disasters, which are expected to rise further over the next decades. Adaptation and mitigation efforts critically hinge on technological change. Previous research documents that directed innovation can compensate for some of the adverse effects of natural disasters (Moscona and Sastry, 2023). In general, however, market competition may provide inefficiently low levels of resilience-enhancing innovation (Acemoglu, 2012).

This paper asks whether industrial policy can steer innovation to support technologies that mitigate the adverse effects of natural disasters. We study the 1871 Chicago Fire, which destroyed large parts of the city center. In response, the municipal authority forbade the construction of wooden buildings within the city perimeter.

Our analysis reveals that the 1871 Fire had large and positive effects on construction innovation in Chicago. The Fire fueled construction manufacturing across a broader set of economic activity indicators compiled from manufacturing censuses, such as the number of construction firms, their output, and various indicators of their size, and architectural heritage sites.

We employ two strategies to link these effects to the construction policy implemented by the municipal authority. First, we analyze the heterogeneous treatment effects of the 1871 Fire on wood- and non-wood innovation and manufacturing in Chicago. Our results indicate that the Chicago Fire disproportionately fostered non-wood-related construction technical change and manufacturing firms, whereas the effects on wood construction are modest. Second, we study Boston in the aftermath of the 1872 Fire, which ravaged its business district but did not trigger any construction policy legislation.

We find no effects of the 1872 Fire on Boston's construction innovation and a moderate increase in manufacturing output.

Our results indicate that Chicago's construction policy channeled the construction demand shock generated by the 1871 Fire into non-wood construction, thereby propelling directed innovation. More generally, they reveal that public policy can effectively sustain adaptation efforts and foster economic growth in response to ever-increasing concerns over deteriorating climate conditions.

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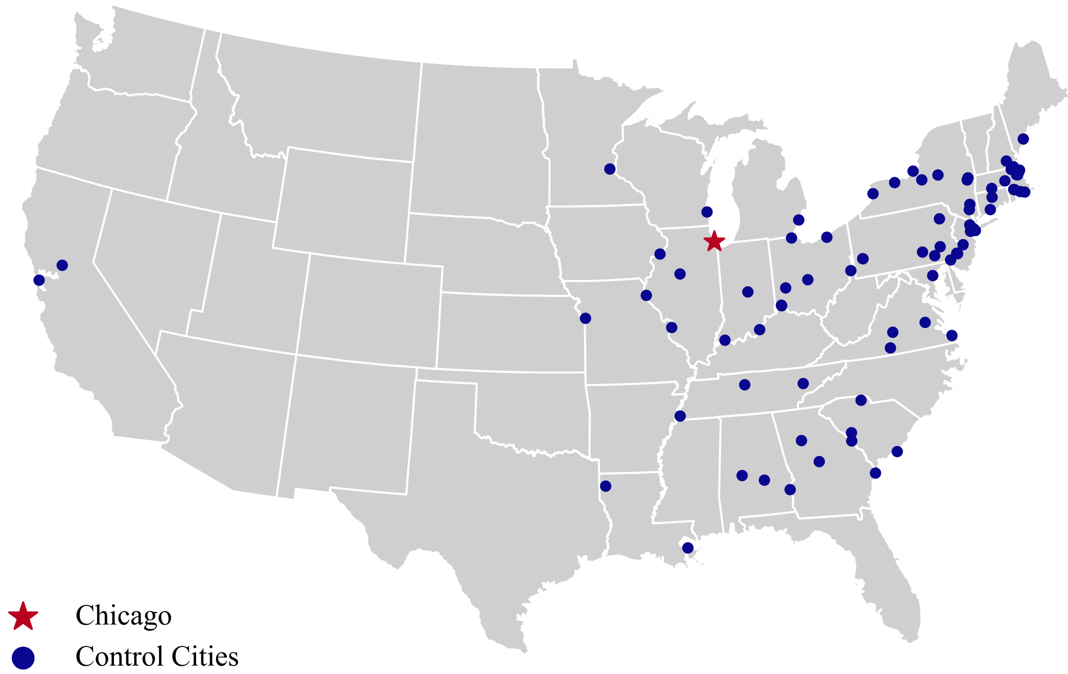
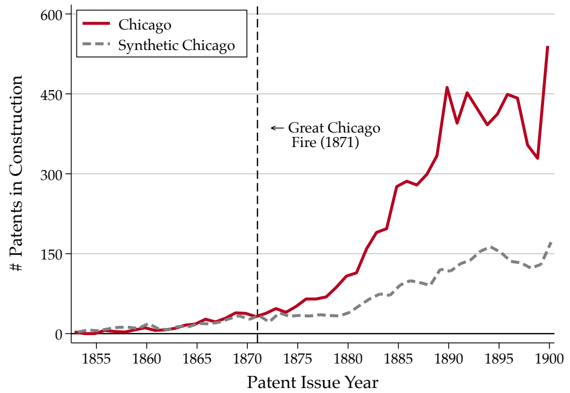
Figure I. Metropolitan Areas Above 20,000 Population



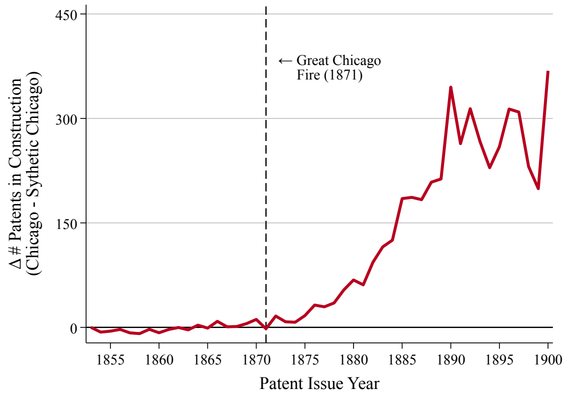
Notes. This map reports the location of the 84 metropolitan areas in the analysis sample. The coordinates of each metropolitan area report the center of its largest city. To construct the metropolitan areas, we retain all cities above 20,000 inhabitants; then, we agglutinate each minor city below the threshold to its closest city within 20 kilometers above the 20,000 population threshold. The red star reports the location of Chicago; the blue dots report the location of all other cities. Cities are overlaid on state borders in 1870, before the Great Chicago Fire (1871). The full list of metropolitan areas is reported in Appendix Table D.2. Referenced on page: 12.

Figure II. Synthetic Control Estimates of the Effect of the Great Chicago Fire on Construction Innovation

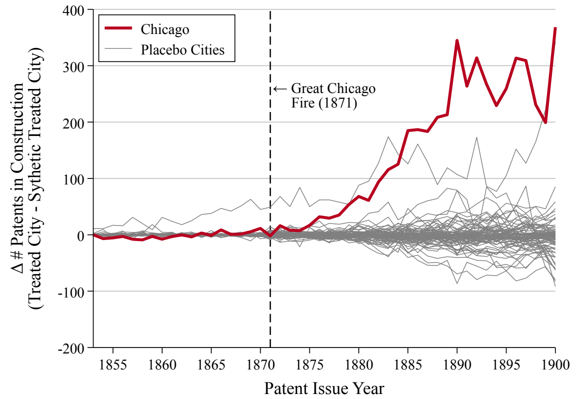
(a) Comparison between Chicago and Synthetic Chicago



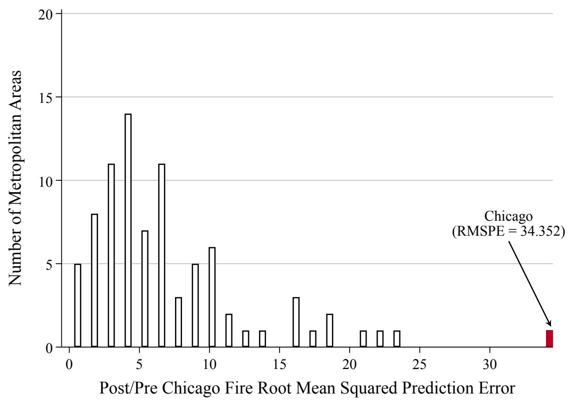
(b) Gap between Chicago and Synthetic Chicago



(c) Comparison between Chicago and Placebo Metropolitan Areas

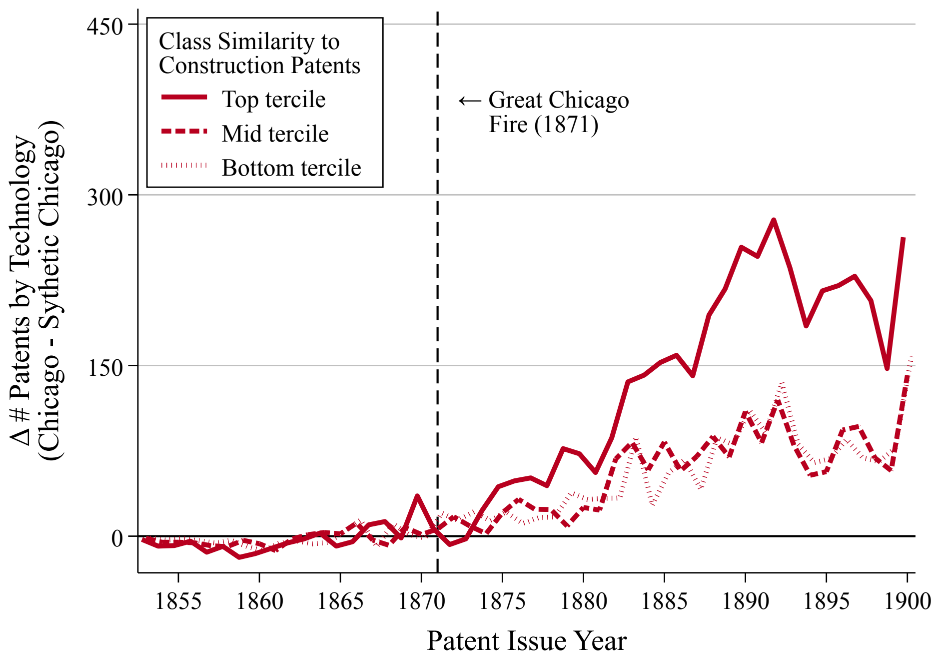


(d) Ratio of Post-to-Pre Mean Squared Prediction Error



Notes. This Figure reports the effect of the Great Chicago Fire (1871) on construction innovation in Chicago. The dependent variable is the number of patents in construction. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. In Panel IIa, we compare trends in construction patenting in Chicago and the control "Synthetic" Chicago; Panel IIb reports the difference between the two. In Panel IIc, we artificially assign the treatment status to each of the 84 metropolitan areas in the sample, and the red line highlights the treatment effect of Chicago. In Panel IId, we report the ratio between the post-Fire and pre-Fire mean squared prediction error across metropolitan areas, and highlight Chicago in red. The black dashed line marks the year of the Great Chicago Fire (1871). Referenced on pages: 16, 17, 27.

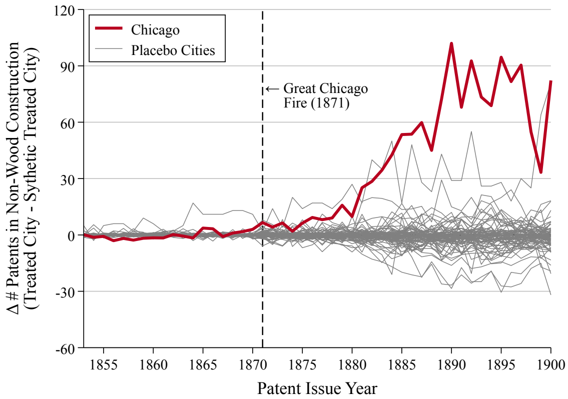
Figure III. Spillover Effects of the Great Chicago Fire on Innovation



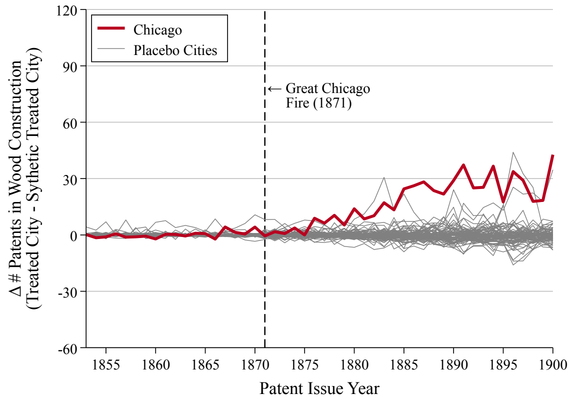
Notes. This Figure reports the effect of the Great Chicago Fire on non-construction innovation. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. The Graph reports the gap between Chicago and Synthetic Chicago. The dependent variable is the number of patents by tercile of technology class-similarity to construction patents. To construct the similarity, we rank technology classes by the share of patents in those classes that are also construction patents. The solid line reports the effect on the top tercile of most similar technology classes, the dashed line reports the effect on the mid tercile, and the dotted line reports the effect on the bottom tercile. The black dashed line marks the year of the Great Chicago Fire (1871). Referenced on pages: 18, 19.

Figure IV. Synthetic Control Estimates of the Effect of the Great Chicago Fire on Non-Wood and Wood Construction Innovation

(a) Non-Wood Construction Innovation

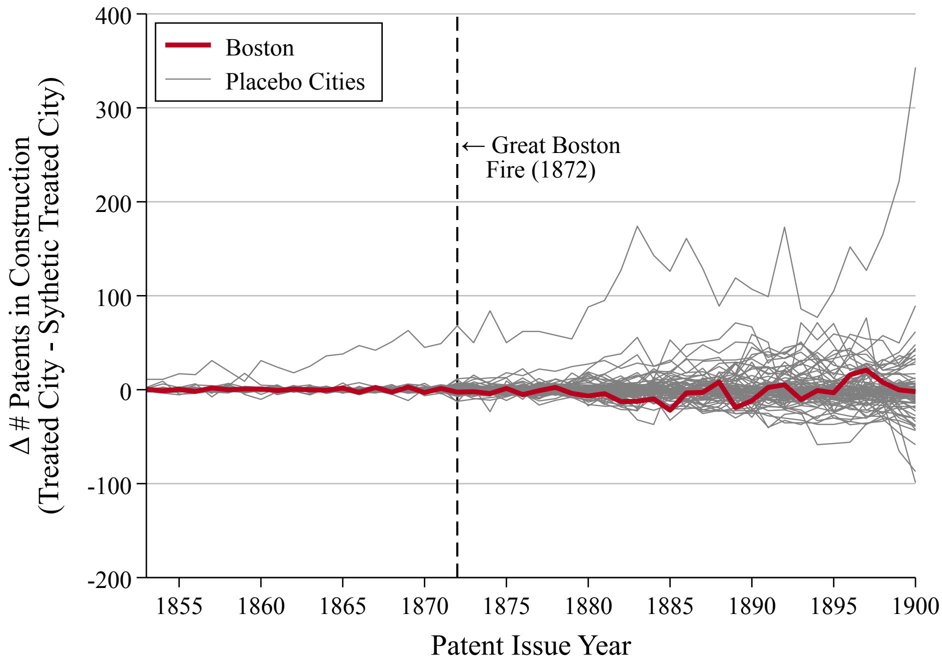


(b) Wood Construction Innovation



Notes. This Figure reports the effect of the Great Chicago Fire (1871) on non-wood- and wood-related construction innovation in Chicago. The dependent variable is the number of patents in construction that are not related to the use of wooden materials (Panel IVa) and those that are related to wooden materials (Panel IVb). The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. In each panel, we artificially assign the treatment status to each of the 84 metropolitan areas in the sample, and the red line highlights the treatment effect of Chicago. The black dashed line marks the year of the Great Chicago Fire (1871). Referenced on page: 22.

