Banking and Innovation: Evidence from the Industrial Revolution

Jinlin Wei

University of Warwick

Motivation (1/2)

- Broad question: How do banks contribute to innovation?
  - Bank loans are important in financing innovation (Kerr and Nanda, 2015).
  - Credit constraints lower innovation (Aghion et al., 2012; Hottenrott and Peters, 2012; Nanda and Nicholas, 2014).
  - Short-term debt of publicly-listed firms (2022): 23.37% in developing countries vs 12.62% world (Damodaran, 2023).
  - I use a historical setting when banks provided short-term credit to borrowers to highlight the impacts of liquidity provision by banks.

Motivation (2/2)

- Specific question: How did the development of country banks in England and Wales increase patenting between 1750 and 1825?
  - *One view:* Banks unimportant during the Industrial Revolution (Gerschenkron, 1962).
  - Rejection from bankers: Boulton & Watts; Richard Arkwright.
  - *But:* Banks useful for the working capital of firms (Cameron et al., 1967).
  - Opposite anecdotal evidence: Samuel Oldknow.
  - There is scope for quantitative evidence to overcome survivorship bias, address this question systematically, and provide credible causal inference.

What I do

- Use a setting where banks generally provided short-term credit, to show the impacts of short-term credit on innovation.
- Construct panel data at the registration district level on patents and country banks between 1750 and 1825.
- Use a two-way fixed effects model with fixed effects for districts and years.
- Utilize the sudden shocks in money supply and the existence of historical post-towns (Heblich and Trew, 2019) to construct instrumental variables.
    - Monetary expansion affects economic activities (Palma, 2022), including bank services.
    - Advantages in towns with post offices because of transportation security, information, and demand from postmen.

Preview of results

- A one standard deviation increase in banking access predicts a 15.6% standard deviation increase in patenting.
- Country banks account for about 38% of the increase in patents between 1750 and 1825.
- Country banks lowered costs of procuring working capital:
  1. Banks alleviated liquidity constraints of industrialists and merchants.
  2. Banks and their London agents: Basis of a national financial market.
  3. Credit from rural areas to industrial areas.
  4. The provision of means of payment: gold coins.

Contribution (1/2)

On the role of banks in innovation

- Banks are often conservative and biased against innovation (Rajan and Zingales, 2001; Hall and Lerner, 2010; Hsu et al., 2014).
- New firm-level empirical evidence shows that banks are important providers of credit, especially for small innovative firms (Amore et al., 2013; Chava et al., 2013; Cornaggia et al., 2015). Lower bank distress mitigated drops in innovation during the Great Depression (Nanda and Nicholas, 2014).
- Alleviating credit constraints increase R&D (Hall, 1992; Brown et al., 2009). Firms facing credit constraints reduce innovation (Mukherjee et al., 2017; Granja and Moreira, 2022).
- This paper demonstrates that short-term credit from banks eased the liquidity constraints of entrepreneurs, reducing bankruptcy and boosting investment.

Contribution (2/2)

On the role of banks during the Industrial Revolution

- English banks were commercial banks and contributed little to British industrialization (Gerschenkron, 1962). The locations of banks are uncorrelated with industrial employment (Mokyr, 2009; Kelly et al., 2023).
- Banks provided firms with working capital, which was important in their balance sheets (Pollard, 1964; Cameron et al., 1967) or supported the adoption of innovation (Brunt, 2006).
- Financial access increased manufacturing employment between the 1810s and 1881 (Heblich and Trew, 2019).
- I use granular data to provide novel quantitative evidence of how banks contributed to innovation in England between 1750 and 1825 during the Industrial Revolution.
- I show the formation process of a national banking system that channeled credit from agriculture to industry.

Historical background: Patents

- The English patent system remained the same until 1852.
- Patents: innovation of high expected economic values.
  - A patent cost 70 - 100 pounds (MacLeod, 1988; Bottomley, 2014), the annual incomes of the top 6% families in 1760 and 21% in 1800 (Hume, 2015)
  - There existed an active patent market (Bottomley, 2014).
- For robustness, I use a constructed patent quality index that is correlated with important inventors and inventions between 1740 and 1840 (Nuvolari and Tartari, 2011).

Historical background: Country banks

- Major financial intermediaries: London private banks, **country banks**, informal financial intermediaries (e.g. attorneys) (Hudson, 1986; Neal, 1994).
- Small and vulnerable to liquidity shocks: average capital about £10,000 (Pressnell, 1956). About 10 - 20 million pounds using GDP per capita as the deflator (Beers et al., 2020), and about 1 million pounds using the inflation calculator by BoE.
- Country banks provided short-term credit by discounting bills and offering overdrafts but rarely lent for fixed capital investment and invention (Pressnell, 1956; Crouzet, 1972; Calomiris and Haber, 2014; Michie, 2016).
- My sample ends in 1825 because English people were allowed to form joint-stock banks freely in 1826 (Michie, 2016).

