

# Banking and Innovation: Evidence from the Industrial Revolution

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## Abstract

How do banks affect innovation when there exist liquidity constraints? Between 1750 and 1825, country banks in England and Wales provided short-term loans to clients due to legal restrictions. Using a new district-level panel dataset on patents and banks, covering almost six hundred registration districts, I find that better access to banking services increased patenting. My baseline estimation, which includes district and year fixed effects, shows that a one standard deviation increase in banking access increased patenting by 15.6% of a standard deviation. I establish a causal relationship by constructing instrumental variables that utilize shocks to the money supply and the locations of historical post towns to predict the growth of country banks. My findings suggest that country banks and their London agents contributed to the formation of an integrated national financial market that channeled surplus funds from rural districts to industrial areas that lacked credit. Country banks increased patents acquired by their clients, who were mainly industrialists and merchants. Banks lowered the costs of procuring working capital by providing short-term credit. The effects of banks were larger in districts subject to tighter credit constraints and lacked access to the London money market.

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# 1 Introduction

*"It is chiefly by discounting bills of exchange, that is, by advancing money upon them before they are due, that the greater part of banks and bankers issue their promissory notes... By means of those cash amounts every merchant can, without imprudence, carry on a greater trade than he otherwise could do."*(Smith, 1796, p.444-446)

How do banks affect innovation when there exist liquidity constraints? External finance is an important source of funds for innovation (Schumpeter, 1961; King and Levine, 1993). Banks, as a traditional and important financial intermediary, can spur innovation by increasing credit provision (Amore et al., 2013; Chava et al., 2013; Cornaggia et al., 2015), while bank distress can reduce innovation (Nanda and Nicholas, 2014; Babina et al., 2023; Granja and Moreira, 2023). Credit provision includes long-term loans that can contribute to higher productivity and short-term loans to cover day-to-day operations (Aghion et al., 2010). It has been documented that credit constraints and cash flow sensitivity reduce innovation and hinder growth (Aghion et al., 2012; Duval et al., 2020). However, the contribution of short-term bank credit to innovation has received less attention, despite the fact that short-term debt makes up 23.37% in emerging markets (Damodaran, 2023a).<sup>1</sup> Across the world, the aggregated accounts receivable is about 17.78% of the amount invested in fixed capital. The proportion is 17.64% for aggregated accounts payable and 18.78% for inventories (Damodaran, 2023b).<sup>2</sup> During the Industrial Revolution, surviving balance sheets of English

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<sup>1</sup>For all developed countries, the average number is 12.62%. For developed countries, the number is 3.44% for the United States, 5.96% for Western Europe, 24.48% for Japan. For developing countries, the number is 26.99% for China and 8.14% for India (Damodaran, 2023a).

<sup>2</sup>Net Working Capital = Aggregated accounts receivables + Inventory – Aggregated accounts Payables. For emerging markets, the proportions are 18.46% for aggregated accounts receivables, 19.63% for aggregated accounts payable and 27.05% for inventories. For the United States, the numbers are 15.87% for aggregated accounts receivables, 14.99% for aggregated accounts payable and 12.54% for inventories. For Western Europe, the numbers are 19.34% for aggregated accounts receivables, 21.22% for aggregated accounts payable and 15.18% for inventories. Net working capital reached about 4.4 billion dollars in 2017 (Windaus et al., 2019) while the amount of private investment was about 20 trillion dollars (IMF, 2021) The estimated amount of net working capital rose from 3.36 trillion euros to 3.87 trillion euros and 4.23 trillion euros in 2018 (Windaus et al., 2019). The sum of public and private investments across the world is 28.51 trillion constant international dollars in 2017 (IMF, 2021).

firms show that the amount of working capital made up more than half and up to almost 80% of the assets of firms (Pollard, 1964)<sup>3</sup>. In this paper, I use a context where banks generally provided short-term credit to borrowers due to legal restrictions to isolate the impacts of short-term credit on innovation.

There is conflicting evidence on the role of banks in innovation during the Industrial Revolution. Gerschenkron (1962) argued that English banks did not contribute to British industrialization because they were only providing short-term credit. Further, there are examples of inventors with high potential being rejected by bankers, including Matthew Boulton, who worked with James Watt on the steam machine, and Richard Arkwright, who invented the famous water frame (Postan, 1935; Fitton, 1989). These examples are consistent with the view that banks are, in general, conservative and biased against innovation (Hall and Lerner, 2010). However, case studies of industrialists and inventors during the Industrial Revolution show that bankers contributed to the formation of capital (Cameron et al., 1967) and promoted innovation (Brunt, 2006; Rimmer, 1960; Cookson, 2003). The limited coverage of, and selection in, qualitative evidence means there is a meaningful contribution to be made using quantitative analysis and causal inference to assess how banks contributed to innovation during the British Industrial Revolution.

In this paper, I introduce a new dataset on patents and country banks in England and Wales between 1750 and 1825 to study how the increase in the number of country banks increased patenting during the British Industrial Revolution. Country banks were small private banks based outside London, having at most six partners. I collect the authorization dates of patents, as well as 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 collect the locations, opening years, and London agents of country banks and then map patents and country

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<sup>3</sup>Working capital is an important component of the production of goods (Ramey, 1989) and it became a large concern for businessmen during the Great Depression (Bernanke, 1983). It is still larger than half of the fixed capital in the modern United States (Fazzari and Petersen, 1993).

banks into 595 distinct registration districts located outside London and Middlesex.<sup>4</sup> 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 affected the number of patents in a district during the Industrial Revolution. My baseline OLS estimates show that the elasticity between banking access and innovation is about 0.115. A one-standard-deviation increase in the independent variable predicts a 15.6% standard deviation increase in the dependent variable.

As there may be endogeneity in the OLS estimation due to omitted variables, I employ an instrumental variables (IV) strategy. I construct my principal instrument based on historical post town status, following Heblich and Trew (2019). A post town is a town with a post office - a term that originated from stables providing horses to the royal postmen in the 16th century. Country banks were more likely to operate in post towns because they were more secure for gold transportation, had access to the latest information delivered by mail, and attracted demand for financial services from the postal system (Dawes and Ward-Perkins, 2000). To address endogeneity concerns, 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 first instrument is the interaction of a dummy for the presence of a post town in the 1670s<sup>5</sup> with the linear variable year. My second instrument is the interaction of the first instrument with the dummy of being after 1797. The elasticities returned by IV estimation are about 1.6 times as large as the OLS estimates, ranging from 0.184 to 0.190. The difference in magnitudes could be due to two factors. First, some country banks were established in agricultural areas with adequate credit to collect deposits and they invested in London but not in local industry. Second, measurement errors in banking access could also contribute to the difference in OLS and IV estimates. Country banks were connected to the London money market via their London agents. Country banks not only served as the local financial intermediaries but also connected the local area to the London money

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<sup>4</sup>Registration districts are one level of census units in 1851, taken from Satchell et al. (2017).

<sup>5</sup>The records are taken from the Britannia (Ogilby, 1675).

market and country banks in other districts. I use the number of banks that were connected to each district via London bankers to construct an alternative measurement of access to financial services. The entry and exits of country banks in other districts from the networks of London agents provide plausibly exogenous shocks to financial access in the local district.

Country banks contributed to innovation by providing short-term credit to clients, including industrialists and merchants, to alleviate their financial constraints.<sup>6</sup> To understand the mechanisms that drive the effects of country banks on innovation, I investigate the effects of banks in different sectors with different innovation strengths and regions with different credit supply. I find that the effects in traditional sectors are driven by patents in the manufacturing sector. However, where the bar to innovation was lower, industrialists played an important role and merchants also contributed, when innovations were made by people who knew about the production procedures (Mokyr, 2009). The impacts of banks on patents of non-trading service professions suggest that there was a group of inventors who responded to market opportunities brought about by banks.

From a geographical perspective, I use agricultural suitability as a proxy for credit constraints, and find that the effects were larger in districts with lower agricultural suitability and thus tighter credit constraints. The impacts of banks on patents were also larger in districts with higher bankruptcies per capita before 1750. I divide connections to country banks in other districts into connections to districts suitable for agriculture and those to districts unsuitable for agriculture. Connecting a district with tight credit constraints to districts with adequate credit increases patents in the district without adequate credit. I also extract information from inventors' and bankers' biographies to provide qualitative evidence about how banks contributed to invention. Short-term credit from country banks protected innovative entrepreneurs from going bankrupt.

I show that my results are robust to different specifications when I divide patents equally among all patentees. Using the interactive fixed effects model, I find the results are still

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<sup>6</sup>Case studies can be found in (Hudson, 1986, 1981).

robust after ruling out the correlations between unobserved factors and the independent variable. The results remain robust when I cluster the standard errors at the county level and use Conley standard errors with cutoffs ranging from 50 km to 500 km. Similar patterns are shown when I use different transformations of patent numbers and focus on banks per capita and patents per capita. To take the quality of patents into account, I use the Woodcroft Quality Index constructed by Nuvolari and Tartari (2011) and find the impacts of banks on patents with higher quality, from 50% to 90% quantiles of the patent quality index, are still robust. The results survive when I use different time windows, of 3 years and 10 years, to aggregate patents and the subsamples with at least one country bank or one patent during the period that I examine. Analyses on spillover effects do not explain the growth of patents but instead show that banks in neighbouring districts led to the drainage of patents.

## 1.1 Contribution to the Literature

This paper engages with the literature on the relationship between finance and innovation. A large literature has documented the importance of financial access in promoting innovation (King and Levine, 1993; Hall and Lerner, 2010; Hsu et al., 2014). Traditional wisdom claims that debt markets serve innovation poorly (Williamson, 1988; Beck and Levine, 2002; Hall and Lerner, 2010; Brown et al., 2012). Commercial banks and debtholders, in this view, are risk-averse and biased against risky research and development projects (Rajan, 1992; Hsu et al., 2014). However, previous research mainly focused on the national-level development of debt markets. In recent years, research using granular firm-level data shows that banking competition increases credit supply and increases innovation, especially by new, innovative firms in industries that rely heavily on external finance (Amore et al., 2013; Chava et al., 2013; Cornaggia et al., 2015; Nanda and Nicholas, 2014; Mao and Wang, 2022). This paper uses a setting where banks generally provide short-term credit, usually due in three months, to clients due to legal restrictions to isolate the impacts of short-term debt (Michie, 2016; Gorton, 2023). The availability of liquidity lowers financial costs, increases the leverage of

entrepreneurs, and helps industrialists avoid bankruptcy.

This paper also contributes to the literature on credit constraints and innovation. Credit markets are important for innovative potential entrants (Robb and Robinson, 2012; Geelen et al., 2021). Firms facing credit constraints lower their investments (Duchin et al., 2010) and innovation (Nanda and Nicholas, 2014; Giebel and Kraft, 2019; Hardy and Sever, 2021; Granja and Moreira, 2023). Increases in corporate taxes lower R & D investments (Mukherjee et al., 2017). Enhancement of borrowers' risk tolerance increases investments in research and development (Chang et al., 2019) and increases in the supply of bank credit enable small innovative firms to stay independent (Cornaggia et al., 2015). Recent theoretical literature has begun to explore the impacts of liquidity on innovations when there are financial frictions (Malamud and Zucchi, 2019). This paper provides new evidence that bank credit could alleviate the credit constraints of industrialists and increase innovation in an emerging financial market.

This paper also relates to the literature on the contribution of banks to the Industrial Revolution in England. The Financial Revolution preceded the Industrial Revolution (Neal, 1990) and provided the financial tools for industrialization in the second half of the 18th century (Neal, 1994). Country banks contributed to the development of multiple industries, mainly by providing short-term credit in the form of inland bills of exchange and overdrafts (Pressnell, 1956; Michie, 2016). Therefore, it is likely that banks complemented the working capital of industrialists by providing short-term credit (Pollard, 1964; Crouzet, 1985). Heblich and Trew (2019) show that banking access increased industrialization in England during the 19th century. However, in the late 18th and early 19th centuries, the number of country banks in the industrializing regions, such as North West England, was lower than in other regions (Mokyr, 2009; Voth, 2018). There is no evidence that the number of country banks in 1796 affected male employment in the textile industry in the 19th century (Kelly et al., 2023). This paper shows that country banks and their London agents formed the basis of an integrated national financial market discussed in North and Weingast (1989).

The financial centre of London was connected to Northwest England by country banks, so the centre of the financial sector and that of the Industrial Revolution does not necessarily overlap geographically.

There is less evidence about the impacts of country banks on innovation than on industrialization during this period. Some country banks acted 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 (Fitton, 1989). If people who failed to invent new products also failed to leave records, selection in case studies would lead to bias towards the claim that bankers promoted invention by providing credit.<sup>7</sup> My study fills this gap and provides the first quantitative evidence about the impacts of banks on innovation during the British Industrial Revolution. I also complement my quantitative evidence with examples from biographies of inventors and bankers during this period.

The remainder of this paper is organized as follows. Section 2 introduces the historical background and section 3 discusses the data that I use. Section 4 discusses my empirical strategy using a two-way fixed effects model and a staggered DID model. In section 5, I discuss the identification of the relationship between banks and patents using an IV strategy and robustness checks using different specifications. In section 6, I discuss how banks increased patents. The networks of country banks across England provided local industrialists with access to the national financial market and increased the supply of short-term credit. Industrialists could therefore allocate more own funds to innovation and fixed capital investments. Section 7 shows the results are robust to different specifications and section 8 concludes the paper.

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<sup>7</sup>The refusal of Richard Arkwright by bankers is recorded because he finally managed to build his water frame and made a fortune.



## 2 Background and Data

### 2.1 Patents of Invention: A Measurement of Profitable Innovation

Patent records can shed some light on the innovation of high economic values during the period I examine, as the patent system in England was expensive to use. The patent fee was about 70 to 100 pounds (Bottomley, 2014, p.74) and remained stable until 1852 (MacLeod, 1988, p.76). The preparation of patent specifications would increase the costs by another 50%. In today's price, a patent would cost 100-250 thousand pounds if nominal GDP per capita is used as the deflator (Broadberry et al., 2015).<sup>8</sup> Therefore, rational patentees would only apply for patents with high expected economic values.

During the Industrial Revolution, there was a very active market for patents in England (Bottomley, 2014, p.202-p.230). Industrialists who were good at adopting inventions in industrial production bought patents and started their own firms. John Marshall started his mechanized flax spinning firm under a license from two patent holders, John Kendrew and Thomas Porthouse (Beresford, 2006). It was unlikely that patentees spent large sums to gain patents that could be easily infringed or that a market existed without sufficient protection for property rights.

To account for the quality of patents, in robustness checks, I use a patent quality index that was constructed by Nuvolari and Tartari (2011) and is based on a reference index of patents (Woodcroft, 1862). Although gaining patents was costly, there were still patents without any practical value like perpetual motion machines (MacLeod, 1988, p.175). Nuvolari and Tartari (2011) argue that the adjusted Woodcroft Reference Index that they constructed could reflect both the quality and economic values of patents during the Industrial Revolution. Therefore, I use the adjusted Woodcroft Reference Index to build subsamples of patents with high quality in robustness checks and check if the impacts of banks are robust

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<sup>8</sup>According to the inflation calculator provided by the Bank of England, £100 in 1750 equals about 18,000 pounds in 2023 and £100 in 1825 equals about 7,500 pounds in 2023. The calculator can be accessed at <https://www.bankofengland.co.uk/monetary-policy/inflation/inflation-calculator>.

to patents of high quality.

## 2.2 Country banks

In the 18th century, major financial intermediaries in England included London private bankers and country banks outside London (Neal, 1994). Attorneys also played an important role as informal financial intermediaries in Lancashire and Yorkshire. Country banks were small private banks based outside London with no more than six partners (Michie, 2016).<sup>9</sup> The Bubble Act of 1720 prevented bankers from forming joint-stock banks with more partners. Therefore, country banks were small, as the average capital of a country bank was about £10,000 by the end of the eighteenth century (Pressnell, 1956). Using GDP per capita as the deflator, £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 (Broadberry et al., 2015).<sup>10</sup>

Country banks provided short-term credit because they were vulnerable to bank runs and they could not charge high interest due to legal restrictions. The Usury Law placed a 5% annual interest rate cap on all private loans. Although the returns to industrial investments were high (Allen, 2009b), the usury law placed a 5% cap on the interest rates that banks could charge (Pressnell, 1956, p.89). Therefore, the profits from long-term loans were too low for country banks given the liquidity risks of long-term loans and insolvency risks due to the small number of borrowers of country banks (Michie, 2016, p.61). Country banks were generally reluctant to lend extensively, except to clients that they knew well (Hudson, 1986) or in industries that they had good knowledge about (Brunt, 2006). Country banks discounted bills, provided overdrafts, and issued notes to facilitate trade (Pressnell, 1956; Crouzet, 1972; Calomiris and Haber, 2014). A bill of exchange was evidence of a loan that one person, or one group of people, borrowed from another and could be traded between different parties (Gorton, 2023). Country banks purchased short-term bills of exchange

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<sup>9</sup>The average number of bank partners was three in 1822 (Neal, 1994, p. 226).

<sup>10</sup>According to the inflation calculator provided by the Bank of England, £10,000 in 1750 equals about 1.75 million pounds in 2023 and £100 in 1825 equals about 750 thousand pounds in 2023. The calculator can be accessed at <https://www.bankofengland.co.uk/monetary-policy/inflation/inflation-calculator>.

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.

Banking access increased rapidly since 1750. There were a dozen country bank offices in 1750 and 395 by 1795.<sup>11</sup> The Bank of England suspended the convertibility of its notes to gold (O'Brien and Palma, 2019) in 1797, which made it possible for the Bank of England to expand the money supply (Michie, 2016). The number of country banks rose quickly across the country due to the high wartime interest rates and the expansion of the money supply (Pressnell, 1956, p.8,94,108).<sup>12</sup> The increases in potential profits attracted new bank entrants in districts without historical post towns.

The legal restriction on the number of partners of country banks lasted until the Country Bankers Act in 1826 (Pressnell, 1956; Michie, 2016). The formation of joint-stock banks with more than six partners was allowed in areas more than 65 miles away from London. Some country banks began to merge into new joint-stock banks that were larger than country banks. The establishment of joint-stock banks makes my baseline measurement of banking access inappropriate for the period after 1825. Therefore, I restrict the sample to the period before 1825.

