The Bankruptcy Express: Market Integration, Organizational Changes, and Financial distress in 19$^{\text{th}}$ century Britain*

Tobias Korn†, Jean Lacroix‡

November 29, 2024

Abstract

This paper shows that amid aggregate gains, market integration generates within-sector reallocation. To measure this effect, we collected new data on personal bankruptcies during the rail expansion in 19$^{\text{th}}$ century Britain. Our estimators leverage within geography-time and within sector-time variation to measure sector-specific effects of the rail on both employment and bankruptcies. A connection to railway increased bankruptcies *only* in the manufacturing sector, despite simultaneously increasing employment in that sector. Both a three-way fixed effects and a Least Cost Path approach validate the causality of our estimates. We further show that organizational changes that occurred in the manufacturing sector upon market integration explain our results: Firms expanded, self-employment decreased, occupations diversified; overall, the nature of labour changed. This biased growth of the manufacturing sector caused financial distress for some of its workers.

Keywords: Bankruptcies, Economic Growth, Structural transformation
JEL Codes: N63, L16, O33, R40, K35

---

*This work has been supported as part of the France 2030 program "ANR-11-IDEX-0003". We thank the participants of the 2024 EPCS, the IfW Kiel Research Seminar, the GDE Conference 2024, the ZEW-ifo Young Scholar Political Economy Workshop 2024, the Beyond Basic Questions Workshop 2024, the EHA Meeting 2024, the ETSG 2024 conference, the KOF research seminar at ETH Zurich, RITM Seminar at Paris Saclay, the CEPR-Banco de España Symposium in Economic History and the University of Mannheim Econ History Colloquium for useful comments and suggestions. We want to thank Dana Behnsen, Basile Blanc and Victor Westergren for their research assistance.

† korn@mak.uni-hannover.de, Leibniz Universität Hannover, Königsworther Platz 1 30167 Hannover & Universität Heidelberg, Bergheimerstr. 58, 69115 Heidelberg.

‡jean.lacroix@universite-paris-saclay.fr, RITM, Universite Paris-Saclay, 54 boulevard Desgranges, 92330 Sceaux.

1 Introduction

With their 2030 Agenda for Sustainable Development, UN member states pledged that "no one will be left behind".[1] Among the agenda's solutions to achieve this objective, two stand out: transport infrastructure and productivity boosts. Indeed, transport infrastructure does spur growth (Hornung, 2015; Donaldson and Hornbeck, 2016; Berger and Enflo, 2017; Jedwab et al., 2017; Donaldson, 2018; Banerjee et al., 2020). Meanwhile, increasing productivity requires new technologies and organizational changes (Sokoloff, 1984). Both market integration and organizational changes redistribute economic gains across space (Autor et al., 2013, 2016; Redding, 2016), and often within sectors (Juhász et al., 2024). Place-based policies help remedy the distributional consequences across space. And job trainings can help workers adapt to changes within their sector. Such policies however potentially miss place-sector specific dynamics that arise from market integration.

Indeed, market integration may trigger deeper organizational changes in sectors that benefit more from economies of scale. This resonates with the theoretical contribution of Melitz (2003), who argues that market integration generates aggregate gains, but is distortionary and may foster the exit of the least productive firms. Market integration consequently reallocates economic gains among actors within the same industry within areas integrated to a wider market. For the moment, empirical papers have mainly shown how international trade may negatively impact a sector's employment (Autor et al., 2013, 2016, 2020). We still lack evidence on the effects of market integration *within* local economic sectors: Does market integration benefit all economic agents within a sector the same way, or is it redistributive? We document this effect during an episode of rampant growth – the rail expansion in 19$^{\text{th}}$ century Britain. Introducing new data on personal bankruptcies, we provide a novel measure for within-sector, within-space reallocation.

Conceptually, the Second Industrial Revolution in Britain provides an interesting case. The railway's freight sector expanded massively during the second half of the 19$^{\text{th}}$ century (Bogart, 2014). As transport costs decreased, market integration allowed the exploitation of additional economies of scale. The exploitation of these economies of scale was possible thanks to organizational changes. As shown in the case of France during the First Industrial Revolution, these changes impacted market structures (Juhász et al., 2024). The manufacturing sector transitioned from workshops to factories (Atack et al., 2008), whereas the transformation of other sectors was not as clear. Echoing Melitz (2003), we argue that changes triggered by market integration potentially caused individual financial distress of some, while the economy overall was prospering. According to our working hypothesis, market structures

[1] See for more information https://sdgs.un.org/2030agenda, last visited Nov. 6th, 2023.

and the nature of labour changed because of the organizational changes following market integration. This could trigger bankruptcies in several ways. For example, larger firms in a monopsony could offer lower wages. Or the least productive firms were forced out of the market and had to let go their workers.

To test this intuition, we have collected a new dataset on the universe of personal bankruptcies in Britain. Combining Optical Character Recognition and text recognition algorithms, we collected all public bankruptcy announcements from the period of the British railway expansion in 1850–1890. Early on, the British bankruptcy law mandated that all insolvencies must be publicly announced in the *London Gazette* so that all creditors could make their claims heard. This practice continues until today.[2] For each bankruptcy case, we geolocated the stated home address of the bankrupt and coded the bankrupt's occupation, assigning it to an economic sector. Our dataset includes information on around 150,000 bankruptcy cases between 1851 and 1890, for which we have information at the sector-geography-time level. We use this dataset together with rail station locations in 1851, 1861, and 1881. In addition, we use employment data from the British censuses in 1851, 1861, and 1881 at the same level of disaggregation to determine whether, within each location, bankruptcies resulted from worker movements within or across sectors. Our empirical analysis begins with a Pseudo Poisson Maximum Likelihood (PPML) estimator that regresses bankruptcies and employment on a dummy variable for rail connection and fixed effects at the geographic and $sector \times time$ level. We further interact the rail dummy with an indicator variable for manufacturing to identify the specific effect of a rail connection on the manufacturing sector. The rail dummy variable and the sector-time fixed effects control for the two main explanations for the redistributive effects of economic growth brought forward in the literature: market integration (rail dummy variable) and sector-level technological and organizational changes (sector-time fixed effects). Our estimator hence measures the interaction of these two phenomena, i.e. how market integration speeds up reallocation within sectors prone to organizational changes. Our estimator is then neither driven by general railway effects, e.g. better access to courts and information, nor by sector-specific changes.

Our results show that during the expansion of the rail, the British manufacturing sector exhibited a pattern that resembles a local within-sector reallocation. In locations with railway access, bankruptcies increased by around 40 percent among employees in the manufacturing sector. At the same time, manufacturing employment in those same places increased by approximately 32 percent. We observe this specific pattern that railway access increased both bankruptcies and employment in no other sector than manufacturing. Our results are robust to different estimation methods and survive several robustness checks which ensure

[2]The London Gazette's homepage still publishes new bankruptcy announcements every week.

that no specific geographic areas drive our results. We also employ an inconsequential places approach to strengthen a causal interpretation of these results. We estimate a local average treatment effect for places along the Least Cost Path between British central railway nodes following (Faber, 2014; Banerjee et al., 2020; Bogart et al., 2022). Finally, we show that the timing of the effect corresponds to the rail construction period. Going as far back as 1800, the manufacturing sector did not exhibit any specific pre-trends in areas that will be connected to the rail later on.

Further extensions present illustrations of the mechanisms at play. First, we provide evidence that the manufacturing sector underwent relevant organizational changes in places that were connected to the rail. Self-employment became less common, and manufacturing labour diversified, i.e. occupation titles were more diverse than in other sectors/places. The demand for unskilled (i.e., child) labour also increased. Second, the effect of the railway was heterogeneous. Even though there was no difference in the employment effects in the manufacturing sector across locations that were connected early or late, bankruptcies responded differently. Locations that were late to the railway network experienced more bankruptcies than early connected locations. We also show that, in general, the existence of large firms in a medium distance (100km to 500km) increased the bankruptcy likelihood of people working in their sector as they become connected via the railway. Third, we show that a connection to the rail increased bankruptcies in the manufacturing sector regardless of changes in creditors' incentives. Our estimator, consequently, captures the financial distress of some workers in the manufacturing sector and not creditors' incentives to file for bankruptcy in those sectors.

Our results contribute to three strands of the literature. First, they offer a reinterpretation of Melitz (2003)'s theory emphasizing how economic changes may trigger intra-sector reallocation. The effect of market integration on firm exits has been widely documented in the trade literature (Autor et al., 2016, 2020; Heblich et al., 2024). This paper investigates an internal trade shock brought about by the railway expansion on a new measure of within-sector reallocation: personal bankruptcies. With the number of personal bankruptcies, we directly identify the characteristics of the people exposed to this reallocation within a geographic unit integrated into a wider market. Previous scholars mainly studied the legal environment of bankruptcies (Davydenko and Franks, 2008; Ponticelli and Alencar, 2016; Bose et al., 2021), their efficiencies (Ayotte, 2007; Gine and Love, 2010; Li and Ponticelli, 2022) and diffusion (Bernstein et al., 2019). Otherwise, the previous literature has mainly emphasized access to credit as an important cause of corporate bankruptcies (Del Angel et al., 2024). This paper identifies how market structure and organizational changes explain *individual* bankruptcies.

Second, this paper emphasizes the consequences of firms' reorganization during the

Industrial Revolution. The reorganization towards more capital-intensive production potentially reduced the demand for some skills and occupations in the past (Goldin and Katz, 1998) and potentially today (Kogan et al., 2023). Similarly, the gains of the Industrial Revolution were unevenly distributed across sectors (Temin, 1997) and within sectors (Crafts, 2022). Juhász et al. (2024) present evidence of within-sector reallocation in the case of cotton spinning in France. In their case, productivity was highly dispersed among firms, and the less productive firms exited as mechanized cotton spinning developed. As Juhász et al. (2024) define within-sector dynamics, our study adds a geographic dimension to this reallocation. It also identifies reallocation within a sector and within a geographic unit integrated to a wider market. Market integration increased within-sector reallocation in a fast-evolving sector despite local aggregate gains. This reallocation has political consequences (Caprettini and Voth, 2020; Rosenberg and Curci, 2023). Yet, the mechanisms driving this destruction remain to be understood.

Third, our paper offers a new perspective on the impact of railways and market integration more broadly. The previous literature has emphasized the positive effect of market integration (Donaldson, 2015). As an illustration, railways increase production (Donaldson, 2018) and productivity (Hornbeck and Rotemberg, 2024). As a consequence, the development of railways spurred economic growth (Donaldson and Hornbeck, 2016). These positive effects could be explained by the impact of railways on the diffusion of ideas (Tsiachtsiras, 2022). Ultimately, railways encouraged industrialization (Berger, 2019; Bogart et al., 2022; Kaboski et al., 2024). This structural change hinged on an organizational change as railways prompted the transition from the workshop to the factory (Atack et al., 2008; Tang, 2014; Berger and Ostermeyer, 2024). The approach of this paper is similar to Bogart et al. (2022). It complements their estimate of the effect of the railways in 19^{th} century England and Wales on urbanization and structural change. Our paper characterizes the nature of this structural change: it was biased. As a consequence of this bias, some underwent financial distress while the majority prospered.

2 The Heterogeneous Effects of Market Integration

2.1 Market Integration spurs Growth

As expected by Adam Smith (Smith, 1776, Book 1, Chapter 1), growth in market size increases efficiency and production. Previous research has emphasized the importance of the rail in this process. Donaldson and Hornbeck (2016), for example, show that the expansion of the rail network in the US has increased "market access." Extended access to the market increased land value in areas connected to the rail. These lands became more valuable as they could achieve higher returns when integrated into larger markets. The literature has documented these positive effects of the rail in a variety of contexts. Donaldson (2018) estimates that railways in India increased real income by 16 percent. This positive effect of the rail can be found in different contexts such as Sweden (Berger and Enflo, 2017), Germany (Hornung, 2015), Britain (Bogart et al., 2022) and Kenya (Jedwab et al., 2017). To explain why the rail increased income, Crafts (2004) shows that the rail increased total factor productivity. These productivity gains however have not been equally distributed across sectors, as the manufacturing sector reaped the most benefits from the rail (Hornbeck and Rotemberg, 2024).

2.2 The Organizational Side of Market Integration

To reap those benefits, the manufacturing sector reorganized. Braun and Franke (2022), for example, show that non-industrial regions did not experience increased income because of the rail while Berger (2019) describes how the rail sped up industrialization in rural Sweden. Similarly, Bogart et al. (2022) observe that the rail increased structural change in Britain. Kaboski et al. (2024) also observe that highways in India and China prompted structural change. The manufacturing sector likely benefits most from market integration due to the organization of its firms. Heightened competition and greater access to factors of production shaped the production process. This has been achieved through new forms of organization or new technologies. In the case of the U.S., Atack et al. (2008) show that the rail led to the transition of the factory system and towards higher reliance on unskilled labour. Tang (2014) also shows that the rail expansion increased investment in firm capitalization in Japan, specifically in manufacturing. In Sweden, railways also have shaped the manufacturing sector and encouraged the transition to the factory system in which the division of labour yields higher returns on economies of scale (Berger and Ostermeyer, 2024).

2.3 Organizational Changes, Labour Changes and Individual Financial Distress

The rail prompted organizational changes yielding aggregate economic gains. The theoretical framework of Melitz (2003) clarifies how such changes may be detrimental for some. First, market integration and trade increase competition, putting pressure on the least productive firms that lose market shares. Second, firms need to invest an entry cost to be able to enter trading. Because of their lower productivity, the least productive firms cannot enter trading and exit the market. Conversely, firms may reorganize to increase productivity and pay the entry cost to access other markets. Such reorganization is vital to fully realizing economies of scale, labour division, and technology adoption to compete in new markets. Juhász et al. (2024) show how much the re-organization of cotton spinning in the First Industrial Revolution increased the sector's productivity. However, this slow reorganization led to the disappearance of the least productive firms in the market. According to Chandler (1977), the same occurred during the Second Industrial Revolution. Some industries have experienced rampant innovation. To adopt new technologies and realize economies of scale, firms hired more white-collar workers to solve new organizational issues. This paper does not disentangle one of these mechanisms from the other, but presents evidence that the manufacturing sector experienced more personal bankruptcies than other sectors following the rail's arrival.

To take stock, according to our hypothesis, the railway expansion increased productivity in the manufacturing sector as it encouraged its reorganization to fully realize economies of scale and division of labour. This reorganization shifted the production from workshops to factories. Labour lost from this reorganization in two cases. First, the emergence of larger firms with monopsony power may have pressured wages down (Autor et al., 2020). Second, the skills needed in manufacturing might have changed with the reorganization of the manufacturing sector (Chandler, 1977; Goldin and Katz, 1998; Atack et al., 2019). Third, workers in the less productive firms that cannot afford the organizational changes to engage in trade disappear Melitz (2003). In all three cases, more workers in the manufacturing sector experience financial distress despite higher productivity and employment in their sector. We measure this negative effect using data on personal bankruptcies.

Table 1 shows the empirical patterns we observe in employment and bankruptcy data as consequences of reallocation. The upper-right and bottom-left cells illustrate observations in line with between-sector reallocation that we usually term structural transformation. While employment decreases in some sectors (upper-right cell), labour moves into another sector, where employment increases (bottom-left cell). Similarly, we would expect that this market restructuring favors workers in the rising (bottom-left) sector, while workers in the declining (upper-right) sector face a higher risk of bankruptcy. Empirically, we would expect bankruptcies to follow the opposite pattern as employment shares: where employment decreases, bankruptcies should become more likely and vice versa. The upper-left cell of Table 1 describes the situation where one observes increasing bankruptcies but non-decreasing employment in a sector. This situation describes within-sector reallocation. Along with the reorganization of a sector towards new modes of production, the least productive labour units would exit the market.

Table 1: Within versus Between Sector Reallocation

	$\nearrow$ Employment	$\searrow$ Employment
$\nearrow$ Bankruptcies	Within-Sector	Between Sectors
$\searrow$ Bankruptcies	Between Sectors	Within-Sector

Notes: $\nearrow$ Arrows mean increasing while $\nearrow$ Arrows mean decreasing. Hence the upper left cell could be interpreted as a case of increasing bankruptcies and employment suggesting within-sector reallocation

Ultimately, this framework defines sector-specific patterns of reallocation due to market integration. Our results section directly tests the two ends of this chain: it articulates results on increasing bankruptcies and increasing employment in manufacturing (Section 5). Later, we test the different mechanisms explaining this causal chain in Section 7.