Figure V. Synthetic Control Estimates of the Effect of the Great Boston Fire on Construction Innovation



Notes. This Figure reports the effect of the Great Chicago Fire on construction innovation in Boston. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. The Graph reports the gap between Boston and Synthetic Boston. The dependent variable is the number of patents in construction. In the Figure, we artificially assign the treatment status to each of the 84 metropolitan areas in the sample minus Chicago, and the red line highlights the treatment effect on Boston. The black dashed line marks the year of the Great Boston Fire (1872). Referenced on page: 27.

Table I. Selected Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Units	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
	City-Level Descriptive Statistics					
Panel A. Innovation Activity						
Total Patents$_{it}$	74.100	159.512	0.000	1721.000	84	4032
Construction Patents$_{it}$	17.241	42.848	0.000	582.000	84	4032
Wood Construction Patents$_{it}$	2.003	4.552	0.000	58.000	84	4032
Non-Wood Construction Patents$_{it}$	3.830	9.761	0.000	118.000	84	4032
Panel B. Demographics						
Population$_i$ (1,000s)	107.901	137.457	20.692	960.329	84	84
Imputed Income per Capita$_i$	710.004	135.903	393.050	1005.388	84	84
Share of Men$_i$ (%)	49.439	2.330	44.960	62.438	84	84
Share Aged 0-25$_i$ (%)	58.457	4.544	48.340	68.534	84	84
Share Aged 26-45$_i$ (%)	27.567	3.354	19.974	40.577	84	84
Share Aged 46+$_i$ (%)	13.975	3.171	7.574	23.648	84	84
Share Literate$_i$ (%)	60.898	15.202	22.098	77.576	84	84
Share of Non-White$_i$ (%)	13.869	22.119	0.102	73.264	84	84
Share of Foreign Born$_i$ (%)	22.024	13.333	0.091	48.258	84	84
Panel C. Employment Shares in Selected Occupations						
Agriculture$_i$ (%)	8.318	8.775	0.141	46.092	84	84
Low-Skilled Manufacture$_i$ (%)	7.232	5.256	0.317	25.899	84	84
High-Skilled Manufacture$_i$ (%)	5.670	1.940	0.406	9.764	84	84
Laborer$_i$ (%)	4.682	1.904	0.095	11.117	84	84
Services$_i$ (%)	4.416	1.981	1.909	10.805	84	84
Panel D. Employment Shares in Selected Industries						
Agriculture$_i$ (%)	8.574	8.729	0.265	46.152	84	84
Liberal Professions$_i$ (%)	6.641	2.246	2.460	13.542	84	84
Utilities$_i$ (%)	4.998	2.100	2.030	12.115	84	84
Construction$_i$ (%)	2.391	0.818	0.177	4.280	84	84
Textiles$_i$ (%)	1.937	4.141	0.000	21.238	84	84
	County-Level Descriptive Statistics					
Panel E. Manufacturing Census						
N. of Establishments$_{ct}$ (1,000s)	0.084	0.320	0.001	11.286	1965	4802
Production Value$_{ct}$ (1,000s)	2168.090	13557.932	0.550	463887.969	1965	4802
Fixed Capital$_{ct}$ (1,000s)	1136.421	6319.986	0.100	186673.594	1965	4802
Cost of Materials$_{ct}$ (1,000s)	1317.791	8234.420	0.100	281470.219	1965	4802
Cost of Labor$_{ct}$ (1,000s)	390.593	2567.445	0.000	95319.352	1965	4802

Notes. This Table reports descriptive statistics for selected variables. Units are metropolitan area in Panels A–D and counties in Panel E. All variables in panels B–E are expressed as percentage shares of the city population and refer to the 1870 census. Data in Panel E are divided by 1,000 for readability and are tabulated from the Census of Manufacturing. Referenced on pages: 10, 11, 9.

Table II. Comparison between Chicago, the Other Metropolitan Areas, and Synthetic Chicago

	Chicago	All Other Cities			Synthetic Chicago		
	Mean	Mean	Difference		Mean	Difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Demographics							
Literacy Rate (%)	69.565	60.793	8.772***	(1.686)	66.582	2.983***	(0.613)
Imputed Income per Capita	843.227	708.399	134.828***	(15.009)	832.100	11.127	(40.070)
Share of Whites (%)	98.788	85.716	13.072***	(2.443)	98.159	0.628	(1.082)
Share of Blacks (%)	1.210	14.022	-12.812***	(2.452)	1.086	0.124	(0.398)
Share of Natives (%)	52.150	78.287	-26.137***	(1.447)	64.686	-12.536**	(6.139)
Panel B. Employment Share (%) by Occupation							
Liberal Profession	1.361	1.030	0.331***	(0.032)	1.308	0.053	(0.155)
Farmer	0.357	8.413	-8.057***	(0.970)	0.549	-0.192	(0.233)
Manager	3.008	1.974	1.034***	(0.081)	3.146	-0.137	(0.161)
Clerical Worker	1.399	0.649	0.750***	(0.037)	1.350	0.050	(0.092)
Sales	2.668	1.368	1.300***	(0.072)	2.788	-0.120	(0.437)
Skilled Manufacture	8.681	5.634	3.047***	(0.212)	7.753	0.928*	(0.519)
Low-Skill Manufacture	6.451	7.241	-0.790	(0.584)	7.580	-1.128	(0.885)
Service	5.375	4.405	0.971***	(0.220)	5.408	-0.032	(0.861)
Panel C. Employment Share (%) by Industry							
Laborer	6.477	4.660	1.816***	(0.210)	5.721	0.755	(0.686)
Agriculture	0.553	8.671	-8.118***	(0.965)	0.770	-0.217	(0.270)
Chemistry	0.068	0.079	-0.010	(0.014)	0.209	-0.141	(0.133)
Construction	3.864	2.373	1.491***	(0.089)	3.210	0.654***	(0.216)
Liberal Professions	8.391	6.620	1.771***	(0.249)	8.353	0.039	(1.069)
Metallurgy	0.689	0.767	-0.077	(0.065)	0.631	0.059***	(0.014)
Public Administration	0.375	0.298	0.076***	(0.027)	0.504	-0.130*	(0.074)
Textiles	0.151	1.959	-1.808***	(0.460)	0.593	-0.442***	(0.102)
Trade	6.738	3.611	3.127***	(0.172)	6.582	0.157	(0.619)
Transports	3.552	1.985	1.566***	(0.098)	3.102	0.450***	(0.160)
Utilities	6.116	4.985	1.131***	(0.233)	6.182	-0.065	(1.004)
Residual Industries	3.702	2.989	0.713***	(0.150)	3.775	-0.073	(0.512)
Engineering	0.456	0.387	0.069**	(0.032)	0.578	-0.122	(0.094)

Notes. This Table compares the values of the balancing variables included in the synthetic control design in Chicago and in the other metropolitan areas in the sample. Column (1) reports the average value of the various variables for Chicago; columns (2) and (5) report the average across all control cities and in synthetic Chicago, respectively. The weights used to compute the co-variates in the synthetic control are obtained by applying the synthetic control approach on construction patenting. In columns (3–4) (resp. 6–7), we report the difference between Chicago and all other cities (resp. synthetic Chicago). Robust standard errors are displayed in parentheses. All data are computed from the 1870 population census and expressed in population percentage. Referenced on page: 15.
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table III. Synthetic Control Estimates of the County-Level Impact of the Great Chicago Fire on Construction Manufacturing

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1) # Estab-lishments	(2) Value of Production	(3) Fixed Capital	(4) Cost of Materials	(5) Cost of Labor
1860 (Pre-Fire)	0.022	-0.497	-0.085	0.174	-6.182
1870 (Pre-Fire)	0.036	-1.288	-0.057	0.351	2.172
1880 (Post-Fire)	31.506	1307.094	427.591	637.748	292.455
Mean Dep. Var. (Before 1870)	8.400	227.314	113.150	73.653	83.904
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Chicago (1871) Fire on manufacturing activity in construction as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each column reports the difference between the observed outcome in Cook County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. Referenced on page: 20.

Table IV. Synthetic Control Estimates of the Impact of the Great Chicago Fire on Historical Landmarks

	Dependent Variable (Treated City - Synthetic Treated City)		
	(1) All Historic Landmarks	(2) Architecture Landmarks	(3) Non-Architecture Landmarks
1851–1860 (Pre-Fire)	-0.540	-0.003	0.003
1861–1870 (Pre-Fire)	0.305	0.001	0.011
1871–1880 (Post-Fire)	16.615	7.652	3.769
1881–1890 (Post-Fire)	39.305	18.625	1.944
1901–1900 (Post-Fire)	56.845	28.492	3.115
Mean Dep. Var. (Before 1870)	9.500	3.000	2.500
Number of Metro Areas	84	84	84
Number of Observations	420	420	420

Notes. This Table reports the effect of the Great Chicago Fire (1871) on historical landmarks in Chicago. The dependent variable is the number of historical landmark buildings listed by construction year (column 1), the number of buildings listed due to architectural significance (column 2), and all other significant buildings (column 3). The unit of observation is a metropolitan area at a decade frequency between 1850 and 1900. The estimates report the difference between the total number of landmark buildings by decade in Chicago and those in the control "Synthetic" Chicago. Referenced on page: 21.

Table V. Synthetic Control Estimates of the County-Level Impact of the Great Chicago Fire on Non-Wood Manufacturing

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1) # Estab-lishments	(2) Value of Production	(3) Fixed Capital	(4) Cost of Materials	(5) Cost of Labor
1860 (Pre-Fire)	0.002	-0.001	0.021	0.002	0.021
1870 (Pre-Fire)	-0.002	-0.068	-0.011	0.006	0.068
1880 (Post-Fire)	2.637	74.742	22.106	9.063	35.840
Mean Dep. Var. (Before 1870)	1.250	36.139	20.335	7.291	17.093
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Chicago Fire (1871) on non-wood-related manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each column reports the difference between the observed outcome in Cook County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. Referenced on page: 24.

Table VI. Individual-Level Impact of the Great Chicago Fire on Construction Employment

	Employed in:			Employed in:		
	(1)	(2)	(3)	(4)	(5)	(6)
	Construction	Non-Wood Construction	Wood Construction	Construction	Non-Wood Construction	Wood Construction
Chicago × Post	2.112***	0.257***	0.596**			
	(0.712)	(0.057)	(0.240)			
Boston × Post				1.455***	0.123	0.312
				(0.427)	(0.102)	(0.277)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of Counties	84	84	84	84	84	84
Observations	3,715,020	3,715,020	3,715,020	3,718,125	3,718,125	3,718,125
Mean Dep. Var.	1.914	0.317	1.106	1.907	0.317	1.103

Notes. This Table reports the effect of living in Chicago (columns 1–3) and Boston (4–6) before their respective fire on subsequent employment in construction. The unit of observation is an individual, observed two times in the 1870 and 1880 population censuses. The dependent variable is a dummy equal to one if the individual in 1880 is recorded working in construction (columns 1 and 4), non-wood-related construction (columns 2 and 5), and wood-related construction (columns 3 and 6). The sample includes individuals who were not working in construction in 1870. The treatment is an interaction term between an indicator variable equal to one if the individual is recorded as living in Chicago (columns 1–3) or Boston (columns 4–6) and zero otherwise, and a dummy equal to one for the post-Fire observation (1880) and zero otherwise. Each specification includes city and census year fixed effects and further controls for individual cohort, race, literacy, internal migration, and occupation status. Standard errors are clustered at the metropolitan area level and are displayed in parentheses. Referenced on pages: 25, 27.

*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table VII. Synthetic Control Estimates of the County-Level Impact of the Great Boston Fire on Non-Wood Manufacturing

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1)	(2)	(3)	(4)	(5)
	# Establishments	Value of Production	Fixed Capital	Cost of Materials	Cost of Labor
Panel A. Construction Manufacturing					
1860 (Pre-Fire)	-0.042	0.973	0.127	-0.043	-0.210
1870 (Pre-Fire)	-0.050	2.229	0.395	0.066	-0.502
1880 (Post-Fire)	-2.512	212.977	-8.575	121.383	-36.838
Mean Dep. Var. (Before 1870)	16.750	540.840	224.501	249.104	145.263
Panel B. Non-Wood Construction Manufacturing					
1860 (Pre-Fire)	0.000	0.094	-0.045	0.008	0.007
1870 (Pre-Fire)	0.013	0.189	-0.070	0.049	0.061
1880 (Post-Fire)	-2.441	-55.599	6.064	-25.567	-18.376
Mean Dep. Var. (Before 1870)	1.150	44.264	3.865	21.810	13.034
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Boston (1872) Fire on construction and non-wood-related manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each column reports the difference between the observed outcome in Suffolk County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. The Table reports separately the effects on overall construction manufacturing (Panel A) and non-wood construction manufacturing (Panel B). Referenced on page: 27.

ONLINE APPENDIX

Natural Disasters, Industrial Policy, and Innovation

Davide M. Coluccia & Mara P. Squicciarini

September, 2025

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A DATA APPENDIX

This section provides further information on the primary data sources underlying the datasets used in the main analysis and the methods adopted to construct them.

A.I Patent Data

We collect a novel dataset of US patents spanning 1853–1900. Compared to existing datasets, we develop a new methodology to extract information from patent texts. This section describes this new repository.

A.I.1 Motivation

Our analysis requires detailed information on each inventor's location to assign the patents to the closest metropolitan area. We also need text data to identify construction, wood- and non-wood-related innovations, and technological classes. Additionally, the United States Patent Office number allows to match patent records to the novelty measure produced by Kelly et al. (2021). We now briefly discuss why publicly available datasets do not satisfy these data requirements.

There are three datasets of US patents covering the period 1850–1900 (Andrews, 2021). Among those, the data produced by Sarada et al. (2019) and Petralia et al. (2016) are publicly available. Sarada et al. (2019) digitize the Annual Reports of the Commissioner of Patents and the Annual Indices of Patents. This dataset starts in 1870 and does not contain geographical information on inventors' addresses beyond their state. In addition, it does not include text data, as the primary source is not the text of the patent but an index.

Petralia et al. (2016) extracted patent information from digitized images of US patents, as we do. The data contain information on the county of the inventors. This data is, therefore, not suited for our analysis, which is performed at a more granular level. Importantly, this dataset does not contain the text of the patents, which we use to identify construction and wood- and non-wood-related construction innovations.

A.I.2 Methodology to Assemble the Dataset

We rely on the corpus of digitized US patents produced by Google Patents. We collect the universe of patent images by adapting the algorithm developed by Moser and San (2020). On top of the patent images, we collect from Google Patents the CPC technological classes of each patent and the backward and forward citations, which we do not use in this paper. Then, we employ a commercial optical character recognition (OCR) software—Amazon's `textract`—to convert the images into machine-readable text.

From the patent texts, we follow a procedure similar to Coluccia and Dossi (2025), who apply it to historical British patents. We use a large language model—`GPT 4o-mini`—to extract the name and surname of the inventors, their address of residence, the filing and issue date of the patent, and information on whether the patent has a firm assignee. Compared to standard extraction methods relying on regular expressions, such as those employed by Berkes (2018), the flexibility of large language models allows us to parse the data even in the presence of minor OCR errors or syntactical inconsistencies.

Lastly, we use a commercial georeference software—`Google Maps API`—to assign latitude and longitude coordinates to the address of each inventor. The address listed on the patent is the residence of the inventor. In small towns, the address indicates the town. In larger cities, the proper address appears on the patent. For consistency, we georeference the town given that the analysis is performed at that level of spatial aggregation.

A.I.3 Comparison with Existing Datasets

The dataset contains information on all patents listed on Google Patents issued between 1853 and 1900. We have the full digitized text of the patent, the name and surname of the inventor(s), their address(es), their latitude and longitude, the filing and issue date of the patent, and an assignee flag. Since the dataset contains the unique patent number, we can match our records with the novelty measure assembled by Kelly et al. (2021). From Google Patents, we also have the CPC technological classification associated with each patent.

