Financial development and patents during the First Industrial Revolution: England and Wales

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[Preliminary draft, please do not circulate]

Abstract

Using a district-level dataset on patents and banks in England and Wales during the First Industrial Revolution, I show that better access to financial services increased patents of invention between 1750 and 1825. My baseline estimation includes district and year fixed effects. I also construct an instrumental variable based on the locations of historical post towns before country banks appeared. Better banking access increased patents by lowering local financial costs. The effects are larger for the patents in the manufacturing sector that lacked credit, and in districts where credit supply was insufficient.

Keywords: banking access, patents, post towns

JEL code: N23 O30 R12

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1 Introduction

Did the development of country banks in England and Wales increase patenting between 1750 and 1825? Country banks were small private banks outside London with at most six partners. There were only ten country banks in 1750, but there were about 650 of them with more than 850 offices all over England in 1810[2]. Evidence about the contribution of banks to innovation during the First Industrial Revolution remains qualitative. There is only contrasting evidence from different cases in which bankers favoured or rejected innovative projects (Brunt, 2006; Allen, 2009a). The limited coverage of qualitative evidence creates scope for the use of quantitative analysis to improve our understanding of how banks affected innovation during the First Industrial Revolution. The relationship between finance and innovation is important in understanding the finance-growth nexus (Schumpeter, 1961; King and Levine, 1993). Both modern and historical evidence from the United States shows that banking access increases innovation, especially for innovative firms that rely heavily on external finance (Nanda and Nicholas, 2014; Cornaggia et al., 2015). The role of bank loans in the operation of firms remains underexplored. In this paper, I seek to understand how short-term credit provided by banks contributed to innovation during the British Industrial Revolution, using a setting where banks generally provided short-term credit to borrowers.

In this paper, I introduce a new dataset on patents and country banks in England and Wales between 1750 and 1825. I collect the dates of patents and the names, locations, and occupations of patentees from a chronologically arranged index of patents of invention in England (Woodcroft, 1854). The data on country banks is digitized from Dawes and Ward-Perkins (2000). I map patents and country banks into 595 distinct registration districts[3] outside London and Middlesex. My baseline regression is a two-way fixed effects model, estimated using ordinary least squares (OLS). I control for district and year fixed effects and explore whether increasing banking access affects the number of patents per capita in the corresponding district during the British Industrial Revolution. My baseline OLS estimates show that the elasticity between banking access and innovation ranges between 0.044 and 0.049. The estimated result corresponds to about 6% of a standard deviation increase in the

[2] Calculated based on the list of country banks in Dawes and Ward-Perkins (2000).

[3] They are consistent registration districts in 1851, taken from Satchell et al. (2017).

dependent variable in response to one standard deviation increase in the independent variable.

As the OLS estimation is subject to endogeneity concerns due to omitted variables, I employ the instrumental variable (IV) strategy. My principal instrument is constructed based on historical post-town status following Heblich and Trew (2019). Country banks were more likely to operate in post towns for safety, information and demand for financial services from the postal system (Dawes and Ward-Perkins, 2000). I use the fact that the number of country banks per capita grew faster in districts with post towns than in those without post towns to construct my instrument. My instrument is the interaction of the dummy of post towns recorded in *Britannia* (Ogilby, 1675) with the linear year variable. The elasticities returned by IV estimation are larger than OLS estimates, ranging from 0.163 to 0.218. The difference in magnitudes might be resulted from banks established in agricultural areas to collect deposits and invest in London, the large increase in credit supply by the Bank of England after 1797 that offset the advantages of post towns and measurement error in banking access.

To understand the mechanisms that drive the effects of country banks, I turn to the effects in different sectors and regions with different credit supply. I show that the effects are mainly driven by patents in the manufacturing sector and larger in districts with tighter credit constraints. The results show that country banks promoted industrial patents mainly by lowering the financial costs of industrialists that lacked access to credit. I also extract information from inventors' and bankers' biographies to provide qualitative evidence about how banks contributed to invention.

I also show that my results are robust to different specifications, patent count windows and transformations of the dependent variables. The results survive when I use subsamples with at least one country bank or one patent during the period that I examine.

This paper contributes to the literature on the role of financial development and banks during the Industrial Revolution. The Financial Revolution preceded the Industrial Revolution (Neal, 1990) and provided the necessary financial tools for industrialization in the second half of the 18th century (Neal, 1994). Country banks contributed to multiple industries mostly by providing short-term credit in the form of inland bills of exchange (Pressnell, 1956). Generally, long-term investments and invention projects are too risky for country banks due to their limited sizes (Michie, 2016; Voth, 2018). Country banks mainly provided short-term credit by bill discounting and rediscounted the bills with other purchasers (Michie, 2016). Therefore, it is possible that banks complemented working capital of industrialists by providing short-term credit (Pollard, 1964; Crouzet, 1972). Banks were also unwilling to lend to outsiders due to information asymmetry (Hudson, 1986). Meanwhile, the development of public finance and wars in the 18th and early 19th century have crowded out loans in the private credit market (Temin and Voth, 2013). Evidence about the contribution of country banks to industrialization is thin, as the number of country banks in industrial North England is lower than other regions (Mokyr, 2009; Voth, 2018).

There is less evidence about the impacts of country banks on innovation than on industrialization during this period. It is argued that some country banks lent like modern venture capital firms to finance the adoption of new technologies (Brunt, 2006). In contrast, Richard Arkwright was refused when he attempted to borrow enough money to build his first water frame model (Allen, 2009a). If people that failed in invention also failed to leave records, selection in case studies will lead to bias towards the claim that bankers promoted invention by providing credit[4]. My study fills in the gap and provides the first piece of quantitative evidence about the impacts of banks on innovation during the British Industrial Revolution. I also complement my quantitative evidence with cases from biographies of inventors and bankers during the Industrial Revolution.

This paper also engages with the literature on the relationship between financial development and innovation. A large literature has documented the importance of financial development in promoting innovation (King and Levine, 1993; Hall and Lerner, 2010; Hsu et al., 2014). Traditional widsom believes that debt markets serve innovation poorly (Williamson, 1988; Beck and Levine, 2002; Hall and Lerner, 2010; Brown et al., 2012). Commercial banks and debtholders are risk-averse and bias against risky research and development projects (Rajan, 1992; Hsu et al., 2014).

Both modern and historical evidence from the United States shows that banking competition increases credit supply and promotes innovation, especially new

[4] The refusal of Richard Arkwright by bankers is recorded because he finally managed to build his water frame and made a fortune.

innovative firms in the industries that rely heavily on external finance (Amore et al., 2013; Chava et al., 2013; Nanda and Nicholas, 2014; Cornaggia et al., 2015; Mao and Wang, 2022). Enhancement in borrowers' risk tolerance increases investments in research and development (Chang et al., 2019) while credit constraint reduces invention and innovation (Giebel and Kraft, 2019; Hardy and Sever, 2021; Granja and Moreira, 2022). This paper adds evidence of the impacts of working capital on innovation, using the setting of country banks in Egland and Wales. The durations of loans from English banks were short, usually three months for bills of exchange during the First Industrial Revolution (Michie, 2016) and on average half a year in late 19th century (Braggion et al., 2017).

The remainder of this paper is organised as follows. Section 2 briefly introduces the historical background and the instrumental variable that I employ. Section 3 discusses my empirical strategy and data source. In section 4, I report the baseline results, validity tests of the instrument, and robustness checks. In section 5, I explore the mechanisms and Section 6 concludes the paper.

2. Background

2.1 Patents of invention

To measure innovation during the British Industrial Revolution, I rely on patent statistics (Sullivan, 1989; Sullivan, 1990). I collect the names, occupations, and locations of patentees and the application date of patents from a chronologically arranged index of patents (Woodcroft, 1854). I construct my district-level measurement of innovation based on patent counts in the baseline regression. For patents that are acquired by several people, I count it as separate patents for each patentee in the baseline regression. In robustness checks, I divide the patent equally among all patentees and count the number of divided patents.

Nuvolari and Tartari (2011) constructed a measurement of the quality of patents during the British Industrial Revolution based on a reference index of patents (Woodcroft, 1862). They argued that their quality indicator, the adjusted *Woodcroft Reference Index* could reflect both the quality and economic values of patents during the Industrial Revolution. Therefore, I complement my patent data with the adjusted *Woodcroft Reference Index* proposed by Nuvolari and Tartari (2011) in robustness checks.

Inventions can be categorized into microinventions and macroinventions that mark the most important technological breakthroughs during the First Industrial Revolution (Mokyr, 1990, p. 13). Microinventions are minor improvements to existing techniques that increase productivity and respond to economic incentives and changes in prices. Due to the nature of scarcity and randomness of macroinventions (Nuvolari et al., 2021), my analysis is more helpful in explaining the differential growth trends of microinventions across different districts in England and Wales.

2.2 Country banks

In the 18th century, major financial intermediaries in England included London private bankers that came from goldsmiths and scriveners, and country banks outside London (Neal, 1994). Attorneys also played an important role in Lancashire and Yorkshire. Country banks are small private banks outside London with no more than six partners (Michie, 2016). Due to the Bubble Act in 1720, country banks could not be formed as joint-stock companies and operated with unlimited liability.

Therefore, country banks were small and vulnerable to external risks, as the average capital of country banks was about £10,000 by the end of the eighteenth century (Pressnell, 1956). Using GDP per capita as the unit of measurement, £10,000 in 1750 is worth about 21 million pounds in 2016 and £10,000 in 1825 is worth about 9.3 million pounds in 2016 (Beers et al., 2020).