## 2.3 The network of country banks centred around London

In the 18th and early 19th centuries, a country bank kept its contact with London via its London agent<sup>13</sup> and the London agent helped the country bank access the London money market (Michie, 2016, p. 63). London agents accepted the notes, conducted stock trades, and facilitated money transactions for country banks (Dawes and Ward-Perkins, 2000, p.25-26). Therefore, London agents had regular contact with country bankers (Pressnell, 1956, p.78-84). London agents were usually London bankers. They purchased the bills created

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<sup>11</sup>Based on my calculation from the list of country banks provided in Dawes and Ward-Perkins (2000).

<sup>12</sup>Between 1796 and 1810, the notes issued by the Bank of England more than doubled, and the value of bills discounted quadrupled (Michie, 2016). The number of bank offices rose to about 900 in 1810.

<sup>13</sup>Banks could change their agents, but they had only one agent at a time in most cases.

by country banks with their deposits or sold them in the London market.<sup>14</sup> In this way, money flowed from areas with surplus funds to areas that were in need of credit (Joplin, 1837). Country banks were connected to each other via the London bankers in the London money market. The connections between country banks and their London agents was likely to facilitate transactions between country banks that were connected to the same London agent.

The number of connections between country banks and London bankers grew slowly in the first 40 years that I examine but grew fast since the 1790s according to the records in Dawes and Ward-Perkins (2000). It is likely due to the rise in the amounts of bills and the development of the London bill market (Pressnell, 1956, p.94). In the 1790s, *the Universal British Directory* provided the first systematic list of country banks and their London agents. The ledgers of Barclays between 1790 and 1810 that I collected show that the number of country banks recorded was only 3 in 1790. The number then rose to 5 in 1795, at least 13 in 1800, and at least 26 in 1810.<sup>15</sup>

The network database that I construct captures the variations in one important connection, agency relationships between country banks and London banks. There could also be other informal relationships between banks. The Gurneys, recorded as the Norwich bank in Figure 1, was one of the three banks that showed up in the country ledgers of the Barclays in 1790. However, the formal agency relationship between the Gurneys and the Barclays was only first recorded in 1797 (Dawes and Ward-Perkins, 2000).<sup>16</sup>

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<sup>14</sup>Some deposits of London bankers came from Southeast England where there was surplus credit. As described in a letter from Thomas Bland (Norwich) to John Gurney junior (London) in 1772, people in these areas tried to find profitable investments in London (Pressnell, 1956). "... —hope thou will find some way of investing as far as abt. £5,000 satisfactorily, so much I think we may at least spare. We emply a good deal too much Money in our Business, wch must be alter'd, or the Loss is prodigious...."

<sup>15</sup>In Figure 1, some of the banks could not be recognized and matched with records about country banks.

<sup>16</sup>Meanwhile, the Barclays Bank in London had connections with the Gurneys in Norwich as late as 1775 through marriage and shared religion (Ackrill and Hannah, 2001, p.41). Therefore, other relationships between banks existed besides the formal agency relationship recorded in the Universal British Directories in 1797. Barclays became the London agent of the Backhouses only in 1838 but they already had business and religious connections in the 18th century (Ackrill and Hannah, 2001, p.41).

|                 |             |                 |
|-----------------|-------------|-----------------|
| Ledger A        |             |                 |
| Norwich         | 3218 1 1    | Norwich         |
| Lynn            | 5531 4 4    | Lynn            |
| Yarmouth        | 490 19 9    | Yarmouth        |
| Wisbech         | 3979 15 6   | Wisbech         |
| Edenham         | 4759 16 6   | Fakenham        |
| Halesworth      | 1110 10 11  | Halesworth      |
| Ledger X 1      |             |                 |
| Exeter          | 35839 4 7   | Exeter          |
| Evesham         | 22081 16 10 | Evesham         |
| Tonbridge       | 14381 8 5   | Tonbridge       |
| Birmingham      | 9590 - 3    | Birmingham      |
| Gosport old     | 103 7 6     | Gosport old     |
| Gosport new     | 3301 - 3    | Gosport new     |
| Nantwich        | 7283 19 8   | Nantwich        |
| Bishop's Cleeve | 2658 5 8    | Bishop's Cleeve |
| Ledger X 2      |             |                 |
| Lancaster       | 17153 17 9  | Lancaster       |
| Carmarthen old  | 11865 2     | Carmarthen old  |
| Carmarthen new  | 22462 19 3  | Carmarthen new  |
| Newark          | 678 11 8    | Newark          |
| Grantham        | 7351 1 1    | Grantham        |
| Haverfordwest   | 78 6 4      | Haverfordwest   |
| Winchester      | 989 7 6     | Winchester      |
| Whitby          | 3908 18 10  | Whitby          |
| Whitby          | 4158 5 6    | Whitby          |
| Hemel Hempstead | 3500        | Hemel Hempstead |
| Hemel Hempstead | 197 2 9     | Hemel Hempstead |
| Ledger X 3      |             |                 |
| Bury            | 4238 19 4   | Bury            |
| Braintree       | 2871 3 10   | Braintree       |
| Stowmarket      | 1527 18     | Stowmarket      |
|                 | 166425 9    | 23940 16 1      |

Figure 1: The Barclays ledger of country banks in 1810: Among the 33 agency relationships recorded in Dawes and Ward-Perkins (2000), 28 are recorded in the 1810 ledger. It shows that the agency relationships recorded in the *Post Office and London Directories* were quite precise. The Gosport old bank, Ed. Jukes, John Langley & Geo. Morse Jukes went bankrupt in 1810. It is consistent with Figure 1 that the bank withdrew money from or borrowed money from Barclays.

Source: Barclays Archive, Reference No: 0364-0062, Archive Description: Balance Sheets, Yearly [076] INC Country Balances. Unsigned. Partners Robert Barclay, David Bevan & John Henton Tritton. Possible Refs to Acc 27/249. Folio Numbers are given but the volumes to which they relate are missing.

## 2.4 Banks and the Industrial Revolution

Evidence about the contribution of country banks to innovation during the Industrial Revolution remains anecdotal. There are examples of how 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 engines and provided a loan of 2,000 pounds to the Boulton-Watt partnership when it faced financial difficulty (Brunt, 2006). However, there are also examples of banks refusing to help innovative partners and firms. Richard Arkwright was refused financial support by two Nottingham bankers because they believed that his water frame would not succeed (Allen, 2009a).

Country bankers sometimes directly supported the invention and patent process, especially when the banker knew 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 inventing and patenting, but also helped them set up a small factory in the 1780s and 1790s (Cookson, 2003). The loans provided by the Backhouses came via London bankers who received the deposits from bankers in rural areas, like the Gurneys in East Anglia (Ackrill and Hannah, 2001).

During the Industrial Revolution, the expansion of industrial enterprises in England relied mostly on internal funds accumulated from retained profits (Crouzet, 1972). Industrialists allocated their capital among working capital, fixed capital, and innovation. Working capital was important as it made up a large proportion of the industrialists' assets (Crouzet, 1985). After country banks entered, the provision of short-term credit by banks complemented the working capital of industrialists and enabled them to allocate more internal funds to fixed capital investments and innovation (Pollard, 1964; Crouzet, 1972; Hudson, 1981).

## 3 Data

### 3.1 Data

To measure innovation during the Industrial Revolution in England, I rely on the patent statistics that are the most comprehensive (Sullivan, 1989, 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).<sup>17</sup> I construct my district-level measurement of innovation based on patent counts in the baseline regression. For patents with several patentees, I count them 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.

Due to the limited information on country banks during this period, I measure banking access using the number of country banks. As 74% of the district-year observations had no banks, I use the inverse hyperbolic sine transformation of banks in a district in the baseline estimation to measure banking access. I collect the year of establishment and location of country banks from Dawes and Ward-Perkins (2000). I map the banks into registration districts and build a database that records the agency relationships between country banks and London banks. I define a country bank as connected to a London bank if it is recorded that the London agent of the country bank was the London bank in Dawes and Ward-Perkins (2000).

I include a few time-varying control variables that might affect patents. They include the natural logarithm of population, the natural logarithm of one plus the 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 linear interpolation to fill in the data for the years between 1801 and

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<sup>17</sup>Then I map all the patents into 595 registration districts outside London.

1825, assuming that the population grew at a constant rate between the two 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 were the same between 1750 and 1800. I calculate the county-level population growth rate based on the estimates of the county-level population reported every decade by Wrigley (2007).

Patents might have been driven by access to other markets and potential business opportunities. Canals were important for the transportation of bulk goods (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 for every decade with the descriptions of navigable waterways from 1750 to 1810 from the London Canal Museum.<sup>18</sup> I define a district as having access to waterways in year  $t$  if a waterway, including natural rivers and canals, crosses this district in this year.

People needed to learn about the patent system before applying for patents. Most of the patents acquired in the first half of the 18th century were by patentees in London. Inventors also needed to collect information and read patent archives in London in person, especially before patent agents became widely accessible around the 1820s (Bottomley, 2014, p.34). 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 of the centroid of the district.<sup>19</sup>

I also control for traveling time to London for passengers using turnpike roads to control for information access.<sup>20</sup> Turnpike roads could also be used for the transportation of goods, especially for inland areas (Alvarez-Palau et al., 2022). Lower transportation time facilitated information collection. To calculate traveling time to London, I use the turnpike road network

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<sup>18</sup>The descriptions can be found at <https://www.canalmuseum.org.uk/history/menu-decades.htm>.

<sup>19</sup>50 km was approximately the distance that newspapers could cover and influence in the 18th century (Black, 1991)

<sup>20</sup>The map of turnpike roads comes from Rosevear et al. (2017).



map digitized by Rosevear et al. (2017), and calculate the average traveling speed on turnpike roads in the 18th and early 19th century. I assume that the traveling speed on turnpike roads was equal to the average speed calculated in Bogart (2005) and that passengers travelled 2 km per hour on the straight path connecting the centre of the district to the nearest turnpike road. I use ArcGIS to calculate traveling time to London on least cost paths using the OD Matrix tool. The calculation equation is  $T_{i,t} = \frac{\text{Turnpike distance}_{i,t}}{\text{Turnpike Speed}_{i,t}} + \frac{\text{distance to Turnpike Road}_{i,t}}{\text{normal speed}_{i,t}}$ .

### 3.2 Summary statistics

My analyses are at the level of the 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). There were 624 registration districts across England and Wales and 595 of them were outside London and Middlesex.

I investigate how banking access in district  $i$  in year  $t$  affected patents in district  $i$  in year  $t+1$  to  $t+5$ . Therefore, the panel data is made up of 595 districts and 15 periods ( $t=1750, 1755, \dots, 1820$ ).

[Insert Table 1]

Descriptive statistics are shown in Table 1. I use data from the years 1750, 1780, 1800, and 1820 to show the 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. From 1750 to 1800, the number of country banks more than doubled each decade.

## 4 Empirical strategy

### 4.1 Baseline estimation

I examine the relationship between banking access and patents using a two-way fixed effect model including district and year fixed effects in equation (1).

$$\text{IHS}(\text{Patents}_{i,t+1 \text{ to } t+5}) = \beta_0 + \beta_1 \times \text{IHS}(\text{Banks}_{i,t}) + x'_{i,t}\gamma + x'_i\zeta_t + \theta'_{t_0}\mu_t + \delta_i + \eta_t + \varepsilon_{i,t} \quad (1)$$

$\text{IHS}(\text{Banks}_{i,t})$  is the inverse hyperbolic sine of the number of country banks in district  $i$  in year  $t$ .  $\text{IHS}(\text{Patents}_{i,t+1 \text{ to } t+5})$  is the inverse hyperbolic sine of the number of patents in district  $i$  within 5 years after year  $t$  ( $t = 1750, 1755, \dots, 1820$ ). I use other windows including 3 years and 10 years in robustness checks. In the baseline estimation, I estimate how changes in banking access in district  $i$  in year  $t$  affect patenting in the future 5 years,  $t+1$  to  $t+5$ .  $x'_{i,t}$  are time-varying controls including population, traveling time to London via turnpike roads, access to waterways and the number of newspapers within 50 km. I include the interaction terms of  $x'_i$ , time-invariant control variables, and  $\zeta_t$ , year fixed effects, to control for different effects of time-invariant controls in different years. To alleviate concerns about unobserved factors that affect the entry time of banks, I include the interaction terms of  $\theta'_{t_0}$ , the fixed effects of the cohorts  $t_0$  when the first country bank was established in district  $i$ , and  $\mu_t$ , year fixed effects.  $\delta_i$  is a vector of district fixed effects that control for time-invariant district-specific unobserved factors.  $\eta_t$  is a vector of year fixed effects that control for time shocks received by all districts in the sample. In baseline regression, I estimate Equation (1) using OLS. The standard errors are clustered at the registration district level in the baseline regression. I cluster standard errors at the county level and use Conley standard errors with the cutoff ranging from 50 to 500 km in robustness checks.

In the baseline estimation, the identifying variation comes from the changes in banking access after deducting the average effects of unobserved factors in the specific district during

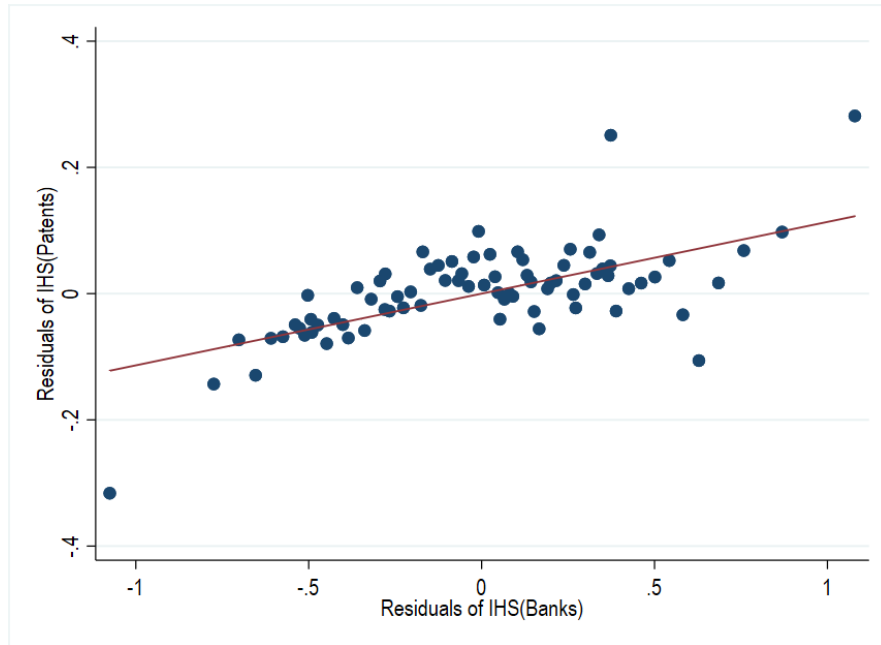


Figure 2: The correlation between banks and patents

the period that I examine and the national-level time shocks received by all districts which were captured by year fixed effects. The identifying assumption for the OLS estimation is that the identifying variation that I use is as good as random across different observations. Figure 2 shows the relationship between variation in banking and variation in patenting after controlling for district and year fixed effects.

## 4.2 Baseline results

Table 2 presents my baseline estimation results on how banking access affected innovation in the 595 registration districts outside London and Middlesex. Column (1) reports OLS estimates with district and year fixed effects and controlling for population. In column (2), I include all time-varying control variables. In column (3), I include the interaction of the fixed effects for the cohort when districts first had a country bank and year fixed effects. In column (4), I include the interaction of time-invariant controls with the year fixed effects and county linear trends.

[Insert Table 2]

My OLS estimates in columns (1) and (2) suggest that the elasticity of patents with respect to banks is about 0.115. At the mean value of the independent variable, a one standard deviation increase in the independent variable (0.653) increases the dependent variable by 15.6% of a standard deviation. This translates into an increase of 47.5% in the number of patents in the next five years. The increase in the number of banks from 1750 to 1820 explains about 38% of the increases in patenting.<sup>21</sup>

The estimate in column (3) is 0.163, larger than those in columns (1) and (2). The larger coefficient indicates that some omitted variables that contributed to the early arrival of banks in specific districts on average negatively affected the growth in patenting. Controlling for these factors makes the OLS estimate larger. Column (4) shows that time-invariant controls and county linear trends also help explain some of the increases in patenting.

### 4.3 Staggered DID

When the groups are treated before being used as the control group, the problem of negative weights might affect the estimation of the two-way fixed effects model. In this section, I use the dummy of having a country bank in the district as the independent variable in this section and use the staggered DID model estimation introduced by Callaway and Sant’Anna (2021).

In the data, I define a district  $i$  as treated if it has at least one country bank in year  $t$ . After a district is treated, it is always treated. The control group is the districts that never had a bank between 1750 and 1825. The base group observations in the treated group are the observations 70 years before the treatment. They are the observations in the year 1750 for the districts that received their first bank in 1820. All coefficients reported in Figure 3 are the differences between treated districts and control districts, compared to the difference between the base group among treated districts and the observations of the control districts in the year 1750. The aggregate of the average treatment effects of the treated groups is

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<sup>21</sup>The mean of the main independent variable increases from 0.0148 to 0.899 while the mean of the dependent variable increases from 0.0310 to 0.368.  $(0.899-0.0148)*0.115/(0.368-0.0310) \approx 38.0\%$ .