Compared to Andrews (2021), whose coverage spans 1870 to 1942, our data has more detailed geographical information, more systematic inventors' names and surnames, full-text access, CPC technology classification information, filing, as well as issue date, and more precise dates. Compared to Petralia et al. (2016), our dataset contains more granular geographical information—down to the georeferenced town of each inventor, as opposed to the county—, CPC classes, filing and issue dates, and full-text access. Our data essentially mimics the state-of-the-art dataset produced by (e.g. Berkes, 2018), which is unfortunately not publicly accessible, over a shorter time window.

A.I.4 External Validation

Even though the existing datasets are not suited for our empirical application, we use them to validate the coverage of our new sample. Figure C.1a compares the number of patents in our dataset with Petralia et al. (2016)—dashed gray line—and Sarada et al. (2019)—dotted gray line. Figure C.1b reports coverage rate, defined as the number of patents in our dataset relative to Petralia et al. (2016)—red solid line—and Sarada et al. (2019)—gray dashed line, expressed in percentage.

Our series mimics Petralia et al. (2016) throughout the period. The coverage rates vary between 90% before the 1870s and 110% during the later part of the period, indicating that our dataset contains more patents. The data by Sarada et al. (2019) is less comprehensive—our dataset contains one-third more patents between 1870 and 1880 and one-tenth more towards the end of the century—but displays a similar co-movement with our series. Importantly, even though we cannot perform validation with the dataset developed by Berkes (2018), their data and that of Petralia et al. (2016) display substantial overlap before 1900, which indicates that our coverage rate of his dataset will mimic that with Petralia et al. (2016).

A.I.5 Methodology to Identify Construction Patents

We adopt a simple dictionary-based procedure to identify patents related to construction, non-wood construction, and wood construction.

First, we generate a dictionary of 30 words related to construction using `GPT-o3`. The words are displayed in Table D.1. Then, we search for the number of instances each word appears in the text of each patent. A patent is identified as "construction-related" if at least one word appears at least five times in its text. The results are not sensitive to alternative, more demanding thresholds, but increasing the required threshold increases the rate of false negatives without significantly impacting the rate of false positives. We provide a more detailed discussion below.

Second, *among construction patents*, we search for wood- and non-wood-related innovations. Using `GPT o1`, we generate a list of 12 wood-related and 11 non-wood-related words. We then count the number of instances each word appears in the patents' texts. A patent is identified as "wood-related construction" if it mentions at least one word from column (1) of Table D.1 at least five times and at least one word from column (2). Analogously, a patent is identified as "non-wood-related construction" if it mentions at least one word from column (1) of Table D.1 at least five times and at least one word from column (3).

We manually check the plausibility of the results obtained using this dictionary-based approach on a random sample of 200 patents. Within this sample, 41 patents were flagged as construction-related, five as wood-construction, and six as non-wood-construction. We did not find false positives, and the algorithm missed four patents that a human would have coded as construction, thus yielding a 10% false negatives rate among construction patents. Increasing the threshold to ten patents over the same sample decreased the rate of false negatives to 5% but decreased the rate of true positives by almost one-third. While suggestive, this exercise indicates that the five-word threshold is reasonable, if ad-hoc, heuristic to identify construction-related innovations.

A.II Population Census

We use individual-level data mapped to CPP locations to compute demographic characteristics of the metropolitan areas and counties. The synthetic control and synthetic difference-in-differences estimates use, as balancing variables, the share of natives, blacks, imputed income per capita (OCC-SCORE), and the employment shares by occupation and industry.

To compute the employment share by occupation, we use the OCC1950 standardized codes to construct a coarser occupational taxonomy that follows from the categories provided by IPUMS: professionals (OCC1950 between 0 and 99), farmers (OCC1950 between 100 and 123 and 810 and 840), managers (OCC1950 between 200 and 290), clerical (OCC1950 between 300 and 390), sales (OCC1950 between 300 and 390), craftsmen (OCC1950 between 500 and 595), operatives (OCC1950 between 600 and 690), services (OCC1950 between 700 and 790), and laborers (OCC1950 between 910 and 970).

Similarly, to construct the employment share by industry, we use the IND1950 standardizes codes to construct a coarser industry taxonomy following IPUMS: agriculture (IND1950 between 105 and 126), chemicals (IND1950 between 466 and 478), construction (IND1950 between 246 and 246), engineering (IND1950 between 367 and 388 or 898), liberal professions (IND1950 between 716 and 897), metallurgy (IND1950 between 336 and 348), miscellaneous manufacturing (IND1950 between 306 and 358, 406 and 429, and 456 and 459), public administration (IND1950 between 906 and 946), textiles (IND1950 between 436 and 449), trade (IND1950 between 606 and 699), transportation (IND1950 between 506 and 579), and utilities (IND1950 between 596 and 598 and 826 and 859).

All variables from the population census are measured in 1870, i.e., the year before the Great Chicago Fire.

A.III Manufacturing Census

We compile manufacturing data—number of establishments, value of production, labor cost, material cost, and capital—from county-by-industry data from the Census of Manufactures transcribed by Hornbeck and Rotemberg (2024). The sample comprises all counties with at least one metropolitan area.

We use the industry concordance table provided by the authors to construct a county-by-industry panel at the decade level between 1860 and 1880. The final sample is a decadal county-level panel that records the various variables for different industries. In particular, we group the "construction," "construction materials," and "furniture" as one "construction" industry, the "brick, stone, and tile," "marble and stone work," and "lime and cement" titles as one "non-wood manufacturing" industry, and the "lumber, sawed," "wood products, other," "wood, turned and carved," "wooden ware," and "saws" titles as one "wood manufacturing" industry. All other industry classifications remain unchanged.

A.IV Historical Landmarks

We collect all historical landmarks from the "National Register of Historic Places" (Stutts, 2024). We georeference each entry using the provided address and `Google Maps API`. We assign latitude and longitude to 99% of the landmarks in the sample. Each landmark is then allotted to the closest CPP location within 20 Km, following the same procedure we apply to the patent records. The National Register does not contain information on the construction year. We thus manually search each entry on Wikipedia and assign a construction year to 77% of the entire dataset. Among the landmarks in the metropolitan analysis sample, 85% have a recorded construction year. We include in the sample entries that do not refer to "buildings" (64% of the sample), thus excluding "districts" (20%), "objects" (0.25%), and "sites" (13%).

B SUMMARY OF THE ROBUSTNESS ANALYSES

This section provides complementary information on the robustness exercises mentioned in passing in the main text.

B.I Patent Novelty Data

We use the text-based measure by Kelly et al. (2021) to explore the effect of the 1871 Fire on economically relevant innovation. Intuitively, a patent that is more similar to future patents than to previous patents is labeled as "more innovative." More formally, let the backward inverse-document frequency associated with word w be defined as

$$\text{BIDF}_{w,t} \equiv \log\left(\frac{\text{Number of Patents Issued Before } t}{1 + \text{Number of Patents Issued Before } t \text{ that contain word } w}\right). \tag{B.1}$$

To each patent-word pair, it associates a variable equal to the number of instances word w appears in patent i, normalized by the patent length. Let i denote the patent and the set of words it contains. The term-frequency weight is equal to

$$\text{TF}_{wi} \equiv \frac{\sum_{c \in i} 1(c = w)}{\sum_{c \in i} 1(c)}, \tag{B.2}$$

where the numerator returns how many times word w appears in patent i, and the denumerator is the number of words in patent i. The TF-BIDF associated with word w, patent i at time t is the product between the TF and the BIDF:

$$\text{TF-BIDF}_{wi,t} \equiv \text{TF}_{wi} \times \text{BIDF}_{w,t}. \tag{B.3}$$

The vector $\text{TF-BIDF}_{i,t}$ thus collects the $\text{TF-BIDF}_{wi,t}$ for all words w in i, normalized by its norm to have unit length.

The approach allows the representation of each patent as a TF-BIDF vector. One can thus compute a measure of similarity—in their case, the cosine similarity—between each patent pair. In particular, the backward similarity is the average similarity between i and all previous patents within τ_1 years:

$$\text{Backward Similarity}_i^{\tau_1} \equiv \frac{1}{|\mathcal{F}_i^{-\tau_1}|} \sum_{j \in \mathcal{F}_i^{-\tau_1}} \rho_{i,j}, \tag{B.4}$$

where the set $\mathcal{F}_i^{-\tau_1}$ denotes the set of US patents issued within τ_1 years from the issue year of patent i and $\rho_{i,j}$ is the cosine similarity between the vectors $\text{TF-BIDF}_{i,t}$ and $\text{TF-BIDF}_{j,t}$. Analogously, the forward similarity is the average similarity with all patents in the later τ years:

$$\text{Forward Similarity}_i^{\tau_2} \equiv \frac{1}{|\mathcal{F}_i^{+\tau_2}|} \sum_{j \in \mathcal{F}_i^{+\tau_2}} \rho_{i,j}, \tag{B.5}$$

where the set $\mathcal{F}_i^{+\tau_2}$ denotes the set of US patents issued τ_2 years after the issue year of patent i. Given these measures, one can compute the similarity of p with future relative to previous patents:

$$\text{Excess Forward Similarity}(\tau_1, \tau_2) \equiv \frac{\sum_{j \in \mathcal{F}_j^{+\tau_2}} \rho_{i,j}}{\sum_{j \in \mathcal{F}_i^{-\tau_1}} \rho_{i,j}}. \tag{B.6}$$

In our application, we take $\tau_1 = \tau_2 = 5$ to have a symmetric 5-year window around each patent. The results remain qualitatively unchanged when using 1- and 10-year symmetric windows. Following Kelly et al. (2021), we partial out year fixed effects from the raw Excess Forward Similarity(τ_1, τ_2) measure to ensure that aggregate trends in language and patent redaction do not influence the results. A patent is then defined as "novel" if it is in the top 20% of the excess forward similarity distribution. The results remain qualitatively unchanged using different thresholds at the 5% and 10%.

Figure C.3 displays the synthetic control results of the effect of the Great Chicago Fire on novel patenting in construction (Figure C.3a), non-wood construction (Figure C.3b) and wood construction (Figure C.3c). The divergent trajectories between Chicago and the synthetic control unit indicate that the effect of the Fire on innovation is not disproportionately driven by economically irrelevant or unoriginal innovation.

B.II Synthetic Difference-in-Differences

The synthetic difference-in-differences estimator developed by Arkhangelsky et al. (2021) nests the insights of standard synthetic control and difference-in-differences estimators. As highlighted by Arkhangelsky et al. (2021), the synthetic control method is typically applied in settings with one or a few treated units, where the parallel trends assumption required by the difference-in-differences estimator is unlikely to hold. The synthetic difference-in-differences estimator weights units in the control group to match the treated unit in terms of a set of specified pre-treatment observable characteristics and the outcome to maximize the empirical plausibility of the parallel trends assumption.

Formally, let i and t denote units and time periods. Exposure to the treatment is $W_{it} = \{0, 1\}$, and Y_{it} denotes the outcome. the synthetic control estimator selects weights ω_i^{sc} to minimize the distance between treated and control units and estimates the treatment effect as

$$\left(\hat{\tau}^{sc}, \hat{\mu}, \hat{\beta}\right) = \arg\min_{\mu,\beta,\tau} \left\{ \sum_i \sum_t \left(Y_{it} - \mu - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{sc} \right\}, \tag{B.7}$$

where $\hat{\tau}^{sc}$ is the estimated treatment effect. The difference in differences estimator, by contrast, weights all units in the same way, but it includes unit fixed effects to leverage within-unit variation:

$$\left(\hat{\tau}^{did}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\mu,\alpha,\beta,\tau} \left\{ \sum_i \sum_t \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \right\}. \tag{B.8}$$

The synthetic difference-in-differences estimator nests these two approaches. First, it selects weights ω_i^{sdid} to minimize the distance between treated and control units in terms of pre-treatment outcome values and characteristics. Moreover, it selects λ_t^{did} that balance pre-exposure time periods with post-exposure ones. Then, it solves for the average treatment effect as in the DiD estimator, applying the so-computed weights:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\mu,\alpha,\beta,\tau} \left\{ \sum_i \sum_t \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}. \tag{B.9}$$

By weighting observations to minimize the distance between treated and control units, the SDiD estimator emphasizes units that are, on average, similar to the treated unit and periods that are, on average, similar to the target periods.

In our application, we compute the SDiD weights by including the population, share of whites and foreign-born, employment shares by occupation, and employment shares by industry. As in the synthetic control baseline case, these variables were measured in the 1870 census, before the Chicago and Boston fires.

We display the SDiD results in terms of standard panel event-study estimates to visualize the evolution of treatment effects over time. In addition, by looking at the pre-treatment differences between the treated (Chicago and Boston) and control units, we can assess the empirical plausibility of the parallel trends assumption. We follow the logic outlined in Clarke, Pailañir, Athey and Imbens (2023) to construct these figures. We wish to estimate, for each period t,

$$(\bar{Y}_t^T - \bar{Y}_t^C) - (\bar{Y}_0^T - \bar{Y}_0^C), \tag{B.10}$$

where $\bar{Y}_t^T$ and $\bar{Y}_t^C$ denote the average outcome for treated and control units at time t, and $\bar{Y}_0^T$ and $\bar{Y}_0^C$ denote the average pre-treatment outcome values for treated and control units. These are computed as

$$\bar{Y}_0^T = \sum_{t=1}^{\tau-1} \hat{\lambda}_t^{sdid} \bar{Y}_t^T, \tag{B.11}$$

for the treatment group and, similarly, as

$$\bar{Y}_0^C = \sum_{t=1}^{\tau-1} \hat{\lambda}_t^{sdid} \bar{Y}_t^C, \tag{B.12}$$

for the control group. The term τ denotes the treatment period. To compute the confidence intervals, we apply block-bootstrap resamples with 100 replications.

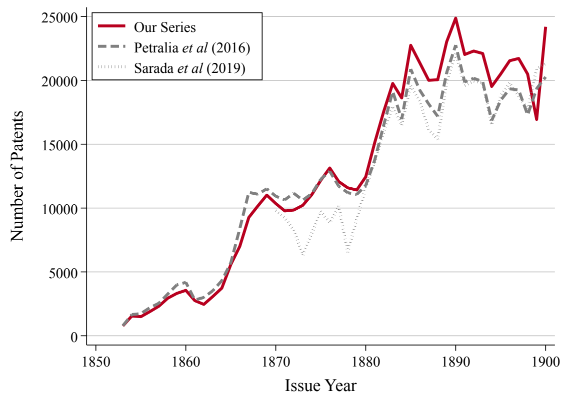
We display SDiD estimates for all the results shown in the main text. Figure C.4 displays the effect of the Great Chicago (Figure C.4a) and Boston (Figure C.4b) Fires on construction innovation. Figure C.10 focuses on the effect of the Chicago Fire on non-wood-related (Figure C.10a) and wood-related (Figure C.10b) patenting. Figure C.9 displays the results on historical landmarks. Analogously, we report the SDiD estimates on construction manufacturing (Figure C.8), as well as non-wood construction manufacturing (Figure C.12).

In all cases, the synthetic DiD estimates confirm the baseline results obtained through the more traditional synthetic control approach. Additionally, in most cases, the pre-treatment differences between treated and control units are statistically insignificant and are always quantitatively very small. These patterns confirm the empirical plausibility of the parallel trends assumption that requires that, in the absence of the Fires, the outcomes in Chicago and Boston and in the control units would have evolved similarly.