3 Historical Background

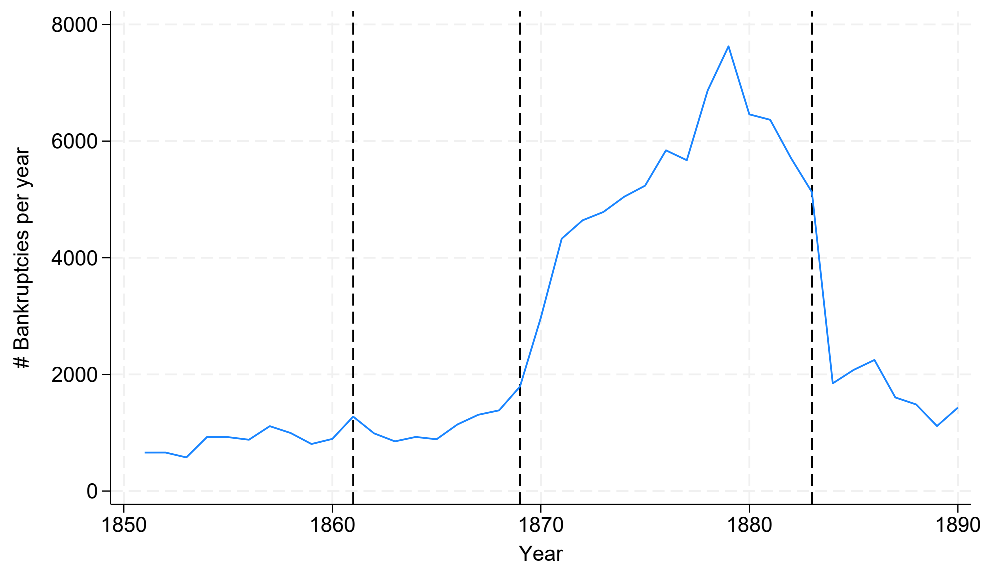
3.1 Bankruptcy Procedures in 19th Century Britain

Bankruptcy procedures were at the forefront of political conversations throughout 19^{th} century England (Lester, 1991). Debtors' prison illustrates well the consequences of bankruptcy, how complex the system was, and how important bankruptcies were in the collective image of 19^{th} century England.[3] At the beginning of the 19th century, it was common for debtors that could not repay their debts to be sent to prison until their labour could repay their debt. Throughout the century, several reforms modernized both the procedure and the role of debtors' prison. From 1831, the procedure implied that officials would be appointed to collect and distribute the assets of bankrupts. Bankruptcy could then be initiated by both debtors and creditors. This doctrine of bankruptcy law called "officialism" was deemed inefficient by entrepreneurs and business elites. The system of "officialism" was costly and its ability to recover unpaid debt was slow and limited. The 1869 Bankruptcy and Debtor Acts massively changed this institution. After this series of reforms, debtors' prison was limited to debtors believed to have the financial means to repay their debt but did not do so. Moreover, the doctrine of "officialism" was repealed and a new system of bankruptcy management was put in place. In this case, if most creditors agreed, they could proceed to manage the bankruptcy themselves.

[3]Debtors are, for example, a common figure of Charles Dickens' work reflecting the author's father's own experience as an inmate in a debtors' prison.

This new management of bankruptcies advantaged creditors. Recovery rates were higher as creditors had direct incentives to recover as much of the debt as possible. They also could avoid recovering small debts whose costs to recover were greater than the debt itself. Our dataset illustrates those changes. Figure 1 presents the evolution of the number of bankruptcies per year in the time frame of our study.

Figure 1: The Evolution of Bankruptcies



Notes: This figure plots the aggregate number of bankruptcies per year based on new data collected by the authors. Dashed vertical lines indicate three significant reforms to the bankruptcy law: In 1861, the bankruptcy law was extended to all occupations. In 1869, bankruptcy management was put into the hands of most creditors. In 1883, bankruptcy management returned to "officialism" where courts presided over bankruptcy cases.

Two other reforms occurred during the period of our study. The 1861 reform broadened the scope of the bankruptcy to all citizens, not only those with trading activity. The 1883 reform reintroduced "Officialism." Figure 1 evidences the importance of the bankruptcy regime in determining the number of bankruptcies. In Section 7.3, we leverage these differences in regimes to inform on the mechanisms potentially explaining more bankruptcies.

3.2 The Railway Expansion in Britain

The rail expansion was the last step in the transport revolution of Britain (Bogart, 2014). In the second half of the 19$^{\text{th}}$ century, the rail became a cheap alternative to transport goods, resources, and persons. The railway mania of the 1840's structured this expansion. Private interests explain this mania. For example, Esteves and Mesevage (2021) show that MPs ruled on railway bills because of their personal interests in 25% of cases. This development of the railway network was economically inefficient (Casson, 2009). Between 1840 and 1870, the output of the rail sector was multiplied by 44 (Bogart, 2014). Beyond the inefficiencies of its development, the rail sector became more dense and more productive. Between 1851 and 1881, the length of the railway network in England and Wales nearly doubled (Bogart et al., 2022). In 1851, the network covered mostly the central region of England. By 1881, it expanded to Wales and the South-Western part of England. Hawke (1970) and Crafts (2004) both emphasize the importance of TFP growth in the sector in its early development. During the second half of the 19$^{\text{th}}$ century, the rail became more frequent and also more efficient. These two dimensions explain the impact of the rail on the economy. Because of technological development, it became a cheap alternative to other modes of transportation. Because of the development of the network, it connected and shaped exchanges throughout Britain. By the end of the 19$^{\text{th}}$ century, the rail became the main mode of transportation for passengers and materials (Bogart et al., 2022).

Previous literature has debated the overall impact of the rail on the British economy. Mitchell (1964), for example, argues that "the introduction of railways in Britain did not have a very great immediate impact on the economy". Hawke (1970) mentions that the social savings generated by railways account for approximately 7.5 percent of Britain's income, and only 4 percent if passengers' comfort is not accounted for in the savings. Overall, Crafts (2004) estimates that 0.05 percent of per capita growth from 1830 to 1860 in Britain can be attributed to the rail. The magnitude of these estimates suggests a rather low impact of the rail on the British economy, at least in the first phase of its development. More recent studies investigated the impact of the rail within Britain during the second development phase. Gregory and Henneberg (2010), for example, argue that areas connected to the railway in Britain experienced an increase in population. Bogart et al. (2022) show that this effect is causal and triggered structural change in Britain. These results suggest that railways reorganized British territory and prompted the transition towards an industrial mode of production.

4 Empirical Strategy

4.1 Data

We construct our main dataset at the grid cell-sector-decade level. Our spatial unit of observation is the hexagonal grid cell with an average area of 214 square kilometers. Within each cell, observations record information for four big sectors (agriculture, manufacturing, trade, and services) across three different census years (1851, 1861, and 1881). We mainly use data on bankruptcies and employment at this level of granularity and complement these data with other control variables such as connection to the rail network and population count.

Bankruptcy Data. We collect information on personal bankruptcy cases from publications in the London Gazette. Starting in the 18$^{\text{th}}$ century, British bankruptcy law required publicizing insolvencies so potential creditors could make their claims official and be considered in debt-clearing. For this purpose, the London Gazette contained a separate section that announced new bankruptcy adjudications and informed debtors on ongoing cases. The London Gazette started out as the main public mouthpiece of the British government in 1665, was delivered on average two to three times per week, and is still being published today. The first bankruptcy notice was published in the issue of June 5$^{\text{th}}$, 1712. We accessed all digitized London Gazette issues from January 1850 until December 1890 via the official London Gazette homepage.[4] These bankruptcy announcements followed a fixed structure, which allowed us to collect and encode individual cases easily.

To gather the personal bankruptcy announcements, we web-scraped scans of the 5,063 London Gazette issues published from 1850–1890 from the London Gazette homepage. We have found 4,086 regular issues to include at least one bankruptcy statement each. Figure 2 illustrates two examples of how the bankruptcy cases were announced in the London Gazette. To convert these images to data, Optical Character Recognition (OCR) software was first used to convert the scans into a machine-readable text format, and then, the computational processing was started. We constructed text recognition algorithms to detect personal bankruptcy announcements based on specific keywords. We extracted the bankrupt's name, address, and occupation for each announcement. In a final computation step, we geolocated each address, usually at the city- or parish-level, and assigned the people's occupation to a sector by assigning History of Work Information (HISCO) codes according to people's occupation description. We describe the data collection process in more detail in Appendix B.

The coding of bankruptcies naturally misses some cases. A number of bankruptcy announcements did not state an occupation, or the OCR did not capture a readable occupation description. We were able to assign an occupation in around 92% of the cases we identified. Similarly, we cannot identify geolocations for all bankruptcies. Some only state the county, some name non-unique parishes, and for others the OCR did not return readable address information. We were able to assign coordinates at the town- or parish level in 91% of cases.

[4]For more information and to access the London Gazette issues, see https://www.thegazette.co.uk/.

Figure 2: Examples of Bankruptcy Announcements

WHEREAS a Petition for adjudication of Bankruptcy, bearing date the 7th day of August, 1858, hath been filed against John Harris Blakemore, of Wednesbury, in the county of Stafford, Brass and Iron Founder, and he being declared bankrupt, is hereby required to surrender himself to John Balguy, Esq., one of Her Majesty's Commissioners of the Birmingham District Court of Bankruptcy, at Birmingham, on the 27th day of August instant, and on the 16th day of September next, at half past eleven of the clock in the forenoon, on each of the said days, and make a full discovery and disclosure of his estate and effects; when and where the creditors are to come prepared to prove their debts, and at the first sitting to choose assignees, and at the last sitting the said bankrupt is required to finish his examination. All persons indebted to the said bankrupt, or that have any of his effects, are not to pay or deliver the same but to Mr. Frederick Whitmore, No. 19, Temple-street, Birmingham, the Official Assignee whom the Commissioner has appointed, and give notice to Mr. John Smith, Solicitor, Birmingham.

(a) Bankruptcy Announcement 1858

The Bankruptcy Act, 1869.
In the London Bankruptcy Court.

In the Matter of a Bankruptcy Petition against George Dighjohn, of No. 31, Walworth-road, in the county of Surrey, Hair Dresser, trading under the name, style, or description of George Alma Gage.

UPON the hearing of this Petition this day, and upon proof satisfactory to the Court of the debt of the Petitioners, and of the trading, and of the act of Bankruptcy alleged to have been committed by the said George Dighjohn having been given, it is ordered that the said George Dighjohn be, and he is hereby, adjudged bankrupt.—Given under the Seal of the Court this 18th day of October, 1877.

By the Court,
***James R. Brougham*, Registrar**

The First General Meeting of the creditors of the said George Dighjohn is hereby summoned *to* be held at the London Bankruptcy Court, Lincoln's-inn-fields, in the county of Middlesex, on the 6th day of November, 1877, at eleven o'clock in the forenoon, and that the Court has ordered the bankrupt to attend thereat for examination, and to produce thereat a statement of his affairs, as required by the statute.

(b) Bankruptcy Announcement 1870

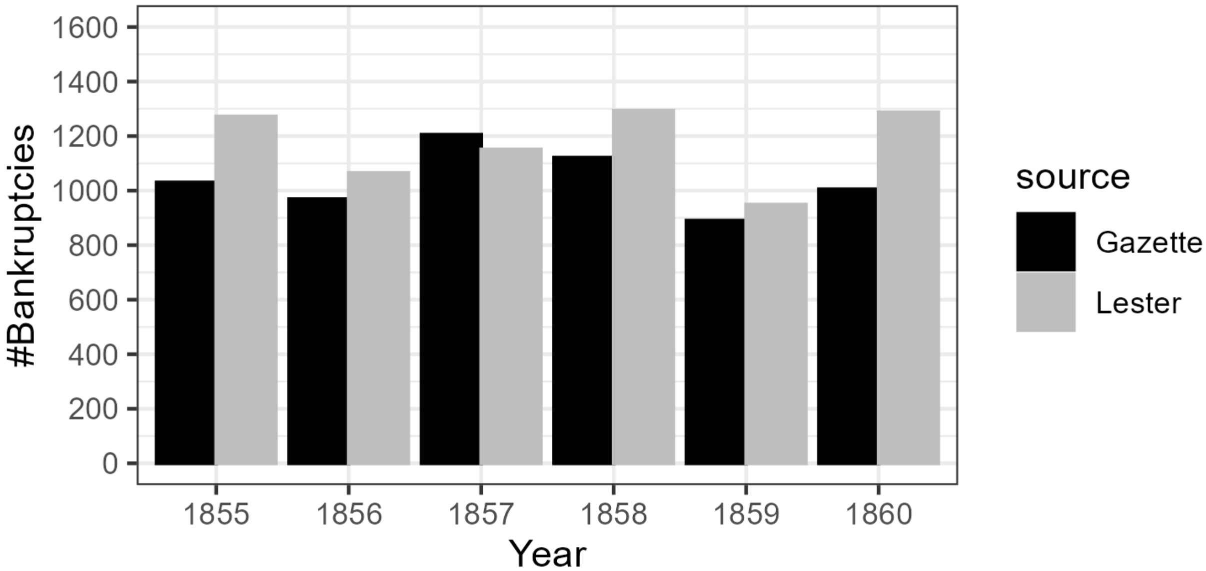
Notes: This figure illustrates the layout of the original London Gazette files based on which the bankruptcy data were collected. Figure (a) shows one from the beginning of our sample period in 1858, and Figure (b) displays a later entry from 1877. From these texts, our algorithm would collect the information on the bankruptcy's name, address, and occupation.

To investigate the comprehensiveness of our dataset, we compare our dataset to available country-level statistics of bankruptcies. Figure 3 compares the yearly number of bankruptcies in our dataset to officially published statistics at the national level as collected by Lester (1991). Our coding follows the general trend very closely. Moreover the estimated number of bankruptcies is very similar to the benchmark provided in Lester (1991). This makes us confident that sampling bias is unlikely to affect our estimations other than by increasing standard errors due to random measurement error.

As our main dependent variable, we add the sector-level annualized number of bankruptcies for each census period. For this, we aggregate all bankruptcy cases in a sector and grid cell between two census periods, divide it by the number of years between the two census periods to control for the longer time span between 1861 and 1881, and assign this number to sector-grid cell observations in the year that begins the respective decade. We aggregate occupation sectors to the highest, 1-digit occupation category, dividing occupations into four main occupation groups.[5] Some observations mention pensioners, rentiers, or unemployed as

[5]The original HISCO coding divides occupations into 10 main categories. For our purposes, we rearranged these ten groups slightly. First, we combine the groups "0" and "1", which refer to "Professional Workers," with the "Services" category. Next, we combine the groups "7", "8" and "9", which all refer to "Production and related workers", into one "Manufacturing" group. We leave the groups for "Agriculture" ("6"), "Services" ("5"),

Figure 3: Comparison to National Statistics



Notes: This figure displays yearly aggregates of the bankruptcy cases in our dataset (black), and compares them to official national statistics collected by Lester (1991) in grey.

occupations. We drop these observations from the analysis.

British Microcensus. We use British micro census data to observe sectoral employment together with a number of additional covariates. These data were made available as part of the Integrated Census Microdata (I-CeM) dataset (Schurer and Higgs, 2023). The I-CeM project digitized full, individual-level census data for England and Wales in 1851, 1861, 1881, 1891, 1901, and 1911. Importantly, all census entries contain information on people's occupations, for which the I-CeM project already coded the associated HISCO codes. Other control variables we add via the micro census data are, among others, local population, age structures, gender ratios, and internal migration stocks. We assigned coordinates to all census observations based on the sub-district stated in the survey and intersected the subdistrict coordinates with our grid cells.[6]

Additional Data. We complement our dataset with additional data sources that vary at the grid cell level, over time, or both. First, we use data on railway station locations in

and "Trade" ("4") as is. Finally, we distribute the groups "2" ("Administrative workers") and "3" ("Clerical workers") into our four main groups based on the occupation category the I-CeM dataset assigned to the individuals within these groups. For example, we assign people with an occupation description of "working and dealing with metals" to manufacturing, and "persons engaged in commercial occupations" to trade. In total, we rearranged 10 occupation categories this way. Note that all our regressions include sector fixed effects such that these coding decisions to not impact our estimates.

[6]As shown in Figure 4 below, we end up with some grid cells in rural regions that do not contain subdistrict coordinates. We, therefore, drop these grid cells from our estimations.

England and Wales in 1851, 1861, and 1881 from Martí-Henneberg et al. (2017a,b,c). We spatially intersect the railway shapefile with our grid cell dataset and assign each grid cell's number of stations in a given year. We further leverage data from Fernihough and O'Rourke (2020), which locates the British towns with access to coal. We calculate the distance of each grid cell's centroid to the closest town with coal access as a proxy for coal availability in a location. We also control for the distance to London, the coast, and UK ports from every grid cell's centroid.