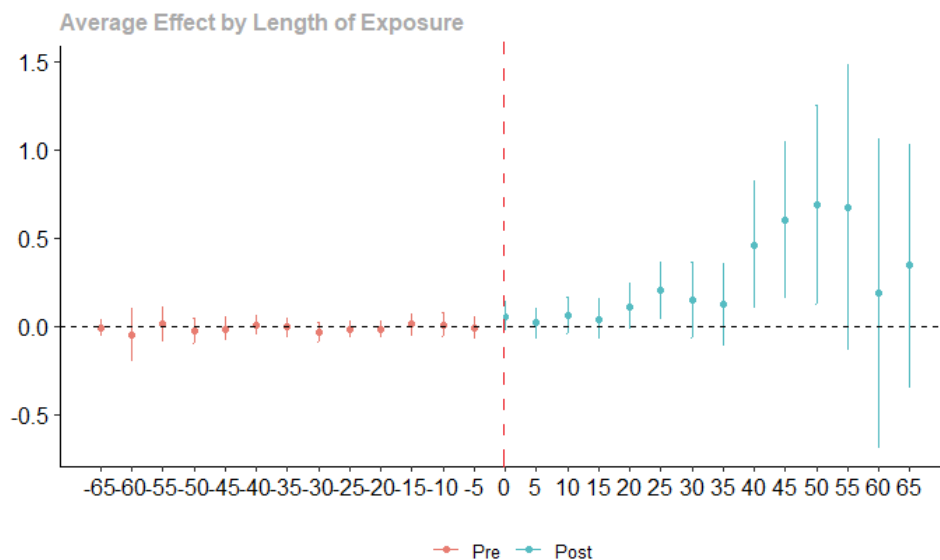


Figure 3: Event-study estimates

0.108, with the confidence interval ranging from 0.0441 to 0.1718.<sup>22</sup>

Figure 3 shows the event-study approach estimation results. As the R package provided by Callaway and Sant’Anna (2021) treats the earliest year before treatment as the baseline of the treated group, the coefficient of the base group 70 years before treatment<sup>23</sup> is 0 and ignored in the figure. It shows that there are no pretrends between districts treated in different periods and the untreated group. Receiving a first bank does not immediately lead to an increase in patenting, indicating that the intensive margins play an important role. It is not having a bank, but having more banks that mattered for patents. About 20 to 30 years after having the first bank, the treatment effects become significantly larger than 0. It is likely due to the increases in the number of banks in the treated groups. The impacts of banks became larger 40 to 55 years after first being treated than they were 20 to 30 years after the first treatment, by about 0.5. This corresponds to the period between 1790 and 1820 for the districts that received banks between 1750 and 1780. This is likely due to the maturity of the bill market in London and the improved connections between country banks nationwide.

<sup>22</sup>This is the specification including district and year fixed effects, and all time-varying controls.

<sup>23</sup>The observations, in 1750, of the districts that received the first bank in 1820.

## 5 Identification

### 5.1 Instrumental variable

Omitted variables, like local prosperity or lags in industrialization, might affect banks and patents at the same time. I construct instrumental variables to identify the estimation results. The variations in the money supply will change the profits of banking businesses. I use the money supply reconstructed by Palma (2018) to provide shifts in the time dimension. In baseline, I use the M2 time series for the instruments.

Inspired by Heblich and Trew (2019), I use post-towns which created differential exposure of different districts to the variations in the money supply to construct the instrumental variable. To receive news from strategic destinations on its borders swiftly, the English government set up post roads to facilitate the movement of royal messengers. Post towns were set up along the post roads to provide fresh horses for couriers as early as the first half of the 16th century, during the reign of Henry VIII. Post roads were established temporarily for wars and later abandoned due to high maintenance costs. In 1635, Thomas Withering revived the postal system on the basis of historical routes (Joyce, 1893). Post houses that used to provide horses became post offices, and the towns that they were in became post towns.

The post roads were built with the strategic aim of connecting London to Scotland, Ireland, the Royal Navy, and the European continent. In the 17th century, to travel as quickly as possible, postmen changed horses every 15 miles on average (Frajola et al., 2005; Heblich and Trew, 2019). Therefore, the locations of post towns were a function of 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 to setting up a bank in a post town (Dawes and Ward-Perkins, 2000). These include better access to information, security for gold transportation,

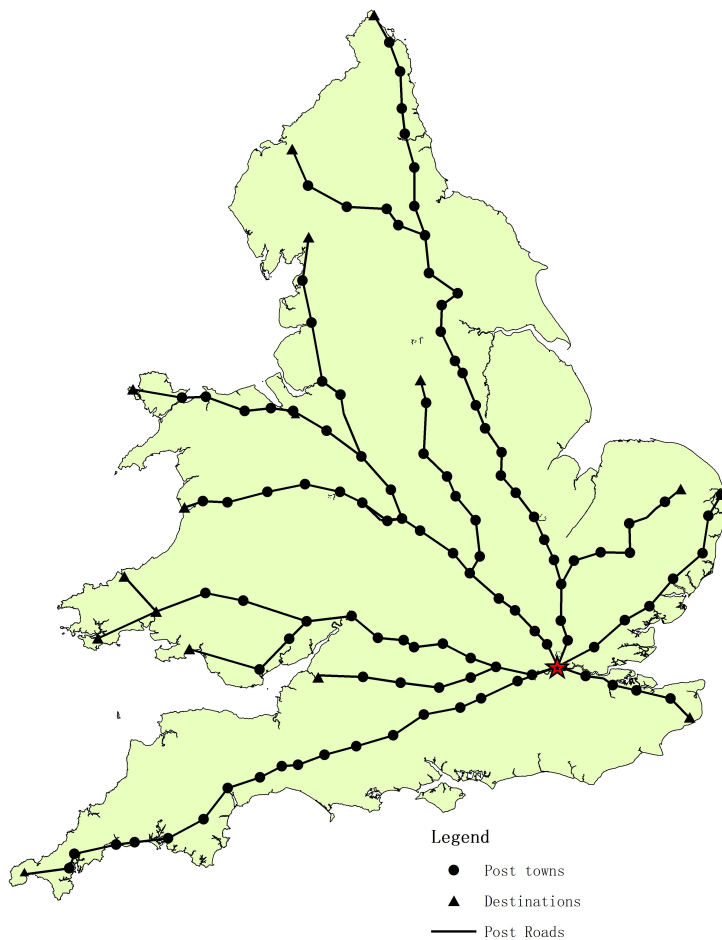


Figure 4: Post roads in 1675

This figure shows the main post roads recorded in the 1670s. The source is the encyclopedia named *Britannia* compiled by John Ogilby in 1675. Post towns in the sample are shown as circle dots. Post towns that were discarded from the instrument, including destinations and those whose distances from the previous post town were too large or too small, are shown as triangle dots. The solid lines are the main post roads.

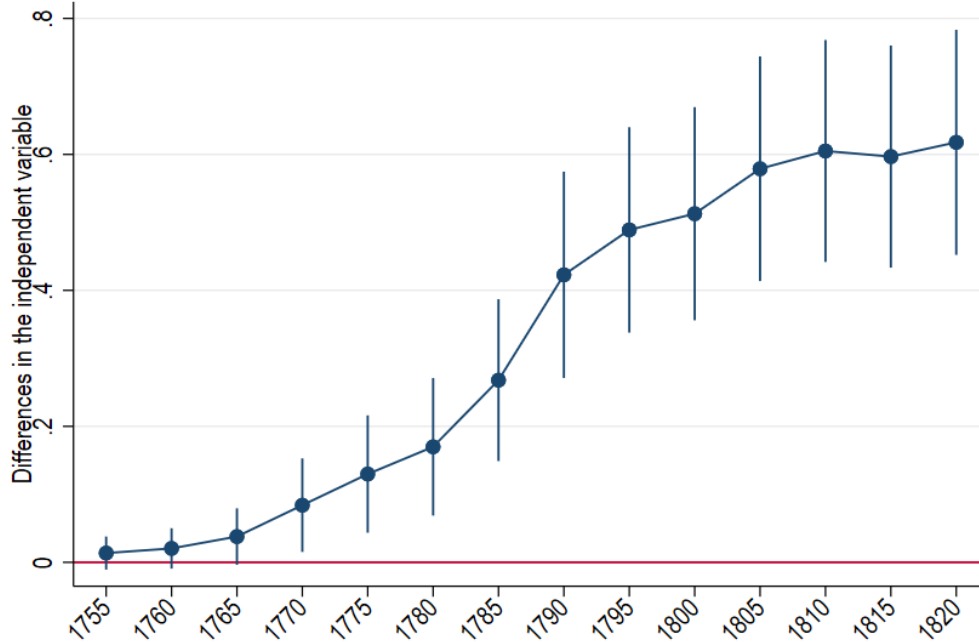


Figure 5: The impacts of post towns on country banks

The figure shows the differences in IHS(banks) across districts with and without historical post towns in different years.

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). Among all the post towns, I am using a subset of them that were plausibly chosen exogenously before the first country bank was established in 1688. By 1825, three-quarters of the districts had at least one post town.<sup>24</sup> The expansion of the postal system increased mail access in previously isolated districts without post towns more than it increased the access of districts with historical post towns in the 17th century. To rule out the impacts of security provided by post roads, I also restrict the sample to districts that were crossed by post roads and compare the districts with and without historical post towns in robustness checks.

In Figure 5, I use the year 1750 as the starting year and compare the number of banks

<sup>24</sup>According to my estimation based on the list of post towns. Source: Ken Smith and Nick Bridgwater, annotated lists of UK post offices, <https://sites.google.com/site/ukpostofficesbycounty/home>.



over time in districts with historical post towns against districts without post towns. Figure 5 shows that the number of country banks grew faster in districts with historical post towns. I use this stylized fact about the growth of banking access as the basis of my instrument, which captures the advantages of historical post towns and changes in money supply over time.

$$\begin{aligned} \text{IHS}(\text{Banks}_{i,t}) &= \beta_0 + \beta_1 \times 1(\text{Post towns}_i) \times \ln(M2_t) \\ &+ \beta_2 \times 1(\text{Post towns}_i) \times \ln(M2_t) \times 1(\text{Year}_t > 1797) + x'_{i,t}\gamma + \delta_i + \eta_t + \zeta_{i,t} \end{aligned} \quad (2)$$

The list of post towns is collected from Ogilby (1675) that recorded post towns in the 1670s. The source was published before the first country bank was established in Nottingham in 1688 to rule out the possibility of banks affecting the locations of post towns. I geocode the locations of historical post towns using Google Earth, then follow Hebllich and Trew (2019) and drop the post towns whose geodesic distances to neighboring post towns are less than 16 km or more than 32 km. These towns might have been selected due to some unobserved factors that predicted differential growth in patents during the Industrial Revolution. 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 from the sample.<sup>25</sup> Towns between London and the strategic destinations became post towns simply because they were on the post roads that were designed to connect to strategic locations.

In Equation (2), The first instrument is the interaction of the natural logarithm of the money supply in England in year t and the existence of historical post towns in district i. The identification of the coefficient between banks and patents is based on the assumption that the variations in money supply were uncorrelated with local factors that affected patenting after controlling for time-varying control variables, district, and year fixed effects.

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<sup>25</sup>The dropped towns include Bristol, Dover, Chester, Penzance, Norwich, Carlisle, Derby, Kendal, Machynlleth and Carmarthen. Berwick is included in districts with post towns because the destination of the Northern Road is Edinburgh.

I also construct the second instrumental variable using the sudden shock that changed the growth trends of banks in different districts following Burgess and Pande (2005). In 1797, a French army landed in Fishguard, Wales, but surrendered in two days (O'Brien and Palma, 2019; Berdell and Mondschean, 2020). The landing of a French Army in Wales created panic, so people tried to convert their Bank of England notes to gold. In response to the panic, the Parliament suspended the convertibility between Bank of England notes and gold, enabling the Bank of England to increase credit supply by discounting more bills without the constraints of its gold reserve (Michie, 2016). The shock also induced a large group of merchants to accept banknotes (O'Brien and Palma, 2019). The second instrument is the interaction of the first instrument with the dummy of year  $t$  being after 1797. I utilize the stylized fact that the difference in the rate of growth in banks between districts with historical post towns and districts without historical post towns became smaller after the suspension of convertibility in 1797. Figure A1 shows that the growth of banks was higher in districts with historical post towns than in districts without historical post towns before 1797. The gap grew much more slowly with the expansion of the money supply after 1797 than before 1797. The second instrument provides another group of exogenous shocks as the timing of the changes in the credit supply policies of the Bank of England was not related to the growth of patents in England. As the Fishguard battle ended in two days without causing actual economic loss, its only substantive impact on the English economy was via the decision to suspend convertibility.<sup>26</sup>

## 5.2 Balance tests

In Table 3, I test whether post towns were selected according to pre-existing characteristics that could affect the growth of patents in the future. The control variables include having a coal mine,<sup>27</sup> access to seaports, the natural logarithm of the distance to the nearest

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<sup>26</sup>It is reasonable to ignore the economic impacts of a French army of about 1,400 men that landed in Pembrokeshire and surrendered in 2 days instead of at the Westminster Bridge.

<sup>27</sup>The coal data is based on the parish-level data of Heblich and Trew (2019).

seaports, the natural logarithm of the distance to the nearest coast,<sup>28</sup> the natural logarithm of the area of the district (in  $km^2$ ), the average slope,<sup>29</sup> and suitability for wheat, rye, barley, and oats,<sup>30</sup> the four main crops in England. Panel A in Table 3 shows that districts with historical post towns had slightly better access to coal mines, lower access to the sea, smaller areas, flatter land and lower agricultural suitability, but the differences are not significantly different from 0. These time-invariant control variables can explain about 1/3 of the changes in patents.<sup>31</sup>

[Insert Table 3]

I test whether other time-varying factors, through which post towns might affect patents besides increasing banking access, were balanced. As above, I control for population, access to waterways, traveling time to London on turnpike roads, and the number of newspapers published within 50 km. Panel B of Table 3 shows that access to the transportation network and information access were not significantly different across districts with and without post towns. Districts with historical post towns had slightly more newspapers within 50 km but the difference is not significantly different from 0. Population growth is significantly slower in districts with historical post towns compared to districts without historical post towns.<sup>32</sup> This is consistent with what Alvarez-Palau et al. (2022) found as the expansion of transportation facilities led to growth in previously isolated and remote areas. The lower population growth in districts with historical post towns helps alleviate concerns about agglomeration effects from historical post towns. If agglomeration effects contributed to the

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<sup>28</sup>The maritime data about coasts and seaports is constructed based on Alvarez-Palau and Dunn (2019) and I have excluded the ports on rivers.

<sup>29</sup>The ruggedness data is calculated based on the SRTM data with the resolution of 90m. The unit of slope is percentage rise.

<sup>30</sup>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.

<sup>31</sup>Including the interaction terms of time-invariant controls with year fixed effects lowers the coefficients in column (3) of Table 2 from 0.163 to 0.119. Adding the county linear trends further lowers the coefficient to 0.107, as reported in column (4) in Table 2.

<sup>32</sup>The relationship between population and historical post towns is still valid if I restrict the sample to years with a census, 1800 to 1820. The growth rate is 1.34% lower per decade in the subsample.

growth of patents, their impacts would be negative for districts with historical post towns, which suffered from lower population growth in the period that I examine.

### 5.3 Baseline 2SLS Results

Table 4 reports the baseline two-stage least squares estimation results. Columns (1) and (2) show the IV estimates when I use the interaction of the natural logarithm of the money supply and the historical post town dummy as the instrument. Columns (3) and (4) show the corresponding results when I include both instruments in the estimation. Note that there are fewer observations in the IV estimation. I drop the destinations of post roads because I use the identifying variation of post towns set up because they were between London and post road destinations. My instrumental variable estimates are larger. The elasticities implied by IV estimation range from 0.185 to 0.190 and the effects expressed in standard deviations range between 24.9% and 25.6%. As the shock brought about by the Fishguard Battle in 1797 was exogenous, the overidentification tests show that the instruments are plausibly unrelated to unobserved factors that affect patents. In column (3) in Table 2, I control for the interaction terms of first bank cohort fixed effects and year fixed effects to rule out the unobserved factors that attracted banks and affected patents. The corresponding OLS coefficient is 0.163, which is close to 0.185. It is likely that the coefficient of the impacts of banking access on patenting falls between 0.16 and 0.19.

[Insert Table 4]

The IV estimates are about 1.6 times as large as the OLS estimates. There are several plausible reasons for this difference. One is a bias towards zero in the OLS estimation due to omitted variables that predict higher growth of banks but lower growth of patents. Banks set up in agricultural areas collected deposits and made use of them in the London money market (Pressnell, 1956, p. 76).<sup>33</sup> Also, Southeast England remained stagnant during the

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<sup>33</sup>The towns where these banks were located included Norwich, King's Lynn, Yarmouth, Wisbech and Fakenham.

| Ledger B        |            | June 28 <sup>th</sup> 1795 |
|-----------------|------------|----------------------------|
| Norwich Bank    | 21231 4 8  | Norwich Bank               |
| Lynn Bank       | 563210 9   | Lynn Bank                  |
| Yarmouth Bank   | 1000 6 3   | Yarmouth Bank              |
| Wisbe(a)ch Bank | 4465 15 8  | Wisbe(a)ch Bank            |
| Fakenham Bank   | 326217 10  | Fakenham Bank              |
| Lynn Bank more  | 35502 15 2 |                            |

Figure 6: The Barclays ledger about country banks in 1795

Source: Barclays Archive, Reference No: 0364-0047, Archive Description: Balance Sheets, Yearly [061] ("Shop Debit & Per Contra Credit") INC Country Balances. Unsigned. Partners Robert Barclay & John Henton Tritton. Possible Refs to Acc 27/140, 27/222. Folio Numbers are given but the volumes to which they relate are missing.

Industrial Revolution, with local industries declining in towns including Norwich due to the high wages in this area (Kelly et al., 2023). Both drainage of funds and low growth potential in rural Southeast England positively predicted the increasing numbers of banks and negatively predicted patents. Therefore, the omitted high savings biased the OLS estimates downward. According to the 1795 ledger of Barclays in Figure 3, the five country banks set up in Southeast England all held positive deposits with Barclays. Figure 1 shows that in 1810, most banks in Southeast England were still depositing money with Barclays. The banks in Southeast England did not have many local industries in which to invest, but instead collected deposits and sent them to the London money market, as described by Joplin (1837).

Another potential explanation is measurement error in measuring banking access. The number of banks does not capture the differences in sizes, assets, loans, and operating strategies of different country banks. Furthermore, the number of clients served by each bank and the deposits that depositors placed in banks varied across different districts and even different banks (Pressnell, 1956, p. 244). The instrument helps correct the bias in OLS estimation introduced by measurement error in banking access. Another possible explanation is a weak

instrument. According to columns (1) and (2) in Table 4, the Kleibergen-Papp F statistics are about 55. It is unlikely that a weak instrument is a plausible explanation in my setting.

## 6 Banks, liquidity constraints, and patents

In this section, I show how banks affected patents. Country banks and their London agents created an integrated national financial market. This system moved surplus funds from Southeast rural England to Northwest England where industrialists and merchants, who were the borrowing clients of country banks, lacked credit. The provision of short-term credit by country banks helped manufacturers avoid bankruptcy or keep lower cash reserves and spend more funds on fixed capital investments and innovation.