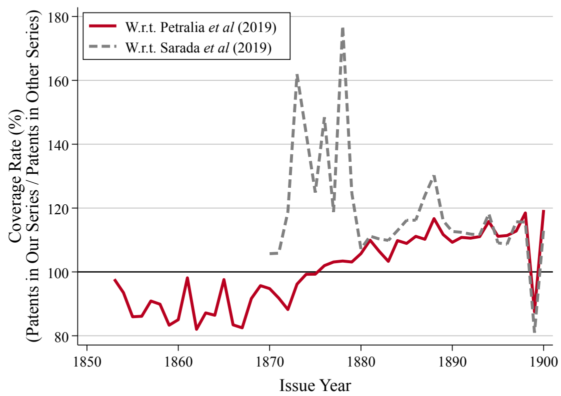
C ADDITIONAL FIGURES

Figure C.1. Comparison of Own and External Patent Repositories

(a) Total Number of Patents

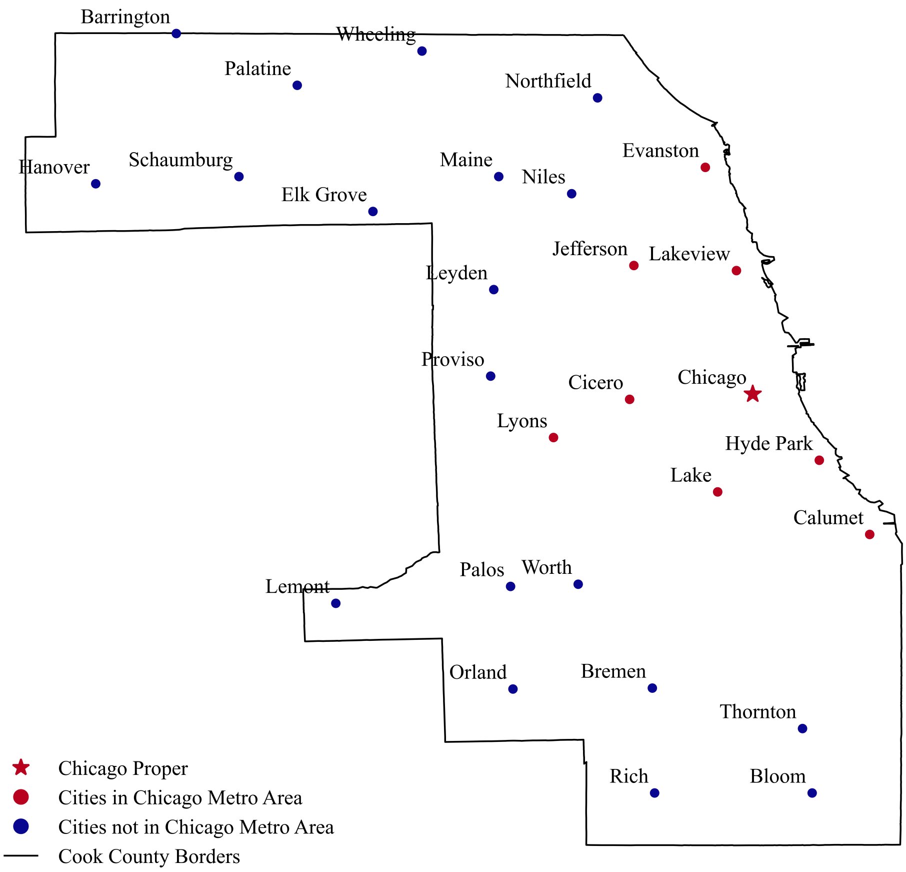


(b) Coverage Rate (%)



Notes. This Figure compares the number of patents in the dataset produced for this paper and data from Petralia et al. (2016) and Sarada et al. (2019). Panel C.1a reports the total number of patents in our data (red line), Petralia et al. (2016) (gray dashed line), and Sarada et al. (2019) (gray dotted line). Panel C.1b reports the coverage rate, computed as the ratio between the number of patents in our dataset and the number of patents in Petralia et al. (2016) (red line) and Sarada et al. (2019) (gray dashed line). The dataset by Sarada et al. (2019) starts in 1870; for comparability, we restrict it to "Utility" patents only. Referenced on page: A3.

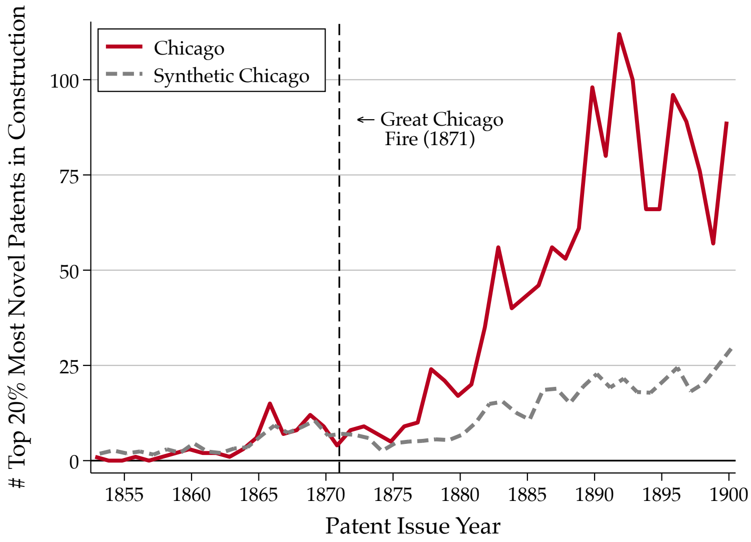
Figure C.2. Example of Metropolitan Area: Chicago



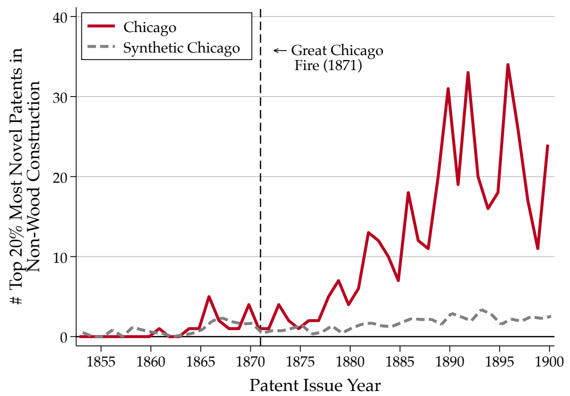
Notes. This Figure displays the construction of the Chicago Metropolitan Area according to the procedure described in Section II.E. Each dot reports the coordinates of a single CPP location in Cook County, whose 1870 borders are displayed in the black solid line. The red star displays the location of Chicago, which is the only CPP location with more than 20,000 inhabitants in Cook County. The red dots are the minor towns—i.e., the CPP locations with less than 20,000 inhabitants—that are closer than 20 kilometers from the center of Chicago and thus are considered part of the Chicago Metropolitan Area. In this case, the Chicago Metropolitan Area includes Evanston, Lakeview, Jefferson, Cicero, Lyons, Lake, Hyde Park, and Calumet. The blue dots are towns below 20,000 inhabitants that are further than 20 kilometers from the center of Chicago and are thus excluded from its metropolitan area. Referenced on page: 12.

Figure C.3. Synthetic Control Estimates of the Effect of the Great Chicago Fire on Construction Innovation: Novel Patents

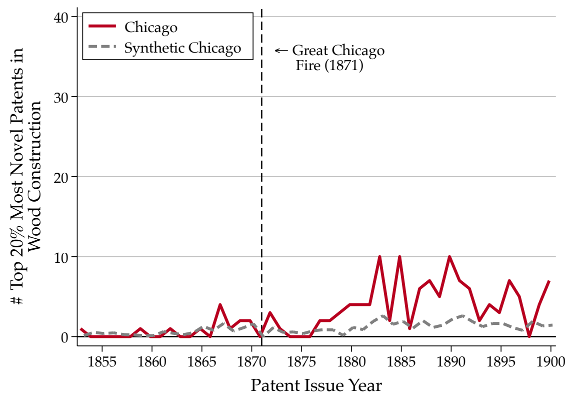
(a) All Construction Patents



(b) Non-Wood Construction Patents



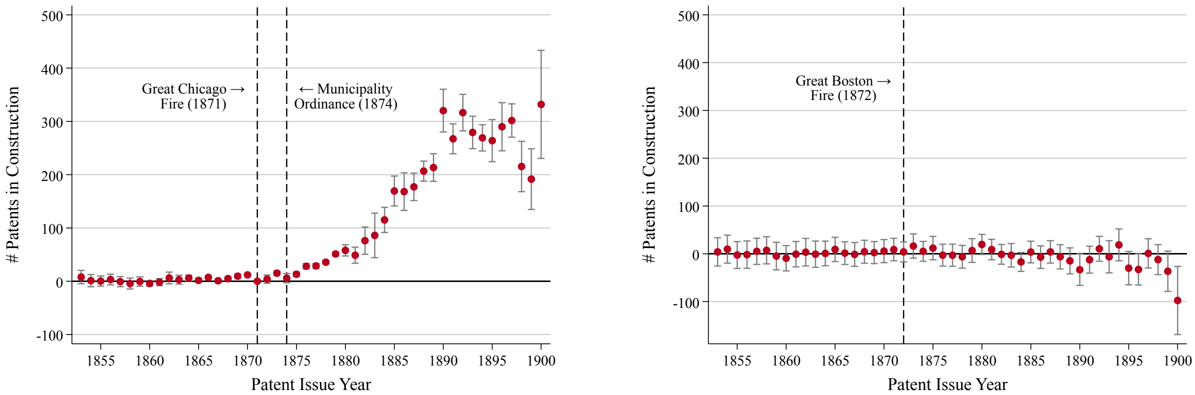
(c) Wood Construction Patents



Notes. This Figure reports the effect of the Great Chicago Fire (1871) on construction innovation in Chicago. The dependent variable is the number of patents in the top 20% of the novelty distribution of the text-based novelty measured developed by Kelly et al. (2021). The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. In Panel C.3a, we look at construction patents; Panel C.3b reports the effect on non-wood construction patents. In Panel C.3c, we report the effect on wood construction patents. The black dashed line marks the year of the Great Chicago Fire (1871). The red line refers to Chicago; the dashed gray line refers to the synthetic control. Referenced on pages: 17, 23, B8.

Figure C.4. Synthetic Difference-in-Differences Estimates of the Effect of the Great Chicago and Boston Fires on Construction Innovation

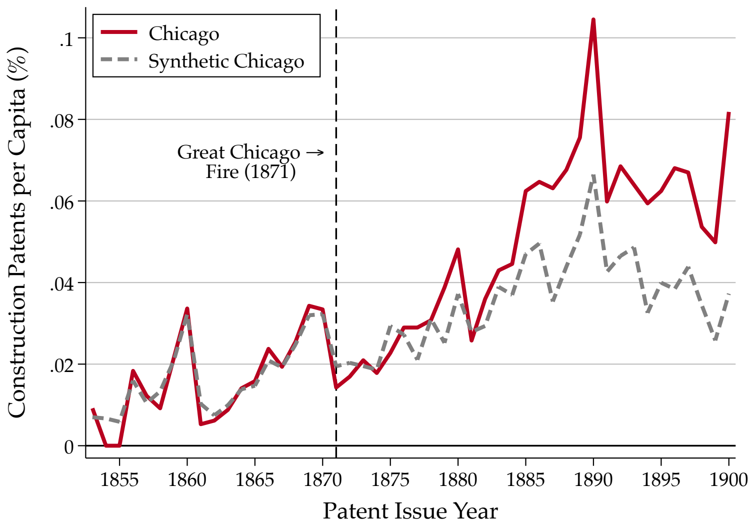
(a) Chicago **(b)** Boston



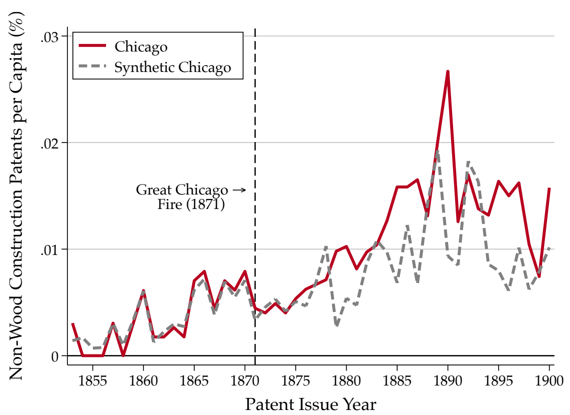
Notes. This Figure reports the effect of the Great Chicago (1871) and Boston (1872) Fires on construction innovation in Chicago (Panel C.4a) and Boston (Panel C.4b). The dependent variable is the number of patents in construction. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. The Figures report event-study coefficients obtained using the synthetic difference-in-differences methods developed by Arkhangelsky et al. (2021) and obtained following the procedure described in Clarke et al. (2023). Standard errors are estimated using bootstrap sampling with 100 replications; gray bars report 95% confidence intervals. The covariates included in the synthetic difference-in-differences estimation are the same as in the synthetic control estimation, except for the pre-treatment outcome values. The black dashed line marks the year of the Great Chicago Fire (1871), the Chicago Municipality Ordinance prohibiting wood construction (1874), and the Great Boston Fire (1872). Referenced on pages: 18, 27, B10.

Figure C.5. Synthetic Control Estimates of the Effect of the Great Chicago Fire on Patenting per Capita

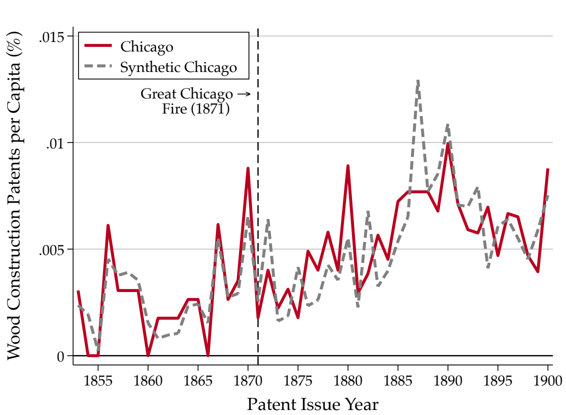
(a) Construction Innovation



(b) Non-Wood Construction



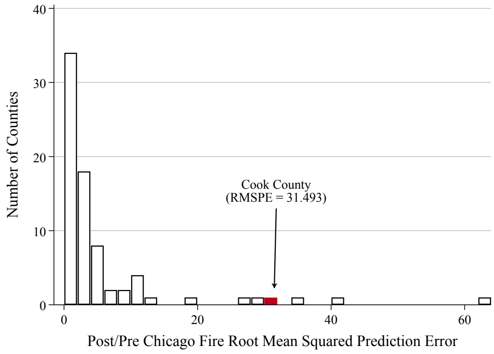
(c) Wood Construction



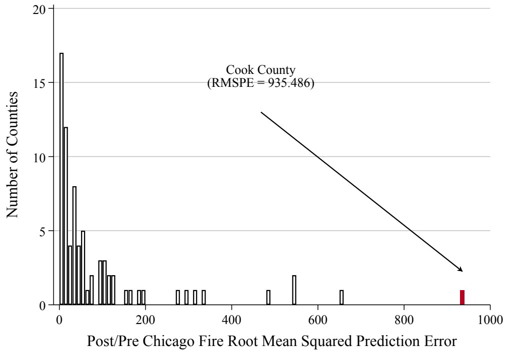
Notes. This Figure reports the effect of the Great Chicago Fire (1871) on construction innovation in Chicago. The dependent variable is the number of patents in construction (Panel C.5a), non-wood construction (Panel C.5b), and wood construction (Panel C.5c). Patenting activity is normalized by each metropolitan area's total employment in the decade, as measured in the population census, and is expressed in percentage terms. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. The black dashed line marks the year of the Great Chicago Fire (1871). The red line refers to Chicago; the dashed gray line refers to the synthetic control. Referenced on pages: 19, 23.