Country banks provided short-term credit by discounting bills and providing overdrafts, and issued notes to facilitate transactions (Pressnell, 1956; Crouzet, 1972; Calomiris and Haber, 2014). Country banks purchased short-term bills of exchange signed by merchants and industrialists at a discounted price (Michie, 2016). The bankers had different choices after purchasing bills, including selling bills to other local banks, sending bills to the London market, or waiting until maturity. Although the returns to industrial investments were high (Ventura and Voth, 2015), the usury law placed a 5% cap on the interest rates that banks could charge (Voth, 2018). Therefore, long-term loans were not cost worthy for country banks. Country banks were generally reluctant to lend extensively, except for clients that they knew well (Hudson, 1986) or industries that they had good knowledge about (Brunt, 2006).

The number of country banks and their branches was only 10 in 1750 and reached 395 in 1795[5]. During the Napoleonic War, people panicked and tended to exchange Bank of England notes for gold. The suspension of convertibility in 1797 made it possible for the Bank of England to increase money supply without the constraint of gold reserve. Between 1796 and 1810, the notes issued by the Bank of England more than doubled, and the amount of bills discounted quadrupled (Michie, 2016). The number of banks and their branches rose to about 1000 in 1810. However, these new banks were weaker and more risk-taking than earlier ones and failed faster (Michie, 2016; Heblich and Trew, 2019). 240 country banks failed due to loans to investments in farms that yield low returns (Ventura and Voth, 2015) between 1814 and 1816 (Powell, 1916, p. 124)

The groups that country banks served were limited (Hudson, 1986) to familiar regions and industries to alleviate the problem of information asymmetry. Established by textile merchants, Bros. Swaine & Company in Halifax mainly served borrowers mostly in the textile industry near its location (Hudson, 1986). There are also exceptions like the extensive loans from Ed. Byrom, Wm. Allen, Roger Sedgwick & Ed. Place in Manchester to Livesey, Hargreaves, and Company in Walton-le-Dale (Riello, 2010). The borrower was connected to William Allen, one of the partners of the bank, by marriage.

Due to the limited information of country banks available today, I measure banking access using the natural logarithm of one plus the number of country banks per million people. I collect the locations and opening years of country banks from Dawes and Ward-Perkins (2000). I map country banks into 595 registration districts outside London and Middlesex.

The legal restriction on country banks lasted until the Country Bankers Act in 1826 (Pressnell, 1956; Michie, 2016). Joint-stock banks became legal in areas more than 65 miles away from London. Some country banks began to merge into new joint-stock banks. Therefore, I stop the sample by 1825 because the usage of bank counts implicitly assumes that the sizes of banks were similar. The establishment of joint-stock banks makes my baseline measurement of banking access inappropriate for the period after 1825.

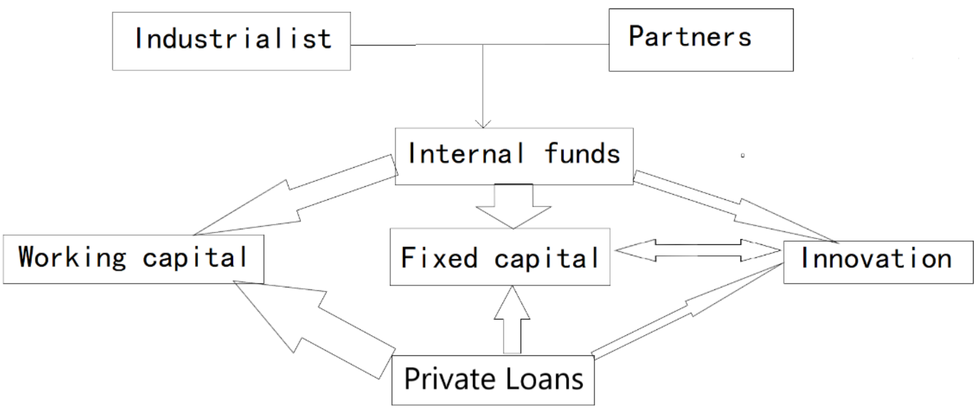
[5] Based on my calculation from the list of country banks provided in Dawes and Ward-Perkins (2000).

Evidence about the contribution of country banks to innovation during the Industrial Revolution remains anecdotal. There are examples that country banks contributed to the adoption of the latest technology. Praed & Co. in Truro provided loans to copper mines in Cornwall to adopt Boulton-Watt steam machines and made large profits (Brunt, 2006). However, there are also examples that banks refused to help innovative partners and firms. Richard Arkwright was refused by two Nottingham bankers because they believed that his water frame did not have a large chance to succeed (Allen, 2009a).

2.3 Theoretical framework

During the First Industrial Revolution, industrial enterprises relied mostly on internal funds accumulated from retained profits (Crouzet, 1972). Industrialists can allocate internal funds freely among working capital, fixed capital and innovation. They can attract partners to enlarge the pool of internal funds and form partnerships. Industrialists could also rely on private loans provided by people that they knew well and knew them well.

After country banks entered, they provided short-term credit by bill discounting and overdrafts to industrialists and rediscounted bills with other purchasers (Michie, 2016). The provision of short-term credit by banks complemented working capital of industrialists and enabled them to allocate more internal funds to fixed capital investments and innovation (Pollard, 1964; Crouzet, 1972). The impacts of banks are illustrated in Figure 1.



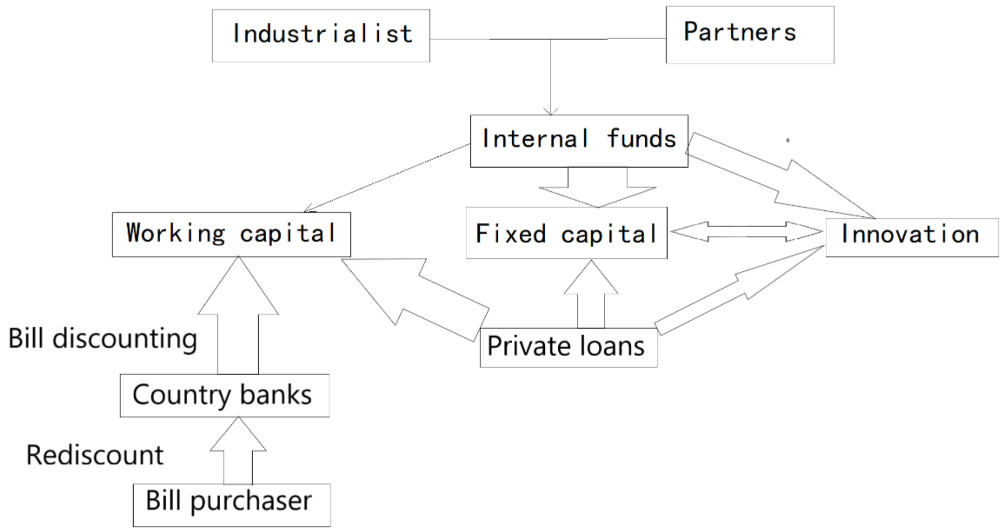


Figure 1 The upper panel illustrates funding of industrialists before country banks entered and the lower panel illustrates the case after country banks entered

3. Empirical strategy

3.1 Summary statistics

My analyses are at the level of registration district, the smallest unit that all patents and banks can be mapped into. I use the fixed boundaries of registration districts in 1851 (Satchell et al., 2017) and do not need to address the changes of boundaries over time. There were 624 registration districts across England and Wales and 595 of them were outside London and Middlesex.

I choose 5 years as the window of patent counts that is longer than the standard 3-year window in the literature about modern patents because the speed of invention and patent applications might be lower when the spread of information was much slower. Therefore, the panel data is made up of 595 districts and 15 periods (t=1750, 1755, …, 1820).

[Insert table 1]

Descriptive statistics are shown in Table 1. I use data from the years of 1750, 1780, 1800, and 1820 to show changes in the number of patents, the number of banks, and time-varying controls. While the population grew by about 40% in the second half of the 18th century, the number of patents increased by about 10 times and the number of banks increased by almost 50 times. Meanwhile, there was a significant fall from 60 hours in 1750 to 25 in 1780 in the mean travelling time to London.

Improvements in horses and coaches brought about slow decrease in the traveling time to London after 1780.

3.2 Time-varying control variables

I include a few time-varying control variables. They include the natural logarithm of population, the natural logarithm of one plus number of newspapers within 50 km, access to navigable waterways, and the natural logarithm of hours taken to travel to London via turnpike roads.

District-level population data for 1801, 1811 and 1821 is collected from census reports (Southall, 2007). I use interpolation to fill in the data for the years between 1801 and 1825, assuming that the population grew at a constant rate between each two consequent census years. To calculate district-level population before 1801, I use extrapolation based on population data from the 1801 Census, assuming that the population growth rates in the same county are the same between 1750 and 1800. I calculate county-level population growth rate based on the estimates of the county-level population by Wrigley (2007).

To control for access to information, I control for the number of newspapers published within 50 km of a district. I collect the locations and surviving periods of newspapers from Richard Heaton's Index to Digitalised British and Irish Newspapers (Heaton, 2015). I measure access to information using the number of newspapers published within 50 km from the centroid of the district. 50 km was approximately the distance that newspapers could cover and influence in the 18th century (Black, 1991).

Canals were important in the transportation of bulk (Bogart et al., 2017). Based on the historical map of waterways in England and Wales in 1820 (Satchell and Shaw-Taylor, 2018). I retrieve the waterway map with descriptions of navigable waterways from 1750 to 1810 by the London Canal Museum[6].

I also control for traveling time to London for passengers using turnpike roads. People could collect information and read patent archives in London in person and lower transportation time facilitated information collection. To calculate traveling time to London, I use the turnpike road network by Rosevear et al. (2017). Bogart (2005) calculates the average traveling speed on turnpike roads in the 18th and early 19th century. Assuming that passengers travel 2 km per hour from their residence to

[6] The descriptions can be found at https://www.canalmuseum.org.uk/history/menu-decades.htm.

the nearest turnpike roads, I calculate traveling time to London as $T_{i,t} = \frac{Turnpike\ distance_{i,t}}{Turnpike\ speed_{i,t}} + \frac{distance\ to\ Turnpike\ Road_{i,t}}{normal\ speed_{i,t}}$.