### 6.1 London agents: Bridges to an integrated national capital market

*"A bank in an agricultural district, say at Norwich, has a super abundance of money. A manufacturing town, say Manchester, has a demand for money. The bank at Norwich will send its money to a bill - broker in London. The bank at Manchester will send its bills to the same broker. A re-discount takes place."*(Gilbart, 1849, p.556)

Credit constraints hinder innovation and economic growth (Aghion et al., 2007, 2012). The words of James William Gilbart <sup>34</sup> show that it is likely that potential patentees in areas that lacked credit would benefit from connections to areas with adequate credit through the London money market. I construct a measurement of the connections between country banks based on the agency relationship between country banks and their London agents. Banks that were connected to the same London banker might trade with each other at a lower cost than with other banks. The entry of country banks in other districts was not affected by local economic conditions but did increase the financial access of the local district to other

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<sup>34</sup>James William Gilbart was a contemporary banker and the General Manager of the London and Westminster Bank that became today's NatWest.

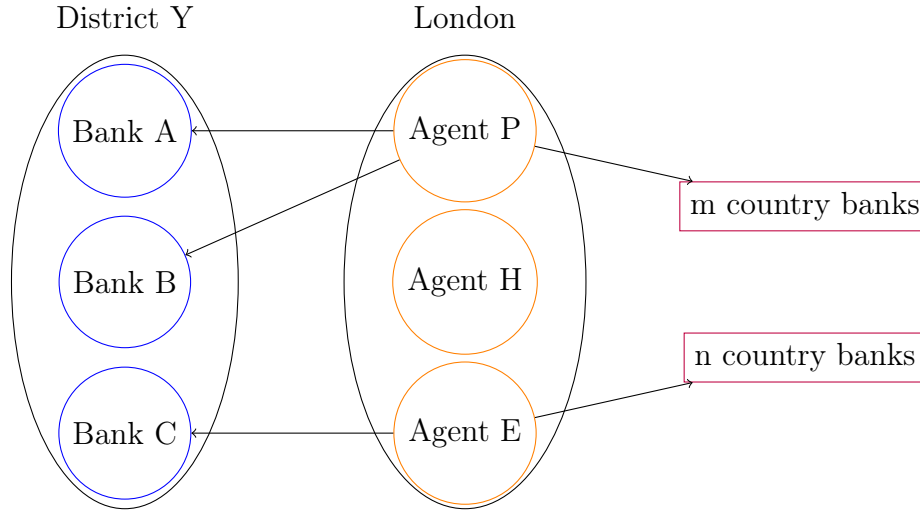


Figure 7: Illustration of bank connection to other districts

districts, if banks in the local district were connected to the new banks through their London agents. Therefore, the entry and exit of country banks in other districts connected via the London agent network created plausible exogenous shocks to the banking access of the local district.

If a country bank was recorded as having an agency relationship with a London banker in a year and the relationship was also recorded in a later year, I assume that the relationship remained unchanged between the two years of records. As shown in Figure 6, for district Y, if there were three country banks, Banks A, B, and C, and Bank A and Bank B were connected to London agent P that connected to  $m$  country banks in other districts, while Bank C was connected to London agent E that connected to  $n$  country banks in other districts. London agent H was not connected to any banks in district Y. I define the number of connections of district Y to banks in other districts as  $(m+n)$ . The variable of bank connections measures the financial resources from other districts that district Y could access via its local country banks and the London agents of the country banks.

[Insert Table 5]

In Table 5, I report the results of estimating the impacts of the number of bank connections on the number of patents. The dependent variable is the inverse hyperbolic sine of the number of patents in 5 years, as in the baseline estimation. The independent variable is the inverse hyperbolic sine of the number of bank connections in district  $i$  in year  $t$ . Column (1) is the same as column (2) in Table 2. In column (2), I report the impacts of bank connections on patenting. A one standard deviation increase in bank connections leads to a 12.0% standard deviation increase in patenting. In column (3), I include both banks and bank connections and the impacts are driven by both the changes in the number of local banks and the changes in bank connections.

As the fast growth of the London money market might have encouraged the formation of agency relationships between country banks and London banks (Pressnell, 1956, p.94), I focus on the period after 1790 in column (4). This is the period when many more records about agency relationships were recorded.<sup>35</sup> Column (4) shows that the impacts of banks were mainly driven by connections to other country banks in other districts in the period after 1790. It is likely that country banks increased patents as local financial intermediaries when bill discounting services were still immature. When the market was more mature, the connection to other districts via the London money market provided the local potential patentees with a more integrated, national-level financial market. The results in Table 5 confirm the existence of an integrated national capital market by the 1790s as discussed in North and Weingast (1989), but the limited availability of other different connections between country banks prevents me from looking at earlier periods.

## 6.2 Patentees supported by banks

As country banks provided short-term credit mainly to industrialists and merchants, the impacts of banks on patents might vary in different sectors.

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<sup>35</sup>Based on my comparison between the records in directories and records in the ledgers of Barclays, the rise of agency relationships happened around 1790. Therefore, the lack of records about agency relationships between country banks and London bankers might be due to the lack of such relationships.



To categorize patents, I divide the occupations of patentees into five groups based on the Primary-Secondary-Tertiary (PST) system (Wrigley, 2010). In Panel A of Table 6, I report the effects of banks on patents acquired by people in agriculture and mining, manufacturing, trading, non-trading services and other occupations respectively from column (1) to (5).<sup>36</sup> Column (2) of Table 6 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 76% as large as that in the baseline regression. The coefficient in column (2) is statistically different from the coefficients in other columns<sup>37</sup> and the impacts of banks on patents in the manufacturing sector are significantly larger than patents in other sectors.

[Insert Table 6]

In Panels B and C in Table 6, I separate patents into innovative modern industries, like Textile and Paper, printing and publishing and traditional industries like Shipbuilding and Mining based on the shares in inventive output (Nuvolari and Tartari, 2011; Squicciarini and Voigtländer, 2015). I find that the impacts of banks on industrialists who participated in production were widespread, both in innovative industries and traditional industries. However, the impacts on merchants were mainly in the innovative industries. Merchants who invested in multiple industries (Crouzet, 1985) would choose to invent products in innovative industries that yielded high returns for new technologies. Also, the impacts of banks on patentees from no-trading services were positive and significantly different from 0 in innovative sectors. The existence of a patent market in England (Bottomley, 2014) suggested that country banks might also increase the demand for inventions and attract inventors to invent in relevant industries.

Some patentees did not mention their occupations,<sup>38</sup> and some people were merchants and

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<sup>36</sup>One example of the patentees that belonged to other occupations is Archibald Cochrane, the 9th Earl of Dundonald. He patented his new chemical in 1794.

<sup>37</sup>The  $\chi^2$  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-values are 0.004, 0.003, 0.044 and 0.001 respectively.

<sup>38</sup>James Watt did not claim his occupation in the patent record of his famous steam machine in 1769.

industrialists at the same time. For robustness, I use the taxonomy proposed by Nuvolari and Tartari (2011) and categorize 21 different industries into the agricultural and manufacturing sector.<sup>39</sup> In column (1) of Table A14, I report the impacts of banks on patents in the agricultural and mining sector. In column (2) of Table A14, I include only the industries that belong to the manufacturing sector without any doubt. I gradually add other industries<sup>40</sup> in columns (3) to (6). The results are also consistent with the results shown in Table 5 that the impacts of banks were mainly driven by patents in the manufacturing sector.

### 6.3 Credit constraints

There is anecdotal evidence that the return on industrial investments was higher than the return on investments in agriculture in the UK (Allen, 2009b). This is consistent with a point made by Thomas Joplin, a banker who was active in the first half of the 19th century, that the industrial areas 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 local interest rates for Britain during the 18th century (Brunt and Cannon, 2009; Keller et al., 2021), scholars have rebuilt county-level average interest rates over a long period based on crop prices. The interest rates in districts with below-median agricultural suitability are about 1.5% to 2.5% higher than in other regions, while the annual interest cap placed by the Usury Law was 5%. In Table 7.1, I test how the impacts of country banks on districts differ in districts with different agricultural suitability, and therefore different levels of credit constraints.

[Insert Table 7.1]

I define a district suitable for a crop if the average crop suitability for this district is

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<sup>39</sup>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).

<sup>40</sup>They are Construction, Leather, Military equipment and weapons, and Medicines.

higher than the median crop suitability across England and Wales. A district is suitable for agriculture if it is suitable for at least 3 of the 4 main crops in England.<sup>41</sup> In columns (1) and (2) of Table 7.1, 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). The impacts of banks are significantly larger in districts unsuitable for agriculture that lacked credit than in districts suitable for agriculture, the areas with abundant credit. In columns (3) and (4), I test how the impacts of bank connections were different in districts with different historical bankruptcy rates before 1750. I calculate the county-level bankruptcy rates using the number of bankruptcy cases between 1720 and 1740 which was counted by Hoppit (1987) divided by the county-level population in 1750 by Wrigley (2007). The impacts of banks were larger in districts with higher historical bankruptcy rates. I report the results using the number of bank connections in columns (5) to (8). The results are similar, showing that banks increased patents more in districts subject to tighter credit constraints.

[Insert Table 7.2]

As agricultural suitability can be used as a proxy for the abundance of credit, I separate the connections to banks in other districts in Section 6.1 into connections to banks in districts suitable for agriculture, those with abundant credit, and connections to banks in districts unsuitable for agriculture, those lacked credit. Then I test the impacts of the two kinds of connections to banks in districts with different agricultural suitability. In Table 7.2, The first row shows how the number of patents was affected by the number of banks with surplus credit accessed by districts that were subject to credit constraints via country banks' London agents. The second row shows the impacts of the banking service provided by banks in areas with surplus credit to districts with surplus credit. The third row shows the impacts of the banking service provided by banks in areas that lacked credit to districts that lacked credit. The fourth row shows the impacts of the banking service provided by banks in areas that

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<sup>41</sup>The four crops are oat, barley, wheat, and rye.

lacked credit to districts with surplus credit. In column (1) and (3), I include district and year fixed effects and control for population. In columns (2) and (4), I add all time-varying controls. The standard errors are clustered at the district level in columns (1) and (2), while at the county level in columns (3) and (4).

## 6.4 Qualitative evidence

In this section, I provide qualitative evidence about several mechanisms through which country banks contributed to the increases in patents during the British Industrial Revolution. The qualitative evidence is drawn from the biographies of the owners of some famous patents.

Banks provided short-term credit that supplemented firms' working capital and enabled industrialists to expand long-term investments. With a higher supply of working capital, industrialists were able to invest more in fixed capital and innovation, which might lead to more patents. The flax-spinning firm of John Marshall that gained a patent in 1793 spent £9,241 on fixed capital including plants, steam engines, machines, and land when their paid-in capital was £10,149.<sup>42</sup> Another example is William Balston, a famous papermaker, who built his mill with all his funds and started on the first day of 1807. He expected to receive all working capital from banks and raw material providers (Balston, 1979, p. 53-62). He used bank loans to keep his mill operating while experimenting with new machines. He was ready to patent a machine for drying papers by June of 1807.<sup>43</sup>

Entrepreneurs also hired engineers to invent and apply for new patents for them. John Marshall employed an engineer, Matthew Murray, to invent a flax-spinning machine for him and Murray successfully patented two machines in June 1790 and December 1793. Another example is Byrom, Allen, Sedgwick, and Place of Manchester, a country bank founded in

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<sup>42</sup>The working capital of this firm came from relatives (£5,517), bank overdrafts (£3,783), and trading debts (£5,915) (Rimmer, 1960). Short-term credit from the country bank made up 25% of all the debt of the firm.

<sup>43</sup>The machine was described as 'Certain Machinery to be used in the drying of Paper, with improvements applicable to Paper and other Manufacturers'. Eventually, his attempt to patent the machine failed because of the incompetence of his solicitor.

1771 (Smith, 2012). The bank provided loans to Livesey, Hargreaves and Company, a textile manufacturer in Preston. The textile firm hired Thomas Bell from Scotland who patented a rotary printing machine that could print different colours at the same time. (Riello, 2010; Woodcroft, 1854). In 1784, he patented an updated version that could print in six colours (Donnachie, 2004).

Without banks, innovative firms might have gone bankrupt and been unable to produce patents. The overdrafts of £3,783 that John Marshall gained from Beckett & Co., a country bank in Leeds, in 1792-1793 saved the flax-spinning firm from going bankrupt (Rimmer, 1960; Crouzet, 1972). In April 1793, during its hardest days, the firm was in deficit of £3,042 while the cash in hand was only £191. Without the overdraft provided by Beckett & Co., the partnership of Marshall might have dissolved and Marshall might have not had the chance to acquire the new patent. Marshall managed to operate the firm and used the new patent to attract new partners whose investments helped him succeed.

There were also cases when some bankers directly participated in industrial production that led to patents. Walter Taylor of Southampton held four nautical patents, as he ran a firm that produced wooden rigging blocks for the Royal Navy. In the 1780s, he formed a partnership with Richard Moody, a local 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 contributed to Taylor's patents in brewery.

## **7 Robustness checks**

### **7.1 Instrument validity**

A potential concern is the direct violation of the exclusion restriction, post towns directly affecting patents. For example, lower postage costs and higher information access could lead to more patents (Hanlon et al., 2022). However, during the period that I examine, the

postal system expanded to many formerly isolated districts.<sup>44</sup> New post towns set up in previously isolated districts connected these districts to the national postal network while only connecting historical post towns to a few previously isolated districts. Therefore, the change in information access is greater in districts without historical post towns than in districts with historical post towns. It is unlikely that post towns directly increased patents through the channel of a larger increase in information access.

To further alleviate concerns about the direct impacts of historical post towns on patents, I compare the number of patents in districts with historical post towns but without banks between 1750 and 1825 to the districts without historical post towns using an event studies framework. Figure A2 shows the estimation results. Prior to 1740, districts with historical post towns but no banks had slightly more patents than districts without historical post towns. However, the difference became negative compared to 1740 and became significantly different from 0 in the 1770s and 1800s. Figure A2 shows that districts with historical post towns but without any banks in the sample period did not have more patents due to the existence of historical post towns. Instead, it further validates my discussion in the previous paragraph. Districts with historical post towns were disadvantaged in the growth of information access due to the expansion of the postal system.

In Table A3, I estimate the impacts of post towns on patents in districts without banks. The post towns included in this table are taken from Ken Smith's UK Post Office List. They include the historical post towns on trunk post roads that I used in the baseline estimation, Columns (1) and (2) show that the numbers of patents were negatively affected by the existence of post towns. In column (3), I expand the subsample to the district-year observations without banks and the result remains robust. In column (4), I separate post towns into the historical post towns in my baseline estimation, other post towns on minor branch roads established by 1750, and post towns set up after 1750. Column (4) shows

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<sup>44</sup>By 1820, 442 districts out of the 585 districts in the sample of IV estimates had at least one post town. The calculation is based on Ken Smith's UK Post Office List at <https://sites.google.com/site/ukpostofficesbycounty/home>.

that all post towns set up before 1750 were slower in patent growth after 1750 due to the expansion of the postal system. For post towns set up after 1750, the impacts were also negative, but not significantly different from 0.

Post roads were guarded (Dawes and Ward-Perkins, 2000), so they might be different from other roads and affect patents as an omitted variable. To rule out concerns about unobserved factors on historical post roads that might affect patents. In Section 4, I have shown that districts with and without historical post towns were balanced in pre-existing time-invariant characteristics. Here, I restrict the subsample to districts crossed by historical post roads. I first show that historical post towns were not different from districts without historical post towns on post roads. Then I use permutation tests to show that it was the historical post towns that mattered, but not other unobserved factors.

Table A4 shows balance tests on the time-invariant variables and time-varying variables in the subsample of districts crossed by historical post roads. On historical post roads, districts with post towns and districts without post towns were not significantly different in time-invariant variables, access to newspapers, waterways, and turnpike roads. The population growth in post towns was slightly lower than in districts without post towns. On post roads, post towns were also plausibly exogenously picked for fresh horses in the 16th century, but not other economic factors that might lead to more patents. 383 districts were crossed by some post roads and there were post towns in only 112 of them. In Figure A3, I randomly assign historical post towns to districts crossed by historical post roads for 1,000 times and redo the 2SLS estimation for each random set of historical post towns. Then, I collect all the t values estimated and plot them in the figure. In the baseline estimation, the t value estimated is 2.23, where the red dashed line marks. The t-values estimated mostly fall between -1 and 1.5, and none of them is larger than 2.23. Therefore, this figure alleviates concerns about the impacts of omitted factors on historical post roads.

Concerns about agglomeration effects also exist. There might have been more facilities that contributed to knowledge spillovers, like pubs and scientific societies, in historical post

towns. These facilities might have promoted innovation but cannot be measured due to data availability. The lower growth of population in districts with historical post towns shown in Panel B of Table 3 and Table A4 can partially alleviate concerns about agglomeration. The populations in districts without historical post towns were growing faster than in districts with post towns and would have gained more patents from agglomeration effects. I cannot rule out the possibility that the share of manufacturing employment increased more in districts with historical post towns while their population increased more slowly. However, this does not conflict with my argument that banks contributed to the Industrial Revolution in England and might be a mechanism that this paper cannot cover due to the lack of granular manufacturing employment data between 1750 and 1820.

To further confirm the relevance between post towns, country banks, and patents, I create placebo post towns 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 of approximately 24 km, the average distance between real post towns. I use placebo post towns to construct instrumental variables and do IV estimations. A map of placebo post towns can be found in Figure A4.

The results of placebo tests are reported in Table A5. I create placebo post towns on pseudo post roads connecting to all strategic locations near borders. I control for district and year fixed effects, and population in column (1) and add all time-varying controls in column (2). The IV estimates are negative and not significantly different from 0. The coefficient in the first stage in columns (1) and (2) both show that the instrument is weak. The KP F statistics is only about 1. In column (3), I drop placebo post towns on the pseudo post roads that did not connect London with the borders, and I further drop the psuedo post towns on the road connecting to Great Yarmouth on the east coast in column (4). Placebo post towns predict banking access poorly. As 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.