4.2 Method

The main econometric specification leverages the three dimensions of information on bankruptcies. To estimate the specific effect of a railway connection on a sector, we use the variation within areas connected to the railway network, and in addition exploit the within sector-time variation in our bankruptcy data. We use the Pseudo-Poisson-Maximum-Likelihood (PPML) estimator to account for the overdispersed distribution of our dependent variable. Railway access varies over time, and we interact this indicator with sector fixed effects to estimate different effects across sectors. Our main specifications take the following form:

$$Bankruptcies_{i,s,t} = exp\left[\beta_{1,s}\mathbb{1}Rail_{i,t} \times Sector_s + \beta_2\mathbb{1}Rail_{i,t} + \Gamma X_{i,s,t} + \nu_{t,s} + \eta_i\right] + \epsilon_{i,s,t}. \quad (1)$$

Our dependent variable, denoted by $Bankruptcies_{i,s,t}$, is the number of bankruptcies in some grid cell i, sector s, and year t. $\mathbb{1}Rail_{i,t}$ is a dummy variable equal to one once a grid cell is connected to the rail network. With $\nu_{t,s}$ and η_i, we include location and sector-time fixed effects, respectively. The identifying variation is within geographic areas connected to the rail and within sector-time. As a consequence, no geographic characteristic (such as the proximity to resources), and no time-varying sector characteristic (such as technological or organizational change at the sectoral level over time) can explain our results. Note that sector-time characteristics also control for national-level shock (such as economic crises). To control for the specific evolution of manufacturing in some areas, the matrix $X_{i,s,t}$ adds several control variables, such as the level of employment in each sector-location-year, to account for a potential scale effect in our more conservative specifications. We also control for the distance to coal, the distance to London, and the distance to the nearest port, each interacted with a manufacturing fixed effect. Distance to coal is an important control variable as it proxies for a location's propensity to industrialize (Fernihough and O'Rourke, 2020). Holding the distance to London constant is necessary to account for differences in the availability of investment capital and production networks. Finally, by controlling for the distance to the closest port, we account for locational differences in the exposure to international trade and migration. By interacting each of these three variables with manufacturing fixed effects, we allow these confounders to have different impacts on bankruptcies or employment for the manufacturing sector. $\epsilon_{i,s,t}$ is the error term.

Note that our specifications derive $\beta_{1,s}$ from the interaction of two baseline variables that are collinear either to the fixed effects or to the $\mathbb{1}Rail_{i,t}$ variable. $\mathbb{1}Rail_{i,t}$ controls for a location's changed access to the railway over time, while sector characteristics are controlled for by the sector-time fixed effects $\nu_{s,t}$ and other local characteristics by η_i. The coefficient $\beta_{1,s}$ captures the *differential effect* the railway expansion has on a specific sector. Our baseline estimations estimate the effect on manufacturing relative to other sectors. In the second step, we estimate the elasticity of the number of bankruptcies for each sector. As the manufacturing sector reorganized following the expansion of railways, a connection to the railway is expected to have had a different effect on this sector than on others. Because we focus on the specific effect of the rail on one sector compared to others, our effect cannot be explained by factors varying over time and space – such as easier access to courts, non-sector specific development, or general migration patterns. Eventually, our estimator uses two types of variation. First, spatial variation from the initial connection to the rail in 1851 at the start of our sample, and second the rail's expansion between 1851 and 1881. The fixed effects are not collinear with the interaction $Rail_{i,t} \times Sector_s$ in 1851. Hence, the results have to be interpreted as the effect of having a connection with the rail network and not as the effect of a station opening in the second phase of the expansion of the railway network. Extensions further disentangle these two dimensions of our main estimator (Table 10). Section 4.2 shows that both the temporality of the effect and its spatiality suggest that the effect we observe is causal.

The coefficient $\beta_{1,s}$ picks up how the manufacturing sector developed differently in locations with access to the rail. Our estimations hold several dimensions constant. First, we hold geography-time specific effects of the rail constant. This includes, among other things, a location's increasing market integration as well as the general equilibrium effects from market integration everywhere else. Second, our estimations control for sector-time specific shocks, e.g., technological changes and innovation, that boost a sector's average productivity over all of England and Wales.

By controlling for the self-selection into rail access and for sector-time fixed effects, our paper departs from other research using geographic variation and within sector variation to study the redistributive nature of growth (Autor et al., 2013; Juhász et al., 2024). Our estimates, however, assess how market integration interacts with sector characteristics such as capacity for organizational changes, thereby generating reallocation.

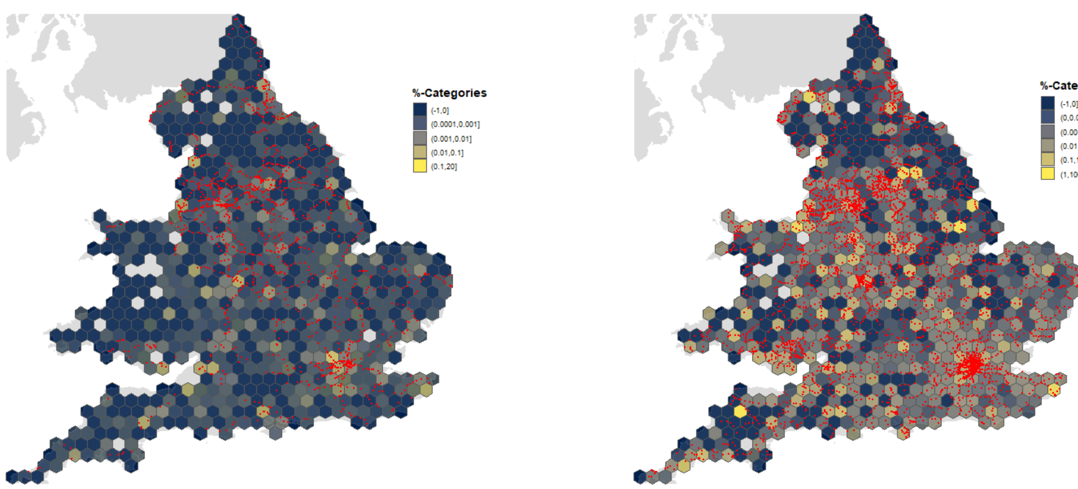
5 Results

5.1 Illustration

Figure 4 illustrates our empirical analysis. The two maps show England and Wales covered by hexagonal grid cells, our unit of observation. Colours indicate the share of bankruptcies with respect to the location's total employment, where we assign the shares to categories for ease of display. The red dots indicate the locations of railway stations.

Figure 4 a) plots the extent of the railway by 1851 together with the aggregate number of bankruptcies from 1851-1860 relative to 1851 employment.[7] Figure 4 b) again illustrates the geographical correlation between the railway expansion and the occurrence of bankruptcies but for bankruptcies in the 1881-1890 period and the railway network in 1881.

Figure 4: Bankruptcy Rates and Railway Expansion



(a) Bankruptcies 1851-1860, Rail Stations 1851.

(b) Bankruptcies 1881-1890, Rail Stations 1881.

Notes: The figures show the share of bankruptcies in total employment by location. Brighter colours indicate higher shares of bankruptcies. The red points indicate railway stations that were established at the beginning of the respective data sample. Light-grey locations are low-populated places and were omitted from the dataset because they do not contain a census sub-district, so we lack any census information for these cells.

[7] Note that the map contains a number of grey cells, especially in the rural regions of Wales or Cornwall. We dropped these grid cells from the dataset because our coding of census sub-districts did not yield any matches for the grid cells in these rural parts of Great Britain.

Both maps illustrate the intuition behind our analysis very well. In 1851, the British railway system was still in its infancy. Only 56% of cells had at least one railway station, and the overall density of railway stations was still low. Similarly, only a small number of bankruptcies occurred between 1851 and 1860. Many grid cells not even experienced one. Of those grid cells that experienced bankruptcies, almost all contain at least one railway station. In 1881, the railway network was much more advanced. More than 90% of cells had at least one railway station. And not only does the overall number of bankruptcy cases increase; we also see many grid cells lighting up now that did not exhibit any bankruptcy cases in the period before. Yet, bankruptcy cases still closely trace the spatial extent of the railway network.

5.2 Baseline Results

Table 2 presents our main results. Column 2.1 presents the coefficient from regressing the number of bankruptcies on the dummy variable capturing connection to the rail network. We do not yet include any controls or fixed effects, and do not distinguish the effect by sector. Our results mirror the image from Figure 4 and demonstrate that on average, being connected to the rail network is associated with a higher number of bankruptcies. According to this estimate, on average, grid cells connected to the rail network experience around 13 times as many bankruptcies as non-connected cells. Note that we interpret the PPML regression coefficients using the e-transformation $(e^{\beta} - 1) \cdot 100\%$. Here, the coefficient 2.62 hence corresponds to an effect size of $(e^{2.62} - 1) \cdot 100\% = 1273.5\%$ We further do not interpret this coefficient as causal as it could result from selection into the rail or other geographic characteristics of connected cells explaining bankruptcies.

In Column 2.2, we add an indicator variable for the manufacturing sector and an interaction term of both explanatory variables to differentiate the effect of the rail by sector. The interaction term suggests that the relationship between the railway expansion and the number of bankruptcies is most predominant in the manufacturing sector. The coefficient implies that a connection to the rail network would increase bankruptcies in the manufacturing sector by around 65 additional percent compared to other sectors.

Table 2: Main Results - The Effect of the Rail on Bankruptcies

		Dependent Variable: #$\text{Bankruptcies}_{i,t,s}$				
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	2.62***	2.46***	0.05	0.08	0.05	0.12
	(0.21)	(0.21)	(0.14)	(0.15)	(0.14)	(0.14)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s		0.50***	0.50***	0.48***	0.56***	0.34***
		(0.07)	(0.07)	(0.06)	(0.07)	(0.08)
Observations	8341	8341	7481	7481	7481	7481
Pseu. R^2	.0765	.092	.8	.801	.801	.813
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector $\text{Employment}_{i,s,t}$				✓	✓	✓
Coal_i $\times$ Manufacturing_s					✓	✓
Port_i $\times$ Manufacturing_s					✓	✓
London_i $\times$ Manufacturing_s					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Across the following columns, we progressively add fixed effects for sector, year, location, and our different control variables. From Column 2.3 to 2.5, the interaction between the rail dummy variable and the manufacturing sector variable remains significant and positive. In contrast, the coefficient for the rail variable turns insignificant once we account for location fixed effects. Accordingly, the average effect of the railway on bankruptcies is zero once we account for location-specific characteristics. Fixed effects and control variables do not change our estimate for the effect of rail access on bankruptcies *in the manufacturing sector*. For this sector, our estimates suggest an increase in bankruptcy incidence by 64 to 75 percent. Neither controlling for employment at the sector-geo-time level nor adding high-dimensional fixed effects changes the estimate significantly. This suggests that the effect we observe goes well beyond a sector size effect and is not solely driven by between-sector reallocation. Similarly, the effect is not explained by the specificities of the manufacturing sector in areas close to coal, ports, or London, which were probably more likely to be connected to the rail.

In Column 2.6, we add sector-time fixed effects to control for time-varying sector characteristics that might explain bankruptcies. Among these time-varying characteristics are the average levels of technological and organizational change at the sector level as emphasized in Juhász et al. (2024). After controlling for sector-level characteristics, our estimates suggest that the rail has increased bankruptcies by 40 percent in the manufacturing sector.

Table 3: Main Results - The Effect of the Rail on Employment

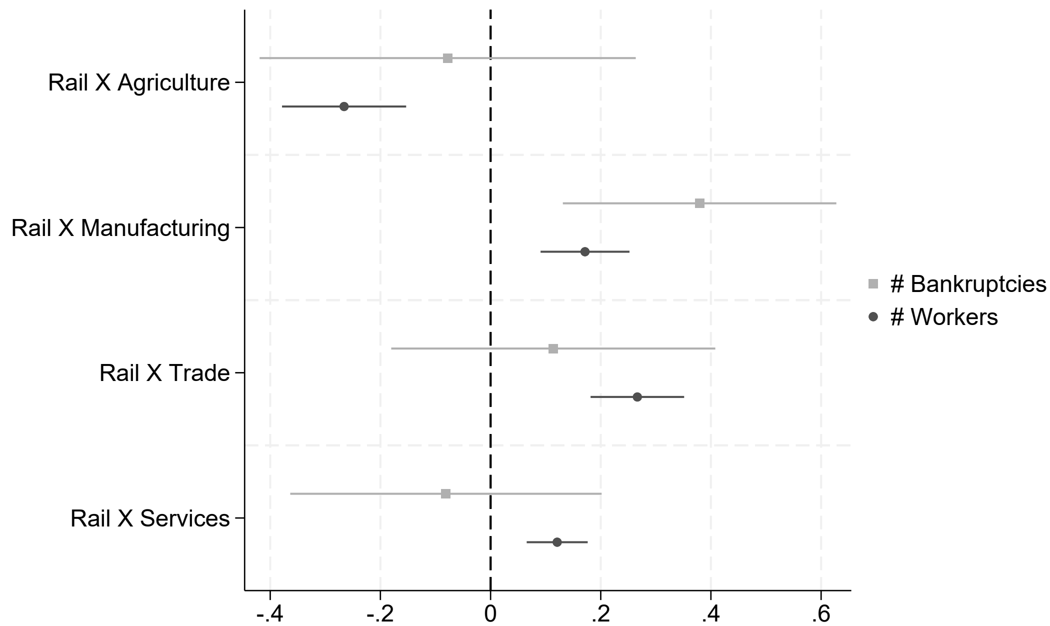
	(1)	Dependent Variable: $\#\text{Employed}_{i,t,s}$ (2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	1.18***	0.91***	-0.42***	-0.27***	-0.11***	-0.11***
	(0.11)	(0.10)	(0.06)	(0.04)	(0.03)	(0.03)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s		0.60***	0.60***	0.60***	0.28***	0.28***
		(0.08)	(0.08)	(0.08)	(0.06)	(0.07)
Observations	8704	8704	8704	8704	8704	8704
Pseu. R^2	.0744	.215	.873	.906	.925	.929
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
$\text{Population}_{i,t}$				✓	✓	✓
Coal_i $\times$ Manufacturing_s					✓	✓
Port_i $\times$ Manufacturing_s					✓	✓
London_i $\times$ Manufacturing_s					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the number of people employed in sector s at census year t and in grid cell i. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the cell's total population and the straight-line distance to the nearest city with coal deposits, to the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$

The increased bankruptcies observed in the manufacturing sector can have two origins. Either they result from a decline in sector activity, or they are the product of labour reallocation because of market integration. To test which of these hypotheses prevail, Table 3 estimates the baseline regression using sectoral employment as the dependent variable. In Column 3.1, we observe that on average, places connected to the rail network have higher employment. Column 3.2 suggests that this effect is larger for the manufacturing sector. Once we add the different fixed effects and the control variables, the coefficient attached to the rail variable turns negative (Columns 3.3 to 3.6). The coefficient for the interaction of the manufacturing sector dummy variable with the rail dummy variable is significantly positive across all columns. The manufacturing sector in cells connected to the rail has almost 20% more employment than in not connected cells.[8] If anything, a connection to the rail network does not seem to trigger a decline in the manufacturing sector but increases its dynamism. As in Bogart et al. (2022), we find that the expansion of the rail triggered a reallocation towards the manufacturing sector and no movement out of it.

[8] We derive this number from the joint effect of the baseline railway effect plus the manufacturing-specific railway effect: $(e^{(-0.11+0.28)} - 1) \cdot 100\% = 18.5\%$

Figure 5: Coefficient plot – The Railway's Effect on Bankruptcies and Employment



Notes: The figure reports the coefficients for the railway expansion by sector. The coefficients result from estimating specifications following Equation 1. Dependent variables are the number of workers (in black) and the number of bankruptcies (in grey) All regressions control for the control variables and fixed effects outlined in equation 1. Confidence intervals are at the 95% level. Standard errors are clustered at the grid cell level. The results of the estimations are available in Appendices B.2 and B.3.

According to our results, the manufacturing sector experienced both an increase in bankruptcies and an increase in the number of employees due to the development of the railway network. Tables C.9 and C.10 show similar results when using the share of employees in a sector and the share of bankrupts in this sector.

The effects documented in Table 2 and 3 are relative to other sectors. To better grasp the between and within sector reallocation, Figure 5 shows the coefficients from interaction terms with the Rail dummy variable and an indicator variable for each sector. This figure summarizes which sectors underwent between-sector or within-sector reallocation. Looking at the estimates in dark grey, we can see that a rail connection decreased the number of workers in the agricultural sector while increasing the number of workers in all other sectors. A connection to the rail also increased employment in manufacturing, trade, and services. Structural change from the primary to secondary sector explains the increase in manufacturing employment, whereas at the same time, employment in services also increased to sustain larger production units (Katz and Margo, 2014). The light grey estimates show a rail connection's effect on bankruptcies for the different sectors. As in Table 2, the Rail $\times$ Manufacturing coefficient is significantly positive. Estimates for other sectors are not different from zero.

The rail hence increased the number of bankruptcies only in the manufacturing sector, while at the same time also increasing manufacturing employment. The manufacturing sector is the only sector that exhibits the dynamics we would expect under within-sector reallocation as outlined in Table 1.