3.3 Baseline estimation

I test the relationship between banking access and patents using a two-way fixed effect model as in equation (1). The identification variation comes from the change of banking access, the independent variable, above common trends given by district and year fixed effects.

$$ln[1 + N(Patents/Population)_{i,t+1\ to\ t+5}] = \beta_0 + \beta_1 * ln[1 + N(Banks/Population)_{i,t}] + x'_{i,t}\gamma + \delta_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

$N(Bank/Population)_{i,t}$ is the number of country banks per million people in district i in year t and $N(Patent/Population)_{i,t+1\ to\ t+5}$ is the number of patents per million people[7] in district i from year t+1 to year t+5, within 5 years after year t. $x'_{i,t}$ are time-varying controls. δ_t is year fixed effects and δ_i is district fixed effects. In baseline regression, I estimate Equation (1) using OLS. The standard errors are clustered at the registration district level in the baseline regression.

[7] The unit of population is million people as the number of patents per capita and number of banks per capita were so small that the ln(1+x) transformation approximates more to x instead of ln(x). Based on the summary statistics, the mean numbers of patents and banks per capita were about at the order of magnitude of 10^{-5},

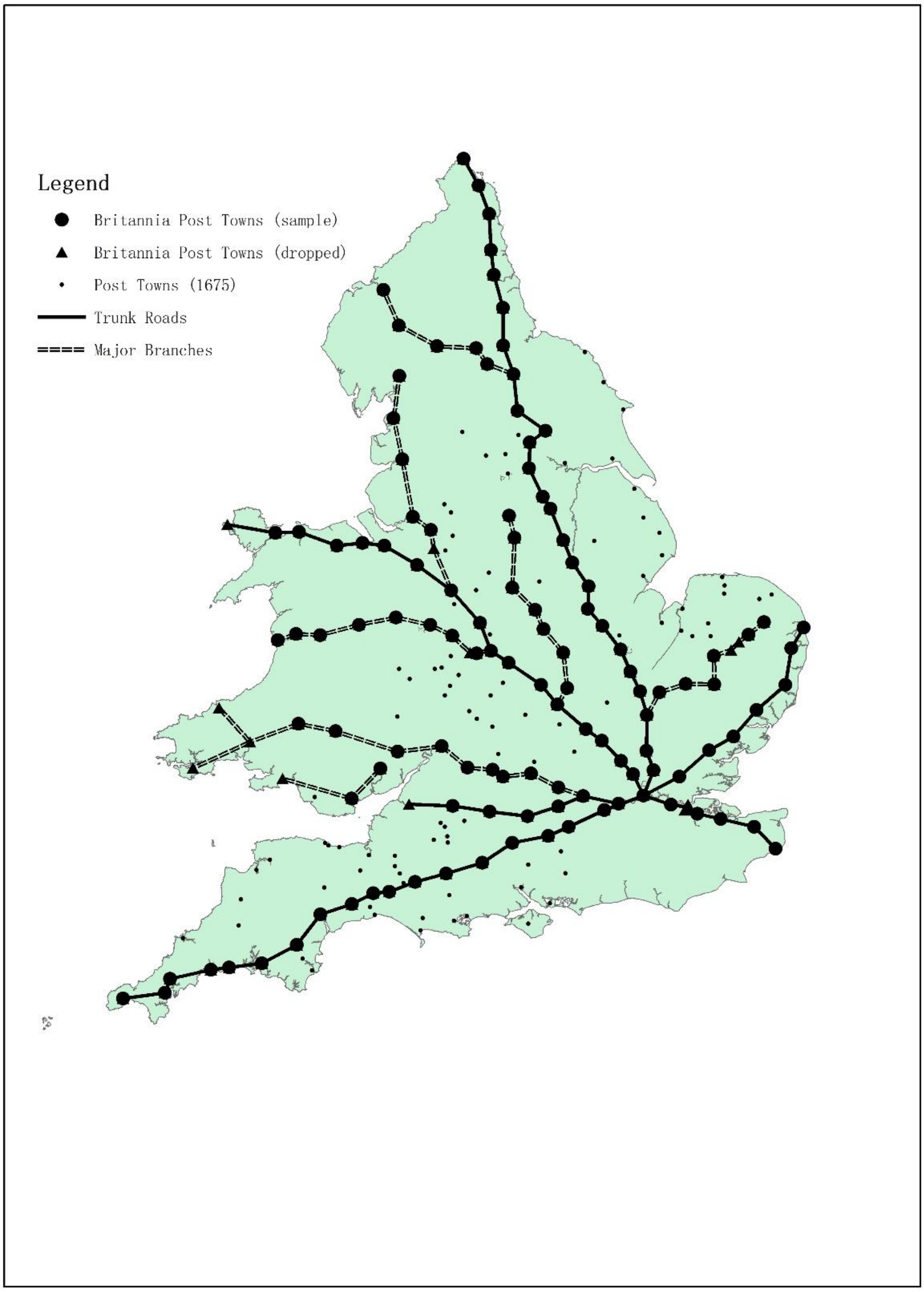


Figure 2 Post roads in 1675. This figure shows the main post roads recorded in Britannia compiled by John Ogilby in 1675. Post towns in the sample are shown in large dots and triangles are some of the post towns dropped due to too large or too small gap distances. The solid lines are trunks while dashed lines are branches with sampled post towns.

3.4 Instrumental variable

Following Heblich and Trew (2019), I use post-town status to construct the instrumental variable. To hear from strategic destinations on borders swiftly, the English government set up posts along the post roads that to provide fresh horses for couriers as early as during the reign of Henry VIII. Post roads were set up temporarily for wars and abandoned after wars due to high maintenance costs. In 1635, Thomas Withering revived the postal system on the basis of historical routes (Joyce, 1893). Post-houses that procured horses gradually became post offices and the towns that they were in became post towns.

The main post roads inherited the strategic aims to connect to Scotland, Ireland, and the European continent. In the 17th century, postmen changed horses every 15 miles on average to travel as fast as possible (Frajola et al., 2005; Heblich and Trew, 2019). Therefore, the locations of post towns were decided based on the physical strength of horses and road conditions in the 17th century. In the second half of the 18th century, traveling on roads became much faster (Bogart, 2005) but post towns remained.

There are several advantages of setting up a bank in a post town (Dawes and Ward-Perkins, 2000). They include better information access, safety for gold transportation and demand for financial services from postmen. Among the towns recorded in the *Universal British Directory* published in the 1790s, 130 out of the 150 towns with banks were post towns (Dawes and Ward-Perkins, 2000).

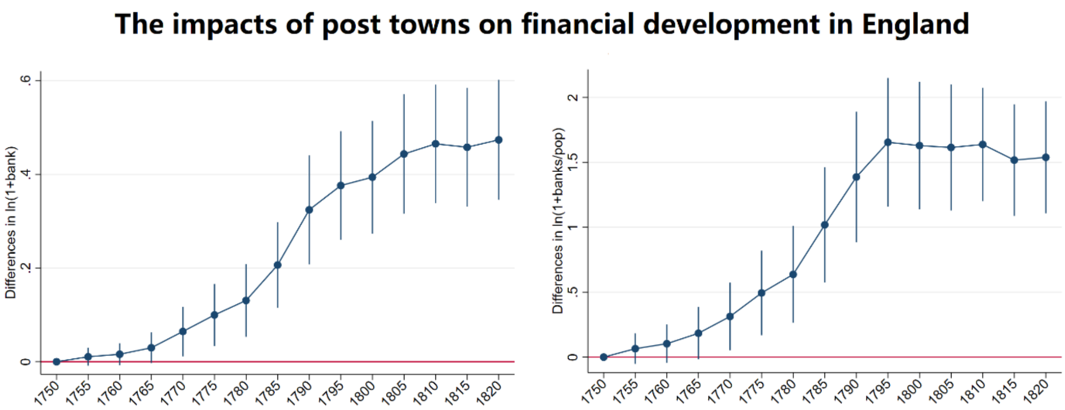


Figure 3 The impacts of post towns on country banks. The left figure shows the differences in ln(1+banks) across districts with and without post towns in different years. The right figure shows the differences in ln(1+banks/population) across districts with and without post towns in different years.

As shown in Figure 3, compared to 1750, the number of country banks and banks per capita grew faster in districts with post towns in 1675 than in districts without post towns. The suspension of convertibility offset the advantages of post towns between 1795 and 1825. I use the fact that the growth of the number of country banks was higher in districts with post towns than in districts without post towns to construct the instrument.

To construct the instrument, I interact the dummy of a post town locating in the district with the linear variable year. The list of post towns is collected from *Britannia* (Ogilby, 1675). I follow Heblich and Trew (2019) and drop the post towns whose distances to other post towns are smaller than 16 km or larger than 32 km. They have been selected due to some specific reasons instead of randomness. To rule out the effects of destinations of post roads that were likely to possess characteristics that affect the future growth rates of patents, I drop the destinations of all post roads[8] from the sample to rule out the selection of destinations according to population. The main idea is that post towns other than destinations became post towns simply because they were on the post roads that were designed to connect to strategic locations.

Identification is based on the exogeneity assumption that post-town status was not selected according to some unobserved pre-existing characteristics that affect patent growth trends in the future and the exclusion restriction assumption that post towns affected patents only through the channel of banks conditional on taking control variables into account.

[Insert Table 2]

In Table 2, I test whether post towns were selected according to some pre-existing characteristics that affect the growth of patents in the future. The characteristics that I assess include access to coal resources[9], access to seaports, the natural logarithm of the distance to the nearest seaports, the nearest coast[10], the natural logarithm of the area (in km^2), the average slope[11], and suitability for wheat, rye, barley and oats[12], the four main crops in England. Panel A in Table 2 shows that these pre-existing characteristics are not significantly different across districts with and without post towns in 1675.