Figure C.6. Construction Manufacturing: Pre-Post Great Chicago Fire Synthetic Control Root Mean Squared Prediction Error Comparison

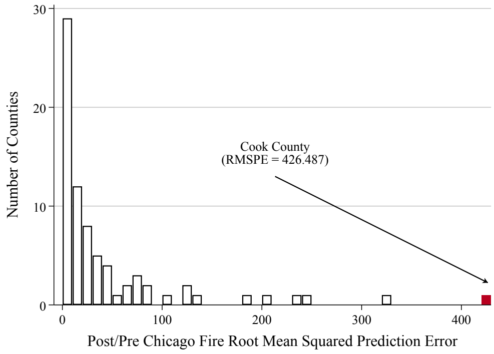
(a) Number of Establishments



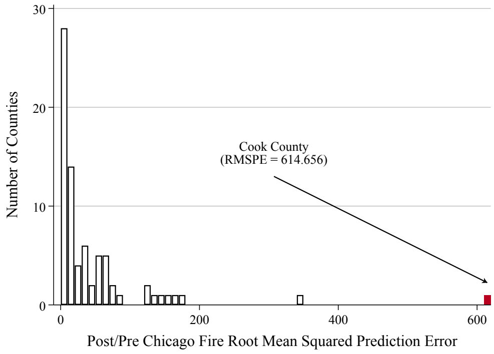
(b) Value of Production



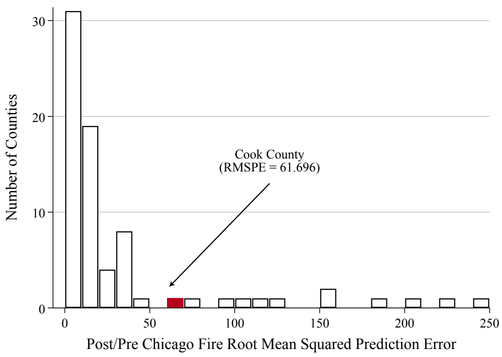
(c) Fixed Capital



(d) Cost of Materials



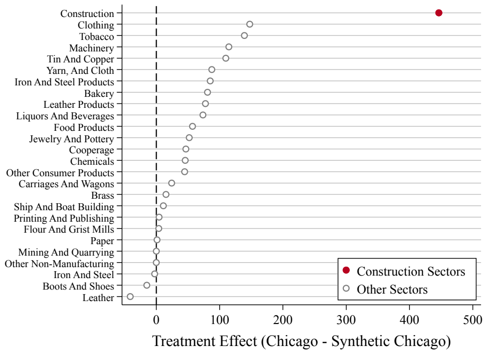
(e) Cost of Labor



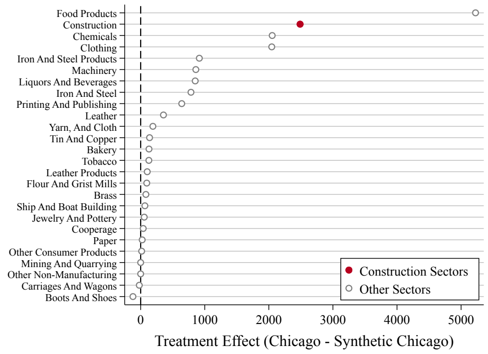
Notes. This Figure reports the impact of the Great Chicago (1871) on construction manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in Panel C.6a, the number of establishments; in Panel C.6b, production value; in Panel C.6c, fixed capital; in Panel C.6d, the cost of materials; in Panel C.6e, the cost of labor. Each figure reports the ratio between the post-Fire and pre-Fire mean squared prediction error across counties and highlights Cook County (IL) in red. The sample includes all counties with at least one metropolitan area. Referenced on page: 20.

Figure C.7. Synthetic Control Estimates of the Effect of the Great Chicago Fire on Manufacturing: Industry-by-Industry Estimates

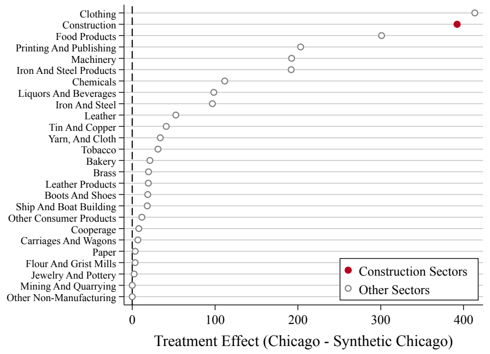
(a) Establishments



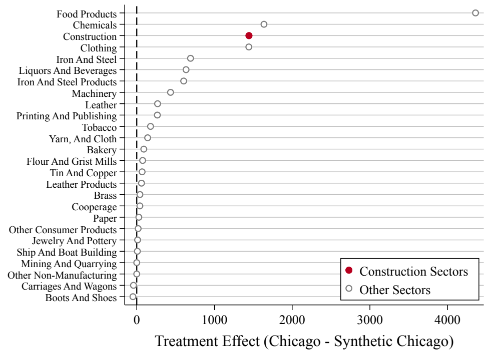
(b) Production Value



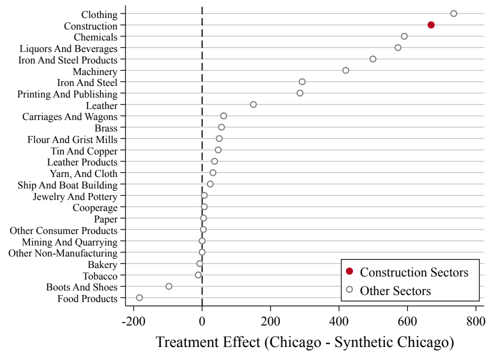
(c) Labor Costs



(d) Material Costs



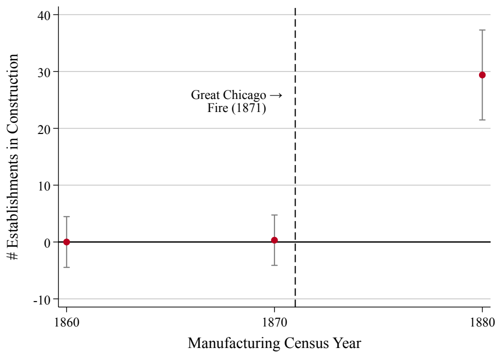
(e) Capital



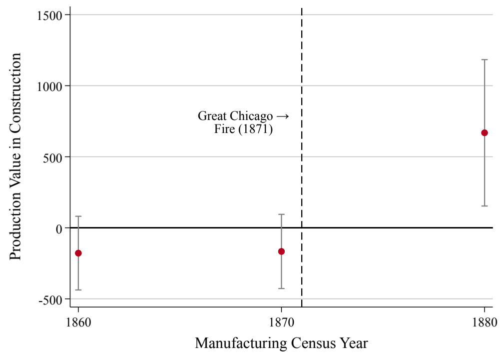
Notes. This Figure reports the impact of the Great Chicago Fire (1871) on manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in Panel C.7a, the number of establishments; in Panel C.7b, production value; in Panel C.7c, the cost of labor; in Panel C.7d, the cost of materials; in Panel C.7e, fixed capital. Each dot plots the treatment effect—i.e., the difference between Chicago and the synthetic control in 1880—by industry. Construction is displayed in red; all other sectors are displayed in gray. The sample includes all counties with at least one metropolitan area. Referenced on page: 20.

Figure C.8. Synthetic Difference-in-Differences Estimates of the Effect of the Great Chicago Fire on Construction Manufacturing

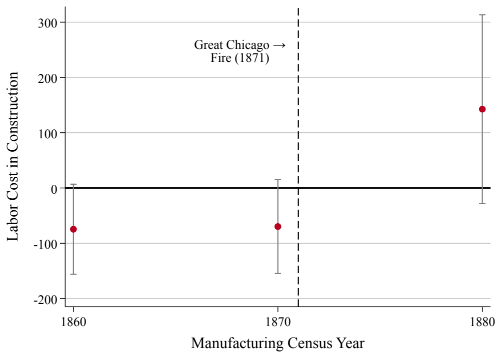
(a) Establishments



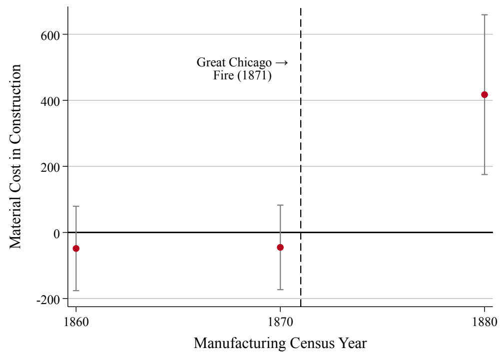
(b) Production Value



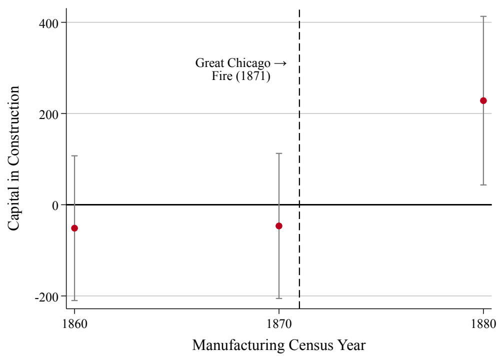
(c) Labor Costs



(d) Material Costs

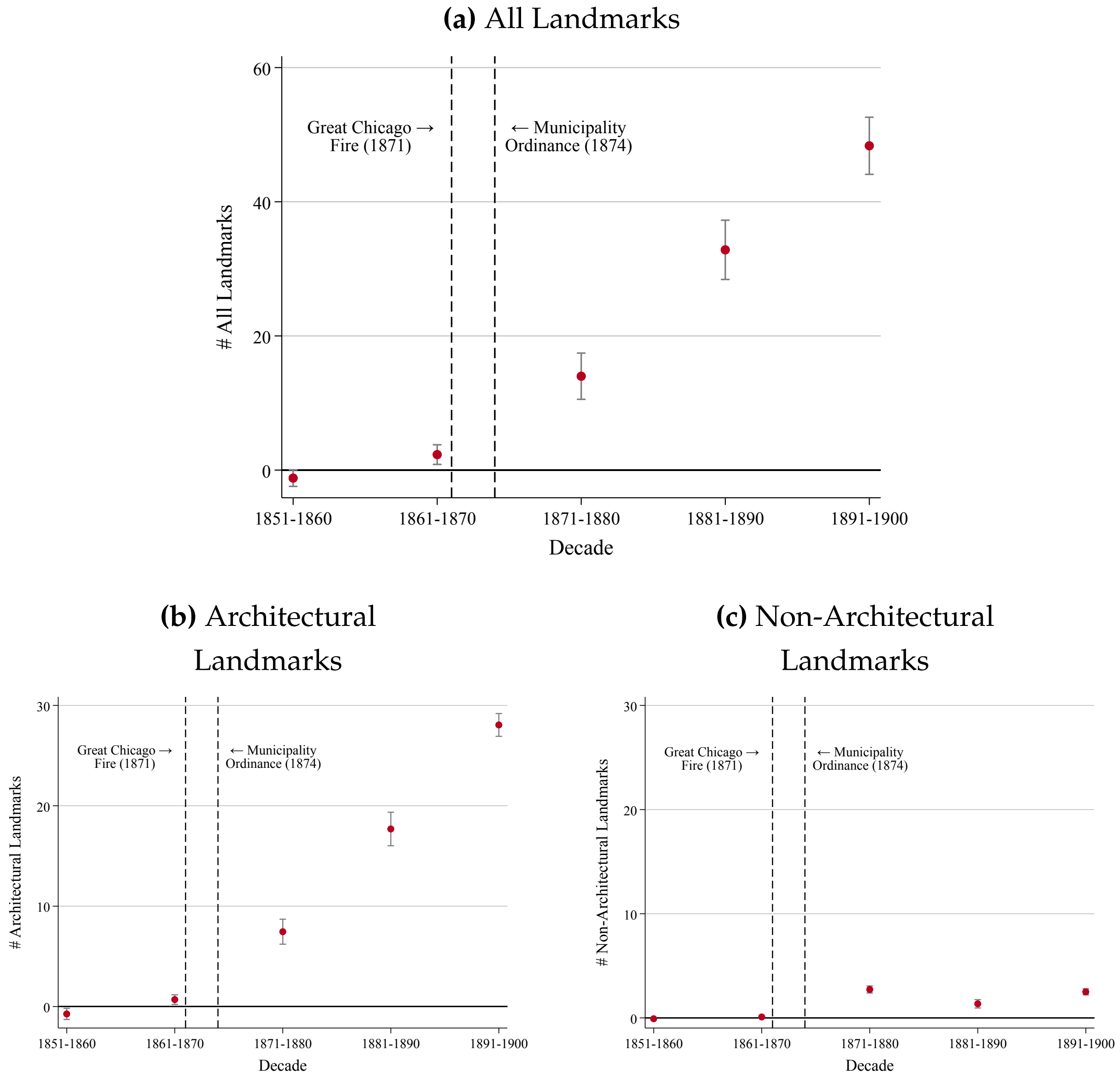


(e) Capital



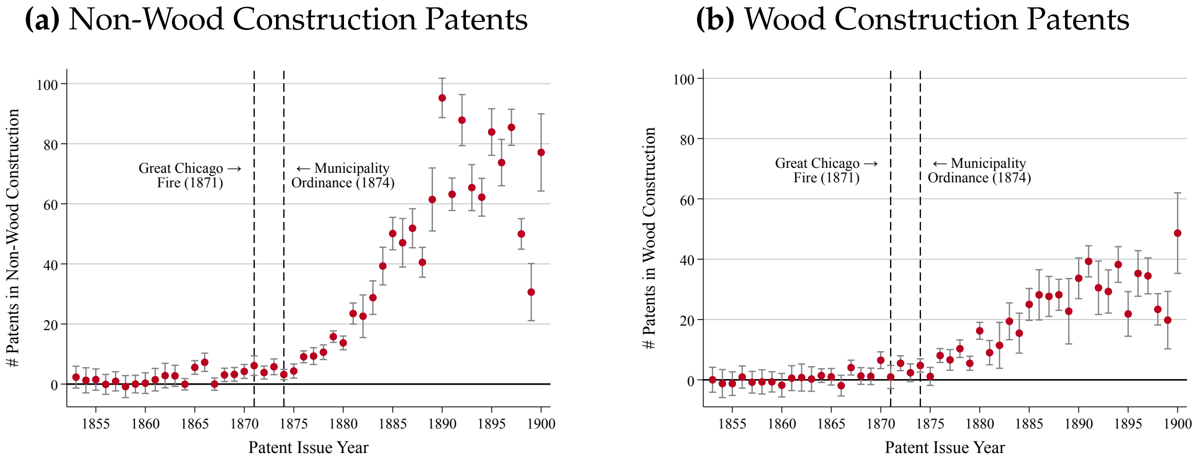
Notes. This Figure reports the impact of the Great Chicago Fire (1871) on construction manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in Panel C.8a, the number of establishments; in Panel C.8b, production value; in Panel C.8c, the cost of labor; in Panel C.8d, the cost of materials; in Panel C.8e, fixed capital. The Figures report event-study coefficients obtained using the synthetic difference-in-differences methods developed by Arkhangelsky et al. (2021) and obtained following the procedure described in Clarke et al. (2023). Standard errors are estimated using bootstrap sampling with 100 replications; gray bars report 95% confidence intervals. The sample includes all counties with at least one metropolitan area. Referenced on pages: 21, B10.

Figure C.9. Synthetic Difference-in-Differences Estimates of the Effect of the Great Chicago Fire on Historical Landmarks



Notes. This Figure reports the effect of the Great Chicago Fire (1871) on historical landmarks in Chicago. The dependent variable is the number of all historical landmark buildings (Panel C.9a), those listed due to architectural significance (Panel C.9b), and all other significant buildings (Panel C.9c). The unit of observation is a metropolitan area at a decade frequency between 1850 and 1900. The Figures report event-study coefficients obtained using the synthetic difference-in-differences methods developed by Arkhangelsky et al. (2021) and obtained following the procedure described in Clarke et al. (2023). Standard errors are estimated using bootstrap sampling with 100 replications; gray bars report 95% confidence intervals. Referenced on pages: 22, B10.