5.3 Robustness

Table 4 presents our main robustness tests. Further tests are presented in Appendix C. The results are robust when we cluster standard errors at the cell-sector level (Column 4.1) or at the three levels of variation (Column 4.2). Our results also do not hinge on rail nodes. They remain significant and of similar magnitude when we exclude railway nodes[9] – places which were at the center of the network – from the sample (Column 4.3). The definition of the size of the grid we use for the estimation also does not drive our results. The results are similar if we multiply the grid cells' area by two or if we divide their area by two (Columns 4.4 and 4.5).

Beyond these first tests, we provide more details on the different robustness checks we have performed in Appendix C. Our results are identical if we use an OLS estimation throughout the different specifications of Table 2 (Appendix C.1). The results are exactly the same if we control for different measures of local economic shocks, such as the number of unemployed in a grid cell, the percentage of the population born in another county, or the percentage of the male population (Appendix C.2). The estimates also remain of the same magnitude when we exclude the 5% most populated cells, the 5% least populated cells, and both of them together (Appendix C.3). Results are further unchanged when we drop the years of significant reforms to the bankruptcy law. We both drop the period 1869-1883 – years of simplified and creditors-led bankruptcies procedures, and the pre-1861 period – when bankruptcies were reserved to citizens declaring a trading activity (Appendix C.4). In Appendix C.5, we also ensure that our results do not hinge on spatial clusters by clustering estimates at the county level or by adding spatial lags. The Appendix Tables C.6 and C.7 further introduce Conley standard errors with a 300km spatial cut-off to our main estimations. All results remain identical. Finally, our results also remain unchanged when we weight observations by the inverse of a cell's population (Appendix C.8).

[9]Following (Bogart et al., 2022), we define nodes as the 99 British towns that had an urban population of at least 5,000 inhabitants in 1801.

Table 4: Main Robustness Tests

Dependent Variable:	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$				
	(1)	(2)	(3)	(4)	(5)
	2 w cluster	3w Cluster	No Nodes	Big Cells	Small Cells
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	0.12	0.12	-0.01	0.22	0.15
	(0.13)	(0.12)	(0.18)	(0.14)	(0.13)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s	0.34^{***}	0.34^{**}	0.41^{***}	0.26^{**}	0.15^{*}
	(0.04)	(0.14)	(0.08)	(0.11)	(0.08)
Observations	7481	7481	6981	4235	11616
Pseu. R^2	.813	.813	.746	.821	.807
Geo FE	✓	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓	✓
$\text{Employment}_{i,t}$	✓	✓	✓	✓	✓
Coal_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓
Port_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓
London_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with in indicator variable for the manufacturing sector. The main control variables are the sector employment in a grid cell and the straight-line distance to the nearest city with coal deposits, the nearest port, and the city of London. Columns (3)–(5) alter the sample for our analysis. In Column (3), we drop all grid cells atop the population distribution in 1850, constituting important railway nodes. In Columns (4) and (5), we double (half) the average area of the grid cells on which we base our sample. Column (1) uses two-way clustered standard errors, at the grid cell and at the sector level. Column (2) uses three-way clustered Standard Errors, in all other columns Standard Errors (in parentheses) are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

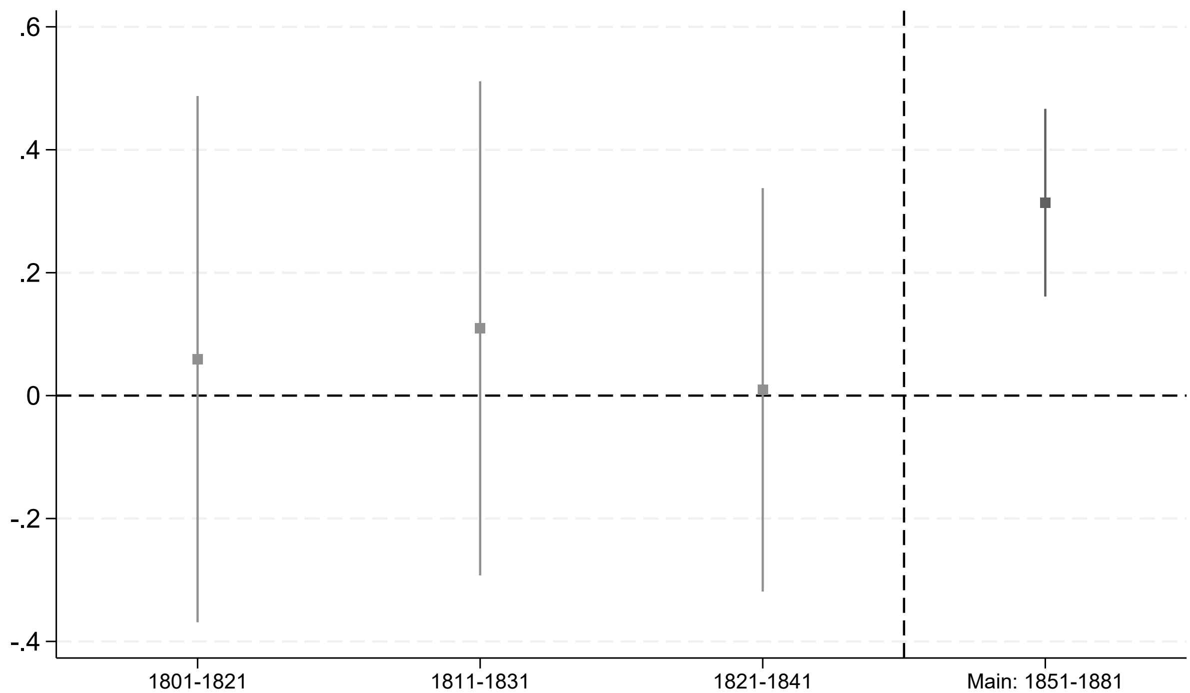
6 Identification

Our estimators add several fixed effects and control variables that could correlate with the connection to the rail network and the number of bankruptcies in the manufacturing sector. The identifying variation excludes geographic features, variation over time, and sector characteristics varying over time. Despite this restrictive set of fixed effects and control variables, one may argue that the interaction of the rail connection variable with the manufacturing sector variable may reflect other dynamics that vary over time and space and affect the manufacturing sector specifically. To circumvent this potential pitfall, we show that the timing of the effect and its spatiality strongly suggest that our estimates can be considered causal.

6.1 Time Dimension – Pre-treatment Placebos

Our panel estimations follow the logic of triple Difference-in-Differences estimations, as we exploit variation across place, time, and sector. We are interested in the coefficients of the interaction between railway expansion and an indicator variable for the manufacturing sector. Our identifying assumption is that the potential outcomes of employment and bankruptcies in the manufacturing sector would have been the same across locations with and without rail access if the railway had not been built. This assumption is close to a parallel trends assumption in a difference-in-differences framework.

Figure 6: Testing Parallel Pre-Trends – Coefficients Rail$_i$ $\times$ $Manufacturing_s$ on Pre-Sample



Notes: The Figure shows the results of placebo estimations from the period before the railway network was constructed. We have created a placebo "Rail" variable that equals the rail expansion from 1851–1881, but assign it to the three earlier periods 1801-1811-1821, 1811-1821-1831, and 1821-1831-1841. We then regress bankruptcies that occurred in these earlier periods on the placebo rail expansion variables using Equation 1.

We test the plausibility of this assumption by looking at bankruptcy trends before the railway was actually built. Leveraging our bankruptcy data that go back until 1788, we estimate placebo regressions that follow our main specifications, use the railway expansion from 1851-1881, but use bankruptcies in the periods 1801-1821, 1811-1831 and 1821-1841 as the dependent variables. Figure 6 presents the coefficient estimates by period for the

$(Rail_{i,t} \times Manufacturing_s)$ interaction in a coefficient plot. None of the coefficients of our placebo pre-treatment estimations is significant. Their standard errors are large and the point estimates are always near zero. Moreover, the coefficients do not exhibit any specific upward or downward trend. Hence, the increase in bankruptcies in the manufacturing sector among places connected to the rail from 1851 onwards was not yet present in the 50 years before the rail was actually constructed.

These placebo estimates show that the manufacturing sector in places connected to the rail from 1851 onwards did not experience more bankruptcies before 1851. Accordingly, the location of the rail from 1851 to 1881 does not pick up any long-term geographic patterns that would be specific to the manufacturing sector. This is particularly reassuring as previous transport networks might correlate with the later presence of the rail. However, should this potential correlation explain bankruptcies, the coefficients on past periods when these other transport networks developed would be significant. This is not the case. Since we have added location fixed effects in our estimations, they also do not capture long-term geographic characteristics that apply to all sectors.

6.2 Space Dimension – Exogenous Rail Access

Our second test leverages an exogenous variation of the connection to the rail. In the main specification, location fixed effects directly control for locations' different exposure to the railway construction. Potentially, the rail could have developed faster in areas where the manufacturing sector was specific. To ensure that this potential selection into the rail does not explain our results, we use a Least Cost Path (LCP) approach similar to Bogart et al. (2022) to model an exogenous variation in access to the rail network.[10] If a location lies along the LCP between two nodes, the railway lines must go through this location. We then construct a 30 kilometers buffer around the LCP. As shown in Appendix D.1, this threshold marks a discontinuity in the probability that grid cells receive a railway access. We however show that proximity to the LCP only predicts the existence of at least one station, but not the number of stations in a cell. This suggests that the LCP does not capture factors that correlate with a denser railway network, such as economic activity or natural resources (Appendix D.1).

Table 5 presents the results of regressions using the LCP. The upper panel presents

[10]Following Bogart et al. (2022), we select the 99 biggest towns in 1850 as natural railway nodes, i.e., as towns that almost certainly would have been among the first to receive a railway station. We then construct LCPs between each of these nodes. These LCPs measure the easiest way to build railway lines between two locations, considering the bilateral distance and the variation in construction costs due to elevation and rivers.

reduced form estimates. Columns 5.1 to 5.3 use different buffers to define the instrument. Being close to the Least Cost Path increases bankruptcies in the manufacturing sector by around 20 percent. Columns 5.4 to 5.6 add spatial spillovers (numbers of bankruptcies in the same sector in neighboring cells or employment in the same sector in neighboring cells) to control for potential spatial correlations that would affect our instrument. Using these estimates, proximity to the Least Cost Path still increases bankruptcies in the manufacturing sector by 26 percent. In the meantime, the bottom panel shows the validity of our approach. Proximity to the LCP indeed increases the probability of connection to the rail by 12 percentage points.

Table 5: Exogenous Variation in Rail – LCP Proximity

Instrument	LCP<30km	LCP<25km	LCP<35km	LCP<30km	LCP<30km	LCP<30km
	(1)	(2)	(3)	(4)	(5)	(6)
	Reduced Form / Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$					
$\mathbb{1}$ $\text{Instrument}_i \times \text{Manufacturing}_s$	0.18**	0.20**	0.18**	0.15*	0.26**	0.23**
	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.12)
Spillovers Bankruptcies $_{s,i,t}$				0.11*		0.06
				(0.07)		(0.06)
Spillovers Employment $_{s,i,t}$					0.27**	0.24*
					(0.12)	(0.12)
Observations	7481	7481	7481	7481	7481	7481
Pseu. R^2	.813	.813	.813	.813	.814	.814
	First stage / Dependent Variable: $\mathbb{1}$ Rail $_{i,t}$					
$\mathbb{1}$ Instrument_i	0.12***	0.12***	0.07**	0.12***	0.11***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Spillovers Bankruptcies $_{s,i,t}$				0.01		0.00
				(0.01)		(0.01)
Spillovers Employment $_{s,i,t}$					0.02**	0.02***
					(0.01)	(0.01)
Observations	7481	7481	7481	7481	7481	7481
Adj. R^2	.207	.207	.199	.207	.208	.208
Geo FE	✓	✓	✓	✓	✓	✓
Year × Sector FE	✓	✓	✓	✓	✓	✓
Sector $\text{Employment}_{i,s,t}$	✓	✓	✓	✓	✓	✓
$\text{Controls}_i \times \text{Manufacturing}_s$	✓	✓	✓	✓	✓	✓

Notes: Table reports results from PPML reduced form regressions (upper panel) and OLS first stage regressions (lower panel) at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods (upper panel) and an indicator for railway access (lower panel). The main explanatory variable is an indicator for a grid cell i being located within a buffer around the Least Cost Path instrument, interacted with an indicator variable for the manufacturing sector. Spillovers indicate the number of bankruptcies and employment, respectively, in the same sector and year of neighboring grid cells. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

The Least Cost Path may, however, also correlate with previous transport networks such as Turnpike roads or waterways. To ensure that the geography of the rail does not pick up a potential effect of these other networks on bankruptcies, Table 6 directly controls for the length of turnpike roads and of waterways interacted with the manufacturing sector both in our main specification and in the specification using proximity to the LCP as an exogenous variation in railway access. The coefficients attached to the rail dummy variable interacted with the manufacturing sector dummy variable are always significant at the one percent-level. The coefficients imply that even after controlling for the geography of other transport networks, a connection to the rail increased bankruptcies in the manufacturing sector by 30 percent (Column 6.3). Meanwhile, the coefficients attached to our instrument also remain similar when controlling for the different pre-rail transportation networks. After controlling for the geography of turnpike roads and of waterways, proximity to the least cost path still increased bankruptcies by 18 percent.

Table 6: Previous Transport Networks – Main Estimates and LCP-Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$					
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s	0.32***	0.27***	0.26***			
	(0.09)	(0.07)	(0.08)			
$\mathbb{1}$ Instrument_i $\times$ Manufacturing_s				0.17**	0.17**	0.16**
				(0.08)	(0.07)	(0.07)
Turnpike_i $\times$ Manufacturing_s	0.07		0.03	0.05		0.01
	(0.06)		(0.06)	(0.06)		(0.05)
Waterways_i $\times$ Manufacturing_s		0.04**	0.04**		0.04***	0.04**
		(0.02)	(0.02)		(0.02)	(0.02)
Observations	7481	7481	7481	7481	7481	7481
Pseu. R^2	.813	.813	.813	.813	.813	.813
Geo FE	✓	✓	✓	✓	✓	✓
Year $\times$ Sector FE	✓	✓	✓	✓	✓	✓
Sector $\text{Employment}_{i,s,t}$	✓	✓	✓	✓	✓	✓
Controls_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. Similarly, we add indicators for grid cells containing a turnpike as well as a navigable river or canal. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

As a second set of tests to ensure that our results can be interpreted as causal, we control in Table D.2 in the Appendix for a counterfactual rail network developed by Casson (2009). This counterfactual rail network is based on the (cost)-efficiency of the rail. It then captures the part of the rail network built for economic (and hence endogenous) reasons. Even after controlling for this counterfactual network, our estimates remain significant at the usual level. Furthermore, in Appendix D.3, we directly control for the selection into connecting to the rail network. Our strategy is similar in spirit to Costas-Fernández et al.

(2020): we consider the geographic selection of rail stations in two different ways. The first variable $\mathbb{1}$ (Ever $\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s codes as one cells that received a rail station at any point in time. Meanwhile, $\mathbb{1}$ (Not Yet $\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s is coded one if a cell will have a station in the next ten years but does not yet have one. Even after controlling for the geographic selection of stations, our estimates remain of the same magnitude as the baseline results, suggesting that our effect is driven by the opening of stations and not by the extension of the rail network towards specific geographic areas prone to bankruptcies. After controlling for geographic selection, rail connection still increases bankruptcies in the manufacturing sector by 27 to 36 percent.[11]

Taking stock, our baseline results appear at the actual date of rail development and not earlier. Moreover, when we replace our main spatial variation with a variable based on an inconsequential places approach, we still find that locations that got a connection to the rail because they were along the way between two important places did also observe a surge in bankruptcies in the manufacturing sector following the arrival of the rail.

7 Mechanisms: Organizational Change, Competition and Market Structures

This section documents the mechanisms driving the specific effect of a connection to the rail on bankruptcies in the manufacturing sector. It provides three sets of results refining our baseline approach. First, subsection 7.1 documents the organizational changes in manufacturing brought by a rail connection. Second, subsection 7.2 uses variation in exposure to competition and leverages the timing of the connection to inform on the market dynamics that generate bankruptcies. Third, we investigate whether the effect of the rail on bankruptcies in the manufacturing sector was different when the incentives to file for bankruptcy have changed (Lester, 1991).

7.1 Organizational Changes at the Firm Level

The expansion of railways prompted the reorganization of firms specifically in the manufacturing sector (Atack et al., 2008; Tang, 2014). In other words, within the manufacturing sector, a connection to the rail spurred organizational changes. Manufacturing had the technological and organizational potential to exploit the gains offered by market integration.

[11] According to the transformation $(e^{0.31} - 1) \cdot 100\% = 36\%$ for the coefficient in Column 4.