I have argued that it is unlikely that the exclusion restriction is violated due to the long-term impacts of historical post towns. In Section 4, I also used the changes in credit supply resulting from the suspension of convertibility to create exogenous shocks to the number of banks. To further add confidence in the instrumental variables, I use linear trends and different transformations of the money supply to create exogenous shocks to banks following Borusyak et al. (2021). In Table A6.1, I use the linear year variable to provide time shocks in columns (1) to (4) assuming that the growth of banks was higher in districts with historical post towns. In columns (1) and (2), I use only the interaction term of historical post town dummy with linear year. In columns (3) and (4), I add the second instrument which is the interaction of the first instrument based on M2 and the dummy of post 1797. The results are similar to the results in columns (1) to (4) in Table 4, showing that the impacts are stable if I only use linear trends.

As the time series of the natural logarithm of M2 contain unit roots and are not stationary, I apply the HP filter to the natural logarithm of M2 between 1740 and 1825 to construct the instruments in columns (5) to (8). The HP parameter value that I use is 6.25. The augmented Dickey–Fuller test shows that the cyclical components in the natural logarithm of M2 are stationary and do not contain unit roots. Therefore, the shocks brought about by the cyclical components in  $\ln(M2)$  bring about consistent results when  $T$  goes to infinity. The instrumental variables constructed using the cyclical components are slightly weaker than the ones using  $\ln(M2)$  and the 2SLS estimation coefficients are slightly larger than those in columns (1) to (4). In columns (9) and (10), I do not use any filters, but just use the changes in  $\ln(M2)$  compared to the previous year as the time shocks in money supply. The instrument is much weaker than the one based on HP filtered money supply series and the coefficients in the 2SLS are still positive. In columns (11) and (12), I take the changes in time trends of the money supply after 1797 into account. I use HP filters for the  $\ln(M2)$  series in two subperiods, one between 1740 and 1796 and the other between 1797 and 1825

to calculate cyclical components in different subperiods. Then I construct the instrument by interacting the historical post town dummy with the cyclical components in  $\ln(M2)$  to create one instrument. The results do not differ significantly from the results in columns (5) and (6).

For robustness, I also use different subsets of post towns to construct the instruments. I show the results of 2SLS regressions using different instruments in Table A6.2. The first-stage estimation results are reported in Table A6.3. In Panel A, I use the interaction of historical post towns with the natural logarithm of the money supply to construct the instrument. In Panel B, I use the interaction of historical post towns with the linear year variable to construct the instrument. Columns (1) and (2) are the same as columns (3) and (4) in Table 4. 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, the connection to these destinations might have involved economic concerns. Compared to column (2), the coefficient drops by about 30%. In column (4), I drop detouring points on post roads which might be more prosperous<sup>45</sup>. 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.

## 7.2 Robustness in specifications

In this section, I use different specifications to test if the relationship between country banks and patents are robust to different specifications.

There were time-invariant unobserved factors that affected the growth of patents in different periods, but we cannot measure them due to the restrictions in data availability. For example, the population at the start of the sample might have led to changes in many other factors that affect the number of patents. In the baseline estimation, I construct the

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<sup>45</sup>For example, there is a detour that goes to York, one of the most important English cities.

district-level population data using the census data in 1801 and use the county level population from Wrigley (2007) to extrapolate, assuming that the population of each district change at the same rate as the county to which they belonged. Districts with larger initial population might have gained larger growth in population due to agglomeration effects or gained smaller growth in population due to the construction of transportation infrastructure (Alvarez-Palau et al., 2022). To control for the impacts of these time-invariant factors, I use the interactive fixed effects model following Bai (2009).

In Table A7, I report the estimation results with the number of interaction terms being 1 and 2 in Panel A and Panel B. When the number of interaction terms is 1, interaction terms of one group of district fixed effects and one group of year fixed effects are added into the regression, assuming that all unobserved time-invariant factors had the same impacts on patents in each distinct year. In Panel A, the coefficients are smaller than those in Table 2, indicating that some historical unobserved factors could explain almost half of the changes in patents. If this was the initial population in 1750, it shows that historical dependence was important in this period, but my results in the baseline estimation are still robust. When the number of interaction terms is 2, the assumption becomes that there were two groups of time-variant factors that had different effects on patents in each distinct year, but all unobserved factors within each group had the same effects. In Panel B, the results in columns (1) and (2) are about 10% smaller than the results in Panel A, showing that the impacts of the second group of unobserved factors were much smaller than the impacts of the main group of unobserved factors. The coefficient estimated in column (3) is close to those in columns (1) and (2), indicating that the second group of unobserved factors might be the ones that predicted early establishment of country banks. Both Panel A and Panel B show that after controlling for the impacts of time-invariant unobserved factors, the impacts of banks and patents are still robust.<sup>46</sup>

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<sup>46</sup>Setting the number of interaction dimensions to 3 will further decrease the coefficient in column (2) to 0.0421, with the p-value being 0.088. Setting the number of interaction dimensions to 4 will return a coefficient of 0.0427, with the p-value being 0.126. Therefore, there are mainly three groups of unobserved factors contributing to patents. The estimation results remain robust. Controlling for too many groups of

Next, I report OLS estimates when clustering the standard errors at different levels. Table A8.1 reports the results when I cluster the standard errors at the county level. The results do not change significantly from the results in Table 3. Table A8.2 reports the results of using Conley standard errors. I use different cutoffs from 50 km, the average diameter of a county, to 100 km, 200 km, 300km, 400 km, and 500 km, the distance between the northern and southern boundaries of England. Although standard errors of the estimated coefficients increased, the estimation results are still robust.

To alleviate concerns about multiple periods in the two-way fixed effects model, I estimate the relationship between banks and patents using the subsample of 1750 and another year.<sup>47</sup> In Figure A5, I show the coefficients of confidence intervals when I estimate the relationship between country banks and patents using a subsample of the observations in the year of 1750 and the observations in another year  $t$ . The coefficient for the subsample made up of observations in 1750 and 1780 is about 0.4, while the estimate for the subsample of 1750 and 1790 is about 0.2. The coefficients are larger for the years between 1765 and 1780, and converge to about 0.2 in later periods. The effects of banks were larger in the early stages of the Industrial Revolution and smaller in later years when there was a higher credit supply, but the effects were still positive and significantly different from 0 for later years.

Some districts might be small and remained stagnant during the Industrial Revolution, so there were no banks and no patents in these districts. I run the regression in districts with at least one country bank during the period I examine, in case the result is driven by districts without country banks or without patents. The results for the subsample that received at least one country bank between 1750 and 1820 are reported in columns (1) to (4) in Table A9. The coefficients are slightly larger than the coefficients in the baseline. Similarly, to rule out the effects of districts without patents, I also run the regression in districts with at least one patent between 1750 and 1825. The results are reported in columns (5) to (8) in Table

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unobserved factors will lower the sample size and make estimation results imprecise.

<sup>47</sup>The estimation of the relationship between  $y$  and  $x$  in 2 periods using a two-way fixed effects model is equivalent to estimating the relationship between changes in  $y$  and changes in  $x$  between the two periods.

A11, the coefficients are slightly smaller than in the baseline estimation.

### 7.3 Robustness in measurement of innovation

In the baseline regression, my dependent variable was constructed based on patentee counts. For patents with multiple patentees, I aggregate the number of patentees in each district. In Table A10, I test whether the results are robust when I divide patents among all the patentees that co-authored on one single patent instead of using patentee counts. I report the OLS estimates in columns (1) to (4) and the 2SLS estimates in columns (5) to (8). As the total number of patents is lower in the specification of Table A10 than the baseline specification, the coefficients estimated are slightly smaller than those in Table 2 and Table 4. However, the standardized coefficients in columns (1) to (4) are very close to those in Table 2. Different measurements of patents do not create results that are too different from the baseline estimation.

I also discuss the robustness of my results to different transformations of patents. When using different transformations, we are changing the variations in the corresponding variable. I first use the  $\ln(1+x)$  transformation of the number of patents, which is a usual transformation when there exist 0-values in the variable, as the dependent variable. The results are reported in columns (1) and (2) of Table A11.1 and the coefficients are about 22% smaller. There are concerns about the transformations of  $\text{IHS}(x)$  and  $\ln(1+x)$  when the value of  $x$  changed from 0 to 1. To alleviate the concerns, I first use a binary model, setting the dummy variable  $1(\text{patent} > 0)$  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). Increases in banking access lead to higher chances of having at least a patent in the future 5 years. Better financial access is not only correlated with a larger number of patents per capita but also with the emergence of a patent. In columns (5) and (6), I use a count model as the numbers of patents were non-negative integers. Further, I use Poisson pseudo-maximum likelihood estimation in columns (7) and (8). Consistent with the baseline results,

better banking access was correlated with larger patent numbers.

More banks do not necessarily mean better access to banks as the local population affects the access of local residents to bank services. Therefore, I replace the dependent variable with the natural logarithm of one plus the number of patents per million people in the next 5 years and the independent variable with the natural logarithm of one plus the number of banks per million people. Results are reported in Table A11.2. I report OLS estimates in columns (1) and (2). IV estimates are in columns (3) and (4), while first-stage results are in columns (5) and (6). The results are still similar.

As I mentioned in Section 2.1, simple patent counts might not reflect the quality of patents. I use the Woodcroft Reference Index and the adjusted index proposed by Nuvolari and Tartari (2011) to reflect the importance of patents during the First Industrial Revolution. The results are reported in Table A12. In columns (1) and (2), I report the estimates for the patents with above-median quality, controlling for population in column (1) and all time-varying controls in column (2). The coefficient in column (2) is about 44% of that in column (2) of Table 2. In column (3), I focus on the patents with top 25% quality, and the coefficient is about 38% of that in column (2) of Table 2. In column (4), when I further restrict to patents with the top 10% quality, the coefficient is about 12% of that in column (2) in Table 2. Country banks not only led to more patents but also patents of higher quality.

The impacts of new banks on patents might be short-term and can be observed only in a short period after they entered. They could also be long-lasting. Therefore, I investigate the impacts of banks on patents using different aggregation windows for patents. The window that other scholars (Cornaggia et al., 2015) use for patent counts in the 1980s is three years. In the baseline estimation, I choose 5 years as standardized methods and procedures for invention did not yet exist, though some inventors began to use scientific methods in their works (MacLeod, 1988). Research and development activities in the 18th century might have taken longer than they do today. In Table A13.1, I report the results of using the windows of 3 years and 10 years and the results are still robust.

Compared to other settings, the impacts of English country banks on patents were smaller than those of free banks in Antebellum America. 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 A13.2. The differences in the estimates are likely to be due to two factors, the smaller sizes and focus on short-term credit of country banks in England compared to American free banks and the higher costs of English patents compared to American patents. 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).<sup>48</sup> Free banks in Antebellum America actively sponsored manufacturers and small businesses and were widely involved in innovation and entrepreneurship (Mao and Wang, 2022), more similar to the universal banks in Germany in the second half of the 19th century (Gerschenkron, 1962). For the costs of patents, an English patent cost 70 - 100 pounds (Bottomley, 2014) while an American patent cost 30 dollars (Khan, 2006), which was smaller than 10% of the English cost.

## 7.4 Spillover effects

Banks had spatial spillovers. Although banks generally provided loans to people nearby with whom they were familiar, there were also examples when industrialists searched for loans in other places. Therefore, I explore the spillover effects of country banks in this section. In Table A15, I calculate the number of banks in the districts which were the neighbours of the local district and add it to the estimation. Column (1) is the same as column (2) in Table 2. In column (2), I add the inverse hyperbolic sine of the number of banks in neighbouring districts and find that banks in the neighbouring districts reduced the number of patents in

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<sup>48</sup>The exchange rate between pounds sterling and US dollars was about 1:5 (Davis and Hughes, 1960) in the 19th century, so an average country bank was about one-tenth as large as an average American Free Bank.

the local district. However, the estimates for local banks were largely unchanged. In column (3), I include only the banks in neighbouring districts, and the coefficient is close to that in column (2). Therefore, the impacts of local banks and banks in neighbouring districts were largely uncorrelated with each other. The banks in neighbouring districts might have attracted inventors to their corresponding districts and lowered the local number of patents. In column (4), I control for bank cohort fixed effects interacted with the year fixed effects and the results remain robust.

## 8 Conclusions

In this paper, I use panel data on banks and patents in England to argue that banks increased innovation during the Industrial Revolution by providing short-term credit to industrialists. Better banking access led to more innovation, as measured by the number of patents, during the British Industrial Revolution. Registration districts where there were more banks witnessed a faster growth in the number of patents between 1750 and 1825.

My finding shows that a standard deviation increase in banking access would lead to a 47.5% increase in the number of patents in the following 5 years. The effects are smaller than free banks in Antebellum America but non-negligible. I further show that country banks contributed to the formation of an integrated national financial market, which is worth further exploration. The effects of banks were mainly driven by industrialists and merchants, the clients that borrowed from country banks to lower the costs of procuring working capital. The role of country banks in promoting growth and lowering bankruptcy risks of innovative entrepreneurs might be helpful in explaining the decreases in the drop of output during recessions in England (Broadberry and Wallis, 2017). My finding supports the claim that financial development increases innovation and helps explain why some parts of England grew faster during the First Industrial Revolution.



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## Appendix

Table 1 Registration district-level descriptive statistics in selected years

|                               | (1)  | (2) | (3)    | (4)    | (5)   | (6)     |
|-------------------------------|------|-----|--------|--------|-------|---------|
| variables                     | year | N   | mean   | sd     | min   | max     |
| No of patents in 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     | 10      |
|                               | 1820 | 595 | 0.822  | 3.390  | 0     | 36      |
| No 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 (passengers)  | 1750 | 595 | 60.48  | 37.51  | 0.453 | 187.4   |
|                               | 1780 | 595 | 25.52  | 14.0   | 0.289 | 84.29   |
|                               | 1800 | 595 | 20.63  | 11.88  | 0.209 | 74.35   |
|                               | 1820 | 595 | 17.37  | 9.974  | 0.197 | 66.87   |
| No 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. [[Back To Text](#)]

Table 2 Baseline results

|                                   | (1)                  | (2)                  | (3)                  | (4)                  |
|-----------------------------------|----------------------|----------------------|----------------------|----------------------|
|                                   | IHS(Patents)         |                      |                      |                      |
| IHS(Banks)                        | 0.115***<br>(0.0207) | 0.115***<br>(0.0207) | 0.163***<br>(0.0387) | 0.107***<br>(0.0383) |
| Observations                      | 8,925                | 8,925                | 8,925                | 8,925                |
| Within R2                         | 0.0409               | 0.0415               | 0.0935               | 0.158                |
| District & Year FEs               | Yes                  | Yes                  | Yes                  | Yes                  |
| Time-Varying Controls             | Population           | All                  | All                  | All                  |
| Bank Cohort FE X Year FE          | No                   | No                   | Yes                  | Yes                  |
| Time-invariant Controls X Year FE | No                   | No                   | No                   | Yes                  |
| County Linear Trends              | No                   | No                   | No                   | Yes                  |
| Standardized B                    | 0.156                | 0.156                | 0.221                | 0.145                |

Notes: This table reports OLS regression estimates of Eq. (1). In column (1), I include district and year fixed effects and control for only population. In column (2), I include all time-varying controls. In column (3), I further include the interaction of first bank cohort fixed effects and year fixed effects. The first bank cohort fixed effect dummy for year  $t$  is 1 if district  $i$  received its first bank between year  $t-4$  and year  $t$ . In column (4), I further include the interaction terms of time-invariant controls and year fixed effects and country linear trends. Time-varying controls include  $\ln(\text{population})$ ,  $\ln(1+\text{newspapers in 50 km})$ ,  $\ln(\text{traveling time to London})$  and access to waterways. Time-invariant variables include access to coal fields, having a sea port,  $\ln(\text{distance to the nearest sea port})$ ,  $\ln(\text{distance to the nearest coast})$ ,  $\ln(\text{area})$ , average terrain slopes (percentage rise), and suitability for wheat, oat, barley, and rye, the four main crops in England. Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively. [Back To Text]

Table 3 Balance tests

| Panel A | Time-invariant variable                 | Mean   | coefficient | SE       |
|---------|---|--------|-------------|----------|
| (1)     | 1 (Coal field)                          | 0.390  | 0.0148      | (0.0532) |
| (2)     | 1 (Sea port)                            | 0.190  | -0.0398     | (0.0428) |
| (3)     | ln(distance to the nearest sea port)    | 10.144 | 0.105       | (0.112)  |
| (4)     | ln(distance to the nearest coast)       | 9.456  | 0.122       | (0.143)  |
| (5)     | ln(area)                                | 5.218  | -0.100      | (0.114)  |
| (6)     | Average slope (percentage rise)         | 6.470  | -0.644      | (0.472)  |
| (7)     | Oat suitability                         | 36.553 | -0.153      | (1.803)  |
| (8)     | Barley suitability                      | 32.171 | 0.779       | (1.450)  |
| (9)     | Rye suitability                         | 33.093 | 0.103       | (1.477)  |
| (10)    | Wheat suitability                       | 33.048 | -0.096      | (1.482)  |
| Panel B | Time-varying variables                  | Mean   | coefficient | SE       |
| (1)     | ln (1+num of newspapers within 50 km)   | 47.581 | 0.109       | (0.0896) |
| (2)     | ln (hours to London via turnpike roads) | 382.02 | 0.0227      | (0.0207) |
| (3)     | ln(population)                          | 904.45 | -0.117***   | (0.0369) |
| (4)     | 1(waterway access)                      | 46.667 | 0.0254      | (0.0757) |

Notes: In Panel A, I report the results of regressing pre-existing time-invariant characteristics 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. The coefficients are multiplied by 100 to facilitate reporting. 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 at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively. [Back To Text]