I also control for other time-varying factors through which post towns might affect patents besides increasing banking access. I control for population, access to

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[8] Berwick is included in districts with post towns as the destination of the Northern Road is Edinburgh.

[9] The coal data is based on the parish-level data of Heblich and Trew (2019).

[10] The maritime data about coasts and sea ports is constructed based on Alvarez-Palau and Dunn (2019) and I have excluded the ports on rivers.

[11] The ruggedness data is calculated based on the SRTM data with the resolution of 90m. The unit of slope is percentage rise.

[12] The agricultural suitability is the crop suitability index (value) in the session of agro-ecological suitability and productivity in the Global Agro-ecological Zones (GAEZ) data published by Food and Agriculture Organization of the United Nations (FAO) spanning the period 1961–1990. I assume rain-fed water supply and low input.

waterways, traveling time to London on turnpike roads and the number of newspapers published within 50 km. Inland transportation of goods relied heavily on waterways while the transportation of passengers relied more on turnpike roads. The speed of turnpike road trips increased a lot between 1750 and 1825 (Bogart, 2005). People outside London gained access to information in London, where the Patent Office was in, from newspapers (Black, 1991) and this was likely to include information about recent patents. Newspapers were usually circulated within the local county in late 18th century.

Panel B of Table 2 shows that access to the transportation network and information was not significantly different across districts with and without post towns. Population growth is slower in districts with post towns and results in OLS regression show that population is positively correlated with patents. In robustness checks, I use different sets of post towns to construct alternative instruments.

4. Results

4.1 Baseline results

Table 3 presents my baseline estimation results of how banking access affected innovation in the 595 sampled registration districts outside London and Middlesex. Column (1) reports OLS estimates with only district and year fixed effects and column (2) includes time-varying control variables. Column (3) and (4) show analogous specifications for my instrumental variable estimates. Column (5) and (6) show corresponding first stage results of the IV estimation in column (3) and (4). Note that there are fewer observations in the IV estimation as I dropped the destinations of post roads.

[Insert Table 3]

My OLS estimates suggest that the elasticities of patents per capita with respect to banks per capita range from 0.044 to 0.049. At the mean value of the independent variable, one standard deviation increase in the independent variable (1.306) increases the dependent variable by 5.97% to 6.70% of a standard deviation. This translates into an increase of 15% in the number of patents per capita in the next five years. The increases of banks from 1750 to 1820 explain about 12% of the increases in patenting.[13] My instrumental variable estimates are larger. The elasticities implied by IV estimation range from 0.163 to 0.218 and the effects expressed in standard deviation range between 22.2% to 29.7%.

IV estimates are about 5 times as large as OLS estimates. There are several plausible reasons for these differences. One is a bias towards zero due to omitted variables that predict growth of banks but lower growth of patents. Banks set up in agricultural areas collected deposits and made use of a large amount of them in the London market (Pressnell, 1956, p. 76). These banks were mainly in Southeast England (Joplin, 1837) that grew much more slowly than the industrializing Northwest England (Kelly et al., 2023). Controlling for the interaction of agricultural suitability makes the OLS coefficient larger, as shown in column (1) in Table A7.1.

Another possible explanation is the difference between local average treatment effects estimated by IV and average treatment effects of the whole population. The suspension of convertibility in 1797 stopped the public from exchanging Bank of England notes for gold. The amount of notes issued by the Bank of England doubled and the amount of bills discounted by the Bank quadrupled in 14 years (Michie, 2016). Increased liquidity provision increased entries of banks that were more speculative than earlier banks (Heblich and Trew, 2019). 240 country banks failed due to loans to agricultural investments (Powell, 1916) that yielded low returns (Ventura and Voth, 2015). According to Figure 3, districts where the growth speed of banks per capita were higher than the common trend predicted by district and year fixed effects before 1797 had similar growth speed in banking access after 1797. The advantages brought about by post towns were offset.

As shown in column (1) and (2) of Table A3, the OLS estimates for the subsample before the suspension of convertibility range between 0.080 and 0.081, almost twice as large as the results in the baseline regression. Meanwhile, the IV estimates range between 0.198 and 0.236 as shown in column (3) and (4), close to the results in the baseline regression. The first-stage regression coefficients are also larger than in the baseline regression as shown in column (5) and (6). It is likely that compliers, districts before 1797, were placed more weights on in IV estimates.

[13] The mean of the main independent variable increases from 0.0756 to 2.8673 while the mean of the independent variable increases from 0.1442 to 1.1477. (2.8673-0.0756)*0.0437/(1.1477-0.1442)≈12.2%.

Another potential explanation is measurement error in measuring banking access. The number of banks per capita does not capture the differences in assets, loans and operating strategies of different country banks. Also the habits of using banks varied in different districts (Pressnell, 1956, p. 244). Another possible concern is weak instrument. According to Table 3, the Kleibergen-Papp F statistics range from 47 to 50. It is unlikely that weak instrument is a plausible explanation in my setting.

4.2 Instrument validity

For robustness, I also use different subsets of post towns to construct the instrument. I show the results of 2SLS regressions using different instruments in Table A4. Column (1) and (2) are the same as column (3) and (4) in Table 3. In column (3), I drop the post towns on the post roads connecting to Derby, Kendal, and Carlisle from the post town set. As Derby and Kendal are not near borders and the post road to Carlisle was redesigned in 1635, it is likely that connection to these destinations involved economic concerns. Comparing to column (2), the coefficient drops by about 15%. In column (4), I drop detouring points on post roads which might be more prosperous[14]. In column (5), I further restrict the range of post towns to those with populations smaller than 5,000 in 1600 (Bairoch, 1991). The results add to my confidence in the validity of my instrument.

Concerns about post roads exist. Post roads were safer for the transportation of gold (Dawes and Ward-Perkins, 2000), it is likely that districts crossed by post roads had different growth trends in banking access. In Section 2, I have argued that districts with and without post towns were balanced in pre-existing characteristics. It is unlikely that post towns were selected based on some pre-existing characteristics that affected the growth of patents in the period that I examine. There is also no evidence that time-varying variables that measure access to transportation networks and information were different across districts with and without post towns. Balance test results are reported in Table A2. Pre-existing characteristics and time-varying controls are not significantly different in districts with post towns from districts without post towns.

To exclude the possible impacts driven by omitted variables that existed on post roads, I do permutation tests. There were 383 districts that were crossed by some post

[14] For example, there is a detour that goes to York, one of the most important English cities.

roads and there were post towns in only 112 of them. In the permutation test, I randomly assign post towns to 112 of the 383 districts that were crossed by some post roads. As I cannot exhaust all possible combinations, I do 1,000 randomizations, rerun the IV estimation, and compare the coefficients to the estimates in the baseline regression reported in Table 3.

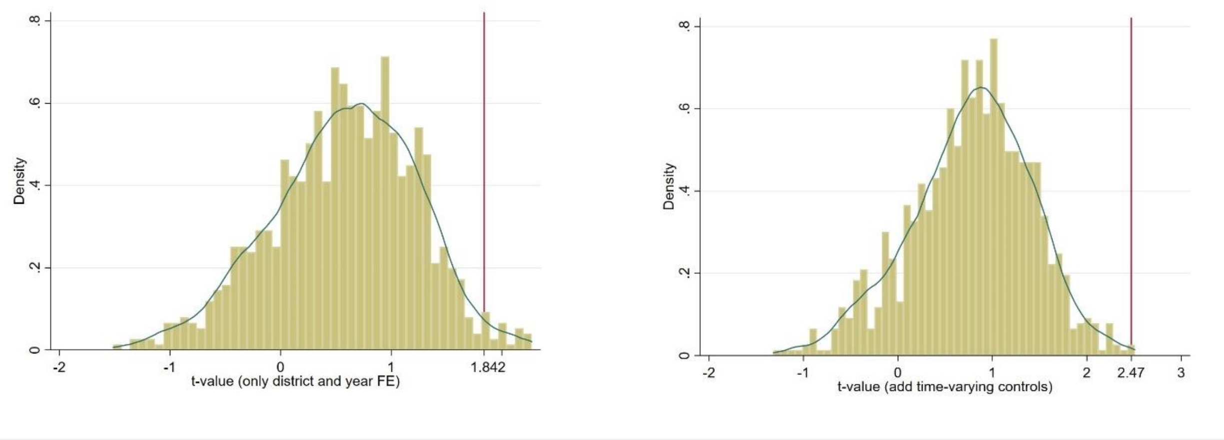

Figure 4 The distribution of t-values estimated in IV regressions based on random samples

Figure 4 shows the histograms of t-values calculated using random post town samples on post roads. In the left panel, I show the results of the setting with only year and district fixed effects. The t-value in the baseline regression is 1.842 and is larger than 98% of the t-values calculated based on randomized samples. In the right panel, I add time-varying controls into the regression. The t-value in the baseline regression is 2.47 and it is among the top 3 largest t-values calculated from the random samples. The results show that it is unlikely that some omitted factors related to post roads drove the empirical results that I observed.

I also conduct placebo tests to test the validity of my instrumental variable. As post roads were designed to connect London to strategic locations, I draw straight pseudo post roads between London and the destinations of post roads. Then I create placebo post towns that divide pseudo post roads into equal distances that are approximately equal to 24 km, the average distances between real post towns. I use placebo post towns to construct instrumental variables and do IV estimation.

The results of placebo tests are reported in Table A5. I create placebo post towns on pseudo post roads connecting to all. I control for only district and year fixed effects in column (1) and add time-varying controls in column (2). The IV estimates are negative and insignificant. The first stage coefficient in column (1) is positive and significant, but is only 1/3 the size of the coefficient in the baseline regression, as shown in column (5) of Table 3. The first stage coefficient in column (2) is insignificant. The KP F statistics is only about 4.2 in column (1) and 2.6 in column (2). In column (3), I drop placebo post towns on the pseudo post roads that did not connect London with the borders, and I further restrict the placebo post towns to those connecting only to strategic destinations in column (4). Placebo post towns predict banking access poorly. As terrains might affect the speeds of horses, the distances between real post towns would not strictly be 24 kilometres. It is unlikely that specific locations on specific roads connecting London and borders affected banks and patents.