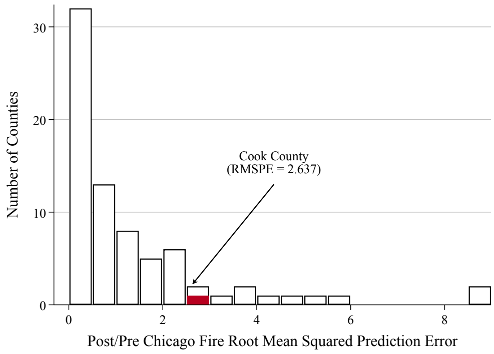
Figure C.10. Synthetic Difference-in-Differences Estimates of the Effect of the Great Chicago Fire on Wood and Non-Wood Construction Innovation



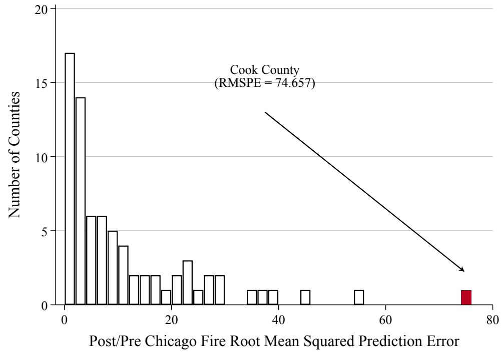
Notes. This Figure reports the effect of the Great Chicago Fire (1871) on innovation in non-wood (Panel C.10a) and wood (Panel C.10b) technologies. The dependent variable is the number of patents in either class. The unit of observation is a metropolitan area at a yearly frequency between 1853 and 1900. The Figures report event-study coefficients obtained using the synthetic difference-in-differences methods developed by Arkhangelsky et al. (2021) and obtained following the procedure described in Clarke et al. (2023). Standard errors are estimated using bootstrap sampling with 100 replications; gray bars report 95% confidence intervals. The covariates included in the synthetic difference-in-differences estimation are the same as in the synthetic control estimation, except for the pre-treatment outcome values. The black dashed line marks the year of the Great Chicago Fire (1871) and the Chicago Municipality Ordinance prohibiting wood construction (1874). Referenced on pages: 23, B10.

Figure C.11. Non-Wood Construction Manufacturing: Pre-Post Great Chicago Fire Synthetic Control Root Mean Squared Prediction Error Comparison

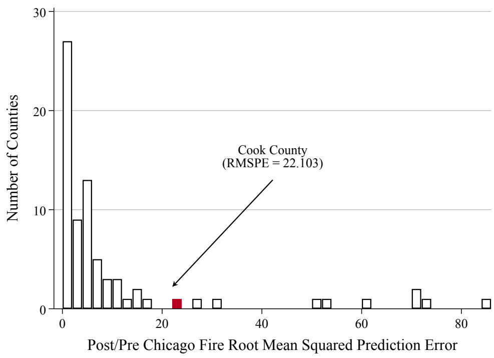
(a) Number of Establishments



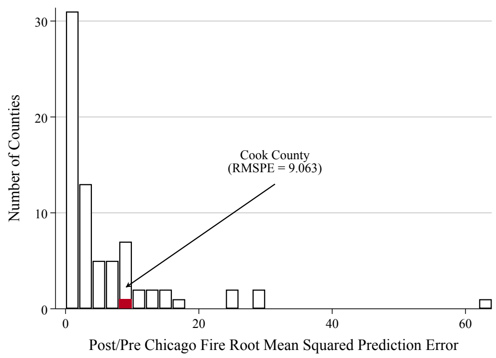
(b) Value of Production



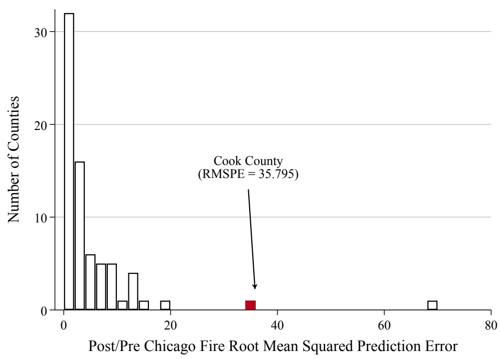
(c) Fixed Capital



(d) Cost of Materials



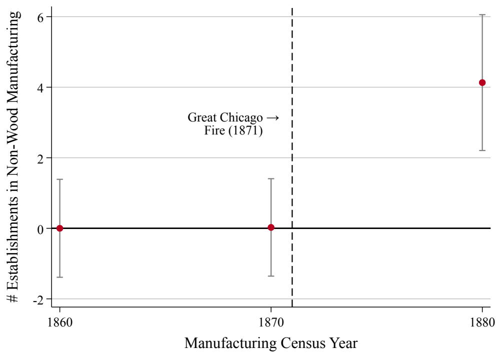
(e) Cost of Labor



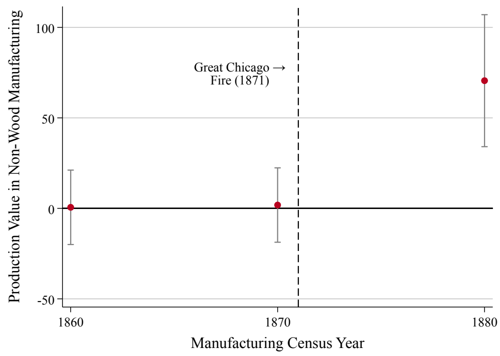
Notes. This Figure reports the impact of the Great Chicago (1871) on non-wood construction manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in Panel C.11a, the number of establishments; in Panel C.11b, production value; in Panel C.11c, fixed capital; in Panel C.11d, the cost of materials; in Panel C.11e, the cost of labor. Each figure reports the ratio between the post-Fire and pre-Fire mean squared prediction error across counties and highlights Cook County (IL) in red. The sample includes all counties with at least one metropolitan area. Referenced on page: 24.

Figure C.12. Synthetic Difference-in-Differences Estimates of the Effect of the Great Chicago Fire on Non-Wood Manufacturing

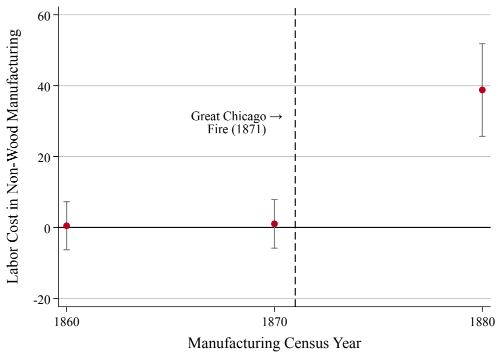
(a) Establishments



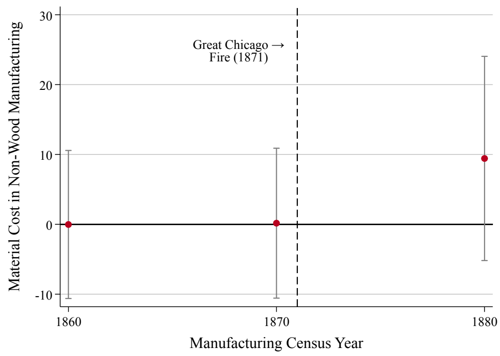
(b) Production Value



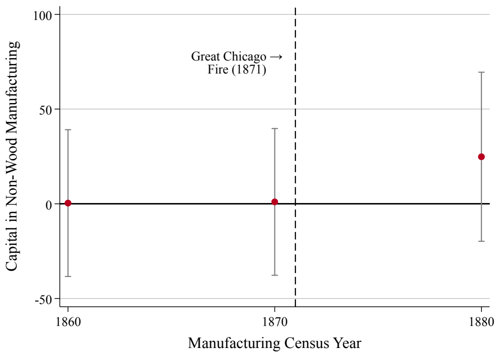
(c) Labor Costs



(d) Material Costs



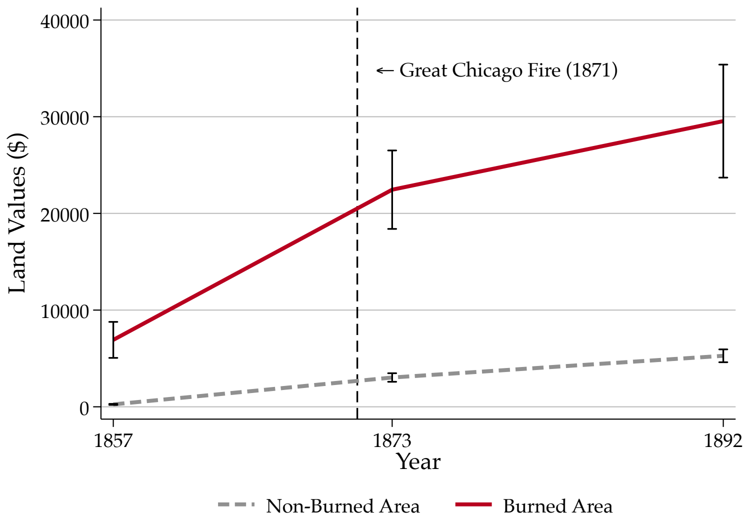
(e) Capital



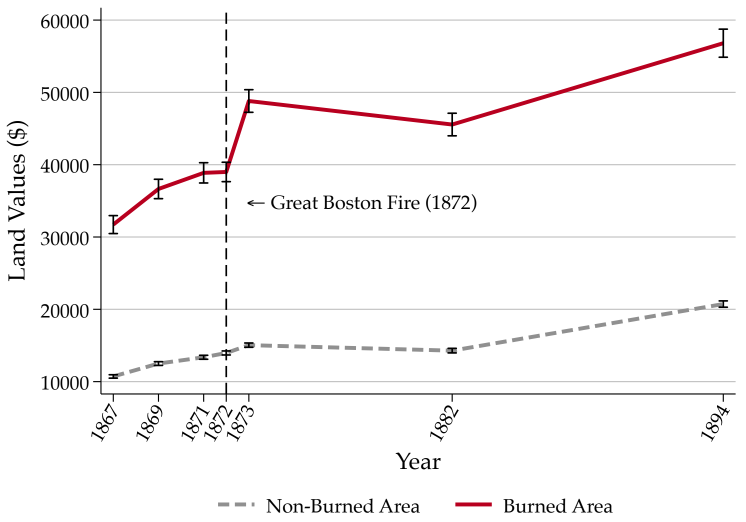
Notes. This Figure reports the impact of the Great Chicago Fire (1871) on non-wood manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in Panel C.12a, the number of establishments; in Panel C.12b, production value; in Panel C.12c, the cost of labor; in Panel C.12d, the cost of materials; in Panel C.12e, fixed capital. The Figures report event-study coefficients obtained using the synthetic difference-in-differences methods developed by Arkhangelsky et al. (2021) and obtained following the procedure described in Clarke et al. (2023). Standard errors are estimated using bootstrap sampling with 100 replications; gray bars report 95% confidence intervals. The sample includes all counties with at least one metropolitan area. Referenced on pages: 24, B10.

Figure C.13. Land Values in Chicago and Boston Before and After the Fires

(a) Chicago



(b) Boston



Notes. This Figure reports the average land values per square mile in Chicago (Panel C.13a and Boston (Panel C.13b) before and after the 1871 and 1872 fires, respectively. Data for Chicago are digitized from Hoyt (1933), while data for Boston are from Hornbeck and Keniston (2017). In each panel, the red line reports land values in areas exposed to the fires, and the gray lines report average land values for the remaining parts of the city. Bands report one-standard-deviation intervals around the mean. Referenced on page: 26.

D ADDITIONAL TABLES

Table D.1. List of Words Related to Construction, Wood-Related, and Non-Wood-Related Patents

Words related to...		
Construction (1)	Wood-Related Construction (2)	Non-wood Related Construction (3)
Construction	Wood	Iron
Building	Timber	Brick
Edifice	Beam	Ston
Frame	Joist	Mortar
Roof	Mortise	Concrete
Wall	Tenon	Steel
Floor	Plank	Cast
Ceiling	Bracing	Lime
Joist	Joinery	Terracotta
Pillar	Lumber	Cement
Foundation	Plywood	Glass
Footing	Veneer	
Slab		
Stair		
Staircase		
Railing		
Balustrade		
Baluster		
Fence		
Gate		
Door		
Window		
Sill		
Lintel		
Arch		
Vault		
Dome		

Notes. This Table reports the keywords that we use to implement the dictionary-based approach to identify patents in construction (column 1), wood-related construction (column 2), and non-wood-related construction (column 3). We flag a patent as construction-related if the total number of mentions of words in column (1) is five or more. A wood-related (resp. non-wood-related) patent is one that further mentions at least one word in column (2) (resp 3). Referenced on pages: 9, A4.

Table D.2. List of Metropolitan Areas in the Sample

Metro Area (1)	City (2)	Metro Area (3)	City (4)	Metro Area (5)	City (6)
Albany	Albany	Albany	Bethlehem	Albany	Coeymans
Albany	Greenbush	Albany	Guilderland	Albany	New Baltimore
Albany	New Scotland	Albany	Niskayuna	Albany	Schodack
Allegheny	Allegheny	Allegheny	Bellevue	Allegheny	Chartiers
Allegheny	Dixmont	Allegheny	Green Tree	Allegheny	Kilbuck
Allegheny	Marshall	Allegheny	Mccandless	Allegheny	Mount Washington
Allegheny	Neville	Allegheny	Ohio	Allegheny	Peters
Allegheny	Pine	Allegheny	Richland	Allegheny	Ross
Allegheny	Scott	Allegheny	South Fayette	Allegheny	Stowe
Allegheny	Upper Saint Clair	Allegheny	Wexford		
Atlanta	Atlanta	Atlanta	Clayton	Atlanta	Decatur
Atlanta	Dekalb	Atlanta	Panthersville		
Augusta	Augusta	Augusta	Hamburg	Augusta	Richmond Factory Pond
Baltimore	Baltimore	Baltimore	Baltimore Zoo	Baltimore	Brooklandville
Baltimore	Brooklyn	Baltimore	Catonsville	Baltimore	Cockeysville
Baltimore	Lutherville	Baltimore	Saint Denis	Baltimore	Texas
Baltimore	Warren				
Boston	Boston	Boston	Braintree	Boston	Milton
Boston	Quincy	Boston	Randolph	Boston	Stoughton
Boston	Weymouth				
Brooklyn	Brooklyn	Brooklyn	College Point	Brooklyn	Columbusville
Brooklyn	Flatbush	Brooklyn	Flatlands	Brooklyn	Flushing
Brooklyn	Gravesend	Brooklyn	Jamaica	Brooklyn	New Lots
Brooklyn	New Utrecht	Brooklyn	Westchester	Brooklyn	Whitestone
Buffalo	Amherst	Buffalo	Buffalo	Buffalo	Cheektowaga
Buffalo	Eden	Buffalo	Grand Island	Buffalo	Hamburg
Buffalo	Tonawanda	Buffalo	West Seneca	Buffalo	Wheatfield
Buffalo	Williamsville				
Camden	Blackwood	Camden	Camden	Camden	Cinnaminson
Camden	Deptford	Camden	Gloucester	Camden	Gloucester City
Camden	Haddon	Camden	Haddonfield	Camden	Harrison
Camden	Mantua	Camden	Merchantville	Camden	Washington
Camden	Woodbury				
Charleston	Charleston	Charleston	James Island	Charleston	Johns Island
Charleston	Saint Andrews				
Charlestown	Charlestown	Charlestown	Chelsea	Charlestown	East Boston
Charlestown	Everett	Charlestown	Malden	Charlestown	Melrose