Table 4 2SLS Estimation

|   | (1)                  | (2)                  | (3)                  | (4)                  |
|---|----------------------|----------------------|----------------------|----------------------|
|   | IHS(patents)         |                      |                      |                      |
| Panel A: 2SLS estimation                |                      |                      |                      |                      |
| IHS(banks)                              | 0.185**<br>(0.0835)  | 0.185**<br>(0.0830)  | 0.190**<br>(0.0825)  | 0.189**<br>(0.0820)  |
| Panel B: First Stage Results            |                      |                      |                      |                      |
| 1(post town) X ln(M2)                   | 0.418***<br>(0.0559) | 0.420***<br>(0.0562) | 0.620***<br>(0.102)  | 0.619***<br>(0.101)  |
| 1(post town) X ln(M2)<br>X 1(Post-1797) |                      |                      | -0.495***<br>(0.185) | -0.486***<br>(0.183) |
| Observations                            | 8,775                | 8,775                | 8,775                | 8,775                |
| Post-1797 Interaction                   | No                   | No                   | Yes                  | Yes                  |
| District & Year FEs                     | Yes                  | Yes                  | Yes                  | Yes                  |
| Time-Varying Controls                   | Population           | All                  | Population           | All                  |
| Kleibergen-Paap F                       | 55.78                | 55.82                | 28.82                | 28.91                |
| Standardized B                          | 0.249                | 0.249                | 0.256                | 0.255                |
| Hansen p-value                          |                      |                      | 0.684                | 0.721                |

Notes: In columns (1) and (2), I use only the interaction of the historical post town dummy and the natural logarithm of the money supply reconstructed by Palma (2018) as the IV. In columns (3) and (4), I include both the IV in columns (1) and (2) and its interaction with the post-1797 dummy. In Panel A, I report the 2SLS estimation results. In Panel B, I report the First-Stage estimation results. The number of observations is smaller than that in Table 2 because I drop the destinations of post roads that might be different from other districts and created different trends in the growth of patents. Time-varying controls include log population, log (1+newspapers in 50 km), log (traveling time to London), and access to waterways. Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively. [Back To Text]

Table 5 The impacts of bank connections on patents

|                                | (1)                  | (2)                   | (3)                   | (4)                  |
|--------------------------------|----------------------|-----------------------|-----------------------|----------------------|
|                                | IHS(patents)         |                       |                       |                      |
| IHS(banks)                     | 0.115***<br>(0.0207) |                       | 0.0861***<br>(0.0230) | 0.0106<br>(0.0277)   |
| IHS(connected banks)           |                      | 0.0385***<br>(0.0076) | 0.0170**<br>(0.0082)  | 0.0186**<br>(0.0080) |
| Observations                   | 8,925                | 8,925                 | 8,925                 | 3,570                |
| Sample                         | Full                 | Full                  | Full                  | Post-1790            |
| Time-Varying Controls          | All                  | All                   | All                   | All                  |
| District & Year FEs            | Yes                  | Yes                   | Yes                   | Yes                  |
| Within R2                      | 0.0415               | 0.0377                | 0.0428                | 0.0093               |
| Standardized B for Banks       | 0.156                |                       | 0.117                 | 0.0137               |
| Standardized B for Connections |                      | 0.120                 | 0.0527                | 0.0604               |

Notes: Column (1) reports the impacts of banks on patents and is the same as column (2) in Table 2. Column (2) reports the impacts of bank connections on patents. Column (3) includes a horse race regression and reports the impacts of local banks and bank connections on patents. Column (4) reports the impacts of local banks and bank connections on patents in the period between 1795 and 1825. 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. [Back To Text]



Table 6 Heterogeneous effects on different sectors (by patentee's occupation)

|                                 | IHS(patents)            |                       |                       |                         |                     |
|---------------------------------|-------------------------|-----------------------|-----------------------|-------------------------|---------------------|
|                                 | (1)                     | (2)                   | (3)                   | (4)                     | (5)                 |
| Panel A: Aggregate              |                         |                       |                       |                         |                     |
| IHS(banks)                      | 0.0036<br>(0.0022)      | 0.0876***<br>(0.0187) | 0.0223***<br>(0.0070) | 0.0331***<br>(0.0118)   | -0.0008<br>(0.0007) |
| p-value against (2)             | 0.0000                  |                       | 0.0001                | 0.001                   | 0.0000              |
| Panel B: Modern industries      |                         |                       |                       |                         |                     |
| IHS(banks)                      | 0.0026<br>(0.0018)      | 0.0728***<br>(0.0167) | 0.0215***<br>(0.0053) | 0.0258***<br>(0.0097)   | -0.0009<br>(0.0007) |
| Panel C: Traditional industries |                         |                       |                       |                         |                     |
| IHS(banks)                      | 0.0008<br>(0.0012)      | 0.0256**<br>(0.0090)  | -0.0024<br>(0.0028)   | 0.0062<br>(0.0047)      | 0.0001<br>(0.0004)  |
| Observations                    | 8,925                   | 8,925                 | 8,925                 | 8,925                   | 8,925               |
| Time-Varying Controls           | All                     | All                   | All                   | All                     | All                 |
| District & Year FE              | Yes                     | Yes                   | Yes                   | Yes                     | Yes                 |
| Sectors                         | Agriculture<br>& Mining | Manufacturing         | Trading               | Non-trading<br>services | Others              |

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the inverse hyperbolic sine of the total number of patents acquired by patentees from different sectors in a district in year  $t+1$  to year  $t+5$ . 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) reports that of other occupations. In Panel A, I report the impacts of banks on all patents gained by patentees in different sectors and compare the coefficients in columns (1), (3), (4), and (5) against the coefficient in column (2). In Panels B and C, I separate the patents into patents in innovative modern sectors, like Textiles and Paper, printing and publishing, and traditional sectors, like Mining and Metal manufacturing, following Squicciarini and Voigtländer (2015). Standard errors are clustered at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively. [Back To Text]

Table 7.1 Heterogeneous effects of banks in districts with different credit constraints

|  | (1)                    | (2)                    | (3)                   | (4)                   |
|--|------------------------|------------------------|-----------------------|-----------------------|
|  | IHS(patents)           |                        |                       |                       |
| IHS(bank)                                | 0.155***<br>(0.0274)   | 0.156***<br>(0.0275)   | 0.0797***<br>(0.0235) | 0.0808***<br>(0.0236) |
| IHS(bank) X 1(Agri-Suitable)             | -0.0831**<br>(0.0335)  | -0.0859**<br>(0.0334)  |                       |                       |
| IHS(bank) X 1(High-Bankruptcy)           |                        |                        | 0.0693*<br>(0.0135)   | 0.0671*<br>(0.0127)   |
|  | (5)                    | (6)                    | (7)                   | (8)                   |
| IHS(connected bank)                      | 0.0553***<br>(0.0111)  | 0.0559***<br>(0.0111)  | 0.0254**<br>(0.0102)  | 0.0258**<br>(0.0102)  |
| IHS(connected bank) X 1(Agri-Suitable)   | -0.0335***<br>(0.0128) | -0.0348***<br>(0.0128) |                       |                       |
| IHS(connected bank) X 1(High Bankruptcy) |                        |                        | 0.0267*<br>(0.0138)   | 0.0258*<br>(0.0137)   |
| Observations                             | 8,925                  | 8,925                  | 8,220                 | 8,220                 |
| District & Year FE                       | Yes                    | Yes                    | Yes                   | Yes                   |
| Time-Varying Controls                    | Pop                    | All                    | Pop                   | All                   |

Notes: In Panel A, Columns (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 variables. Column (3) and (4) report the different effects of bank connections in districts with different agricultural suitability. In column (3) I include only district and year fixed effects and in column (4) I add time-varying variables. Standard errors clustered on the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels. [Back To Text]

Table 7.2 The impacts of different bank connections

|   | (1)                 | (2)                 | (3)                  | (4)                  |
|---|---------------------|---------------------|----------------------|----------------------|
|   | IHS(patents)        |                     |                      |                      |
| IHS(Bank connections from non-agri to agri areas)     | 0.0706*<br>(0.0427) | 0.0701<br>(0.0428)  | 0.0706**<br>(0.0326) | 0.0701**<br>(0.0324) |
| IHS(Bank connections from agri to agri areas)         | -0.0586<br>(0.0492) | -0.0590<br>(0.0493) | -0.0586<br>(0.0432)  | -0.0590<br>(0.0432)  |
| IHS(Bank connections from non-agri to non-agri areas) | -0.0013<br>(0.0399) | -0.0000<br>(0.0400) | -0.0013<br>(0.0353)  | -0.0000<br>(0.0351)  |
| IHS(Bank connections from agri to non-agri areas)     | 0.0167<br>(0.0468)  | 0.0156<br>(0.0469)  | 0.0167<br>(0.0445)   | 0.0156<br>(0.0442)   |
| Observations  | 8,925               | 8,925               | 8,925                | 8,925                |
| Time-Varying Controls                                 | Pop                 | All                 | Pop                  | All                  |
| District & Year FE                                    | Yes                 | Yes                 | Yes                  | Yes                  |
| Clustering  | District            | District            | County               | County               |

Notes: This table reports how the connections from different districts to banks in districts with different credit constraints, or with different agricultural suitability, affected the number of patents. The first row shows how the numbers of patents were affected by the number of banks with surplus credit accessed by districts that were subject to credit constraints via country banks' London agents. The second row shows the impacts of the banking service provided by banks in areas with surplus credit to districts with surplus credit. The third row shows the impacts of the banking service provided by banks in areas that lacked credit to districts that lacked credit. The fourth row shows the impacts of the banking service provided by banks in areas that lacked credit to districts with surplus credit. Standard errors clustered on the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels. [Back To Text]

Table A1 Data sources

|      | Data   | Source  | Notes   |
|------|--|---|---|
| (1)  | Patents  | Woodcroft (1854)  | correct errors in texts digitized by Google, geocode locations, and map into districts  |
| (2)  | Country banks                                    | Dawes & Ward-Perkins (2000)   | digitize, geocode locations and map into registration districts   |
| (3)  | Post towns                                       | Ogilby (1675)   |   |
| (4)  | Population                                       | Great Britain Historical GIS Project & Wrigley (2007)                     | extrapolation   |
| (5)  | Newspapers                                       | Richard Heaton's Index to Digitalised British and Irish newspapers (2015) | From <a href="https://freepages.rootsweb.com/~lieul/genealogy/index.html">https://freepages.rootsweb.com/~lieul/genealogy/index.html</a>  |
| (6)  | Turnpike road network                            | Rosevear, Satchell, Bogart, Sugden & Shaw Taylor (2017)                   |   |
| (7)  | Canals   | The Cambridge Group for the History of Population and Social Structure    | One map in 1820 and retrieved other earlier maps according to <a href="https://www.canalmuseum.org.uk/history/1750/index1750.htm">https://www.canalmuseum.org.uk/history/1750/index1750.htm</a> |
| (8)  | Crop suitability                                 | Global Agro-ecological Zones by FAO                                       |   |
| (9)  | Slope  | SRTM data by NASA (resolution: 90 metres)                                 |   |
| (10) | sea port   | Alvarez-Palau, Dunn, Bogart, Satchell, & Shaw-Taylor (2019)               |   |
| (11) | map of English registration district (and coast) | Satchell, Kitson, Newton, Shaw-Taylor & Wrigley (2018)                    | merged to one polygon to draw the coastline   |
| (12) | Woodcroft Reference Index                        | Nuvolari & Tartari (2011)   |   |
| (13) | Taxonomy according to subjects                   | Nuvolari & Tartari (2011)   |   |
| (14) | PST system                                       | Wrigley (2010)  |   |
| (15) | Crop price changes                               | Keller, Shiue & Wang (2021)   |   |

Table A2 The relationship between post town status and banks

|              | first year with banks |                      | 1 (banks in 1825)     |                       |
|--------------|-----------------------|----------------------|-----------------------|-----------------------|
|              | (1)                   | (2)                  | (3)                   | (4)                   |
| 1(post town) | -9.168***<br>(1.697)  | -8.600***<br>(1.609) | -0.249***<br>(0.0504) | -0.205***<br>(0.0482) |
| Observations | 390                   | 390                  | 585                   | 585                   |
| Controls     | None                  | Yes                  | None                  | Yes                   |

Notes: Standard errors are clustered on the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Figure A1 The impacts of post towns and money supply on the number of country banks

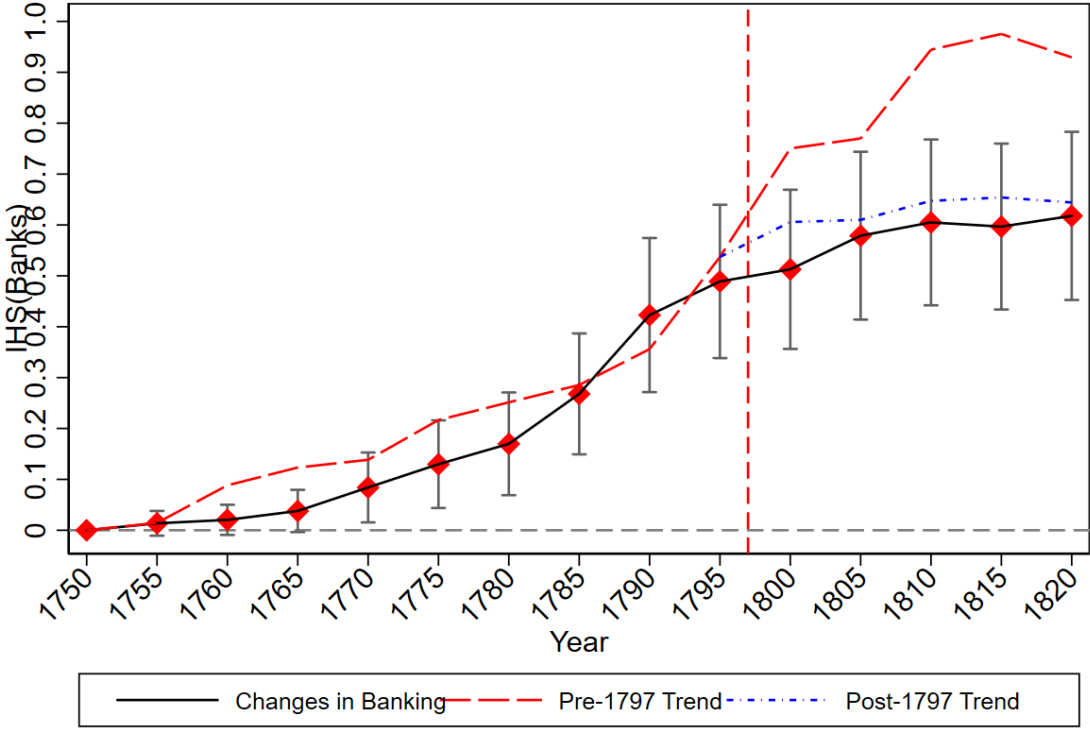


Figure A2 Placebo test: Districts with historical post towns but no banks vs Districts without post towns

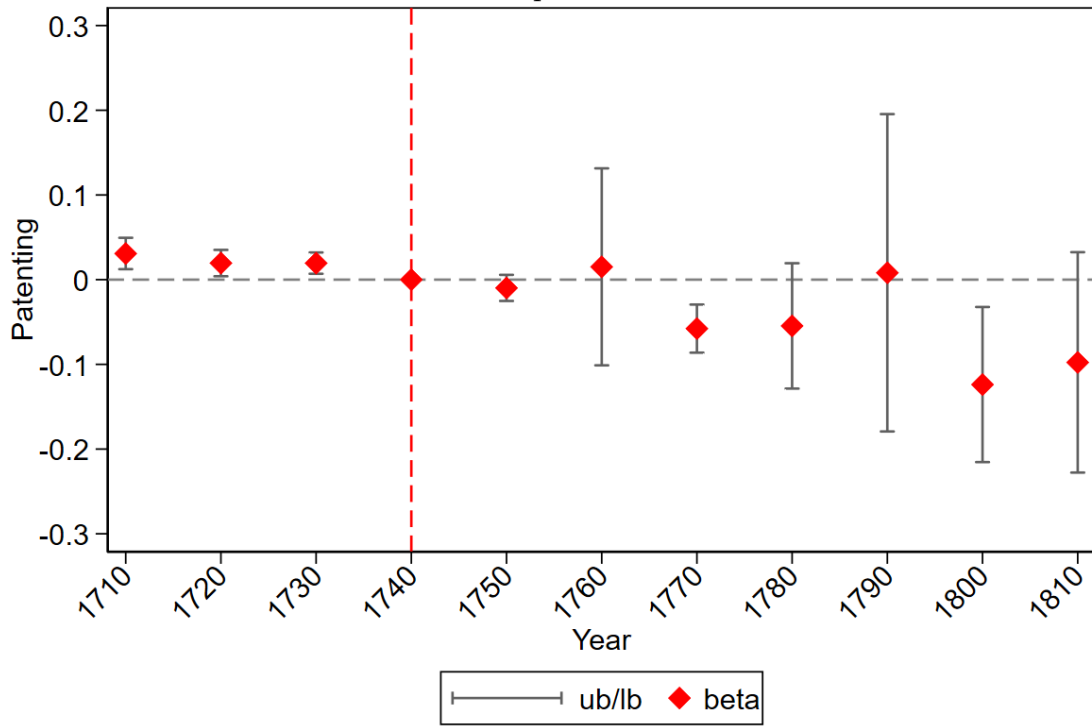


Table A3 Falsification tests

|                               | (1)                   | (2)                  | (3)                  | (4)                  |
|-------------------------------|-----------------------|----------------------|----------------------|----------------------|
|                               | IHS(patents)          |                      |                      |                      |
| 1(all post town)*year         | -0.225***<br>(0.0890) | -0.221**<br>(0.0866) | -0.169**<br>(0.0689) |                      |
| 1(historical post town)*year  |                       |                      |                      | -0.200**<br>(0.0946) |
| 1(minor post town)*year       |                       |                      |                      | -0.242**<br>(0.102)  |
| 1(post town after 1750)*year  |                       |                      |                      | -0.200<br>(0.126)    |
| Observations                  | 2,925                 | 2,925                | 6,565                | 2,925                |
| Subsample                     | Never<br>banks        | Never<br>banks       | No banks             | Never<br>banks       |
| Time-Varying Controls         | Pop                   | All                  | All                  | All                  |
| District & Year Fixed Effects | Yes                   | Yes                  | Yes                  | Yes                  |