4.3 Robustness checks

4.3.1 Patent and bank counts

I discuss the robustness of my results to different specification. If patents and banks can only be accessed by some wealthy people, per capita number of country banks might not be a good measurement of banking access. Such is also the case for number of patents per capita. Therefore, I replace the dependent variable with the natural logarithm of one plus number of patents in the next 5 years and the independent variable with the natural logarithm of one plus the number of banks. Results are reported in Table A6.1. I report OLS estimates in column (1) and (2). IV estimates are in column (3) and (4), while first-stage results are in column (5) and (6). In Column (7) and (8), I measure innovation by number of patents and estimate a count model as there are many 0's, some 1's and 2's and a few larger number in patent counts. Consistent the baseline results, better banking access is correlated with larger patent numbers.

My results can be compared to another research about how banks affected patents in the future 3 years in the 19th century (Mao and Wang, 2022). Mao and Wang (2022) consider the changes in the number of patents and free banks at the county level within 3 years of the passage of free banking laws. The elasticities that they estimate are about 0.36 in Antebellum America. My estimates using a similar setting are about 0.080 as shown in Table A6.2.

The impacts of English country banks on patents were much smaller than free banks in Antebellum America. It is likely to be due to the smaller sizes and more conservative operations of country banks in England comparing to American free banks. The estimated average capital of country banks was about ￡10,000 by the end of the eighteenth century (Pressnell, 1956). While the average free bank assets in Antebellum America were about 500,000 US dollars (Mao and Wang, 2022). Considering that the exchange rate between pounds sterling and US dollars was about 1:5 (Davis and Hughes, 1960) in the 19^{th} century. An average country bank was about one-tenth as large as an average American Free Bank. Due to their small sizes and the 5% interest cap placed by the usury law, country banks were more focused on provision of short-term credit. Their peers in Antebellum America actively sponsored manufacturers and small businesses and were widely involved in innovation and entrepreneurship (Mao and Wang, 2022).

4.3.2 Additional robustness checks

First, I control for the interaction of time-invariant controls[15] and year fixed effects, county and district linear trends to rule out the impacts of pre-existing characteristics and differential growth trends in banks and patents in different districts during the period that I examine. The results are reported in column (1) to (4) of Table A7.1. In column (5) to (8), I report OLS estimates similar to the setting in baseline regression and cluster the standard errors on the county level. Table A7.2 reports the results of using Conley standard errors. The results do not change significantly.

Next, I deal with concerns about the workhorse transformation of ln(1+x). Therefore, I use inverse hyperbolic sine model instead of ln(1+x) in measuring innovations. The results are reported in Column (1) and (2) of Table A8.1 and the coefficients are about 20% larger. Also, I use other methods to measure innovation. I first use a binary model, setting the dummy variable 1(patent>0) to be 1 if the number of patents in a district in the next five years is larger than 0 and 0 if there were no patents. Results are reported in Column (3) and Column (4). Better financial access is not only correlated with larger number of patents per capita, but also with the emergence of a patent. In Column (5) and (6), I use Poisson pseudo-maximum likelihood estimation. Consistent the baseline results, better banking access is correlated with larger patent numbers.

In the baseline regression, my dependent variable was constructed based on patentee counts. In Table A8.2, I also test whether the results are robust when I divide

[15] Time-invariant controls include latitude, longitude, natural logarithm of the area, natural logarithm of the distance to the nearest sea port, natural logarithm of the distance to the nearest coast, with coal fields, with sea ports, ruggedness and suitability of main crops.

patents among all the patentees that co-authored on one single patent instead of using patentee counts.

As mentioned in Section 2.1, simple patent counts might not reflect the quality of patents. I weight the patents using the *Woodcroft Reference Index* and the adjusted index proposed by Nuvolari and Tartari (2011) to reflect the economic values and importance of patents during the First Industrial Revolution. The results are reported in Table A9.1 and Table A9.2. Country banks not only led to more patents, but also patents of higher quality.

The window that other scholars (Cornaggia et al., 2015) use for patent counts is 3 years. Inventors began to use scientific methods in their works (MacLeod, 1988) but standardized methods and procedures did not exist yet by then. There were few professional inventors or research and development professions, therefore, research and development activities in the 18^{th} century might take longer time than today. In baseline regression, I use 5 years as the window and count patents from year t+1 to year t+5 as shown in equation (1). In Table A10, I report the results of using the windows of 3 years and 10 years and the results are still robust.

There were few patents in districts without country banks, so including districts without banks would make the effect larger. I run the regression in districts ever with at least one country bank during the period I examine in case that the result is driven by districts without country banks. The results are reported in column (1) to (4) in Table A11. As expected, the coefficients are smaller than the coefficients in the baseline. Similarly, to rule out the effects of districts without patents, I also run the regression in districts ever with at least one patent during the period I examine. The results are reported in column (5) to (8) in Table A11.

5. Mechanism

5.1 Heterogeneous effects on different sectors

The impacts of banks on patents vary in different sectors. To categorize patents, I divide the occupations of patentees into five groups based on the Primary-Secondary-Tertiary (PST) system (Wrigley, 2010). In Table 4, I report the effects of banks on patents acquired by people in agriculture and mining, manufacturing, trading, non-trading services and other occupations[16] respectively from column (1) to (5). Column (2) of Table 4 shows that the effects of banks on patents were mainly driven by patents acquired by patentees in the industrial sector. While only 58% of the patents in my sample were acquired by patentees working in the manufacturing sector, the coefficient in column (2) is almost as large as 90% of that in the baseline regression. The coefficient in column (2) is statistically different from the coefficients in other columns[17] and the impacts of banks on patents in the manufacturing sector are significantly larger than patents in other sectors.

[Insert Table 4 here]

Some patentees did not mention their occupations[18] and some people were merchants and industrialists at the same time. For robustness, I use the taxonomy proposed by Nuvolari and Tartari (2011) and categorize 21 different industries[19] into the agricultural and manufacturing sector. In column (1) of Table A12, I report the impacts of banks on patents in agricultural and mining sector. In column (2) of Table 6, I include only the industries that belong to the manufacturing sector without any doubt. I gradually add other industries[20] in column (3) to (6). The results are also consistent with the results shown in Table 4 that the impacts of banks were mainly driven by patents in the manufacturing sector.

The impacts of banks on patents were more expressed in the industrial sector. This is consistent with the theory that banks contributed to innovation by lowering financial costs of industrialists. Provision of short-term credit of country banks allowed manufacturers to keep lower cash reserves and spend more internal funds on fixed capital investments and innovation.

5.2 Credit constraints

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[16] One example of the patentees that belonged to other occupations is Archibald Cochrane, the 9th Earl of Dundonald. He patented for his new chemical in 1794.

[17] The χ^2 value of testing differences between the coefficients in column (2) and column (1), (3), (4), (5) are 8.27, 8.87, 4.05 and 12.04 respectively. The p-vales are 0.004, 0.003, 0.044 and 0.001 respectively.

[18] James Watt did not claim his occupation in the patent record of his famous steam machine in 1769.

[19] They are Carriages, vehicles and railways, Chemical and allied industries, Clothing, Engines (steam engines, water wheels), Furniture, Glass, Hardware (edge tools, locks, grates), Instruments (scientific instruments, watches, measuring devices), Manufacturing machinery (other), Metal manufacturing, Paper, printing and publishing, Pottery, bricks and artificial stone, Shipbuilding, Textiles, Construction, Leather, Military equipment and weapons, and Medicines (drugs, surgical and dental instruments, other medical devices).

[20] They are construction, leather, military equipment and weapons and medicines. See Table A13 for my classification of the 21 industries.

Due to financial frictions, interest rates in different districts in England varied. The return to investments in agriculture was lower than the return to industrial investments in UK (Allen, 2009b; Ventura and Voth, 2015). Districts in Southeast England possessed surplus funds while industrialists in Northwest England were constrained by credit (Joplin, 1837). In districts with higher interest rates, it is more likely that country banks have larger impacts on patents. As there were no systematic records of interest rates for Britain during the 18th century (Brunt and Cannon, 2009; Keller et al., 2021), scholar have rebuilt interest rates based on crop prices. Table A14 shows that different measurements of interest rates are negatively correlated with agricultural suitability. The interest rates in districts with below-median agricultural suitability are about 1.5% to 2.5% higher than other regions while the annual interest cap placed by the Usury Law was 5%. In Table 5, I test how the impacts of country banks on districts differ in districts with different agricultural suitability, and therefore different level of credit constraints.

[Insert Table 5 here]

In Table 5, I look into the heterogeneous impacts of banks on districts with higher agricultural suitability. I define a district suitable for a crop if the average crop suitability for this district is higher than the median crop suitability across England and Wales. In column (1) and (2) of Table 5, I look into the heterogeneous impacts of banks on patents in districts with different suitability for agriculture. I include only district and year fixed effects in column (1) and add time-varying controls in column (2). In column (3), I define a district as suitable for agriculture if crop suitability is higher than median for more than 1 crop. In column (4), I define a district as suitable for agriculture if crop suitability is higher than median for all crops. The interaction term of banking access and agricultural suitability shows that the impacts of banks are smaller in districts more suitable for agriculture. The results in Table 5 are also consistent with the theory that country banks promoted patents by lowering financial costs for manufacturing firms in districts subject to tighter credit constraints.

5.3 Qualitative Evidence

In this section, I provide qualitative evidence about several mechanisms through which country banks contributed to patents during the British Industrial Revolution. I extract the qualitative evidence from the biographies of some famous patents of invention.