Charlestown	Wakefield				
Chatham	Chatham	Chatham	Whitmell		
Chicago	Calumet	Chicago	Chicago	Chicago	Cicero
Chicago	Evanston	Chicago	Hyde Park	Chicago	Jefferson
Chicago	Lake	Chicago	Lakeview	Chicago	Lyons
Cincinnati	Bromley	Cincinnati	Cincinnati	Cincinnati	Colerain
Cincinnati	Cumminsville	Cincinnati	Delhi	Cincinnati	Glendale
Cincinnati	Green	Cincinnati	Ludlow	Cincinnati	Millcreek
Cincinnati	Springdale	Cincinnati	Springfield	Cincinnati	Taylorsport
Cincinnati	West Covington				
Cleveland	Bedford	Cleveland	Brecksville	Cleveland	Brooklyn
Cleveland	Cleveland	Cleveland	East Cleveland	Cleveland	Independence
Cleveland	Newburg	Cleveland	Parma	Cleveland	Rockport
Cleveland	Royalton				
Columbus	Blendon	Columbus	Clinton	Columbus	Columbus
Columbus	Franklin	Columbus	Groveport	Columbus	Hamilton
Columbus	Harrison	Columbus	Jackson	Columbus	Madison
Columbus	Mifflin	Columbus	Norwich	Columbus	Orange
Columbus	Perry	Columbus	Scioto	Columbus	Sharon
Columbus	Truro	Columbus	Westerville		
Covington	Alexandria	Covington	Anderson	Covington	Bank Lick
Covington	Cold Spring	Covington	Columbia	Covington	Covington
Covington	Dayton	Covington	Florence	Covington	Independence
Covington	Johns Hill	Covington	Kenton	Covington	Newport
Covington	Pendleton	Covington	Scott	Covington	Visalia
Davenport	Andalusia	Davenport	Blackhawk	Davenport	Bowling
Davenport	Buffalo	Davenport	Butler	Davenport	Coal Valley
Davenport	Davenport	Davenport	Hampton	Davenport	Lincoln
Davenport	Moline	Davenport	Pleasant Valley	Davenport	Preemption
Davenport	Rock Island	Davenport	Rockingham	Davenport	Sheridan
Davenport	Winfield				
Dayton	Bath	Dayton	Beavercreek	Dayton	Bellbrook
Dayton	Bethel	Dayton	Brandt	Dayton	Butler
Dayton	Clear Creek	Dayton	Dayton	Dayton	Harrison
Dayton	Jefferson	Dayton	Mad River	Dayton	Madison
Dayton	Miami	Dayton	Miamisburg	Dayton	Monroe
Dayton	Randolph	Dayton	Sugarcreek	Dayton	Vandalia
Dayton	Washington	Dayton	Wayne	Dayton	West Charleston
Detroit	Dearborn	Detroit	Detroit	Detroit	Ecorse
Detroit	Fort Wayne	Detroit	Grosse Pointe	Detroit	Hamtramck
Detroit	Roseville	Detroit	Royal Oak	Detroit	Springwells
Detroit	Warren	Detroit	Wyandotte		
Edgefield	Edgefield	Edgefield	Fruit Hill	Edgefield	Johnston
Edgefield	Meeting Street				

Elizabeth	Clark	Elizabeth	Elizabeth	Elizabeth	Keyport
Elizabeth	Linden	Elizabeth	Livingston	Elizabeth	Millburn
Elizabeth	New Dorp	Elizabeth	New Springville	Elizabeth	Perth Amboy
Elizabeth	Port Richmond	Elizabeth	Rahway	Elizabeth	Richmond
Elizabeth	South Amboy	Elizabeth	South Orange	Elizabeth	Springfield
Elizabeth	Summit	Elizabeth	Tottenville	Elizabeth	Westfield
Elizabeth	Woodbridge				
Eufaula	Eufaula	Eufaula	Georgetown		
Evansville	Armstrong	Evansville	Campbell	Evansville	Center
Evansville	Evansville	Evansville	German	Evansville	Henderson
Evansville	Knight	Evansville	Ohio	Evansville	Perry
Evansville	Pigeon	Evansville	Scott	Evansville	Spottsville
Evansville	Union				
Fall River	Berkley	Fall River	Bristol	Fall River	Dighton
Fall River	Fall River	Fall River	Little Compton	Fall River	Middletown
Fall River	Portsmouth	Fall River	Rehoboth	Fall River	Somerset
Fall River	Swansea	Fall River	Taunton	Fall River	Tiverton
Fall River	Warren	Fall River	Westport		
Harrisburg	Dauphin	Harrisburg	Duncannon	Harrisburg	East Pennsboro
Harrisburg	Fairview	Harrisburg	Goldsboro	Harrisburg	Halifax
Harrisburg	Hampden	Harrisburg	Harrisburg	Harrisburg	Highspire
Harrisburg	Hummelstown	Harrisburg	Lewisberry	Harrisburg	Lower Allen
Harrisburg	Lower Paxton	Harrisburg	Lower Swatara	Harrisburg	Marysville
Harrisburg	Mechanicsburg	Harrisburg	Middle Paxton	Harrisburg	Middletown
Harrisburg	Monaghan	Harrisburg	New Buffalo	Harrisburg	New Cumberland
Harrisburg	Newberry	Harrisburg	Penn	Harrisburg	Reed
Harrisburg	Rockville	Harrisburg	Rye	Harrisburg	Silver Spring
Harrisburg	South Hanover	Harrisburg	Susquehanna	Harrisburg	Upper Allen
Harrisburg	Warrington	Harrisburg	Watts	Harrisburg	West Hanover
Hartford	Avon	Hartford	Berlin	Hartford	Bloomfield
Hartford	Cromwell	Hartford	East Granby	Hartford	East Hartford
Hartford	East Windsor Hill	Hartford	Farmington	Hartford	Glastonbury
Hartford	Granby	Hartford	Hartford	Hartford	Manchester
Hartford	Middletown	Hartford	New Britain	Hartford	Portland
Hartford	Rocky Hill	Hartford	Simsbury	Hartford	South Windsor
Hartford	West Hartford	Hartford	Wethersfield	Hartford	Windsor
Hoboken	Hackensack	Hoboken	Hoboken	Hoboken	North Bergen
Hoboken	Weehawken				
Indianapolis	Allisonville	Indianapolis	Carmel	Indianapolis	Center
Indianapolis	Clay	Indianapolis	Decatur	Indianapolis	Eagle
Indianapolis	Franklin	Indianapolis	Indianapolis	Indianapolis	Lawrence
Indianapolis	Millersville	Indianapolis	Perry	Indianapolis	Pike

Indianapolis	Pleasant	Indianapolis	Warren	Indianapolis	Washington
Indianapolis	Wayne	Indianapolis	White River		
Jersey City	Bayonne	Jersey City	Greenville	Jersey City	Jersey City
Jersey City	New Brighton	Jersey City	Rutherford Park	Jersey City	Tompkinsville
Kansas City	Gallatin	Kansas City	Independence	Kansas City	Kansas City
Kansas City	Pettis	Kansas City	Quindaro	Kansas City	Shawnee
Kansas City	Westport				
Knoxville	Beaver Ridge	Knoxville	Knoxville	Knoxville	Louisville
Knoxville	Maryville	Knoxville	Rockford		
Lancaster	Clay	Lancaster	Conestoga	Lancaster	East Hempfield
Lancaster	East Lampeter	Lancaster	Eden	Lancaster	Elizabeth
Lancaster	Ephrata	Lancaster	Lancaster	Lancaster	Leacock
Lancaster	Manheim	Lancaster	Manor	Lancaster	Martic
Lancaster	Millersville	Lancaster	New Providence	Lancaster	Paradise
Lancaster	Penn	Lancaster	Pequea	Lancaster	Rapho
Lancaster	Strasburg	Lancaster	Upper Leacock	Lancaster	Warwick
Lancaster	West Earl	Lancaster	West Hempfield	Lancaster	West Lampeter
Lawrence	Andover	Lawrence	Atkinson	Lawrence	Bradford
Lawrence	Danville	Lawrence	Georgetown	Lawrence	Groveland
Lawrence	Hampstead	Lawrence	Haverhill	Lawrence	Lawrence
Lawrence	Methuen	Lawrence	Newton	Lawrence	North Andover
Lawrence	North Reading	Lawrence	Plaistow	Lawrence	Salem
Lawrence	Sandown	Lawrence	Wilmington		
Louisville	Carr	Louisville	Charlestown	Louisville	Franklin
Louisville	Harrods Creek	Louisville	Jeffersonville	Louisville	Lafayette
Louisville	Louisville	Louisville	New Albany	Louisville	Newburg
Louisville	Saint Matthews	Louisville	Shively	Louisville	Silver Creek
Louisville	Springdale	Louisville	Union	Louisville	Utica
Louisville	nan				
Lowell	Acton	Lowell	Bedford	Lowell	Billerica
Lowell	Carlisle	Lowell	Chelmsford	Lowell	Concord
Lowell	Dracut	Lowell	Dunstable	Lowell	Hudson
Lowell	Lincoln	Lowell	Lowell	Lowell	Pelham
Lowell	Tewksbury	Lowell	Tyngsborough	Lowell	Westford
Lowell	Windham				
Lynchburg	Amherst	Lynchburg	Brookville	Lynchburg	Coolwell
Lynchburg	Elon	Lynchburg	Forest	Lynchburg	Lynchburg
Lynchburg	New London				
Lynn	Hingham	Lynn	Hull	Lynn	Lynn
Lynn	Lynnfield	Lynn	Middleton	Lynn	Nahant
Lynn	Saugus	Lynn	Swampscott	Lynn	Winthrop
Macon	Clinton	Macon	Macon		
Manchester	Allenstown	Manchester	Auburn	Manchester	Bedford
Manchester	Bow	Manchester	Concord	Manchester	Derry

Manchester	Dunbarton	Manchester	Goffstown	Manchester	Hooksett
Manchester	Litchfield	Manchester	Londonderry	Manchester	Manchester
Manchester	Merrimack	Manchester	Nashua	Manchester	Pembroke
Marion	Marion	Marion	Perry		
Memphis	Cuba	Memphis	Desoto	Memphis	Hopefield
Memphis	Horn Lake	Memphis	Memphis		
Milwaukee	Caledonia	Milwaukee	Franklin	Milwaukee	Granville
Milwaukee	Greenfield	Milwaukee	Lake	Milwaukee	Mequon
Milwaukee	Milwaukee	Milwaukee	Oak Creek	Milwaukee	Wauwatosa
Montgomery	Autauga	Montgomery	Elmore	Montgomery	Montgomery
Montgomery	Prattville	Montgomery	Wetumpka		
Nashville	Brentwood	Nashville	Goodlettsville	Nashville	Madison
Nashville	Nashville				
New Bedford	Acushnet	New Bedford	Dartmouth	New Bedford	Fairhaven
New Bedford	Freetown	New Bedford	Gosnold	New Bedford	Lakeville
New Bedford	Marion	New Bedford	Mattapoisett	New Bedford	New Bedford
New Bedford	Rochester				
New Haven	Ansonia	New Haven	Bethany	New Haven	Branford
New Haven	Cheshire	New Haven	Derby	New Haven	East Haven
New Haven	Hamden	New Haven	Milford	New Haven	New Haven
New Haven	North Branford	New Haven	North Haven	New Haven	Orange
New Haven	Prospect	New Haven	Seymour	New Haven	Wallingford
New Haven	West Haven	New Haven	Woodbridge		
New Orleans	Carrollton	New Orleans	Kenner	New Orleans	Metairie
New Orleans	New Orleans	New Orleans	Shrewsbury		
New York	Astoria	New York	Belmont	New York	Fordham
New York	Long Island City	New York	Morrisania	New York	New York
New York	Tremont	New York	West Farms		
Newark	Belleville	Newark	Bloomfield	Newark	East Orange
Newark	Harrison	Newark	Kearny	Newark	Montclair
Newark	Newark	Newark	Orange	Newark	West Orange
Newburgh	Cold Spring	Newburgh	Cornwall	Newburgh	Fishkill
Newburgh	Fishkill Landing	Newburgh	Glenham	Newburgh	New Windsor
Newburgh	Newburgh	Newburgh	Philipstown	Newburgh	Plattekill
Newburgh	West Point				
Norfolk	Deep Creek	Norfolk	Fort Monroe	Norfolk	Great Bridge
Norfolk	Hampton	Norfolk	Kempsville	Norfolk	Norfolk
Norfolk	Old Point Comfort Marina	Norfolk	Portsmouth	Norfolk	Tanner Creek
Norfolk	Western Branch Park	Norfolk	Wythe		
North Providence	Bellingham	North Providence	Blackstone	North Providence	Cumberland

North Providence	Johnston	North Providence	North Providence	North Providence	Scituate
North Providence	Smithfield	North Providence	Woonsocket		
Old Cambridge	Arlington	Old Cambridge	Belmont	Old Cambridge	Brighton
Old Cambridge	Brookline	Old Cambridge	Burlington	Old Cambridge	Canton
Old Cambridge	Dedham	Old Cambridge	Hyde Park	Old Cambridge	Lexington
Old Cambridge	Medford	Old Cambridge	Needham	Old Cambridge	Newton
Old Cambridge	Old Cambridge	Old Cambridge	Reading	Old Cambridge	Somerville
Old Cambridge	Stoneham	Old Cambridge	Waltham	Old Cambridge	Watertown
Old Cambridge	West Roxbury	Old Cambridge	Winchester	Old Cambridge	Woburn
Oswego	Fulton	Oswego	Granby	Oswego	Hannibal
Oswego	Ira	Oswego	Martville	Oswego	Oswego
Oswego	Scriba	Oswego	Sterling	Oswego	Sterling Valley
Oswego	Volney				
Paterson	Caldwell	Paterson	Clinton	Paterson	Hohokus
Paterson	Little Falls	Paterson	Lodi	Paterson	Passaic
Paterson	Paterson	Paterson	Pequannock	Paterson	Pompton
Paterson	Ramapo	Paterson	Ramsey	Paterson	Saddle River
Paterson	Washington	Paterson	Wayne		
Peoria	Akron	Peoria	Cincinnati	Peoria	Dillon
Peoria	Elm Grove	Peoria	Fondulac	Peoria	Groveland
Peoria	Hallock	Peoria	Hollis	Peoria	Kickapoo
Peoria	Limestone	Peoria	Medina	Peoria	Morton
Peoria	Pekin	Peoria	Peoria	Peoria	Radnor
Peoria	Richwoods	Peoria	Spring Bay	Peoria	Tremont
Peoria	Worth				
Philadelphia	Abington	Philadelphia	Cheltenham	Philadelphia	Conshohocken
Philadelphia	Darby	Philadelphia	Greenwich	Philadelphia	Haverford
Philadelphia	Horsham	Philadelphia	Lower Merion	Philadelphia	Oreland
Philadelphia	Philadelphia	Philadelphia	Ridley	Philadelphia	Springfield
Philadelphia	Springfield	Philadelphia	Tinicum	Philadelphia	Upper Darby
Philadelphia	Upper Dublin	Philadelphia	Whitemarsh		
Pittsburgh	Allentown	Pittsburgh	Baldwin	Pittsburgh	Braddock
Pittsburgh	East Pittsburgh	Pittsburgh	Elizabeth	Pittsburgh	Etna
Pittsburgh	Hampton	Pittsburgh	Indiana	Pittsburgh	Lincoln
Pittsburgh	Mckeesport	Pittsburgh	Mifflin	Pittsburgh	Millvale
Pittsburgh	Pittsburgh	Pittsburgh	Reserve	Pittsburgh	Shaler
Pittsburgh	Sharpsburg	Pittsburgh	Snowden	Pittsburgh	Surgeon Hall
Pittsburgh	Union	Pittsburgh	West Elizabeth	Pittsburgh	Wilkins
Portland	Cape Elizabeth	Portland	Cumberland	Portland	Falmouth
Portland	Gray	Portland	North Yarmouth	Portland	Portland
Portland	Scarborough	Portland	Westbrook	Portland	Yarmouth
Poughkeepsie	Clinton	Poughkeepsie	East Fishkill	Poughkeepsie	Esopus