Table 7 provides measures of this phenomenon focusing on firms' level of employment from the I-CeM project (Schurer and Higgs, 2023). These measures capture the extent to which small and (very) large firms may coexist at the national level in a sector illustrating the ongoing transformation within this sector as in Cabral and Mata (2003). This heterogeneity indirectly captures the extent of the organizational change that a sector experiences. Some firms did undergo reorganization and were already large. Still, some were small, a sign that the transition to the factory was not yet achieved.[12]

Table 7: Heterogeneity in Firms' Size by Sector – 1851

Measure	Manufacturing	Agriculture	Trade	Services
S.d	149.3	10.5	38.6	27.8
5^{th} largest/Median	334.3	115.7	150.0	35
Gini	0.77	0.55	0.66	0.70
GE(1)	2.05	0.64	1.32	1.32

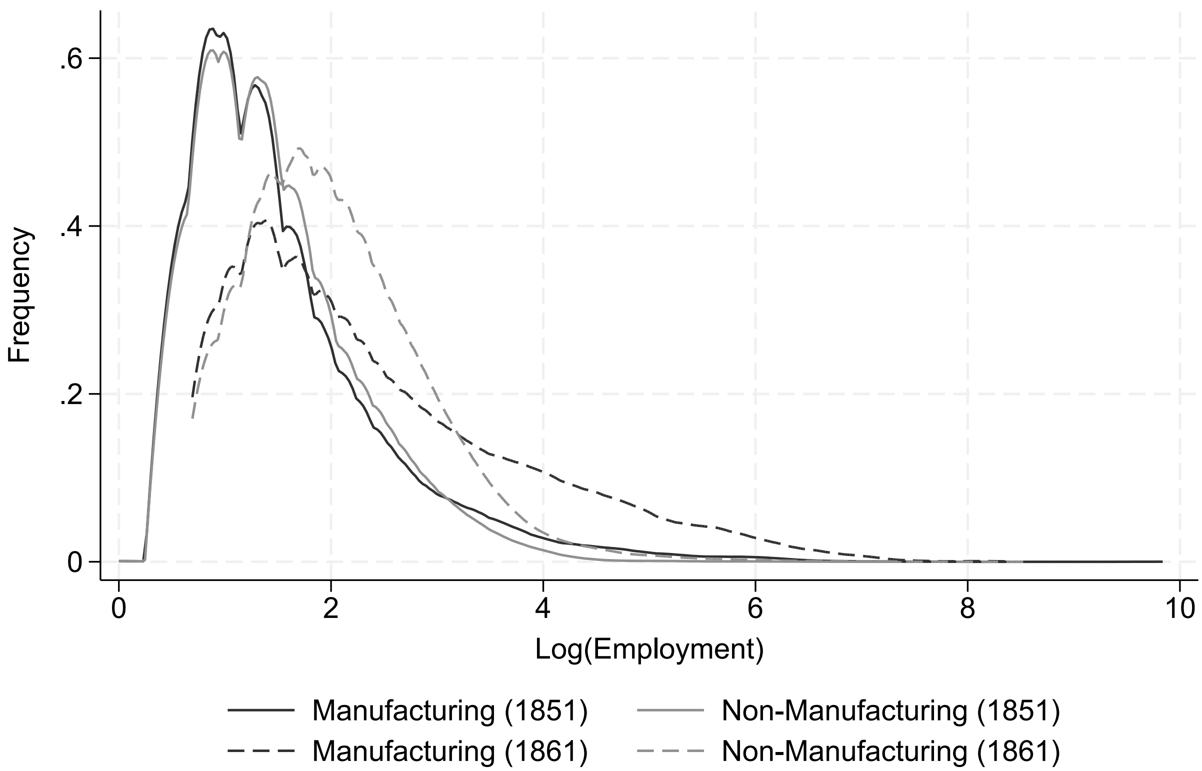
Notes: This table displays different measures of heterogeneity based on data on firm owners from the British 1851 census. All heterogeneity measures were calculated based on firms' number of employees, separately for the four main sectors manufacturing, agriculture, trade, and services. The heterogeneity measures are 1) the standard deviation across employee numbers, 2) the share of employees in the 5th largest to the median firm, 3) the Gini coefficient and 4) the general entropy score across employee numbers.

The heterogeneity of firms within the manufacturing sector can be observed in 1851, the start of our sample. In the manufacturing sector, the standard deviation in the number of employees was 4 to 10 times bigger than in other sectors. The fifth-largest firm was 334 times larger than the median firm in the manufacturing sector. In other sectors, it was only 35 to 115 times larger. The manufacturing sector also has the highest Gini coefficient and the highest general entropy score for the number of employees. Overall, hence, the manufacturing sector was more heterogeneous than other sectors.

To see how the distribution of firms evolved over time, Figure 7 plots the firm size distribution for 1851 and 1861, the two censuses that included open items where firm owners could state their occupation. In 1851, the plain lines show that the density function of the manufacturing sector is quite similar to the density function of other sectors. As expected, the distribution's right tail is slightly thicker for the manufacturing sector, reflecting the existence of some larger firms in this sector.

[12]For the years 1851 and 1861, these census tables include occupation descriptions for tens of thousands of firm owners. We combine text recognition algorithms with an updated occupation dictionary (see below) to assign one of over 1,500 occupation titles in our dictionary to each occupation description. Then, we assign the occupation titles to the manufacturing, trade, services, or agricultural sector based on the "History of Work (HISCO)" classification. See https://historyofwork.iisg.amsterdam/index.php for more information. We were able to assign over 98% of firms in the business census to one of the four sectors that way.

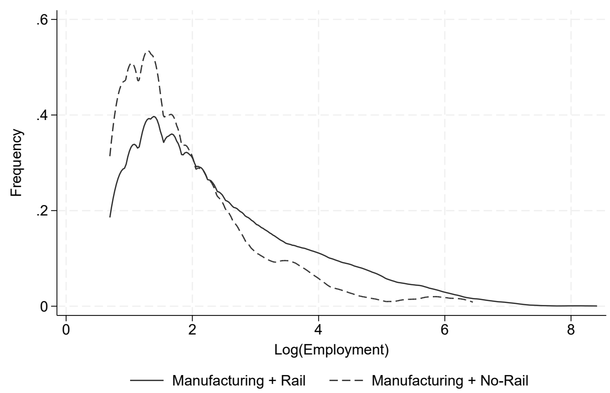
Figure 7: Firms' Size by Sector in 1851 and 1861



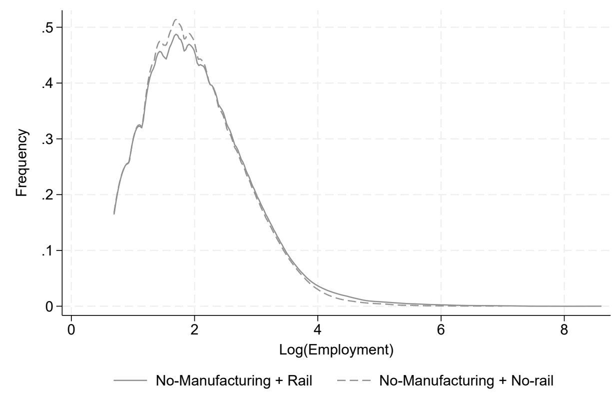
Notes: This figure displays Kernel density functions for the number of employees based on data on business owners from the British 1851 and 1861 censuses. Bold lines display the densities from the 1851 census, dashed lines from the 1861 census. Dark grey lines display density functions for the manufacturing sector and light grey lines for all other sectors.

The distributions diverge in 1861 as shown by the dashed lines. Both distributions shift to the right. However, they do not look alike anymore. The right tail of the manufacturing sector is now different from the right tail of the other sectors. The kernel density of manufacturing firms became flatter and the number of smaller- to medium-sized firms decreased. Figure 8 further investigates the reason for this shift by distinguishing the distributions of firms by sector in 1861 concerning their access to the rail network in 1851. The distribution of non-manufacturing firms (right panel) is exactly the same whether the firms are connected to the rail or not. In contrast, the distribution of firms in the manufacturing sector depends on whether or not they were connected to the rail in 1851 (left panel). Compared to the non-manufacturing sectors, the manufacturing firms connected to the rail (black plain line) have a density function that differs greatly from the others. The right tail is thicker, meaning that the rail promoted the growth of many exceptionally large firms.

Figure 8: Firms Size in 1861 and Rail presence



(a) Firms' Size by Rail connections – Manufacturing



(b) Firms' Size by Rail connections – Non-Manufacturing

Notes: These figures display Kernel density functions for the number of employees based on data on business owners from the British 1861 census. The left panel shows the density in the manufacturing sector, the right panel shows the density for the remaining sectors. Bold lines display the density functions across locations with railway access, while dashed lines show density functions for locations without railway access in 1861.

We further test the effect of the rail on firms' organizations after 1861 in other dimensions. Table 8 presents estimates of the specific effect of the rail in the manufacturing sector on several proxies for firm organization. We assess these organizational changes along three dimensions: self-employment (Panel A), occupation diversity (Panel B), and presence of unskilled labour (Panel C).

According to the mechanism emphasized in Melitz (2003), market integration increases the exit rate of the smallest firms as they cannot afford to reorganize to enter the trading sector. In Panel A, the coefficient attached to the interaction of the manufacturing and rail variables is negative and significant at the one or five-percent level. A connection to the rail changed the employment composition: it decreased self-employment by 6 percent. This coefficient effect could be explained either by the "exit" of small firms or by a concentration of the workforce in larger firms having monopsony power on wages. Both mechanisms may explain additional bankruptcies. We hypothesize that these organizational changes toward larger firms brought new tasks and, hence, new occupations. Larger firms became more complex in terms of occupational composition. We test whether a rail connection increased the complexity of firms in the manufacturing sector. In Panel B, the dependent variable is a Herfindahl index based on the number of workers working in different occupations within each occupation category. As new occupations appear, the Herfindahl index decreases as the "market concentration" on specific occupations decreases. The most conservative estimate (Column 5) implies that a connection to the rail decreased the "concentration" of manufacturing towards some occupations by 10 percent. Within in a given year, manufacturing occupations hence became more diversified in places connected to the rail.

Table 8: Organizational Change – Measuring Organizational Changes with the Arrival of the Rail

	(1)	(2)	(3)	(4)	(5)
	Panel A) Dependent Variable: SelfEmployed$_{i,t,s}$				
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	-0.03**	0.03**	0.03**	0.03**	0.03*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	-0.12***	-0.12***	-0.12***	-0.13***	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	8341	8341	8341	8341	8341
Pseu. R^2	.00988	.117	.12	.121	.123
	Panel B) Dependent Variable: Herfindahl Occup$_{i,t,s}$				
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	-0.03*	0.01	0.01	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	-0.23***	-0.16***	-0.17***	-0.06*	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	6011	6008	6008	6008	6008
Pseu. R^2	.0974	.655	.673	.686	.698
	Panel C) Dependent Variable: ChildLabour$_{i,t,s}$				
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	-0.42***	-0.03	-0.03	-0.02	-0.03
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	0.30***	0.30***	0.27***	0.15***	0.25***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Observations	8341	8337	8337	8337	8337
Pseu. R^2	.0223	.0734	.0735	.0738	.0745
Geo FE		✓	✓	✓	✓
Sector FE		✓	✓	✓	
Year FE		✓	✓	✓	
Sector × Year FE					✓
Sector Employment$_{i,s,t}$			✓	✓	✓
Coal$_i$ × Manufacturing$_s$				✓	✓
Port$_i$ × Manufacturing$_s$				✓	✓
London$_i$ × Manufacturing$_s$				✓	✓

Notes: This table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variables are the number of self-employed individuals (Panel A), the Herfindahl index of the distribution of workers across occupation categories (Panel B), and the share of workers that are children under the age of 12 (Panel C). The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with an indicator for the manufacturing sector s. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

To indirectly capture which occupations suffered from the reorganization of the manufacturing sector, Table 8 investigates the effect of a rail connection on child labour. The share of child labour proxies a reorganization towards less skill-intensive tasks (Humphries, 2013). The coefficients attached to the rail variable interacted with manufacturing are always positive and significant at least at the five percent level. Accordingly, a connection to the rail increased child labour by 28 percent. These results, taken together, clarify the organizational changes brought by the rail in the manufacturing sector. These changes impacted market structures and the labour market. When connected to the rail, firms in the manufacturing sector got larger and more complex than others. The rail sped up the organizational changes occurring in the manufacturing sector. These transformations shaped the demand for labour and impacted individuals.

7.2 Organizational Changes at the Market Level

Our baseline estimations identify the potential for organizational changes via the sector of activity: manufacturing. Despite the imperfection of firm-level data during this period, we can capture within-sector heterogeneity directly. We build several measures of exposure to large firms within a sector. Based on the British business census for 1851, we identify large firms as those that belong to the top decile in terms of employment. Our first variable identifies the employment in these large firms located in each cell and sector. Next, we construct different "market access" measures by counting the large-firm employment for each sector in grid cells connected to the railway within 100km, over 100km but within 250km, over 250km but within 500km, and over 500km away. Table 9 then estimates the effect of a connection to the rail depending on the exposure to large firms in the same sector that are either located in the same cell or located farther away but connected to the railway network. We should note that the coefficients are to be interpreted as the effect of large firms within each buffer compared to large firms outside these buffers but also in the same sector.

Column 9.1 tests the argument using the employment of the largest firms in the same cell. The interaction with the rail variable bears a negative sign and implies that when cells where many workers are already employed in large firms get connected to the rail, bankruptcies were less likely to occur. In those markets, large firms might have benefited from the connection to the rail and, hence, did not suffer as much from competition. At the same time, local competition might already have driven small productive units to bankruptcy. Once the cells with large firms are connected to the rail, no small firms in their sector would potentially suffer from a connection to the rail.

Table 9: Rail, Existing Market Structure and Bankruptcies

	Dependent Variable: #Bankruptcies$_{i,t,s}$				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Employees in Large Firms $_{i,t,s}$	-0.31***				
	(0.02)				
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Large (Dist<100km) $_{i,t,s}$		0.02			
		(0.03)			
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Large (100<Dist< 250km) $_{i,t,s}$			0.07***		
			(0.02)		
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Large (250<Dist< 500km) $_{i,t,s}$				0.08***	
				(0.02)	
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Large (Dist>500km) $_{i,t,s}$					-0.05**
					(0.03)
Observations	7481	7481	7481	7481	7481
Pseu. R^2	.816	.816	.816	.816	.816
Geo FE	✓	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓	✓
Sector Employment$_{i,s,t}$	✓	✓	✓	✓	✓
Coal$_i$ × Manufacturing$_s$	✓	✓	✓	✓	✓
Port$_i$ × Manufacturing$_s$	✓	✓	✓	✓	✓
London$_i$ × Manufacturing$_s$	✓	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with the log-transformed number of employees in large firms in that sector located in different distance categories and connected to the rail. The main control variables are the number of people employed in sector s and the straight-line distance to the nearest city with coal deposits, the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

Columns 9.2 to 9.5 test the effect of a connection to the rail interacted with the employment in large firms at different distance buffers. According to Column 9.2, large firms within a 100km radius do not impact the number of bankruptcies in their sector when connected to the rail. Large firms within a 100km radius logically were already quite accessible using other modes of transportation. Yet, large-firm employment in cells between 100km and 500km from a treated cell is associated with a significant increase in bankruptcies in their sector in cells connected to the rail. The coefficients attached to employment in large firms are positive and significant at the one-percent level. In this radius, a one percent increase in the number of large firm-employees increased bankruptcies by 0.07 to 0.08 percent. In Column 9.5, we observe that the effect becomes negative. Competition from firms farther away has less of an effect on bankruptcies than large firms' employment at short distances.

Beyond the distance of connections to competitors, the timing of market integration may also matter. In the first cells connected to the rail, the manufacturing sector was not exposed to high competition and probably benefited from higher connections to intermediary goods and additional markets to a greater extent than later connected workers. At the same time, the dire consequences of market integration materialized to a greater extent in the latest connected cells. Our baseline effect encompasses the effect for both groups. It considers three different treatments. First, in Columns 10.1 and 10.4, the treatment is equal to one from 1851 onwards if a grid cell was connected to the rail in 1851. Second, in Columns 10.2 and 10.5, the treatment is equal to one from 1861 onwards if a grid cell was connected to the rail in 1861. Third, in Columns 10.3 and 10.6, the treatment is equal to one from 1881 onwards if a grid cell was connected to the rail in 1881.