Notes: This table reports the impacts of post towns on patents in districts without banks. The subsample for column (1), (2) and (4) is districts that never had a bank during the period that I examine. Column (1) includes only district and year fixed effects and I add time-varying controls in column (2). The subsample in column (3) is all district-year observations with 0 banks. In column (4), I separate post towns into post towns used for IV, minor post towns chosen for other reasons, and post towns built after 1750. 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 Robustness checks: balance tests on post roads

| Panel A | Time-invariant variable                 | Mean    | coefficient | SE       |
|---------|---|---------|-------------|----------|
| (1)     | 1 (Coal field)                          | 0.384   | 0.0304      | (0.0574) |
| (2)     | 1 (Sea port)                            | 0.198   | -0.0689     | (0.0469) |
| (3)     | ln(distance to the nearest sea port)    | 10.109  | 0.205       | (0.126)  |
| (4)     | ln(distance to the nearest coast)       | 9.422   | 0.237       | (0.155)  |
| (5)     | ln(area)                                | 5.206   | -0.054      | (0.134)  |
| (6)     | Average slope (percentage rise)         | 5.877   | 0.155       | (0.446)  |
| (7)     | Oat suitability                         | 38.126  | -2.473      | (1.904)  |
| (8)     | Barley suitability                      | 33.201  | -0.560      | (1.544)  |
| (9)     | Rye suitability                         | 34.316  | -1.594      | (1.564)  |
| (10)    | Wheat suitability                       | 34.291  | -1.855      | (1.573)  |
| Panel B | Time-varying variables                  | Mean    | coefficient | SE       |
| (1)     | ln (1+num of newspapers within 50 km)   | 83.513  | 0.102       | (0.101)  |
| (2)     | ln (hours to London via turnpike roads) | 308.076 | 0.017       | (0.023)  |
| (3)     | ln(population)                          | 936.60  | -0.071*     | (0.0386) |
| (4)     | 1(waterway access)                      | 62.957  | -0.0033     | (0.0853) |

Notes: In Panel A, I report the results of regressing pre-existing time-invariant characteristics 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. The coefficients are multiplied by 100 to facilitate reporting. 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 at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Figure A3 Permutation test: Historical post towns matter

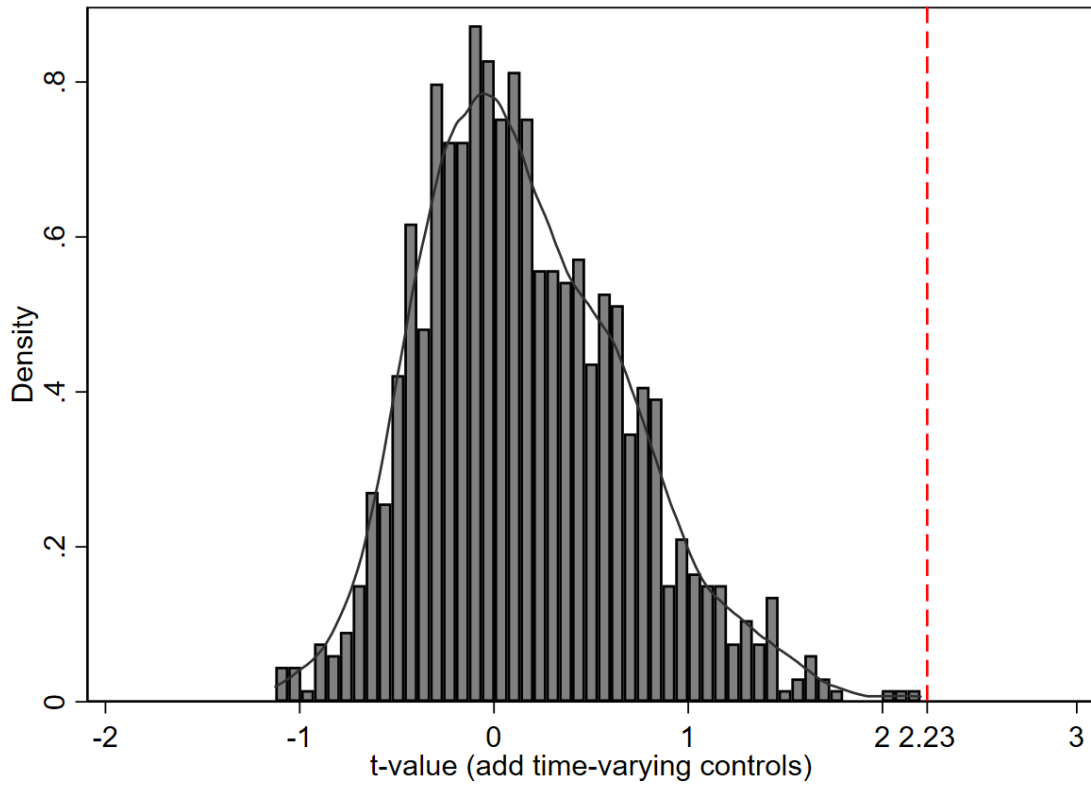


Figure A4 Placebo post towns

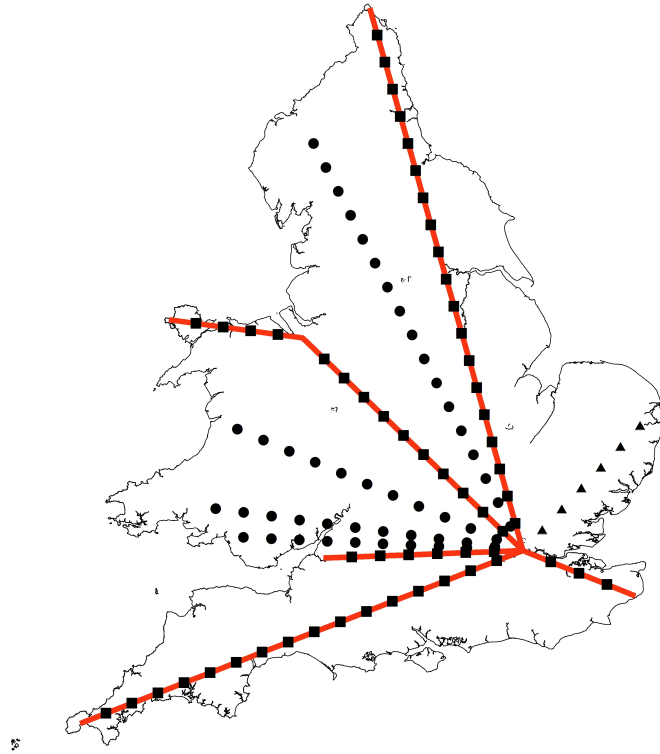


Table A5 Placebo tests

|                               | (1)               | (2)               | (3)                          | (4)                    |
|-------------------------------|-------------------|-------------------|------------------------------|------------------------|
|                               | IHS(patents)      |                   |                              |                        |
| IHS(banks)                    | -0.148<br>(0.400) | -0.183<br>(0.430) | -2.054<br>(8.191)            | 4.677<br>(44.58)       |
| First Stage                   |                   |                   |                              |                        |
| 1(Placebo post town)*year/100 | 0.208<br>(0.150)  | 0.196<br>(0.150)  | 0.045<br>(0.175)             | -0.019<br>(0.180)      |
| Observations                  | 8,775             | 8,775             | 8,850                        | 8,865                  |
| Destination sets              | Baseline          | Baseline          | Drop non-border destinations | Strategic destinations |
| KP F Statistics               | 1.258             | 1.125             | 0.0250                       | 0.0291                 |
| Time-Varying Controls         | Pop               | All               | All                          | All                    |
| District & Year Fixed Effects | Yes               | Yes               | Yes                          | Yes                    |

Notes: This table reports IV estimation results using instruments constructed based on placebo post towns. Column (1) report IV estimates of Eq. (1) with only district and year fixed effects and I add time-varying controls in column (2). 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 2SLS Estimation Using Alternative IVs

|                       | (1)                 | (2)                 | (3)                           | (4)                 |
|-----------------------|---------------------|---------------------|-------------------------------|---------------------|
|                       | IHS(patents)        |                     |                               |                     |
| IHS(banks)            | 0.185**<br>(0.0830) | 0.184**<br>(0.0822) | 0.190**<br>(0.0829)           | 0.188**<br>(0.0822) |
| Time variation        | Linear Year         |                     | Linear Year                   |                     |
| Post-1797 Interaction | No                  | No                  | Yes                           | Yes                 |
| Kleibergen-Paap F     | 58.18               | 58.43               | 29.20                         | 29.35               |
| Hansen p-value        |                     |                     | 0.111                         | 0.122               |
|                       | (5)                 | (6)                 | (7)                           | (8)                 |
| IHS(banks)            | 0.239**<br>(0.109)  | 0.239**<br>(0.109)  | 0.209**<br>(0.102)            | 0.209**<br>(0.103)  |
| Time variation        | HP Filtered ln(M2)  |                     | HP Filtered ln(M2)            |                     |
| Post-1797 Interaction | No                  | No                  | Yes                           | Yes                 |
| Kleibergen-Paap F     | 46.32               | 45.77               | 23.34                         | 23.13               |
| Hansen p-value        |                     |                     | 0.130                         | 0.131               |
|                       | (9)                 | (10)                | (11)                          | (12)                |
| IHS(banks)            | 0.451*<br>(0.269)   | 0.458<br>(0.278)    | 0.235**<br>(0.105)            | 0.235**<br>(0.105)  |
| Time variation        | $\Delta \ln(M2)$    |                     | Two-period HP Filtered ln(M2) |                     |
| Kleibergen-Paap F     | 16.03               | 15.12               | 47.03                         | 46.55               |
| Observations          | 8,775               | 8,775               | 8,775                         | 8,775               |
| Time-Varying Controls | Population          | All                 | Population                    | All                 |

Notes: This table reports 2SLS regression estimates of Eq. (1) using different IVs. The dependent variable is the inverse hyperbolic sine 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 columns (1) and (2), the instrument I use is the interaction of the dummy of having a historical post town in the registration district and the linear year variable. In columns (3) and (4), I include the instrument in columns (1) and (2) and its interaction with the post-1797 dummy. In columns (5) and (6), the instrument I use is the interaction of the dummy of having a historical post town in the registration district and the cyclical component of the natural logarithm of M2 reconstructed by Palma (2018) after using HP Filter for the whole period between 1750 and 1825. In columns (7) and (8), I include the instrument in columns (5) and (6) and its interaction with the post-1797 dummy. In columns (9) and (10) the instrument I use is the interaction of the dummy of having a historical post town in the registration district and the first-order difference of the natural logarithm of M2. In columns (11) and (12), I use HP Filter for the subperiods of 1750 - 1796 and 1797 - 1825 separately, and the instrument is the interaction of the dummy of having a historical post town in the registration district and the cyclical components in the natural logarithm of M2.

Table A6.2 Alternative IV constructed using refined post towns

|  | (1)                 | (2)                 | (3)                          | (4)                | (5)                |
|--|---------------------|---------------------|------------------------------|--------------------|--------------------|
|  | IHS(Patents)        |                     |                              |                    |                    |
| <i>Panel A: Baseline IV</i>            |                     |                     |                              |                    |                    |
| IHS(Banks)                             | 0.185**<br>(0.0835) | 0.185**<br>(0.0830) | 0.132*<br>(0.0736)           | 0.138*<br>(0.0769) | 0.148*<br>(0.0894) |
| Kleibergen-Paap F statistic            | 55.83               | 55.90               | 55.89                        | 51.71              | 38.83              |
| <i>Panel B: IV using linear trends</i> |                     |                     |                              |                    |                    |
| IHS(Banks)                             | 0.185**<br>(0.0830) | 0.184**<br>(0.0822) | 0.129*<br>(0.0718)           | 0.135*<br>(0.0754) | 0.139<br>(0.0893)  |
| Kleibergen-Paap F statistic            | 58.18               | 58.43               | 58.05                        | 53.38              | 39.62              |
| Observations                           | 8,775               | 8,775               | 8,820                        | 8,820              | 8,820              |
| Sample to construct IV                 | all<br>towns        | post<br>towns       | Drop non-<br>border<br>towns | Drop de-<br>tours  | Population<br>≤ 5k |
| Controls                               | Pop                 | All                 | All                          | All                | All                |
| District & Year Fixed Effects          | Yes                 | Yes                 | Yes                          | Yes                | Yes                |
| Clustering                             | District            | District            | District                     | District           | District           |

Notes: In this table, I report 2SLS estimation results after refining the sample used to construct the instrument. In columns (1) and (2), I use the baseline group. In column (3), I drop towns on post roads connecting to Sheffield, Kendal and Carlisle from the post town list. In column (4), I drop detouring towns from the post town list. In column (5), I drop towns with population larger than 5,000 in 1600 from the post town list. There are 102 plausibly exogenously selected post towns in the first two columns, 91 in column (3), 89 in column (4) and 83 in column (5). In Panel A, I construct the instrument by interacting the dummy of historical post towns with the natural logarithm of M2 in England by Palma (2018). In Panel B, I construct the instrument by interacting the dummy of historical post towns with the linear year variable. Standard errors clustered on the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A6.3 The First Stage results of 2SLS

|  | (1)                  | (2)                  | (3)                   | (4)                  | (5)                  |
|--|----------------------|----------------------|-----------------------|----------------------|----------------------|
|  | IHS(Patents)         |                      |                       |                      |                      |
| <i>Panel A: Baseline IV</i>            |                      |                      |                       |                      |                      |
| 1(post town)*ln(M2)                    | 0.418***<br>(0.0559) | 0.420***<br>(0.0562) | 0.473***<br>(0.0633)  | 0.459***<br>(0.0638) | 0.406***<br>(0.0651) |
| <i>Panel B: IV using linear trends</i> |                      |                      |                       |                      |                      |
| 1(post town) *year/10                  | 0.109***<br>(0.0143) | 0.110***<br>(0.0144) | 0.117***<br>(0.0154)  | 0.113***<br>(0.0155) | 0.098***<br>(0.0156) |
| Observations                           | 8,775                | 8,775                | 8,820                 | 8,820                | 8,820                |
| Sample to construct IV                 | all post towns       | all post towns       | Drop non-border towns | Drop detours         | Population $\leq$ 5k |
| Controls                               | Pop                  | All                  | All                   | All                  | All                  |
| Fixed Effects                          | District, Year       | District, Year       | District, Year        | District, Year       | District, Year       |
| Clustering                             | District             | District             | District              | District             | District             |

Notes: In this table, I report the first-stage results of the 2SLS estimation after refining the sample used to construct the instrument. In columns (1) and (2), I use the baseline group. In column (3), I drop towns on post roads connecting to Sheffield, Kendal and Carlisle from the post town list. In column (4), I drop detouring towns from the post town list. In column (5), I drop towns with population larger than 5,000 in 1600 from the post town list. There are 102 plausibly exogenously selected post towns in the first two columns, 91 in column (3), 89 in column (4) and 83 in column (5). In Panel A, I construct the instrument by interacting the dummy of historical post towns with the natural logarithm of M2 in England by Palma (2018). In Panel B, I construct the instrument by interacting the dummy of historical post towns with the linear year variable. Standard errors clustered on the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A7 Interactive Fixed Effects

|                                   | (1)                   | (2)                   | (3)                 | (4)                   |
|-----------------------------------|-----------------------|-----------------------|---------------------|-----------------------|
|                                   | ln(1+patents/pop)     |                       |                     |                       |
| Panel A: Interaction Dimension=1  |                       |                       |                     |                       |
| ln(1+banks/pop)                   | 0.0602***<br>(0.0185) | 0.0588***<br>(0.0185) | 0.0737*<br>(0.0379) | 0.0565***<br>(0.0206) |
| Panel B: Interaction Dimensions=2 |                       |                       |                     |                       |
| ln(1+banks/pop)                   | 0.0544***<br>(0.0186) | 0.0529***<br>(0.0187) | 0.0568<br>(0.0414)  | 0.0538**<br>(0.0215)  |
| Observations                      | 8,925                 | 8,925                 | 8,925               | 8,925                 |
| District & Year Fixed Effects     | Yes                   | Yes                   | Yes                 | Yes                   |
| Time-Varying Controls             | Pop                   | All                   | All                 | All                   |
| Bank Cohort FE X Year FE          | No                    | No                    | Yes                 | No                    |
| Fixed Controls X Year FE          | No                    | No                    | No                  | Yes                   |

Notes: In this table, I report the estimation results using the interactive fixed effects model to take correlations between the independent variable and unobserved factors. Panel A reports the results when using one interactive term of fixed effects. Panel B reports the results when using two interactive terms of fixed effects. In column (1), I include district and year fixed effects and control for only the population. In column (2), I include all time-varying controls. In column (3), I further include the interaction of first bank cohort fixed effects and year fixed effects. The first bank cohort fixed effect dummy for year  $t$  is 1 if district  $i$  received its first bank between year  $t-4$  and year  $t$ . In column (4), I include the interaction terms of time-invariant controls and year fixed effects. Time-varying controls include ln(population), ln(1+newspapers in 50 km), ln(traveling time to London), and access to waterways. Time-invariant variables include access to coal fields, having a seaport, ln(distance to the nearest seaport), ln(distance to the nearest coast), ln(area), average terrain slopes (percentage rise), and suitability for wheat, oat, barley, and rye, the four main crops in England. Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.