Banks provided credit that complemented working capital to firms. Industrialists were able to invest more in innovation and it is more likely that engineers employed by industrialists created new patents. Byrom, Allen, Sedgwick and Place of Manchester, founded in 1771 (Smith, 2012), provided a large amount of loans to Livesey, Hargreaves and Company, a textile manufacturer in Preston, through the connection of marriage. Thomas Bell came from Scotland and worked at Livesey, Hargreaves Hall and Co. (Riello, 2010). In 1783, he registered a patent for a rotary printing machine that could print several different colours at the same time (Woodcroft, 1854). In 1784, he patented an updated version that could print in six colours (Donnachie, 2004).

Another mechanism is direct sponsorship. Country banks sometimes directly supported the invention and patent process, especially when the banker knows the client well. John Kendrew, a Quaker, and Thomas Porthouse from Darlington developed a flax-spinning machine in 1787 (Woodcroft, 1854). They were financially supported by James Backhouse, who was also a Quaker and founded a family bank in Darlington in 1774. James Backhouse not only supported them during the process of invention and patenting, but also helped them set up a small factory in the 1780s and 1790s (Cookson, 2003). The loans provided by the Backhouse's came from London bankers that received the deposits from bankers in rural areas, like the Gurney's in East Anglia (Ackrill and Hannah, 2001).

Some bankers directly participated in industrial production and led to patents. Walter Taylor of Southampton held 4 nautical patents as he was the owner of his family firm that produced wooden rigging blocks for the Royal Navy. In the 1780s, he formed a partnership in Southampton with Richard Moody, a banker and brewer (Dykes, 1999). Taylor patented an invention related to malting and brewing in 1786 (Nuvolari and Sumner, 2013). It is likely that the partnership with a banker and brewer have contributed to Taylor's patents in brewery.

Another potential mechanism is organising infrastructure construction and investments. In the late 18th and early 19th century, local bankers usually involved in the construction and financing of canals (Bogart, 2014). William Mackworth Praed from the Praed family[21] initiated the Grand Junction Canal and became the first Chairman of the canal company. In 1806, John Woodhouse patented boat lifts that was used for canals to deal with different elevations. John and his brother Jonathan were employed by the Grand Junction Canal in 1802 as members of a syndicate to complete the Bilsworth Tunnel (Petticrew and Austin, 2012) and became the area engineer of the Northern district of the company in 1805.

6. Conclusions

In this paper, I use panel data on banks and patents in England to argue that banks contributed to innovation during the First Industrial Revolution by providing short-term credit to industrialists. This paper presents new quantitative evidence on the contribution of banks to innovation using a setting where banks generally provided short-term credit to borrowers. I find that better banking access led to more innovation, as measured by the number of patents per capita, during the British Industrial Revolution. Registration districts where there were more banks witnessed a faster growth of patents between 1750 and 1825. Short-term credit promotes innovation by complementing working capital of industrialists and allowing more investments from internal funds in innovation.

My finding shows that a standard deviation increase in banking access would lead to a 15% increase in patents per capita in the following 5 years. The effects are smaller than free banks in Antebellum America and the smaller effects might be due to smaller sizes and more conservative operation strategies of country banks. I further show that the effects of banks are more expressed in the manufacturing sector and in districts that were subject to tighter credit constraints. Qualitative evidence extracted from the biographies of inventors and bankers show that banks contributed to innovation by providing credit, direct sponsorship and organising infrastructure construction. My finding supports the claim that financial development increases innovation and helps explain why some parts of England grew faster in the First Industrial Revolution from the perspective of finance.

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[21] The Praed family owned the Cornwall bank of Praed & Co that once lent a lot to copper mines to promote the usage of the Watt-Boulton steam machine (Brunt, 2006).

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Table 1 Registration-level descriptive statistics for four selected years, 1750, 1780, 1800 and 1820

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	year	N	mean	sd	min	max
number of patents in the next 5 years	1750	595	0.0370	0.214	0	2
	1780	595	0.195	0.769	0	10
	1800	595	0.420	1.279	0	12
	1820	595	0.822	3.390	0	46
number of country banks	1750	595	0.0168	0.129	0	1
	1780	595	0.166	0.572	0	5
	1800	595	0.840	1.286	0	8
	1820	595	1.506	1.880	0	14
population	1750	595	9,663	5,029	1,086	35,784
	1780	595	11,333	6,173	1,165	49,602
	1800	595	13,474	8,130	1,306	79,115
	1820	595	17,969	12,215	1,778	120,731
hours to London via turnpike roads	1750	595	60.48	37.51	0.453	187.4
	1780	595	25.52	14.96	0.289	84.29
	1800	595	20.63	11.88	0.209	74.35
	1820	595	17.37	9.974	0.197	66.87
access to waterways	1750	595	0.474	0.500	0	1
	1780	595	0.560	0.497	0	1
	1800	595	0.666	0.472	0	1
	1820	595	0.721	0.449	0	1
number of newspapers within 50 km	1750	595	4.267	15.49	0	67
	1780	595	7.486	25.21	0	109
	1800	595	8.466	28.00	0	121
	1820	595	9.790	29.27	0	128

Notes: This table presents summary statistics of country banks, patents and time-varying control variables. All variables are means across 595 registration districts outside London and Middlesex.

Table 2 Balance Tests of pre-existing characteristics and time-varying controls

		Coefficient	Standard Error
Panel 1: Pre-existing characteristics			
(1)	1 (Coal field in the district)	0.399	(0.535)
(2)	1 (Sea port in the district)	-0.0398	(0.0428)
(3)	Natural logarithm of the distance to the nearest sea port	0.105	(0.112)
(4)	Natural logarithm of the distance to the nearest coast	0.122	(0.143)
(5)	Natural logarithm of the area	-0.100	(0.114)
(6)	Average slope (percentage rise)	-0.644	(0.472)
(7)	Oat suitability	-0.610	(1.957)
(8)	Barley suitability	-0.526	(1.634)
(9)	Rye suitability	-0.411	(1.645)
(10)	Wheat suitability	-0.599	(1.647)
Panel 2: Time-varying characteristics			
(1)	ln (1+num of newspapers within 50 km)	0.00103	(0.000903)
(2)	ln (hours to London via turnpike roads)	0.000163	(0.000207)
(3)	ln(population)	-0.00113***	(0.000371)
(4)	1(waterway access)	-0.000121	(0.000739)

Notes: In Panel A, I report the results of regressing pre-existing time-invariant characteristic on the post town dummy. Panel A shows the differences in pre-existing characteristics across districts with and without post towns. In Panel B, I report the results of regressing time varying controls on the interaction of the post town dummy with linear year variable. Panel B shows the differences in growth rates of time-varying controls across districts with and without post towns. The coefficient column reports the coefficient of the main variable. Standard errors are clustered on the registration district level.

Table 3 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents/pop)				ln(1+banks/pop)	
	OLS		IV		First Stage	
ln(1+banks/pop)	0.0437***	0.0490***	0.163*	0.218**		
	(0.0145)	(0.0141)	(0.0884)	(0.0881)		
1(post town)*year					0.0285***	0.0280***
					(0.00400)	(0.00406)
Observations	8,925	8,925	8,775	8,775	8,775	8,775
Within R2	0.00204	0.0125				
KP F Statistics			50.66	47.55		
Time-Varying Controls	None	Yes	None	Yes	None	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
LHS SD	1.536	1.536	1.522	1.522		
RHS SD	2.099	2.099	2.077	2.077		
Standardized B	0.0597	0.0670	0.222	0.297		

Notes: Column (1) and (2) report OLS estimates of Eq. (1) and column (3) and (4) report the IV estimates. Column (5) and (6) report the first stage results of IV estimation. Time-varying controls include log population, log (1+newspapers in 50 km), log (traveling time to London) and access to waterways. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table 4 Heterogeneous effects on different sectors (by patentee's self-claimed occupation)

	ln(1+patents/pop)				
	(1)	(2)	(3)	(4)	(5)
	Agriculture & Mining	Manufacturing	Trading	Non-trading services	Others
ln(1+banks/pop)	0.00515	0.0393***	0.00495	0.0129	-0.00114
	(0.00317)	(0.0115)	(0.00506)	(0.00931)	(0.00100)
Observations	8,925	8,925	8,925	8,925	8,925
Time-varying Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District and Year	District and Year	District and Year	District and Year	District and Year
Clustering	District	District	District	District	District

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the natural logarithm of one plus the total number of patents acquired by patentees from different sectors in a district in year t+1 to year t+5 per million people in the district. Column (1) reports the result of patents whose patentees were from agriculture and mining. Column (2) reports the result of patents whose patentees were from the manufacturing sector. Column (3) reports the result of patents acquired by traders, column (4) reports the result of non-trading services and column (5) are other occupations. Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table 5 The impacts of banks in districts with different agricultural suitability

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.0792***	0.0724***	0.0749***	0.0746***
	(0.0206)	(0.0201)	(0.0207)	(0.0191)
ln(1+banks/pop)*1(agriculture suitable)	-0.0639***	-0.0415*	-0.0449*	-0.0487**
	(0.0243)	(0.0238)	(0.0241)	(0.0234)
Observations	8,925	8,925	8,925	8,925
Within R2	0.00389	0.0130	0.0131	0.0133
Time-Varying Controls	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year

Notes: Column (1) and (2) report the different effects of banks in districts with different agricultural suitability. I define a district suitable for agriculture if the crop suitability is higher than the median of crop suitability for more than 2 crops among oat, barley, wheat and rye. In column (1) I include only district and year fixed effects and in column (2) I add time-varying costs. In column (3), I define a district as suitable for agriculture if crop suitability is higher than median for more than 1 crop. In column (4), I define a district as suitable for agriculture if crop suitability is higher than median for all crops. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix

Table A1 Data sources

Data	Source	Notes
Patents	Woodcroft (1854)	correct errors in texts digitized by Google, geocode locations, and map into registration districts
Country banka	Dawes & Ward-Perkins (2000)	digitize, geocode locations, and map into registration districts
Post towns	Ogilby (1675)	
Population	Great Britain Historical GIS Project & Wrigley (2007)	extrapolation
Newspapers	Richard Heaton's Index to Digitalised British and Irish newspapers (2015)	
Turnpike road network	Rosevear, Satchell, Bogart, Sugden & Shaw Taylor (2017)	
Canals	Satchell & Shaw-Taylor (2018) & London Canal Museum	navigable waterways from 1750 to 1810 retrieved according to the records at https://www.canalmuseum.org.uk/history/menu-decades.htm.
Crop suitability	Global Agro-ecological Zones by FAO	
Slope	SRTM data with resolution of 90 metres	
Sea ports	Alvarez-Palau & Dunn (2019)	
Map of English registration district (and coast)	Satchell, Kitson, Newton, Shaw-Taylor & Wrigley (2018)	merged to one polygon to draw the coastline
Woodcroft Reference Index	Nuvolari & Tartari (2011)	
Taxonomy according to subjects	Nuvolari & Tartari (2011)	
PST system	Wrigley (2010)	
Crop prices	London Gazette	to use the result of Keller, Shiue & Wang (2021) in the future

Table A2 Robustness checks: balance tests on post roads

		Coefficient	Standard Error
Panel A: Pre-existing characteristics			
(1)	1 (Coal field in the district)	0.0488	(0.0545)
(2)	1 (Sea port in the district)	-0.0689	(0.0469)
(3)	Natural logarithm of the distance to the nearest sea port	0.205	(0.126)
(4)	Natural logarithm of the distance to the nearest coast	0.237	(0.155)
(5)	Natural logarithm of the area	-0.0542	(0.134)
(6)	Average slope (percentage rise)	0.155	(0.446)
(7)	Oat suitability	-2.279	(2.122)
(8)	Barley suitability	-1.764	(1.778)
(9)	Rye suitability	-1.638	(1.801)
(10)	Wheat suitability	-1.883	(1.805)
Panel B: Time-varying characteristics			
(1)	ln(1+num of newspapers within 50 km)	0.000843	(0.000992)
(2)	ln(hours to London via turnpike roads)	0.000161	(0.000220)
(3)	ln(population)	-0.000620*	(0.000373)
(4)	1(waterway access)	-0.000283	(0.000810)

Notes: In this table, I do balance tests across districts on post roads. In Panel A, I report the results of regressing pre-existing time-invariant characteristic on the post town dummy. Panel A shows the differences in pre-existing characteristics across districts with and without post towns. In Panel B, I report the results of regressing time varying controls on the interaction of the post town dummy with linear year variable. Panel B shows the differences in growth rates of time-varying controls across districts with and without post towns. The coefficient column reports the coefficient of the main variable. Standard errors are clustered on the registration district level.

Table A3 Before the suspension of convertibility in 1797

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents/pop)				ln(1+banks/pop)	
ln(1+banks/pop)	0.0797***	0.0811***	0.198*	0.236**		
	(0.0231)	(0.0227)	(0.104)	(0.102)		
1(post town) * year					0.0367***	0.0362***
					(0.00595)	(0.00593)
Observations	5,950	5,950	5,850	5,850	5,850	5,850
KPF			38.01	37.23		
Model	OLS	OLS	IV	IV	First Stage	First Stage
Time-Varying Controls	None	Yes	None	Yes	None	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year

Notes: This table reports the estimation results when I use the sample before the suspension of convertibility in 1797 and run regression separately in two subsamples. Column (1) and (2) report OLS estimates of Eq. (1) and column (3) and (4) report the IV estimates. Column (5) and (6) report the first stage results of IV estimation. Time-varying controls include log population, log (1+newspapers in 50 km), log (traveling time to London) and access to waterways. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A4 Two stage least squares regression results

	(1)	(2)	(3)	(4)	(5)
			ln(1+patents/pop)		
ln(1+banks/pop)	0.163*	0.218**	0.183**	0.191**	0.184*
	(0.0884)	(0.0881)	(0.0921)	(0.0971)	(0.106)
First Stage					
1(post town)*year	0.0285***	0.0280***	0.0281***	0.0273***	0.0253***
	(0.00400)	(0.00406)	(0.00425)	(0.00429)	(0.00443)
Observations	8,775	8,775	8,820	8,820	8,820
Time-varying Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year
Kleibergen-Paap F statistics	50.66	47.55	43.80	40.49	32.67

Notes: This table reports 2SLS regression estimates of Eq. (1). The dependent variable is the natural logarithm of one plus the total number of patents acquired in a district in year t+1 to year t+5 per million people in the district. The instrument I use is the interaction of the dummy of having a post town in the registration district and linear year variable. In Column (1) and (2), I construct the instrumental variable based on all post towns that satisfy gap distances falling between 16 and 30 km. In column (3), I drop towns on post roads connecting to Derby, Kendal and Carlisle. In column (4), I drop detouring towns when I construct the instrumental variable. In column (5), I drop towns with population larger than 5,000 in 1600 when I construct the instrumental variable. There are 112 post towns in the first two columns, 98 in column (3), 96 in column (4) and 90 in column (5). Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A5 Placebo tests

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	-0.393	-0.239	-0.598	-1.113
	(0.333)	(0.353)	(1.030)	(3.267)
First Stage				
1(Placebo post town)*year	0.00897**	0.00714	0.00398	0.00210
	(0.00435)	(0.00439)	(0.00552)	(0.00576)
Observations	8,775	8,775	8,775	8,775
Destination sets	Baseline	Baseline	Drop non-border destinations	Strategic destinations
KP F Statistics	4.246	2.641	0.521	0.133
Time-Varying Controls	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year

Notes: This table reports IV estimation results using instruments constructed based on placebo post towns. Column (1) reports IV estimates of Eq. (1) with only district and year fixed effects and column (2) includes time-varying controls. In column (3), I keep only placebo post towns on post roads connecting to borders when I construct the instrument. In column (4), I further refine the post town sets to post roads connecting to strategic locations on borders. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A6.1 Robustness checks with different measures of banking access and innovation

	（1）	（2）	（3）	（4）
	ln(1+patents)			
	OLS		IV	
ln(1+banks)	0.118***	0.118***	0.129	0.191**
	(0.0231)	(0.0218)	(0.0928)	(0.0865)
Observations	8925	8925	8775	8775
Within R2	0.0164	0.0425		
KPF			56.43	57.61
	（5）	（6）	（7）	（8）
	ln(1+banks)		N(banks)	
	First Stage		Poisson	
ln(1+banks)			0.1807**	0.1920**
			(0.0784)	(0.0797)
1(post town)*year	0.00831***	0.00844***		
	(0.00111)	(0.00111)		
Observations	8775	8775	5325	5325
Time-Varying Controls	None	Yes	None	Yes
Fixed Effects	District and Year	District and Year	District and Year	District and Year

Notes: This table reports OLS regression estimates of Eq. (1) and the dependent variable is the natural logarithm of one plus the total number of patents in a district in year t+1 to year t+5 in the district. In this table, I divide patents among patentees before adding to district patent counts. In column (1) I only control for district and year fixed effects. I add time-varying controls in column (2). Column (3) and (4) show IV estimates and column (5) and (6) report first stage results. Column (7) and (8) show Poisson estimates using a count model. Standard errors are clustered on the registration district level. The results do not change significantly when I cluster standard errors at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A6.2 Comparison of coefficients against Mao and Wang (2022)

	(1)	(2)	(3)	(4)
	ln(1+patents)			
ln(1+banks)	0.0750***	0.0736***	0.0736***	0.0759***
	(0.0171)	(0.0162)	(0.0162)	(0.0153)
Observations	14,874	14,874	14,874	14,874
Within R2	0.00963	0.0268	0.0268	0.0422
Years of Lag	3	3	3	3
Fixed Effects	District and Year	District and Year	District and Year	District and Year
Time-Varying Controls	No	Yes	Yes	Yes
Time invariant controls X Year FE	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes

Notes: I count patents within 3 years after year t in this table. The independent variable is the natural logarithm of one plus the number of banks and the dependent variable is the natural logarithm of one plus the number of patents in district i. This setting is similar to county-level analysis in Table 6 of Mao & Wang (2021). I add only district and year fixed effects in column (1), time-varying controls in column (2), interaction of time-invariant variables and year fixed effects in column (3) and county linear trends in column (4). Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A7.1 Robustness: additional controls and standard errors clustered on the county level

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.0515***	0.0451***	0.0439***	0.0371**
	(0.0138)	(0.0140)	(0.0139)	(0.0181)
Observations	8925	8925	8925	8925
Within R2	0.0243	0.0537	0.0663	0.1575
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	Yes	Yes	Yes	Yes
Agri-suitability X Year FE	Yes	No	No	No
Time invariant controls X Year FE	No	Yes	Yes	Yes
County Linear Trends	No	No	Yes	No
District Linear Trends	No	No	No	Yes
Cluster	District	District	District	District
	(5)	(6)	(7)	(8)
ln(1+banks/pop)	0.0437**	0.0490***	0.0451***	0.0439***
	(0.0178)	(0.0159)	(0.0145)	(0.0152)
Observations	8925	8925	8925	8925
Within R2	0.00204	0.0125	0.0537	0.0663
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	No	Yes	Yes	Yes
Time invariant controls X Year FE	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes
Cluster	County	County	County	County