Table 10: First Movers and the Effect of Railway Expansion

Dependent Variable:	$\#\text{Bankruptcies}_{i,t,s}$			$\#\text{Employed}_{i,t,s}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ ($\text{Rail}_{i,1851} > 0$) $\times$ Manufacturing_s	0.18***			0.29***		
	(0.06)			(0.06)		
$\mathbb{1}$ ($\text{Rail}_{i,1861} > 0$) $\times$ Manufacturing_s		0.38***			0.29***	
		(0.07)			(0.07)	
$\mathbb{1}$ ($\text{Rail}_{i,1881} > 0$) $\times$ Manufacturing_s			0.57***			0.30**
			(0.18)			(0.12)
Observations	7481	7481	7481	8704	8704	8704
Pseu. R^2	.813	.813	.813	.929	.928	.928
Geo FE	✓	✓	✓	✓	✓	✓
Sector $\times$ Year FE	✓	✓	✓	✓	✓	✓
Sector $\text{Emp}_{i,t,s}$	✓	✓	✓			
$\text{Pop}_{i,t}$				✓	✓	✓
Coal_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓	✓
Port_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓	✓
London_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variables are the annualized number of bankruptcies that occurred between two census periods (Columns (1) to (3)), and the number of employed people in a census year (Columns (4) to (6)). The main explanatory variables are indicators for a grid cell i having at least one rail station recorded (in 1851, in 1861 and in 1881) from 1851, 1861 and 1881, interacted with an indicator variable for the manufacturing sector. The main control variables are the number of people employed in sector s, the total population, and the straight-line distance to the nearest city with coal deposits, to the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

In Table 10, from Columns 1 to 3, the coefficient attached to the rail treatment increases over the years. All coefficients are significant at the one percent level. Accordingly, no matter the timing of the connection, the rail generated bankruptcies. A connection to the rail from 1851 increased bankruptcies by 19 percent. A connection to the rail in 1881 increased bankruptcies by 77 percent.[13] From Columns 4 to 6, we observe that the effect of a connection to the rail increased employment in manufacturing in a similar way over the years. The

[13] According to $(e^{0.57} - 1) \cdot 100\% = 76.8\%$.

magnitude of the coefficients implies that the rail increased employment in manufacturing by 33 to 35 percent. Hence, no matter the timing of the connection, the rail triggered structural change and an increase in the dynamism of the manufacturing sector in a similar manner.

Interestingly, the positive effect on employment and bankruptcies is still present using either of these variations. This suggests that the rail triggered a reallocation towards manufacturing even for the late-connected locations. Those late-connected locations moreover experienced more bankruptcies than the early-connected ones as both groups faced a different nature of market integration.

7.3 Creditors' Demand for Capital or debtors' Insolvency?

The argument we developed so far rests on market structure and the cost of market integration for heterogeneous firms. A counterargument would be that with the arrival of the rail, some investors might have been harsher towards their debtors due to better re-investment alternatives. Investors would have triggered bankruptcies to get part of the debtors' assets in that case.

To test this alternative explanation, we use the changes produced by two reforms of bankruptcy laws in 1869 and 1883. In 1869, England repealed the "officialism" doctrine for bankruptcies (Lester, 1991). Before this reform, bankruptcies were managed by local courts, often taking a long time to resolve and their outcome uncertain. We hypothesize that creditors' "reinvestment" motive to file bankruptcy was limited during this period. After the 1869 reform, bankruptcies were managed by creditors if a majority of them agreed. This procedure advantaged creditors and increased their incentives to file for bankruptcies for quick reinvestment. In 1883, England went back to the "officialism" doctrine.

The evolution of the number of bankruptcies over time (Figure 1) illustrates the first fact about the repeal of "officialism." Creditors indeed filed bankruptcies more than under "officialism," as we see two discontinuities at the two timings of repealing and re-introducing "officialism." These reforms created variation in creditors' incentives to file bankruptcy. Bankruptcies before the 1869 reform and after the 1883 reform can be considered an imprint of the debtors' financial situation. Between the two reforms, bankruptcies capture the financial situation of debtors and creditors' interest. After the 1883 reform, the number of bankruptcies returns to the pre-1869 reform level lending more credence to our interpretation that the surge in bankruptcies in the 1869-1883 period was mainly due to the repeal of "officialism" and variation in creditors' incentives to file for bankruptcies.

If our effect would be explained by creditors' incentives, then we would expect a connection to the rail to increase the number of bankruptcies even more when "officialism" was repealed. We test this hypothesis using the dataset of bankruptcies at the yearly frequency. Table 11 uses a triple-interaction $\mathbb{1}(\text{Rail}_{i,t} > 0) \times \text{Manufacturing}_s \times \text{Reform}_t$ on top of our previous estimations. This triple interaction investigates whether the shift in incentives towards creditors impacts the main effects. As previously, we restrict our sample to 1861 to 1881 to focus on only two different bankruptcy regimes.[14] Table 11 shows that this triple-interaction does not turn significant. Moreover, the magnitude of the treatment variable is similar to the main results even though this approach uses finer fixed effects (sector-year FE instead of sector-census year FE) and a dataset with yearly observations. Accordingly, the main results are driven by the financial situations of debtors more than by the motivation of creditors to trigger the bankruptcies of some creditors on the edge.

Table 11: Incentives and the 1869/1883 Reforms

	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$	
	(1)	(2)
$\mathbb{1}$ $(\text{Rail}_{i,t} > 0) \times \text{Manufacturing}_s$	0.40***	0.39***
	(0.12)	(0.13)
$\mathbb{1}$ $(\text{Rail}_{i,t} > 0) \times \text{Man}_s \times \text{Ref}_t$	0.07	0.08
	(0.12)	(0.12)
Observations	97200	97200
Pseu. R^2	.797	.797
Geo FE	✓	✓
Sector × Year FE	✓	✓
Sector $\text{Emp}_{i,t,s}$	✓	✓
$\text{Coal}_i \times \text{Manufacturing}_s$		✓
$\text{Port}_i \times \text{Manufacturing}_s$		✓
$\text{London}_i \times \text{Manufacturing}_s$		✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with an indicator for the manufacturing sector and an indicator for years 1869–1881 when the "officialism" system was repealed. The main control variables are the number of people employed in sector s and the straight-line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

[14]Since before 1861, only individuals with a status of "merchant" could file for bankruptcy.

7.4 Mechanisms: Discussion and Alternative Explanations.

These results have to be put in perspective. While a wealth of evidence suggests that a rail connection increased bankruptcies in the manufacturing sector because of its reorganization between firms and within firms, other channels may also play a role in a similar dynamic. The rail could have attracted new individuals in booming sectors and these new individuals could have gone bankrupt more easily. In that case, the bankruptcies would result from manufacturing's power of attraction towards new workers. In such a case, our employment variable would not capture all the flows of workers potentially exposed to bankruptcies in the sector between two census waves. Appendix C.11 minimizes these concerns by reducing our estimates to the impact of the rail on bankruptcies in the two years following the census/railway data. If anything, results are stronger using this approach. Another approach confirms this intuition. In Table C.2, we control for county migrants in a cell (=individuals born in a different county than the one they live in). In Table C.2, our estimators are still significant and of a magnitude similar to baseline estimates.

This section documented the mechanisms behind our first compound effect. Within-sector reallocation is dynamic. Consequently, connecting to the rail first does not have the same effect as getting this connection later. This integration into the market increases the number of bankruptcies because it triggers organizational changes. We observe these changes within the manufacturing sector over time. In other words, for a given year within the manufacturing sector, cells connected to the rail experienced more changes than others. We observe those changes within firms and in market structures. Within firms, manufacturing firms connected to the rail were larger, employed a wider variety of occupations, and employed more unskilled labour. Market structures also mediate our effect. We observe that bankruptcies were particularly large in cells that were in a medium distance to large firms in their sector and in manufacturing firms that had a connection to the rail later in our sample. Hence the rail changed dynamics within firms and between firms.

Importantly, we do not rule out that, beyond organizational changes between and within firms, other factors do explain why the rail increased bankruptcies in the manufacturing sector. Theoretically, creditors' and workers' occupational choices are important drivers of our effect. In our context, they did not mitigate the effect of the rail. These two other channels may, however, offer policy solutions to detrimental organizational changes. For example, facilitating workers' transition may reduce personal bankruptcies. Access to additional funds could also solve part of the effect of market integration. Indeed, Appendix B.5 shows that within the manufacturing sector, the effect of the rail decreased with the historical presence of county banks using data from Heblich and Trew (2018). Our results point to some explanations of individual financial distress in places and sectors that, on average, are booming. They also are a call for future research considering this empirical evidence to document the factors that could solve part of the detrimental consequences of within sector-space reallocation.

8 Conclusion

Market integration provides an opportunity for growth (Donaldson, 2018; Jedwab et al., 2017). This opportunity rests on exploiting economies of scale and a new organization of labour. In this paper, we show that this reorganization generates reallocation within a booming sector, within a booming geographic area. To document this effect during market integration, we continue the work of Atack et al. (2008) by connecting the literature on firms' organization during the industrial revolution (Juhász et al., 2024) with the literature on the effect of market integration (Melitz, 2003; Bogart, 2014). This approach still has value today as the merits of globalization are being questioned (Autor et al., 2020) and concerns on the future organization of firms arise (Varian, 2019).

The extension of the railway in England and Wales during the 19^{th} century provides us with a perfect setting to understand how market integration may prompt this biased firms' reorganization within some sectors. The rapid expansion of the rail did not impact all sectors in the same way. Manufacturing, in particular, transited to a factory system. In this sector, firms needed to change their organization to fully exploit the division of labour and the economies of scale allowed by railways (Atack et al., 2008). This new organization was detrimental for some occupations and skills while generating aggregate welfare gains as theoretically proposed by Melitz (2003) and shown by Bogart et al. (2022).

Our results show that the expansion of railways in Britain created financial distress among workers in the manufacturing sector. As firms reorganized to compete in larger markets, some skills lost value. Contrary to previous estimates of the effect of market integration (Autor et al., 2013, 2016, 2020), manufacturing did not plummet in connected areas but flourished. At the same time, some of its workers experienced financial distress. Market integration brought *within*-sector *within*-space reallocation.

These results clarify some of the dynamics driving the evolution of market structure, trade, and inequality during the Industrial Revolution and its immediate aftermath (Nye, 1987; O'Rourke and Williamson, 2005; Desmet and Parente, 2012; Desmet et al., 2020; Juhász et al., 2024). They also shed new light on the factors potentially explaining how spatial and sectoral inequality may interact today (Autor et al., 2020). This research emphasizes that despite positive aggregate effects technology and trade are redistributive by nature. This redistribution has important (political) consequences (Frey et al., 2018; Lacroix, 2018; Autor et al., 2020; Caprettini and Voth, 2020). Understanding how market integration leads to reallocation between sectors/places and, in our case, within sectors/places is then of first importance for persons in charge of designing efficient market and firm organization: policy-makers, firm owners, or regulators. In particular, previous research has focused on the geographic nature of the reallocation from market integration (Redding, 2016), or the within-sector between places reallocation from market integration (Autor et al., 2013, 2016, 2020). Our results show reallocation within a location connected to the rail. In other words, a connection to the rail increased employment in manufacturing. At the same time, a connection to the rail also triggered a wave of individual financial distress in this sector. Beyond employment data, one should then use data identifying reallocation despite aggregate gains (in the same place). Future research could build on these new results to better understand how to mitigate these distributional consequences of growth.

References

Atack, J., M. R. Haines, and R. A. Margo (2008). *Railroads and the Rise of the Factory: Evidence for the United States, 1850-1870*, Volume 14410. 2, 5, 6, 27, 38

Atack, J., R. A. Margo, and P. W. Rhode (2019). "Automation" of manufacturing in the late nineteenth century: The hand and machine labor study. *Journal of Economic Perspectives 33*(2), 51–70. 7

Autor, D., D. Dorn, G. Hanson, and K. Majlesi (2020). Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review 110*(10), 3139–3183. 2, 4, 38, 39

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *Quarterly Journal of Economics 135*(2), 645–709. 7, 39

Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review 103*(6), 2121–2168. 2, 15, 38, 39

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The China shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics 8*, 205–240. 2, 4, 38, 39

Ayotte, K. (2007). Bankruptcy and entrepreneurship: The value of a fresh start. *Journal of Law, Economics, & Organization 23*(1), 161–185. 4

Banerjee, A., E. Duflo, and N. Qian (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics 145*, 102442. 2, 4

Berger, T. (2019). Railroads and rural industrialization: Evidence from a historical policy experiment. *Explorations in Economic History 74*, 101277. 5, 6

Berger, T. and K. Enflo (2017). Locomotives of local growth: The short-and long-term impact of railroads in Sweden. *Journal of Urban Economics 98*, 124–138. 2, 6

Berger, T. and V. Ostermeyer (2024). Firm survival and the rise of the factory. *Economic History Review*. 5, 6

Bernstein, S., E. Colonnelli, X. Giroud, and B. Iverson (2019). Bankruptcy spillovers. *Journal of Financial Economics 133*(3), 608–633. 4

Bogart, D. (2014). The transport revolution in industrialising Britain. *Cambridge economic history of modern Britain 1*, 368–391. 2, 9, 10, 38

Bogart, D., X. You, E. J. Alvarez-Palau, M. Satchell, and L. Shaw-Taylor (2022). Railways, divergence, and structural change in 19th century England and Wales. *Journal of Urban Economics 128*, 103390. 4, 5, 6, 10, 19, 21, 24, 38

Bose, U., S. Filomeni, and S. Mallick (2021). Does bankruptcy law improve the fate of distressed firms? The role of credit channels. *Journal of Corporate Finance 68*, 101836. 4

Braun, S. T. and R. Franke (2022). Railways, growth, and industrialization in a developing German economy, 1829–1910. *Journal of Economic History 82*(4), 1183–1221. 6

Cabral, L. M. B. and J. Mata (2003). On the evolution of the firm size distribution: Facts and theory. *American Economic Review 93*(4), 1075–1090. 28

Caprettini, B. and H.-J. Voth (2020). Rage against the machines: Labor-saving technology and unrest in industrializing England. *American Economic Review: Insights 2*(3), 305–20. 5, 39

Casson, M. (2009). *The world's first railway system: enterprise, competition, and regulation on the railway network in Victorian Britain*. OUP Oxford. 10, 26

Chandler, A. D. (1977). *The visible hand*. Harvard university press. 7

Costas-Fernández, J., J.-A. Guerra, and M. Mohnen (2020). Train to opportunity: The effect of infrastructure on intergenerational mobility. *Documento CEDE* (48). 26

Crafts, N. (2004). Steam as a general purpose technology: A growth accounting perspective. *Economic Journal 114* (495), 338–351. 6, 10

Crafts, N. (2022). Slow real wage growth during the industrial revolution: Productivity paradox or pro-rich growth? *Oxford Economic Papers 74* (1), 1–13. 5

Davydenko, S. A. and J. R. Franks (2008). Do bankruptcy codes matter? A study of defaults in France, Germany, and the UK. *Journal of Finance 63* (2), 565–608. 4

Del Angel, M., G. Richardson, and M. Gou (2024). Bank failures and economic activity. Evidence from the Progressive Era. *Available at SSRN 4756705*. 4

Desmet, K., A. Greif, and S. L. Parente (2020). Spatial competition, innovation and institutions: The industrial revolution and the Great Divergence. *Journal of Economic Growth 25*, 1–35. 38

Desmet, K. and S. L. Parente (2012). The evolution of markets and the revolution of industry: A unified theory of growth. *Journal of Economic Growth 17*, 205–234. 38

Donaldson, D. (2015). The gains from market integration. *Annual Review of Economics 7* (1), 619–647. 5

Donaldson, D. (2018). Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review 108* (4-5), 899–934. 2, 5, 6, 38

Donaldson, D. and R. Hornbeck (2016). Railroads and American economic growth: A "market access" approach. *Quarterly Journal of Economics 131* (2), 799–858. 2, 5

Esteves, R. and G. G. Mesevage (2021). Private benefits, public vices: Railways and logrolling in the nineteenth-century British parliament. *Journal of Economic History 81* (4), 975–1014. 9

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from China's national trunk highway system. *Review of Economic Studies 81* (3), 1046–1070. 4

Fernihough, A. and K. H. O'Rourke (2020). Coal and the European Industrial Revolution. *Economic Journal 131*(635), 1135–1149. 14

Frey, C. B., T. Berger, and C. Chen (2018). Political machinery: Did robots swing the 2016 US presidential election? *Oxford Review of Economic Policy 34*(3), 418–442. 39

Gine, X. and I. Love (2010). Do reorganization costs matter for efficiency? Evidence from a bankruptcy reform in Colombia. *Journal of Law and Economics 53*(4), 833–864. 4

Goldin, C. and L. F. Katz (1998). The origins of technology-skill complementarity. *Quarterly Journal of Economics 113*(3), 693–732. 5, 7

Gregory, I. N. and J. M. Henneberg (2010). The railways, urbanization, and local demography in England and Wales, 1825–1911. *Social Science History 34*(2), 199–228. 10

Hawke, G. R. (1970). *Railways and economic growth in England and Wales, 1840-1870*. Oxford University Press. 10

Heblich, S., S. J. Redding, and Y. Zylberberg (2024). The distributional consequences of trade: Evidence from the grain invasion. *NBER Working Paper No. 32958*. 4

Heblich, S. and A. Trew (2018). Banking and industrialization. *Journal of the European Economic Association 17*(6), 1753–1796. 38

Hornbeck, R. and M. Rotemberg (2024). Growth off the rails: Aggregate productivity growth in distorted economies. *Journal of Political Economy 132*(11), 3547–3602. 5, 6

Hornung, E. (2015). Railroads and Growth in Prussia. *Journal of the European Economic Association 13*(4), 699–736. 2, 6