Table A8.1 Robustness: standard errors clustered at the county level

|                                   | (1)                  | (2)                  | (3)                 | (4)                |
|-----------------------------------|----------------------|----------------------|---------------------|--------------------|
|                                   | IHS(patents)         |                      |                     |                    |
| IHS(banks)                        | 0.115***<br>(0.0311) | 0.115***<br>(0.0308) | 0.163**<br>(0.0557) | 0.107*<br>(0.0542) |
| Observations                      | 8,925                | 8,925                | 8,925               | 8,925              |
| District & Year Fixed Effects     | Yes                  | Yes                  | Yes                 | Yes                |
| Within R2                         | 0.0409               | 0.0415               | 0.0935              | 0.297              |
| Time-Varying Controls             | Pop                  | All                  | All                 | All                |
| Bank Cohort FE X Year FE          | No                   | No                   | Yes                 | Yes                |
| Time invariant controls X Year FE | No                   | No                   | Yes                 | Yes                |
| County Linear Trends              | No                   | No                   | No                  | Yes                |

Notes: This table reports OLS regression estimates of Eq. (1). In column (1), I include district and year fixed effects and control for only the population. In column (2), I include all time-varying controls. In column (3), I further include the interaction of first bank cohort fixed effects and year fixed effects. The first bank cohort fixed effect dummy for year  $t$  is 1 if district  $i$  received its first bank between year  $t-4$  and year  $t$ . In column (4), I further include the interaction terms of time-invariant controls and year fixed effects, and country linear trends. Time-varying controls include  $\ln(\text{population})$ ,  $\ln(1+\text{newspapers in 50 km})$ ,  $\ln(\text{traveling time to London})$ , and access to waterways. Time-invariant variables include access to coal fields, having a seaport,  $\ln(\text{distance to the nearest seaport})$ ,  $\ln(\text{distance to the nearest coast})$ ,  $\ln(\text{area})$ , average terrain slopes (percentage rise), and suitability for wheat, oat, barley, and rye, the four main crops in England. Standard errors clustered at the 1831 county level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A8.2 Conley standard errors

|                                     | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|-------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                     | IHS(patents)         |                      |                      |                      |                      |                      |
| Distance cut-off                    | 50km                 | 100km                | 200km                | 300km                | 400km                | 500km                |
| Panel A: Control for Population     |                      |                      |                      |                      |                      |                      |
| IHS(Banks)                          | 0.115***<br>(0.0146) | 0.115***<br>(0.0166) | 0.115***<br>(0.0179) | 0.115***<br>(0.0177) | 0.115***<br>(0.0172) | 0.115***<br>(0.0171) |
| Panel B: With time-varying controls |                      |                      |                      |                      |                      |                      |
| IHS(Banks)                          | 0.115***<br>(0.0145) | 0.115***<br>(0.0164) | 0.115***<br>(0.0177) | 0.115***<br>(0.0174) | 0.115***<br>(0.0170) | 0.115***<br>(0.0170) |
| Observations                        | 8,925                | 8,925                | 8,925                | 8,925                | 8,925                | 8,925                |
| Fixed Effects                       | District,<br>Year    | District,<br>Year    | District,<br>Year    | District,<br>Year    | District,<br>Year    | District,<br>Year    |

Notes: This table reports the estimation results when I use Conley standard errors. I include district and year fixed effects and the natural logarithm of population in Panel A. I include all time-varying controls in Panel B. 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.

Figure A5 Long differences using the subsample of 1750 and another year

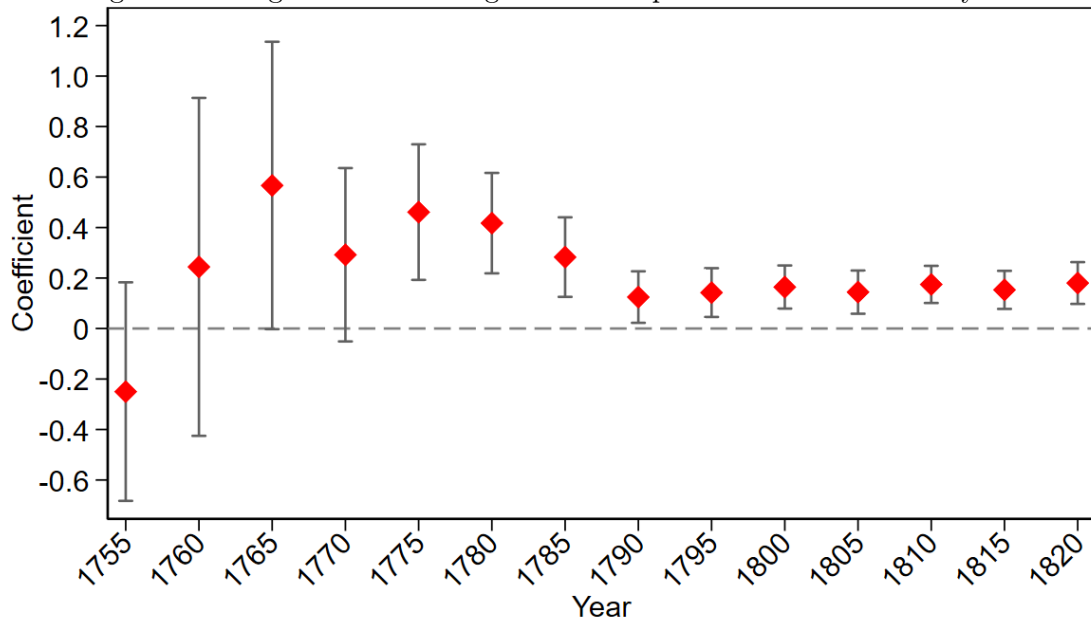


Table A9 Robustness checks: Restricted samples

| IHS(patents)                      |                      |                      |                      |                     |
|-----------------------------------|----------------------|----------------------|----------------------|---------------------|
| Panel A: Districts with banks     |                      |                      |                      |                     |
|                                   | (1)                  | (2)                  | (3)                  | (4)                 |
| IHS(banks)                        | 0.136***<br>(0.0236) | 0.137***<br>(0.0236) | 0.163***<br>(0.0389) | 0.105**<br>(0.0390) |
| Observations                      | 6,000                | 6,000                | 6,000                | 6,000               |
| Panel B: Districts with patents   |                      |                      |                      |                     |
|                                   | (5)                  | (6)                  | (7)                  | (8)                 |
| IHS(banks)                        | 0.112***<br>(0.0277) | 0.113***<br>(0.0277) | 0.195***<br>(0.0516) | 0.105**<br>(0.0509) |
| Observations                      | 5,325                | 5,325                | 5,325                | 5,325               |
| Time-varying Controls             | Pop                  | Yes                  | Yes                  | Yes                 |
| District & Year Fixed Effects     | Yes                  | Yes                  | Yes                  | Yes                 |
| Bank Cohort FE X Year FE          | No                   | No                   | Yes                  | Yes                 |
| County Linear Trends              | No                   | No                   | No                   | Yes                 |
| Time-invariant controls * Year FE | 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 inverse hyperbolic sine of the total number of patents acquired in a district in year  $t+1$  to year  $t+5$ . Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A10 Robustness checks with alternative measurements of innovation

|                               | (1)                  | (2)                  | (3)                  | (4)                  |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|
|                               | IHS(patents)         |                      |                      |                      |
| IHS(banks)                    | 0.108***<br>(0.0201) | 0.109***<br>(0.0201) | 0.156***<br>(0.0366) | 0.104***<br>(0.0358) |
| Observations                  | 8,925                | 8,925                | 8,925                | 8,925                |
| Within R2                     | 0.0422               | 0.0429               | 0.0978               | 0.164                |
| Bank Cohort FE X Year FE      | No                   | No                   | Yes                  | Yes                  |
| Fixed Controls X Year FE      | No                   | No                   | No                   | Yes                  |
| County Linear Trends          | No                   | No                   | No                   | Yes                  |
| Standardized B                | 0.155                | 0.156                | 0.224                | 0.148                |
|                               | (5)                  | (6)                  | (7)                  | (8)                  |
| IHS(banks)                    | 0.170*<br>(0.0795)   | 0.169**<br>(0.0788)  | 0.175**<br>(0.0794)  | 0.173**<br>(0.0787)  |
| Observations                  | 8,775                | 8,775                | 8,775                | 8,775                |
| KPF                           | 58.18                | 58.43                | 29.20                | 29.35                |
| Standardized B                | 0.242                | 0.239                | 0.249                | 0.245                |
| Hansen p                      |                      |                      | 0.103                | 0.113                |
| Time-Varying Controls         | Pop                  | All                  | Pop                  | All                  |
| District & Year Fixed Effects | Yes                  | Yes                  | Yes                  | Yes                  |

Notes: In this table, I divide patents equally among all patentees. Panel A reports OLS estimation results. In column (1), I include district and year fixed effects and control for only the population. In column (2), I include all time-varying controls. In column (3), I further include the interaction of first bank cohort fixed effects and year fixed effects. The first bank cohort fixed effect dummy for year  $t$  is 1 if district  $i$  received its first bank between year  $t-4$  and year  $t$ . In column (4), I further include the interaction terms of time-invariant controls and year fixed effects and country linear trends. Panel B reports 2SLS estimation results. In columns (5) and (6), the instrument I use is the interaction of the dummy of having a historical post town in the registration district and the linear year variable. In columns (7) and (8), I include the instrument in columns (5) and (6) and its interaction with the post-1797 dummy. Time-varying controls include  $\ln(\text{population})$ ,  $\ln(1+\text{newspapers in 50 km})$ ,  $\ln(\text{traveling time to London})$ , and access to waterways. Time-invariant variables include access to coal fields, having a seaport,  $\ln(\text{distance to the nearest seaport})$ ,  $\ln(\text{distance to the nearest coast})$ ,  $\ln(\text{area})$ , average terrain slopes (percentage rise), and suitability for wheat, oat, barley, and rye, the four main crops in England. Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A11.1 Robustness checks with different measures of innovation

|                                | (1)                   | (2)                   | (3)                   | (4)                   |
|--------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
|                                | ln(1+patents)         |                       | 1(patent>0)           |                       |
| IHS(banks)                     | 0.0897***<br>(0.0165) | 0.0898***<br>(0.0164) | 0.0716***<br>(0.0114) | 0.0716***<br>(0.0114) |
| Observations                   | 8,925                 | 8,925                 | 8,925                 | 8,925                 |
|                                | (5)                   | (6)                   | (7)                   | (8)                   |
|                                | N(patents)            |                       | IHS(patents)          |                       |
| IHS(banks)                     | 0.152**<br>(0.0624)   | 0.150**<br>(0.0623)   | 0.116*<br>(0.0685)    | 0.112<br>(0.0691)     |
| Observations                   | 5,325                 | 5,325                 | 5,325                 | 5,325                 |
| Time-Varying Controls          | Pop                   | All                   | Pop                   | All                   |
| Districts & Year Fixed Effects | Yes                   | Yes                   | Yes                   | Yes                   |

Notes: In Column (1) & (2), the dependent variable ln(1+patents) denotes the natural logarithm of 1 plus the number of patents. In column (3) & (4), the dependent variable is 1 if there exists a patent within a registration district in the future 5 years. Column (5) & (6) report estimation results of a Count Model and the dependent variable is the number of patents. Column (7) & (8) report estimation results of a Poisson pseudo-likelihood Model and the dependent variable is the inverse hyperbolic sine of the number of patents. Standard errors are clustered at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A11.2 Robustness checks with different measures of banking access and innovation

|                       | (1)                   | (2)                   | (3)                 | (4)                 | (5)                  | (6)                  |
|-----------------------|-----------------------|-----------------------|---------------------|---------------------|----------------------|----------------------|
|                       | ln(1+patents/pop)     |                       |                     |                     | ln(1+banks/pop)      |                      |
|                       | OLS                   |                       | IV                  |                     | First Stage          |                      |
| ln(1+banks/pop)       | 0.0497***<br>(0.0141) | 0.0490***<br>(0.0141) | 0.220**<br>(0.0883) | 0.218**<br>(0.0881) |                      |                      |
| 1(post town)*year/10  |                       |                       |                     |                     | 0.278***<br>(0.0402) | 0.280***<br>(0.0406) |
| Observations          | 8,925                 | 8,925                 | 8,775               | 8,775               | 8,775                | 8,775                |
| Within R2             | 0.0121                | 0.0125                |                     |                     |                      |                      |
| KPF                   |                       |                       | 47.86               | 47.55               |                      |                      |
| Time-Varying Controls | Pop                   | All                   | Pop                 | All                 | Pop                  | All                  |
| Fixed Effects         | District,<br>Year     | District,<br>Year     | District,<br>Year   | District,<br>Year   | District,<br>Year    | District,<br>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 column (1) I only control for district and year fixed effects, and population. I add all time-varying controls in column (2). Columns (3) and (4) show IV estimates and columns (5) and (6) report first stage results. Standard errors are clustered at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A12 Robustness: Patents of high quality

|                               | (1)                   | (2)                   | (3)                   | (4)                  |
|-------------------------------|-----------------------|-----------------------|-----------------------|----------------------|
|                               | IHS(patents)          |                       |                       |                      |
| IHS(banks)                    | 0.0511***<br>(0.0134) | 0.0511***<br>(0.0134) | 0.0436***<br>(0.0127) | 0.0140*<br>(0.00755) |
| Observations                  | 8,925                 | 8,925                 | 8,925                 | 8,925                |
| Adjusted WRI threshold        | Median                | Median                | 75%                   | 90%                  |
| Within R2                     | 0.0224                | 0.0230                | 0.0350                | 0.0151               |
| Time-Varying Controls         | Pop                   | All                   | All                   | All                  |
| District & Year Fixed Effects | Yes                   | Yes                   | Yes                   | 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 and population in column (1), all time-varying controls in column (2). In column (3), I restrict patents to those in the top 25% percentile and in column (4), I further restrict patents to those in the top 10 % percentile. Standard errors clustered at the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.



Table A13.1 Robustness: patent counts within a 3-year or a 10-year window

| IHS(patents)                      |                       |                       |                      |                       |
|-----------------------------------|-----------------------|-----------------------|----------------------|-----------------------|
| Panel A Window: 3 years           |                       |                       |                      |                       |
|                                   | (1)                   | (2)                   | (3)                  | (4)                   |
| IHS(banks)                        | 0.0773***<br>(0.0162) | 0.0775***<br>(0.0161) | 0.103***<br>(0.0270) | 0.0733***<br>(0.0258) |
| Observations                      | 14,280                | 14,280                | 14,280               | 14,280                |
| Panel B Window: 10 years          |                       |                       |                      |                       |
|                                   | (5)                   | (6)                   | (7)                  | (8)                   |
| IHS(banks)                        | 0.187***<br>(0.0222)  | 0.187***<br>(0.0220)  | 0.295***<br>(0.0603) | 0.226***<br>(0.0617)  |
| Observations                      | 4,165                 | 4,165                 | 4,165                | 4,165                 |
| Time-varying Controls             | Pop                   | All                   | All                  | All                   |
| Districts & Year Fixed Effects    | Yes                   | Yes                   | Yes                  | Yes                   |
| Bank Cohort FE X Year FE          | No                    | No                    | Yes                  | Yes                   |
| Time-invariant controls X Year FE | No                    | No                    | No                   | Yes                   |
| County Linear Trends              | No                    | No                    | No                   | Yes                   |

Notes: In Panel A, I count patents within 3 years after year  $t$  in columns (1) to (4). In Panel B, I count patents within 10 years in columns (5) to (8). I add only district and year fixed effects and population in column (1), all time-varying controls in column (2), interaction of first bank cohort fixed effects and year fixed effects in column (3) and the interaction terms of time-invariant controls and year fixed effects, and county linear trends in column (4). The settings in columns (5) to (8) are similar to those in columns (1) to (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 A13.2 Comparison of coefficients against Mao and Wang (2023)

|                                   | (1)                   | (2)                   | (3)                  | (4)                   |
|-----------------------------------|-----------------------|-----------------------|----------------------|-----------------------|
|                                   | ln(1+patents)         |                       |                      |                       |
| ln(1+banks)                       | 0.0805***<br>(0.0180) | 0.0800***<br>(0.0169) | 0.111***<br>(0.0294) | 0.0803***<br>(0.0276) |
| Observations                      | 14,875                | 14,875                | 14,875               | 14,875                |
| Within R2                         | 0.0109                | 0.0325                | 0.117                | 0.173                 |
| District & Year Fixed Effects     | Yes                   | Yes                   | Yes                  | Yes                   |
| Time-Varying Controls             | None                  | All                   | All                  | All                   |
| Bank Cohort FE X Year FE          | No                    | No                    | Yes                  | Yes                   |
| Time invariant controls X Year FE | No                    | No                    | No                   | Yes                   |
| County Linear Trends              | No                    | No                    | No                   | Yes                   |

Notes: I count patents with 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 5 of Mao & Wang (2023). I add only district and year fixed effects in column (1), time-varying controls in column (2), interaction of first bank cohort fixed effects and year fixed effects in column (3) and interaction of time-invariant variables and year fixed effects and county linear trends in column (4). Standard errors are clustered at the registration district level. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A14 Heterogeneous effects on different sectors (by the industry of patents)

|                               | IHS(patents)         |                       |                         |                      |                      |                      |
|-------------------------------|----------------------|-----------------------|-------------------------|----------------------|----------------------|----------------------|
|                               | (1)                  | (2)                   | (3)                     | (4)                  | (5)                  | (6)                  |
| IHS(banks)                    | 0.0138**<br>(0.0068) | 0.102***<br>(0.0191)  | 0.106***<br>(0.0195)    | 0.106***<br>(0.0196) | 0.104***<br>(0.0199) | 0.108***<br>(0.0202) |
| Observations                  | 8,925                | 8,925                 | 8,925                   | 8,925                | 8,925                | 8,925                |
| Time-Varying Controls         | All                  | All                   | All                     | All                  | All                  | All                  |
| District & Year Fixed Effects | Yes                  | Yes                   | Yes                     | Yes                  | Yes                  | Yes                  |
| Sector                        | Primary sector       | Secondary<br>baseline | (2) + construc-<br>tion | (3) + Leather        | (4) + Military       | (5) + Medicine       |

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the inverse hyperbolic sine of the total number of patents in different sectors in a district in year  $t+1$  to year  $t+5$ . 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. Corresponding industries include 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 and Textiles. Column (3) reports the result of secondary sector patents after including Construction and column (4) further adds Leather. Column (5) adds Military equipment and weapons while column (6) adds Medicines. Standard errors clustered on the registration district level are reported in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels respectively.

Table A15 Spillover effects of banks in neighbouring districts

|                              | (1)                  | (2)                   | (3)                   | (4)                   |
|------------------------------|----------------------|-----------------------|-----------------------|-----------------------|
|                              | IHS(patents)         |                       |                       |                       |
| IHS(banks)                   | 0.115***<br>(0.0207) | 0.114***<br>(0.0205)  |                       | 0.160***<br>(0.0385)  |
| IHS(neighbour banks)         |                      | -0.051***<br>(0.0161) | -0.052***<br>(0.0164) | -0.041***<br>(0.0157) |
| Observations                 | 8,925                | 8,925                 | 8,925                 | 8,925                 |
| Within R2                    | 0.0415               | 0.0461                | 0.0304                | 0.0963                |
| District& Year Fixed Effects | Yes                  | Yes                   | Yes                   | Yes                   |
| Time-Varying Controls        | All                  | All                   | All                   | All                   |
| Bank Cohort FE X Year FE     | No                   | No                    | No                    | Yes                   |

Notes: Column (1) reports the impacts of banks on patents and column (2) reports the impacts of banks on patents after controlling for banks in neighbouring districts. Column (3) reports the impacts of neighbouring banks on patents. In column (4), I add the interactions of the first bank cohort fixed effects with year fixed effects. 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.