Notes: In column (1) to (4), standard errors are clustered on the district level. In column (1), I include the interaction of agricultural suitability with year fixed effects. In column (2), I include the interaction of time-invariant controls with year fixed effects. In column (3), I further add country linear trends. In column (4), I further add district linear trends. In column (5) to (8), the standard errors are clustered on county level. I include only district and year fixed effects in column (5), add time-varying controls in column (6), interaction of time-invariant controls and year fixed effects in column (7) and county linear trends in column (8). ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A7.2 Conley standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents/pop)					
Distance cut-off	50km	100km	200km	300km	400km	500km
Panel A: With district and year fixed effects						
ln(1+banks/pop)	0.044***	0.044***	0.044***	0.044***	0.044***	0.044***
	(0.0117)	(0.0125)	(0.0126)	(0.0122)	(0.0121)	(0.0122)
Panel B: With time-varying controls						
ln(1+banks/pop)	0.049***	0.049***	0.049***	0.049***	0.049***	0.049***
	(0.0114)	(0.0121)	(0.0123)	(0.0120)	(0.0120)	(0.0121)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Fixed Effects	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year

Notes: This table reports the estimation results when I use Conley standard errors. I use different distance cut-offs of 50 km, 100 km, 200 km, 300 km, 400km, and 500 km in column (1) to (6). The lags are set to 2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A8.1 Robustness checks with different models

	IHS(patents/pop)		1(patent>0)		ln(1+patents/pop)	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+banks/pop)	0.0509***	0.0571***	0.0107***	0.0120***	0.0425*	0.0387*
	(0.0166)	(0.0162)	(0.00316)	(0.00308)	(0.0219)	(0.0220)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Model	Hyperbolic sine	Hyperbolic sine	Binary	Binary	PPML	PPML
Time-varying Controls	No	Yes	No	Yes	No	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year

Notes: This table reports robustness checks conducted using different models. In column (1) and (2) the dependent variable is the hyperbolic sine transformation of the total number of patents acquired in a district in year t+1 to year t+5 over the population in the district. In column (3) and (4) the dependent variable is a binary variable. It is 0 if the number of patents acquired in a district in year t+1 to year t+5 is 0 and it is 1 if the number of patents is larger than 0. I use a Poisson pseudo-maximum likelihood model in column (5) and (6). The dependent variable is the total number of patents acquired in a district in year t+1 to year t+5. Standard errors clustered on the registration district level are reported in paratheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A8.2 Robustness checks with different measurements of innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents/pop)				ln(1+banks/pop)	
	OLS		IV		First Stage	
ln(1+banks/pop)	0.0427***	0.0480***	0.155*	0.209**		
	(0.0142)	(0.0138)	(0.0864)	(0.0858)		
1(post town)*year					0.0285***	0.0280***
					(0.00400)	(0.00406)
Observations	8,925	8,925	8,775	8,775	8,775	8,775
Within R2	0.00202	0.0125				
KP F statistics			50.66	47.55		
Time-Varying Controls	Yes	Yes	None	Yes	None	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year

Notes: This table reports OLS estimates of Eq. (1) and the dependent variable is the natural logarithm of one plus the total number of patents in a district in year t+1 to year t+5 per million people in the district. In this table, I divide patents among patentees before adding to district patent counts. In column (1) I only control for district and year fixed effects. I add time-varying controls in column (2). Column (3) and (4) show IV estimates and column (5) and (6) report first stage results. Standard errors are clustered at the registration district level. The results do not change significantly when I cluster standard errors at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively

Table A9.1 Robustness: patent counts weighted with WRI

	(1)	(2)	(3)	(4)
	ln(1+weighted patents/pop)			
ln(1+banks/pop)	0.0486***	0.0555***	0.0544***	0.0513***
	(0.0167)	(0.0162)	(0.0170)	(0.0164)
Observations	8,925	8,925	8,925	8,925
Within R2	0.00191	0.0147	0.204	0.221
Fixed Effects	District and Year	District and Year	District and Year	District and Year
Time-Varying Controls	None	Yes	Yes	Yes
Time invariant controls X Year FE	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes

Notes: The dependent variable is constructed based on patent counts weighted with Woodcroft Reference Index proposed by Nuvolari & Tartari (2011). I add only district and year fixed effects in column (1), time-varying controls in column (2), the interaction of time-invariant variables and year fixed effects in column (3) and county linear trends in column (4). Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A9.2 Robustness: patent counts weighted with adjusted WRI

	(1)	(2)	(3)	(4)
	ln(1+weighted patents/pop)			
ln(1+banks/pop)	0.0407***	0.0461***	0.0453***	0.0426***
	(0.0140)	(0.0137)	(0.0144)	(0.0139)
Observations	8,925	8,925	8,925	8,925
Within R2	0.00184	0.0129	0.202	0.219
Fixed Effects	District and Year	District and Year	District and Year	District and Year
Time-Varying Controls	None	Yes	Yes	Yes
Time invariant controls X Year FE	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes

Notes: The dependent variable is constructed based on patent counts weighted with adjusted Woodcroft Reference Index proposed by Nuvolari & Tartari (2011). I add only district and year fixed effects in column (1), time-varying controls in column (2), interaction of time-invariant variables and year fixed effects in column (3) and county linear trends in column (4). Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A10 Robustness: patent counts within a 3-year or a 10-year window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(1+patents/pop)							
Window of patent counts	3-year				10-year			
ln(1+banks/pop)	0.0272***	0.0308***	0.0308***	0.0295***	0.0621***	0.0663***	0.0611***	0.0557***
	(0.0102)	(0.00985)	(0.00985)	(0.00969)	(0.0199)	(0.0196)	(0.0194)	(0.0196)
Observations	14,280	14,280	14,280	14,280	4,759	4,759	4,759	4,759
Years of Lag	3	3	3	3	10	10	10	10
Fixed Effects	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year
Time-Varying Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time invariant controls X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes	No	No	No	Yes

Notes: Instead of counting patents within 5 years in the baseline regression. I count patents within 3 years after year t in column (1) to (4) and patents within 10 years in column (5) to (8). I add only district and year fixed effects in column (1), time-varying controls in column (2), interaction of time-invariant variables and year fixed effects in column (3) and county linear trends in column (4). The settings in column (5) to (8) are similar to those in column (1) to (4). Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A11 Robustness checks: Restricted samples

	ln(1+patents/pop)							
	districts with banks				districts with patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+banks/pop)	0.0327*	0.0418**	0.0335**	0.0330*	0.0329	0.0405*	0.0458**	0.0445**
	(0.0173)	(0.0174)	(0.0170)	(0.0171)	(0.0216)	(0.0213)	(0.0210)	(0.0209)
Observations	6,000	6,000	6,000	6,000	5,325	5,325	5,325	5,325
Time-varying Controls	None	Yes	Yes	Yes	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Time-invariant controls X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes	No	No	No	Yes

Notes: This table reports OLS regression estimates of Eq. (1) with restricted samples. The results in Column (1) to (4) are results from the sample of registration districts that at least one country bank ever established in. The results in Column (5) to (8) are results from the sample of registration districts that at least one patentee was from. The dependent variable is the natural logarithm of one plus the total number of patents acquired in a district in year t+1 to year t+5 over the population in the district. The unit of population is million people. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A12 Heterogeneous effects on different sectors (based on patent subjects)

	ln(1+patents/pop)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+banks/pop)	0.00856	0.0414***	0.0439***	0.0458***	0.0432***	0.0447***
	(0.00611)	(0.0124)	(0.0129)	(0.0130)	(0.0134)	(0.0135)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Time-varying Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year
Sector	Primary Sector	Secondary Baseline	(2) + Construction	(3) + Leather	(4) + Military	(5) + Medicine

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the natural logarithm of one plus the total number of patents in different sectors in a district in year t+1 to year t+5 per million people. The taxonomy of patents are based on Nuvolari and Tartari (2011). Column (1) reports the result of patents related to Agriculture, Food and drink and Mining. Column (2) reports the result of patents in the baseline manufacturing sector. See Table A5 for detailed classification. Column (3) reports the result of secondary sector patents after including Construction and column (4) further includes Leather. Column (5) includes Military equipment and weapons while column (6) includes Medicines. Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Table A13 Classification of patents according to Nuvolari and Tartari (2011)

taxonomy of Nuvolari & Tartari (2011)	secondary sector1	secondary sector2	secondary sector3	secondary sector4	secondary sector5
Carriages, vehicles, railways	√	√	√	√	√
Chemical and allied industries	√	√	√	√	√
Clothing	√	√	√	√	√
Engines (steam engines, water wheels)	√	√	√	√	√
Furniture	√	√	√	√	√
Glass	√	√	√	√	√
Hardware (edge tools, locks, grates)	√	√	√	√	√
Instruments (scientific instruments, watches, measuring devices)	√	√	√	√	√
Manufacturing machinery (other)	√	√	√	√	√
Metal manufacturing	√	√	√	√	√
Paper, printing and publishing	√	√	√	√	√
Pottery, bricks, artificial stone	√	√	√	√	√
Shipbuilding	√	√	√	√	√
Textiles	√	√	√	√	√
Construction		√	√	√	√
Leather			√	√	√
Military equipment and weapons				√	√
Medicines (drugs, surgical and dental instruments, other medical devices)					√
Agriculture	primary	primary	primary	primary	primary
Food and drink	primary	primary	primary	primary	primary
Mining	primary	primary	primary	primary	primary

Table A14 The relationship between interest rates and agricultural suitability

	(1)	(2)	(3)	(4)	(5)	(6)
	interest rates					
1(agriculture suitable)	-2.742***	-2.698***	-2.338***	-1.687***	-1.653***	-1.302***
	(0.385)	(0.382)	(0.363)	(0.212)	(0.211)	(0.181)
Observations	595	595	595	595	595	595
R-squared	0.078	0.077	0.065	0.096	0.094	0.079

Notes: The interest rates are calculated using the replication data of Keller, Shiue and Wang (2021).The interest rates correspond to crop price changes with no adjustment, adjusted for climate, adjusted for climate and trade from column (1) to (3). In column (4) to (6), interest rates are calculated in the subsample that typically exhibit price increases larger than zero with no adjustment, adjusted for climate, adjusted for climate and trade. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.