Humphries, J. (2013). Childhood and child labour in the British industrial revolution 1. *Economic History Review 66*(2), 395–418. 32

Jedwab, R., E. Kerby, and A. Moradi (2017). History, path dependence and development: Evidence from colonial railways, settlers and cities in Kenya. *Economic Journal 127*(603), 1467–1494. 2, 6, 38

Juhász, R., M. P. Squicciarini, and N. Voigtländer (2024). Technology adoption and productivity growth: Evidence from industrialization in France. *Journal of Political Economy 132*(10), 3215–3259. 2, 5, 7, 15, 18, 38

Kaboski, J. P., W. Lu, W. Qian, and L. Ren (2024). Melitz meets Lewis: The impacts of roads on structural transformation and businesses. *NBER Working paper 4820042*. 5, 6

Katz, L. F. and R. A. Margo (2014). Technical change and the relative demand for skilled labor: The United States in historical perspective. In *Human capital in history: The American record*, pp. 15–57. University of Chicago Press. 20

Kogan, L., D. Papanikolaou, L. D. Schmidt, and B. Seegmiller (2023). Technology and labor displacement: Evidence from linking patents with worker-level data. *NBER Working Paper No. 31846*. 5

Lacroix, J. (2018). Steam democracy up! Industrialization-led opposition in Napoleonic plebiscites. *European Review of Economic History 22*(2), 135–160. 39

Lester, V. M. (1991). *Insolvency and reform of English bankruptcy law, 1831-1914*. Ph. D. thesis, University of Oxford. 8, 12, 13, 27, 35

Li, B. and J. Ponticelli (2022). Going bankrupt in China. *Review of Finance 26*(3), 449–486. 4

Martí-Henneberg, J., M. Satchell, X. You, L. Shaw-Taylor, and E. Wrigley (2017a). 1851 England, Wales and Scotland railway stations shapefile. 14

Martí-Henneberg, J., M. Satchell, X. You, L. Shaw-Taylor, and E. Wrigley (2017b). 1861 England, Wales and Scotland railway stations shapefile. 14

Martí-Henneberg, J., M. Satchell, X. You, L. Shaw-Taylor, and E. Wrigley (2017c). 1881 England, Wales and Scotland railway stations shapefile. 14

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725. 2, 4, 6, 7, 30, 38

Mitchell, B. R. (1964). The coming of the railway and United Kingdom economic growth. *Journal of Economic History 24*(3), 315–336. 10

Nye, J. V. (1987). Firm size and economic backwardness: A new look at the French industrialization debate. *Journal of Economic History 47*(3), 649–669. 38

O'Rourke, K. H. and J. G. Williamson (2005). From Malthus to Ohlin: Trade, industrialisation and distribution since 1500. *Journal of Economic Growth 10*, 5–34. 38

Ponticelli, J. and L. S. Alencar (2016). Court enforcement, bank loans, and firm investment: Evidence from a bankruptcy reform in Brazil. *Quarterly Journal of Economics 131*(3), 1365–1413. 4

Redding, S. J. (2016). Goods trade, factor mobility and welfare. *Journal of International Economics 101*, 148–167. 2, 39

Rosenberg, M. and F. Curci (2023). Factory location: Resistance to technology adoption and local institutions. *Available at SSRN 4428398*. 5

Schurer, K. and E. Higgs (2023). Integrated Census Microdata (I-CeM) Names and Addresses, 1851-1911. *UK Data Service SN: 7856* (2nd Edition), DOI: http://doi.org/10.5255/UKDA–SN–7856–2. 13, 28

Smith, A. (1776). *The Wealth of Nations.* W. Strahan and T. Cadell, London. 5

Sokoloff, K. L. (1984). Was the transition from the artisanal shop to the nonmechanized factory associated with gains in efficiency? evidence from the US manufacturing censuses of 1820 and 1850. *Explorations in Economic History 21* (4), 351–382. 2

Tang, J. P. (2014). Railroad expansion and industrialization: Evidence from Meiji Japan. *Journal of Economic History 74* (3), 863–886. 5, 6, 27

Temin, P. (1997). Two views of the British industrial revolution. *Journal of Economic History 57* (1), 63–82. 5

Tsiachtsiras, G. (2022). Changing the perception of time: Railroads, access to knowledge and innovation in nineteenth century France. *Access to Knowledge and Innovation in Nineteenth Century France*. 5

Varian, H. (2019). Artificial intelligence, economics, and industrial organization. *Economics of Artificial Intelligence: An Agenda*, 399. 38

A Appendix A – Detecting Bankruptcies

We extracted personal bankruptcy announcements using a combination of Optical Character Recognition (OCR) software and text recognition algorithms. After web-scraping the 42,771 London Gazette issues that were published between 1788–1986 from the London Gazette homepage, we converted the scan images to readable text using OCR. Next, we wrote various text recognition algorithms to search each issue for bankruptcy announcements. We found at least one such announcement across 21,292 issues. The other issues were mostly supplements, which provide special information outside the Gazette's regular announcements.

We had to adapt our text recognition algorithms to different periods of the Gazette. Our goal was to identify individual announcements based on specific keywords. The layout of the announcements and, hence, the relevant keywords, however, changed over time. For example, the earliest issues, starting in 1788 and going until 1861, listed bankruptcy announcements toward the end of an issue. Each announcement received its own paragraph, starting with the introduction "Whereas a Commission of Bankrupt(cy) was awarded (and issued forth) against." Starting in 1861, the sections of bankruptcy announcements received their own headlines and internal structure. Since then, announcements have become separated into first meetings, i.e. the assessment of bankruptcy and collection of claims, later meetings to distribute funds, and final meetings to resolve open cases. For example, first meetings would be introduced under the headline "The Bankruptcy Act, 1861. Notice of Adjudications and First Meeting of Creditors." The London Gazette maintained this structure for most of the time. The only exception is 1919 when they published notices of first meetings, intermediate meetings, and final meetings in separate tables at the end of an issue. Finally, from 1920 until 1986 the London Gazette returned to the structured text format illustrated in Figure 2 (b). Only after 1986 did lawyers and solicitors take over the management of bankruptcy cases and publish announcements individually. We, therefore, focus our systematic data collection on the 1788–1986 period when bankruptcy announcements followed systematic and easy-to-code patterns.

To extract individual announcements from an issue, we wrote various algorithms that, depending on the announcement pattern of a given time period, identified the start of a new announcement. For example, in the early issues from 1788 to 1861, the algorithm looked for different variations of the text pattern, "Whereas a Commission of Bankrupt is awarded and issued forth against", to determine the start of a bankruptcy announcement.[15] From

[15] The actual pattern switch occurred with the new bankruptcy act in the issue 22,564 from November 12th, 1861. While the overall pattern remained stable across announcements, the individual solicitors who published the announcements would vary the text pattern somewhat, e.g. using past tense ("was awarded"

1861 onwards, we searched the issues for the headlines introducing the "First Meetings" of bankruptcies to focus our algorithm on the text between this headline and the following one, and then collecting the individual announcements with the procedure explained above.[16]

Our algorithm detected a total of 422,769 bankruptcy cases, i.e., on average, 19.9 bankruptcy announcements per issue, with a median of 14 announcements per issue. For each bankruptcy case we detected, we extracted the first 300 letters after starting a bankruptcy paragraph for further processing. Within each text sample, we let our algorithm find the information on a) the name of the person, b) the person's current address, and c) the person's current occupation. To identify this information, we used detected commas in the text to separate the information. Usually, the information would be presented in the format *name, address, occupation*, so detecting commas as breakpoints helped structure the text. Using these comma-break points as general hints for where to look for certain information, we ran the specific text subsets against lists of city-, county-, borough-, and parish names and a list of (historical) census occupations, respectively, to detect matches.

Due to the occasionally bad quality of the scans, this required a lot of pre-processing. Among other things, we corrected common typos that the OCR introduced by misreading certain letters and used fuzzy text matching procedures where direct pattern matching did not yield a result. Finally, we used the information on locations and occupations to encode it in a usable format. We geocoded the place information as accurately as possible. We could link many locations to the coordinates for a specific parish or city, but for some, we could only geocode at the county level. Our analysis only uses bankruptcy cases that we could link to the city-level or below. To make use of the occupation titles, we assigned them to 5-digit historical international classification of occupations (HISCO) codes as defined by the International Institute of Social History Amsterdam.[17] Despite the pre-and post-processing steps, we were not able to acquire full information for all bankruptcy cases that our algorithm collected. We could geocode 373,555 bankruptcy cases (343,091 cases to the city- or parish-level) and assign HISCO codes to 373,010 cases.

or "has been issued forth") or dropping the "awarded" or "issued forth" part of the introduction. We went through several issues manually to include as many variations as possible in our algorithm. We returned to issues with an unusually low number of detected announcements to look for pattern variations that we might have overlooked.

[16]For the short period when the announcements were published in a table format, we accessed the Google Vision API to detect the table structure accurately and directly transfer the relevant information into a digital table format.

[17]See their homepage https://iisg.amsterdam/en/data/data-websites/history-of-work for further information

B Appendix B – Supporting Evidence

Table B.1: Sector Definitions

Sector	Description
Agriculture	All occupations that involve farm work, garden work, fishing, and animal husbandry. Common job descriptions are, for example, “farmer”, "gardener”, “dairyman”, “nurseryman”.
Manufacturing	Occupations in this sector turn raw materials into intermediate or final goods, or work in the extraction of non-agricultural natural resources. Common job descriptions are, for example, “butcher”, “baker”, “brewer”, “tailor”, “engineer”, “plumber”, “jeweller”, “smith”, “shoe maker”, “builder” or “manufacturer”.
Trade	Workers in this category work in retail sales, as travelling sales agents, shop keepers, or on the import and export of goods from/to other countries. Common job descriptions are, for example, “chapman”, “merchant”, “dealer”, “grocer”, “salesman”, “retailer”, and “tobacconist”.
Services	This category combines jobs that require specific skills, but do not produce physical goods. This includes education and military personnel, artists, medical practitioners, managers, gastronomy workers, clerical workers, and other service providers. Common job descriptions are, for example, “victualler”, “inn keeper”, “hair dresser”, “contractor”, “surgeon”, “attorney”, “schoolmaster”, “artist”, “registrar”, “house keeper”, “accountant”, “clerk”, and “secretary”.

Table B.2: Estimates by Sector – Bankruptcies

	Dependent Variable: #Bankruptcies$_{i,t,s}$		
	(1)	(2)	(3)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Agr$_s$	-0.10	0.28	-0.08
	(0.19)	(0.19)	(0.17)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Manufacturing$_s$	0.56***	0.57***	0.38***
	(0.13)	(0.14)	(0.13)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Trade$_s$	0.11	-0.03	0.11
	(0.16)	(0.15)	(0.15)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Services$_s$	0.07	0.11	-0.08
	(0.15)	(0.16)	(0.14)
Observations	7481	7481	7481
Pseu. R^2	.801	.804	.816
Geo FE	✓	✓	✓
Sector FE	✓	✓	
Year FE	✓	✓	
Sector × Year FE			✓
Sector Employment$_{i,s,t}$	✓	✓	✓
Coal$_i$ × Manufacturing$_s$		✓	✓
Port$_i$ × Manufacturing$_s$		✓	✓
London$_i$ × Manufacturing$_s$		✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with an indicator variable for the observed sector. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table B.3: Estimates by Sector – Employment

	Dependent Variable: #Employed$_{i,t,s}$		
	(1)	(2)	(3)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Agr$_s$	-0.84***	-0.37***	-0.27***
	(0.09)	(0.05)	(0.06)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	0.33***	0.16***	0.17***
	(0.05)	(0.04)	(0.04)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Trade$_s$	0.52***	0.36***	0.27***
	(0.06)	(0.04)	(0.04)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Services$_s$	0.15***	0.14***	0.12***
	(0.05)	(0.03)	(0.03)
Observations	8704	8704	8704
Pseu. R^2	.913	.948	.95
Geo FE	✓	✓	✓
Sector FE	✓	✓	
Year FE	✓	✓	
Sector × Year FE			✓
Population$_{i,t}$	✓	✓	✓
Coal$_i$ × Manufacturing$_s$		✓	✓
Port$_i$ × Manufacturing$_s$		✓	✓
London$_i$ × Manufacturing$_s$		✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the number of people employed in sector s at census-year t in location i. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t, interacted with an indicator variable for the observed sector. The main control variables are population and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table B.4: Intensive Margin instead of Extensive Margin

	Dependent Variable: $\mathbb{1}(\#\text{Bankruptcies}_{i,t,s} > 0)$					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Rail$_{i,t}$)	1.41***	1.38***	-0.13	-0.15	-0.19*	-0.15
	(0.13)	(0.14)	(0.10)	(0.10)	(0.11)	(0.11)
Log(Rail$_{i,t}$) × Manufacturing$_s$		0.06**	0.06**	0.06***	0.17***	0.05
		(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Observations	8341	8341	7481	7481	7481	7481
Pseu. R^2	.31	.326	.8	.801	.802	.813
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector Employment$_{i,s,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is the natural logarithm of the number of railway stations that are active in grid cell i in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table B.5: The Effect of the Rail on Bankruptcies – Controlling for County Banks

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: $\#Bankruptcies_{i,t,s}$				
$\mathbb{1}$ ($Rail_{i,t} > 0$)	2.12***	0.13	0.16	0.13	0.18
	(0.25)	(0.17)	(0.17)	(0.17)	(0.18)
$\mathbb{1}$ ($Rail_{i,t} > 0$) × $Manufacturing_s$	0.47***	0.47***	0.48***	0.55***	0.40***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
$\mathbb{1}$ ($Rail_{i,t} > 0$) × $CountyBanks_i$	0.30	-0.16	-0.17	-0.18	-0.12
	(0.23)	(0.15)	(0.15)	(0.15)	(0.15)
$Manufacturing_s$ × $CountyBanks_i$	-0.02	-0.02	-0.01	0.00	0.22**
	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
$\mathbb{1}$ ($Rail_{i,t} > 0$) × $Manufacturing_s$ × $CountyBanks_i$	0.05	0.05	0.01	0.01	-0.21**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
Observations	8277	7473	7473	7473	7473
Pseu. R^2	.127	.8	.801	.801	.813
Geo FE		✓	✓	✓	✓
Sector FE		✓	✓	✓	
Year FE		✓	✓	✓	
Sector-Year FE					✓
Sector $Employment_{i,s,t}$			✓	✓	✓
$Coal_i$ × $Manufacturing_s$				✓	✓
$Port_i$ × $Manufacturing_s$				✓	✓
$London_i$ × $Manufacturing_s$				✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The additional interaction variable $CountyBanks_i$ indicates the existence of local county banks before the start of the railway expansion in 1850. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

C Appendix C – Robustness checks (Main estimates)

Table C.1: OLS Estimations

	Dependent Variable: ln(1+#Bankruptcies$_{i,t,s}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ (Rail$_{i,t} > 0$)	0.26***	0.23***	-0.13***	-0.12***	-0.11***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Manufacturing$_s$		0.16***	0.16***	0.13***	0.08***	0.02*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	8341	8341	8341	8341	8341	8341
Adj. R^2	.0468	.0589	.684	.702	.705	.71
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector Employment$_{i,s,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from OLS regressions at the grid cell-sector-census year level. The dependent variable is the natural logarithm of the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

Table C.2: Local Shocks

	Dependent Variable: #Bankruptcies$_{i,t,s}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	0.09	0.12	0.05	0.02
	(0.15)	(0.14)	(0.14)	(0.15)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	0.33***	0.34***	0.33***	0.33***
	(0.08)	(0.08)	(0.08)	(0.08)
Unemployment$_{i,t}$	0.52			0.63*
	(0.34)			(0.38)
Migrants$_{i,t}$		-0.16		-0.22
		(0.78)		(0.61)
Male pop$_{i,t}$			-0.40***	-0.41***
			(0.08)	(0.08)
Observations	7481	7481	7481	7481
Pseu. R^2	.813	.813	.814	.814
Geo FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Sector Employment$_{i,s,t}$	✓	✓	✓	✓
Coal$_i$ × Manufacturing$_s$	✓	✓	✓	✓
Port$_i$ × Manufacturing$_s$	✓	✓	✓	✓
London$_i$ × Manufacturing$_s$	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Additional control variables are the unemployment rate, the number of people born in another county, and the share of the male population in location i in census-year t. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table C.3: Excluding Cells with low/high Levels of Population