Poughkeepsie	Fishkill Plains	Poughkeepsie	Hyde Park	Poughkeepsie	La Grange
Poughkeepsie	Lloyd	Poughkeepsie	Marlborough	Poughkeepsie	New Paltz
Poughkeepsie	Pleasant Valley	Poughkeepsie	Port Ewen	Poughkeepsie	Poughkeepsie
Poughkeepsie	Rhinebeck	Poughkeepsie	Rondout	Poughkeepsie	Sleightsburg
Poughkeepsie	Wappingers Falls				
Providence	Attleboro	Providence	Barrington	Providence	Cranston
Providence	East Greenwich	Providence	East Providence	Providence	Pawtucket
Providence	Providence	Providence	Seekonk	Providence	Warwick
Quincy	Burton	Quincy	Ellington	Quincy	Fabius
Quincy	Fall Creek	Quincy	La Grange	Quincy	Liberty
Quincy	Melrose	Quincy	Mendon	Quincy	Miller
Quincy	Palmyra	Quincy	Quincy	Quincy	South River
Quincy	Ursa				
Reading	Adamstown	Reading	Alsace	Reading	Bern
Reading	Brecknock	Reading	Brecknock	Reading	Caernarvon
Reading	Caernarvon	Reading	Centre	Reading	Cumru
Reading	Exeter	Reading	Hamburg	Reading	Maiden Creek
Reading	Muhlenberg	Reading	Oley	Reading	Ontelaunee
Reading	Penn	Reading	Perry	Reading	Reading
Reading	Richmond	Reading	Robeson	Reading	Ruscombmanor
Reading	South Heidelberg	Reading	Spring	Reading	Union
Richmond	Bermuda	Richmond	Brookland	Richmond	Chester
Richmond	Chesterfield	Richmond	Clover Hill	Richmond	Dale
Richmond	Fairfield	Richmond	Manchester	Richmond	Richmond
Richmond	Tuckahoe	Richmond	Varina		
Rochester	Brighton	Rochester	Chili	Rochester	Gates
Rochester	Greece	Rochester	Henrietta	Rochester	Honeoye Falls
Rochester	Irondequoit	Rochester	Mendon	Rochester	Penfield
Rochester	Pittsford	Rochester	Rochester	Rochester	Rush
Rochester	Scottsville				
Sacramento	Brighton	Sacramento	Franklin	Sacramento	Fremont
Sacramento	Sacramento				
Saint Louis	Brooklyn	Saint Louis	Carondelet	Saint Louis	Caseyville
Saint Louis	Columbia	Saint Louis	East Saint Louis	Saint Louis	French
Saint Louis	Gartside	Saint Louis	Madison	Saint Louis	Millstadt
Saint Louis	Saint Ferdinand	Saint Louis	Saint Louis	Saint Louis	Venice
Saint Paul	Centerville	Saint Paul	Cottage Grove	Saint Paul	Eagan
Saint Paul	Inver Grove	Saint Paul	Mendota	Saint Paul	Minneapolis
Saint Paul	Mounds View	Saint Paul	Newport	Saint Paul	Oakdale
Saint Paul	Rosemount	Saint Paul	Roseville	Saint Paul	Saint Anthony
Saint Paul	Saint Paul	Saint Paul	West Saint Paul	Saint Paul	White Bear
Saint Paul	Woodbury				

Salem	Beverly	Salem	Boxford	Salem	Danvers
Salem	Essex	Salem	Hamilton	Salem	Ipswich
Salem	Manchester	Salem	Marblehead	Salem	Peabody
Salem	Rowley	Salem	Salem	Salem	Topsfield
Salem	Wenham				
San Francisco	Alameda	San Francisco	Oakland	San Francisco	San Bruno
San Francisco	San Francisco	San Francisco	San Pablo	San Francisco	Sausalito
Savannah	Hardeeville	Savannah	Savannah	Savannah	Thunderbolt
Savannah	White Bluff				
Scranton	Archbald	Scranton	Benton	Scranton	Blakely
Scranton	Dunmore	Scranton	Exeter	Scranton	Greenfield
Scranton	Hyde Park	Scranton	Jefferson	Scranton	Jenkins
Scranton	North Abington	Scranton	Old Forge	Scranton	Olyphant
Scranton	Pittston	Scranton	Ransom	Scranton	Scott
Scranton	Scranton	Scranton	South Abington	Scranton	Spring Brook
Scranton	Waverly	Scranton	West Pittston		
Shreveport	Bossier City	Shreveport	Shreveport		
Springfield	Agawam	Springfield	Chicopee	Springfield	Easthampton
Springfield	Enfield	Springfield	Granby	Springfield	Hadley
Springfield	Holyoke	Springfield	Longmeadow	Springfield	Ludlow
Springfield	Northampton	Springfield	Somers	Springfield	South Hadley
Springfield	Southampton	Springfield	Springfield	Springfield	Suffield
Springfield	West Springfield	Springfield	Westfield	Springfield	Wilbraham
Springfield	Windsor Locks				
Syracuse	Amboy	Syracuse	Belgium	Syracuse	Belleisle
Syracuse	Brewerton	Syracuse	Camillus	Syracuse	Cardiff
Syracuse	Caughdenoy	Syracuse	Central Square	Syracuse	Cicero
Syracuse	Clay	Syracuse	Dewitt	Syracuse	Euclid
Syracuse	Fayetteville	Syracuse	Geddes	Syracuse	Jamesville
Syracuse	Lafayette	Syracuse	Liverpool	Syracuse	Manlius
Syracuse	Navarino	Syracuse	Onondaga	Syracuse	Otisco
Syracuse	Pompey	Syracuse	Salina	Syracuse	South Onondaga
Syracuse	Syracuse	Syracuse	Threerivers	Syracuse	Van Buren
Toledo	Bedford	Toledo	Erie	Toledo	Lake
Toledo	Maumee	Toledo	Oregon	Toledo	Perrysburg
Toledo	Sylvania	Toledo	Toledo	Toledo	Troy
Toledo	Washington	Toledo	Webster	Toledo	Whiteford
Trenton	Bordentown	Trenton	Bristol	Trenton	Burlington
Trenton	Chesterfield	Trenton	Ewing	Trenton	Falls
Trenton	Hamilton	Trenton	Hamilton Square	Trenton	Hopewell
Trenton	Lawrence	Trenton	Lower Makefield	Trenton	Mansfield
Trenton	Middletown	Trenton	Morrisville	Trenton	Mount Holly
Trenton	Princeton	Trenton	Springfield	Trenton	Trenton

Trenton	West Windsor	Trenton	Westampton		
Troy	Brunswick	Troy	Clifton Park	Troy	Cohoes
Troy	Green Island	Troy	Halfmoon	Troy	Lansingburgh
Troy	Mechanicville	Troy	Nassau	Troy	North Greenbush
Troy	Poestenkill	Troy	Sand Lake	Troy	Schaghticoke
Troy	Stillwater	Troy	Troy	Troy	Waterford
Troy	Watervliet	Troy	West Sand Lake		
Utica	Bridgewater	Utica	Cassville	Utica	Clark Mills
Utica	Clayville	Utica	Clinton	Utica	Deerfield
Utica	Floyd	Utica	Frankfort	Utica	Gravesville
Utica	Holland Patent	Utica	Kirkland	Utica	Litchfield
Utica	Marcy	Utica	Marshall	Utica	New Hartford
Utica	New York Mills	Utica	Oriskany	Utica	Paris
Utica	Prospect	Utica	Remsen	Utica	Sauquoit
Utica	Schuyler	Utica	South Trenton	Utica	Steuben

Notes. This Table reports the list of metropolitan areas (columns 1, 3, and 5) and all the cities below 20,000 inhabitants that are part of them. There is a total of 84 metropolitan areas comprising 1,048 smaller towns. Referenced on page: 12.

Table D.3. Synthetic Control Weights for Boston and Chicago

Metropolitan Area (1)	Synthetic Chicago (2)	Synthetic Boston (3)
New Orleans	0.0	0.024
San Francisco	0.093	0.413
Cincinnati	0.0	0.112
Kansas City	0.02	0.0
New York	0.254	0.166
Jersey City	0.304	0.0
Springfield	0.0	0.008
Charlestown	0.328	0.277

Notes. This Table presents the weights assigned to the metropolitan areas listed in column (1) to construct the synthetic Chicago (column 2) and Boston (column 3) control units. Weights are selected following a data-driven optimization algorithm that minimizes the distance between the treated unit and the synthetic control in terms of a set of balancing variables. The balancing variables are population, the share of men, the share of US-born, the share of literate, employment shares by occupation, and employment shares by industry. Shares are expressed in terms of population. All balancing variables are constructed from the 1870 population census. The weights are obtained by applying the synthetic control approach on construction patenting. Referenced on page: 14.

Table D.4. Comparison between Boston, the Other Metropolitan Areas, and Synthetic Boston

	Boston	All Other Cities			Synthetic Boston		
	Mean	Mean	Difference		Mean	Difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Demographics							
Literacy Rate (%)	70.645	60.780	9.865***	(1.685)	68.193	2.452	(1.739)
Imputed Income per Capita	893.628	707.792	185.837***	(14.929)	895.798	-2.170	(52.655)
Share of Whites (%)	98.886	85.715	13.171***	(2.443)	94.992	3.894	(2.684)
Share of Blacks (%)	1.110	14.023	-12.913***	(2.452)	1.697	-0.587	(1.079)
Share of Natives (%)	66.585	78.113	-11.528***	(1.475)	61.703	4.883	(7.343)
Panel B. Employment Share (%) by Occupation							
Liberal Profession	1.412	1.029	0.383***	(0.032)	1.632	-0.220	(0.254)
Farmer	0.620	8.410	-7.790***	(0.970)	1.008	-0.388	(0.372)
Manager	2.768	1.977	0.791***	(0.082)	3.382	-0.615	(0.404)
Clerical Worker	1.373	0.650	0.723***	(0.037)	1.202	0.171***	(0.057)
Sales	3.063	1.363	1.700***	(0.071)	2.862	0.201	(0.284)
Skilled Manufacture	8.168	5.640	2.528***	(0.213)	7.884	0.284	(0.293)
Low-Skill Manufacture	9.904	7.200	2.704***	(0.583)	8.651	1.253***	(0.242)
Service	6.692	4.389	2.303***	(0.218)	6.360	0.331	(1.134)
Panel C. Employment Share (%) by Industry							
Laborer	5.783	4.669	1.114***	(0.211)	6.055	-0.272	(0.712)
Agriculture	0.843	8.667	-7.824***	(0.965)	1.308	-0.465	(0.496)
Chemistry	0.092	0.078	0.014	(0.014)	0.187	-0.095	(0.124)
Construction	3.336	2.379	0.957***	(0.090)	3.201	0.136	(0.183)
Liberal Professions	10.275	6.597	3.678***	(0.245)	10.078	0.198	(1.578)
Metallurgy	0.730	0.766	-0.037	(0.066)	0.686	0.043	(0.051)
Public Administration	0.500	0.297	0.204***	(0.027)	0.673	-0.173	(0.144)
Textiles	0.918	1.949	-1.031**	(0.460)	0.641	0.277	(0.240)
Trade	7.158	3.606	3.552***	(0.171)	6.789	0.369	(0.280)
Transports	3.048	1.991	1.057***	(0.099)	3.266	-0.218	(0.407)
Utilities	8.025	4.962	3.063***	(0.230)	7.679	0.346	(1.362)
Residual Industries	3.946	2.986	0.959***	(0.149)	4.145	-0.200	(0.172)
Engineering	0.528	0.386	0.142***	(0.032)	0.606	-0.078	(0.088)

Notes. This Table compares the values of the balancing variables included in the synthetic control design in Boston and in the other metropolitan areas in the sample. Column (1) reports the average value of the various variables for Boston; columns (2) and (5) report the average across all control cities and in synthetic Boston, respectively. The weights used to compute the co-variates in the synthetic control are obtained by applying the synthetic control approach on construction patenting. In columns (3–4) (resp. 6–7), we report the difference between Boston and all other cities (resp. synthetic Boston). Robust standard errors are displayed in parentheses. All data are computed from the 1870 population census and expressed in population percentage. Referenced on page: 15.
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table D.5. Synthetic Control Estimates of the County-Level Impact of the Great Chicago Fire on per Capita Manufacturing Activity

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1)	(2)	(3)	(4)	(5)
	# Establishments	Value of Production	Fixed Capital	Cost of Materials	Cost of Labor
Panel A. Construction Manufacturing					
1860 (Pre-Fire)	0.000	3.247	-0.741	-1.726	-0.793
1870 (Pre-Fire)	-0.001	-0.070	-3.776	-2.314	-0.355
1880 (Post-Fire)	0.065	3320.363	749.794	1836.556	904.345
Mean Dep. Var. (Before 1870)	0.118	2596.728	1314.480	870.335	930.620
Panel B. Non-Wood Manufacturing					
1860 (Pre-Fire)	0.000	0.222	6.317	0.002	-0.118
1870 (Pre-Fire)	0.000	-0.727	6.214	-0.272	0.599
1880 (Post-Fire)	0.008	138.772	-23.062	11.504	120.543
Mean Dep. Var. (Before 1870)	0.015	425.407	255.699	74.280	219.966
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Chicago (1871) Fire on construction and non-wood-related manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each dependent variable is normalized by the county's total employment, as measured in the population census, and expressed in percentage terms. Each column reports the difference between the observed outcome in Cook County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. The Table reports separately the effects on overall construction manufacturing (Panel A) and non-wood construction manufacturing (Panel B). Referenced on pages: 19, 20, 24.

Table D.6. Synthetic Control Estimates of the County-Level Estimates of the Impact of the Great Chicago Fire on Wood Manufacturing

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1) # Establishments	(2) Value of Production	(3) Fixed Capital	(4) Cost of Materials	(5) Cost of Labor
1860 (Pre-Fire)	0.000	-38.942	-2.560	-31.377	-1.253
1870 (Pre-Fire)	1.300	313.823	96.100	239.464	25.101
1880 (Post-Fire)	0.400	360.009	9.851	317.960	18.798
Mean Dep. Var. (Before 1870)	2.000	358.670	104.075	269.963	40.599
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Chicago (1871) Fire on wood-related manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each column reports the difference between the observed outcome in Cook County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. Referenced on page: 24.

Table D.7. Synthetic Control Estimates of the County-Level Estimates of the Impact of the Great Boston Fire on Wood Manufacturing

	Dependent Variable (Treated County - Synthetic Treated County)				
	(1)	(2)	(3)	(4)	(5)
	# Establishments	Value of Production	Fixed Capital	Cost of Materials	Cost of Labor
Panel A. Construction Manufacturing					
1860 (Pre-Fire)	0.000	17.223	-0.012	12.848	-0.002
1870 (Pre-Fire)	-0.001	1.153	-0.041	0.799	-0.035
1880 (Post-Fire)	-0.310	-174.464	-5.451	-154.345	-11.866
Mean Dep. Var. (Before 1870)	1.350	221.230	57.305	165.920	28.675
Number of Counties	76	76	76	76	76
Number of Observations	228	228	228	228	228

Notes. This Table reports the impact of the Great Boston (1872) Fire on wood-related manufacturing activity as measured in the Census of Manufacturing. The unit of observation is a county at a decade frequency between 1860 and 1880. The dependent variable is: in column (1), the number of establishments; in column (2), production value; in column (3), fixed capital; in column (4), the cost of materials; in column (5), the cost of labor. Each column reports the difference between the observed outcome in Suffolk County and a synthetic control constructed using the baseline balancing variables and pre-treatment outcome values. The sample includes all counties with at least one metropolitan area. Referenced on page: 27.

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