	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$				
	(1)	(2)	(3)	(4)	(5)
	w.o Top5 %	w.o Bottom5 %	w.o Both5 %	w.o Nodes	w.o Previous
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	-0.09	0.12	-0.09	0.10	-0.05
	(0.15)	(0.14)	(0.15)	(0.16)	(0.15)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s	0.36^{***}	0.34^{***}	0.36^{***}	0.30^{***}	0.28^{***}
	(0.08)	(0.08)	(0.08)	(0.07)	(0.06)
Observations	7237	7464	7220	6693	6596
Pseu. R^2	.737	.813	.737	.691	.627
Geo FE	✓	✓	✓	✓	✓
Sector $\times$ Year FE	✓	✓	✓	✓	✓
Sector $\text{Employment}_{i,t}$	✓	✓	✓	✓	✓
Coal_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓
Port_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓
London_i $\times$ Manufacturing_s	✓	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Columns (1)-(5) employ different sample restrictions; Column (1) drops the grid cells with the 5% highest population, Column (2) the grid cells with the 5% lowest population, and Column (3) both types of extreme cells. Column (4) excludes grid cells that contain a railway node, i.e. one of the 100 most populous towns in 1851. Column (5) applies all three sample restrictions at the same time. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table C.4: Excluding Reform Years

	(1)	(2)	(3)	(4)	(5)	(6)
		Dependent Variable: #Bankruptcies$_{i,t,s}$				
			Excluding 1869 - 1883 and pre-1861			
$\mathbb{1}$ (Rail$_{i,t} > 0$)	2.78***	2.61***	0.15	0.21	0.21	0.23
	(0.25)	(0.27)	(0.35)	(0.35)	(0.35)	(0.35)
$\mathbb{1}$ (Rail$_{i,t} > 0$) × Manufacturing$_s$		0.52***	0.52***	0.47***	0.45***	0.38***
		(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Observations	5465	5465	4425	4425	4425	4425
Pseu. R^2	.0466	.0602	.687	.689	.69	.691
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector Employment$_{i,s,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Panel (A) excludes bankruptcies that occurred between 1869 and 1883, when a temporary policy change allowed settling bankruptcies outside courts. Panel (B) additionally excludes bankruptcies that occurred before 1861. Before a reform in 1861, only merchants were allowed to go bankrupt. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table C.5: Considering Spatial Autocorrelation

Dep Variable:	#Bankruptcies$_{i,t,s}$		#Employment$_{i,t,s}$	
	(1)	(2)	(3)	(4)
	County Cluster	Spatial Lag	County Cluster	Spatial Lag
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	0.12	0.13	-0.11***	-0.00
	(0.14)	(0.14)	(0.03)	(0.03)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$	0.34***	0.33***	0.28***	0.20***
	(0.07)	(0.08)	(0.08)	(0.07)
Bankruptcies Neigh$_{i,s,t}$		0.12*		
		(0.07)		
Employment Neigh$_{i,s,t}$				0.60***
				(0.06)
Observations	7481	7481	8704	8341
Pseu. R^2	.813	.813	.929	.949
Geo FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Sector Employment$_{i,t,s}$	✓	✓		
Population$_{i,t}$			✓	✓
Coal$_i$ × Manufacturing$_s$	✓	✓	✓	✓
Port$_i$ × Manufacturing$_s$	✓	✓	✓	✓
London$_i$ × Manufacturing$_s$	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variables are the annualized number of bankruptcies that occurred between two census periods (Columns (1) and (2)), and the number of employed people in a census year (Columns (3) and (4)). The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. We additionally include spatial lags, i.e. the number of bankruptcies in neighboring cells (Column (2)) and the number of people employed in a neighboring cell (Column (4)). The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01.

Table C.6: The Effect of the Rail on Bankruptcies (Conley Standard Errors)

	Dependent Variable: #Bankruptcies$_{i,t,s}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	2.62***	2.46***	0.05***	0.08***	0.05	0.12***
	(0.22)	(0.21)	(0.02)	(0.02)	(0.04)	(0.04)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$		0.50***	0.50***	0.48***	0.56***	0.34***
		(0.04)	(0.04)	(0.05)	(0.06)	(0.07)
Pseu. R^2	0.076	0.092	0.767	0.768	0.768	0.780
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector Employment$_{i,s,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Conley Standard Errors in parentheses (300km threshold), * p< 0.1, ** p< 0.05, *** p< 0.01.

Table C.7: The Effect of the Rail on Employment (Conley Standard Errors)

	Dependent Variable: #Employed$_{i,t,s}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	1.18***	0.91***	-0.42***	-0.27***	-0.11***	-0.11***
	(0.10)	(0.05)	(0.02)	(0.06)	(0.03)	(0.03)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$		0.60***	0.60***	0.60***	0.28***	0.28***
		(0.15)	(0.14)	(0.14)	(0.10)	(0.10)
Pseu. R^2	0.074	0.215	0.873	0.906	0.923	0.929
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Population$_{i,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the number of people employed in sector s at census year t and in grid cell i. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the cell's total population and the straight-line distance to the nearest city with coal deposits, to the nearest port, and the city of London. Conley Standard Errors in parentheses (300km), * p< 0.1, ** p< 0.05, *** p< 0.01

Table C.8: The Effect of the Rail on Bankruptcies – Inverse Probability Weighting

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$					
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	2.09***	1.93***	-0.27*	-0.27*	-0.25*	-0.24*
	(0.24)	(0.24)	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) $\times$ Manufacturing_s		0.47***	0.42***	0.44***	0.38**	0.34***
		(0.10)	(0.11)	(0.10)	(0.16)	(0.10)
Observations	8341	8341	7481	7481	7481	7481
Pseu. R^2	.0942	.103	.609	.611	.611	.622
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector $\text{Employment}_{i,s,t}$				✓	✓	✓
Coal_i $\times$ Manufacturing_s					✓	✓
Port_i $\times$ Manufacturing_s					✓	✓
London_i $\times$ Manufacturing_s					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Observations are weighted by the inverse of cell i's population. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

Table C.9: The Effect of the Rail on Employment Shares

Dependent Variable:	$\#\text{Employed}_{i,t,s}/\#\text{Population}_{i,t}$		
	(1)	(2)	(3)
$\mathbb{1}$ $(\text{Rail}_{i,t} > 0)$	-0.14***	-0.09***	-0.09***
	(0.02)	(0.02)	(0.02)
$\mathbb{1}$ $(\text{Rail}_{i,t} > 0) \times \text{Manufacturing}_s$	0.41***	0.27***	0.29***
	(0.04)	(0.04)	(0.04)
Observations	8344	8344	8344
Pseu. R^2	.0682	.0727	.0736
Geo FE	✓	✓	✓
Sector FE	✓	✓	
Year FE	✓	✓	
Sector × Year FE			✓
$\text{Population}_{i,t}$	✓	✓	✓
$\text{Coal}_i \times \text{Manufacturing}_s$		✓	✓
$\text{Port}_i \times \text{Manufacturing}_s$		✓	✓
$\text{London}_i \times \text{Manufacturing}_s$		✓	✓

Notes: Table reports results from OLS regressions at the grid cell-sector-census year level. The dependent variable is the share of people employed in sector s at census year t and in grid cell i. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the cell's total population and the straight-line distance to the nearest city with coal deposits, to the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

Table C.10: The Effect of the Rail on Bankruptcy Shares

Dependent Variable:	$\text{Log}(\text{Bankrupt}_{i,t,s}/\text{Employed}_{i,t,s})$		
	(1)	(2)	(3)
$\mathbb{1}\ (\text{Rail}_{i,t} > 0)$	-0.45***	-0.45***	-0.40***
	(0.17)	(0.17)	(0.16)
$\mathbb{1}\ (\text{Rail}_{i,t} > 0) \times \text{Manufacturing}_s$	0.43***	0.46**	0.22**
	(0.13)	(0.18)	(0.10)
Observations	7481	7481	7481
Pseu. R^2	.365	.365	.367
Geo FE	✓	✓	✓
Sector FE	✓	✓	
Year FE	✓	✓	
Sector × Year FE			✓
Sector $\text{Employment}_{i,s,t}$	✓	✓	✓
$\text{Coal}_i \times \text{Manufacturing}_s$		✓	✓
$\text{Port}_i \times \text{Manufacturing}_s$		✓	✓
$\text{London}_i \times \text{Manufacturing}_s$		✓	✓

Notes: Table reports results from OLS regressions at the grid cell-sector-census year level. The dependent variable is the log-share of bankrupts in sector s at census year t and in grid cell i. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the cell's total population and the straight-line distance to the nearest city with coal deposits, to the nearest port, and the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

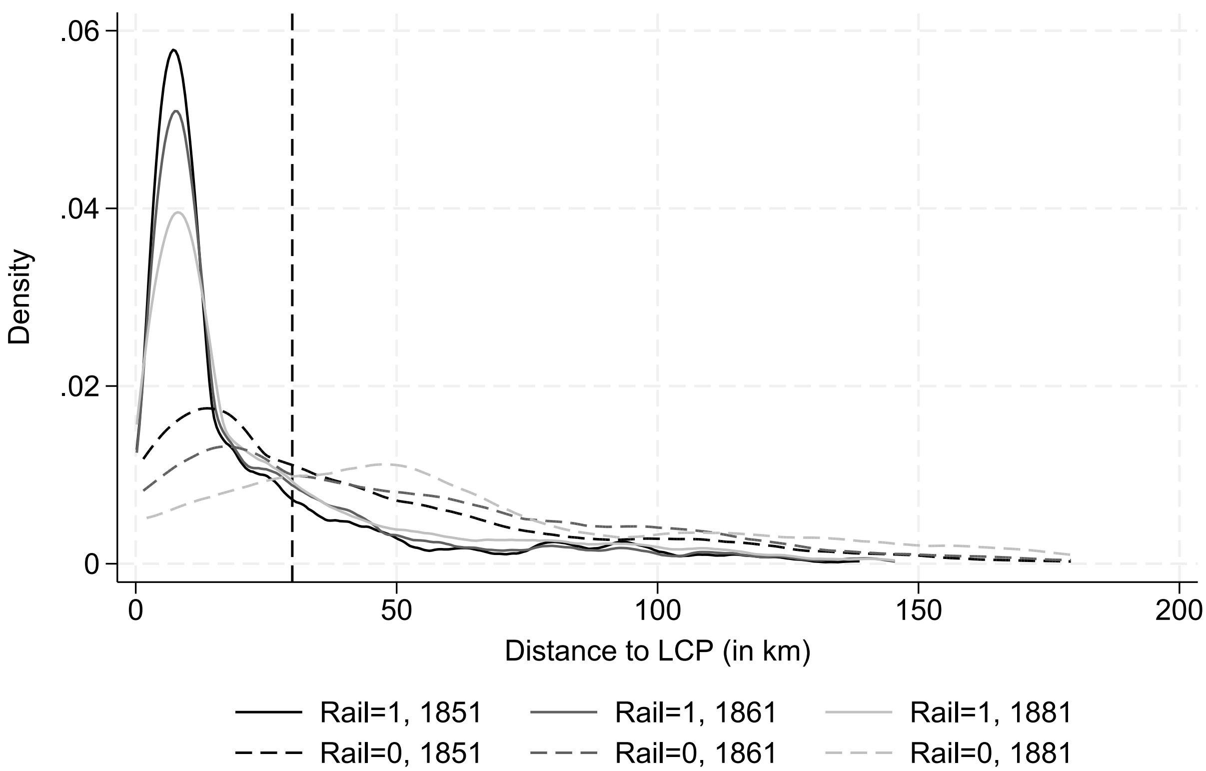
Table C.11: The Effect of the Rail on Bankruptcies – Short Windows

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: #Bankruptcies$_{i,t,s}$ for 2 years					
$\mathbb{1}$ (Rail$_{i,t}$ > 0)	3.50***	3.30***	0.29	0.35	0.34	0.43*
	(0.27)	(0.27)	(0.25)	(0.25)	(0.25)	(0.24)
$\mathbb{1}$ (Rail$_{i,t}$ > 0) × Manufacturing$_s$		0.65***	0.65***	0.60***	0.63***	0.27**
		(0.12)	(0.12)	(0.12)	(0.13)	(0.14)
Observations	8341	8341	6678	6678	6678	6678
Pseu. R^2	.082	.095	.839	.841	.841	.852
Geo FE			✓	✓	✓	✓
Sector FE			✓	✓	✓	
Year FE			✓	✓	✓	
Sector-Year FE						✓
Sector Employment$_{i,s,t}$				✓	✓	✓
Coal$_i$ × Manufacturing$_s$					✓	✓
Port$_i$ × Manufacturing$_s$					✓	✓
London$_i$ × Manufacturing$_s$					✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the number of bankruptcies that occurred within 2 years of a census-year. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

D Appendix D – Robustness (Identification)

Figure D.1: Kernel Density - Grid cells, Access to the Rail, and Distance to LCP



Notes: This figure displays Kernel density functions for grid cells connected to the rail in different years (plain lines) and grid cells not connected to the rail (dashed lines) depending on the distance to the LCP. Different years are represented by various shades of grey, the darker means more ancient sample.

Table D.1: Placebo Test – LCP Proximity and Number of Stations

Instrument	LCP<30km	LCP<25km	LCP<35km	LCP<30km	LCP<30km	LCP<30km
	(1)	(2)	(3)	(4)	(5)	(6)
	First stage / Dependent Variable: Nb Rail $_{i,t}$					
$\mathbb{1}$ Rail$_{i,t}$	1.26***	1.26***	1.27***	1.26***	1.26***	1.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{1}$ Instrument$_i$	-0.01	0.00	-0.06	-0.02	-0.03	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Spillovers Bankrupt $_{s,i,t}$				0.08***		0.07***
				(0.02)		(0.02)
Spillovers Employ $_{s,i,t}$					0.06***	0.05***
					(0.01)	(0.01)
Observations	7481	7481	7481	7481	7481	7481
Adj. R^2	.728	.728	.729	.734	.733	.737
Geo FE	✓	✓	✓	✓	✓	✓
Year × Sector FE	✓	✓	✓	✓	✓	✓
Sector Employment$_{i,s,t}$	✓	✓	✓	✓	✓	✓
Controls$_i$ × Manufacturing$_s$	✓	✓	✓	✓	✓	✓

Notes: Table reports results from OLS regressions at the grid cell-sector-census year level. The dependent variable is the number of railway stations in a location i in census year t. The main explanatory variables are an indicator variable for at least one railway station being present, and an indicator for a location i being within 30km to the Least Cost Path instrument. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

Table D.2: The Effect of the Rail on Bankruptcies – Controlling for a Counterfactual Network

	Dependent Variable: $\#\text{Bankruptcies}_{i,t,s}$				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$)	1.96***	0.12	0.15	0.13	0.10
	(0.23)	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}$ ($\text{Rail}_{i,t} > 0$) × Manufacturing_s	0.27***	0.26***	0.24***	0.29***	0.31***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Observations	8341	7481	7481	7481	7481
Pseu. R^2	.159	.804	.806	.806	.813
Geo FE		✓	✓	✓	✓
Sector FE		✓	✓	✓	
Year FE		✓	✓	✓	
Sector-Year FE					✓
Sector $\text{Employment}_{i,s,t}$			✓	✓	✓
Coal_i × Manufacturing_s				✓	✓
Port_i × Manufacturing_s				✓	✓
London_i × Manufacturing_s				✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. All regressions additionally include an indicator variable for location i hosting at least one station of the counterfactual, "cost-efficient" railway network. Standard Errors in parentheses are clustered at the grid cell level, * p< 0.1, ** p< 0.05, *** p< 0.01

Table D.3: Exploiting the Timing of Connection – Controlling for Selection into the Railway

	Dependent Variable: #Bankruptcies$_{i,t,s}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}$ (Ever Rail$_{i,t} > 0$) $\times$ Manufacturing$_s$	0.17***		0.16***	
	(0.04)		(0.04)	
$\mathbb{1}$ (Not Yet Rail$_{i,t} > 0$) $\times$ Manufacturing$_s$		0.09**		0.08**
		(0.04)		(0.04)
$\mathbb{1}$ (Rail$_{i,t} > 0$)			0.15	0.13
			(0.14)	(0.15)
$\mathbb{1}$ (Rail$_{i,t} > 0$) $\times$ Manufacturing$_s$			0.24***	0.31***
			(0.08)	(0.08)
Observations	7481	7481	7481	7481
Pseu. R^2	.813	.813	.813	.813
Geo FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓
Sector Employment$_{i,s,t}$	✓	✓	✓	✓
Coal$_i$ $\times$ Manufacturing$_s$	✓	✓	✓	✓
Port$_i$ $\times$ Manufacturing$_s$	✓	✓	✓	✓
London$_i$ $\times$ Manufacturing$_s$	✓	✓	✓	✓

Notes: Table reports results from PPML regressions at the grid cell-sector-census year level. The dependent variable is the annualized number of bankruptcies that occurred between two census periods. The main explanatory variable is an indicator for a grid cell i having at least one rail station recorded in census year t. The main control variables are the number of people employed in sector s and the straight line distance to the nearest city with coal deposits, to the nearest port, and to the city of London. In addition, regressions control for an indicator whether a location receives a station at any point until 1950 (Columns 1 and 3), and an indicator whether a location receives a station until the next census year (Columns 2 and 4). Standard Errors in parentheses are clustered at the grid cell level, * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$