Motivating example: How banks saved an innovative firm

- The partnership of John Marshall had a paid-in capital of £10,149, loans from relatives and friends of £5,517, trade credit of £5,915 and gained overdrafts of £3,783 from Beckett & Co., a country bank, in 1792-1793 (Rimmer, 1960; Crouzet, 1972)
- The partnership spent £9,241 on fixed capital and £10,660 on working capital.
- The partnership might have gone bankrupt without the overdraft because the deficit of the firm reached £3,042 in April 1793 during its hardest days.
- Matthew Murray, an engineer that John employed to invent a new flax-spinning machine, patented it in December 1793. John Marshall managed to succeed with the new patent and died with a fortune of about 2 million pounds.

Data

- Locations, opening periods, and London agents of country banks from 1750 to 1825 from Dawes and Ward-Perkins (2000).
- Dates of patents, addresses and occupations of patentees in England and Wales from Woodcroft (1854).
- Patent statistics as a measure of innovation (Sokoloff, 1988; Sullivan, 1989; Moser and Voena, 2012).
- I geocode locations of patents and banks using Google Earth and map them into 595 registration districts outside London and Middlesex.

Summary Statistics

Table 1 Registration district-level descriptive statistics in selected years

	(1)	(2)	(3)	(4)	(5)	(6)
	year	N	mean	sd	min	max
Number of patents in the next 5 years	1750	595	0.0370	0.214	0	2
	1780	595	0.195	0.769	0	10
	1800	595	0.420	1.279	0	10
	1820	595	0.822	3.390	0	36
Number of country banks	1750	595	0.0168	0.129	0	1
	1780	595	0.166	0.572	0	5
	1800	595	0.840	1.286	0	8
	1820	595	1.506	1.880	0	14
Population	1750	595	9,663	5,029	1,086	35,784
	1780	595	11,333	6,173	1,165	49,602
	1800	595	13,474	8,130	1,306	79,115
	1820	595	17,969	12,215	1,778	120,731
Hours to London (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
Number of newspapers within 50 km	1750	595	4.267	15.49	0	67
	1780	595	7.486	25.21	0	109
	1800	595	8.466	28.00	0	121
	1820	595	9.790	29.27	0	128

Baseline estimation

$$\begin{aligned}\mathrm{IHS}(Patents_{i,t+1\ to\ t+5}) = &\beta_0 + \beta_1 \times \mathrm{IHS}(Banks_{i,t}) + x_{i,t}^{'}\gamma \\ &+ \delta_i + \eta_t + \varepsilon_{i,t}\end{aligned} \tag{1}$$

- $\mathrm{IHS}(Patents_{i,t+1\ to\ t+5})$ is the inverse hyperbolic sine of the number of patents in district i within 5 years after year t (t= 1750, 1755, ...,1820).
- $\mathrm{IHS}(Banks_{i,t})$ is the inverse hyperbolic sine of the number of country banks in district i in year t.
- $x_{i,t}^{'}$ are time-varying controls that might affect patenting, including population, access to waterways, traveling time to London via turnpike roads, number of newspapers published within 50 km.
- δ_i includes district fixed effects and η_t includes year fixed effects.
- I cluster the standard errors at the registration district level in the baseline estimation.

Baseline Results

- One standard deviation increase (0.653) in banking access (mean 0.352) ⇒ 47.5% increase in the number of patents (mean of dependent variable: 0.164)

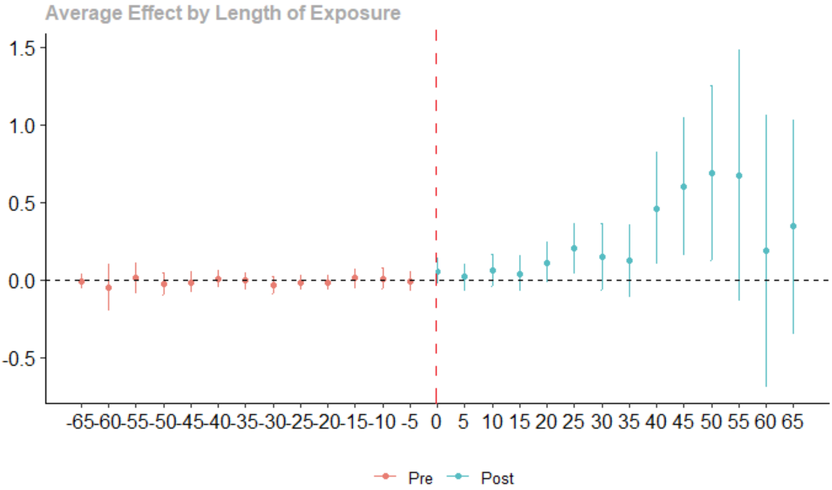
Table 2 Baseline results

	(1)	(2)	(3)	(4)
	IHS(Patents)			
IHS(Banks)	0.115***	0.115***	0.163***	0.107***
	(0.0207)	(0.0207)	(0.0387)	(0.0383)
Observations	8,925	8,925	8,925	8,925
Within R2	0.0409	0.0415	0.0935	0.158
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	Population	All	All	All
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	0.156	0.156	0.221	0.145

Staggered DID

- Follow Callaway and Sant'Anna (2021) to identify the effects of having the first bank on patents.
- Control group: Districts that never had a bank between 1750 and 1820.
- Base group of the treated: The 1750 observations of districts that received treatment during the period of 1816 to 1820.
- The mean value of the average treatment effects of the treated groups is 0.0657, the confidence interval is [0.0118,0.1196].

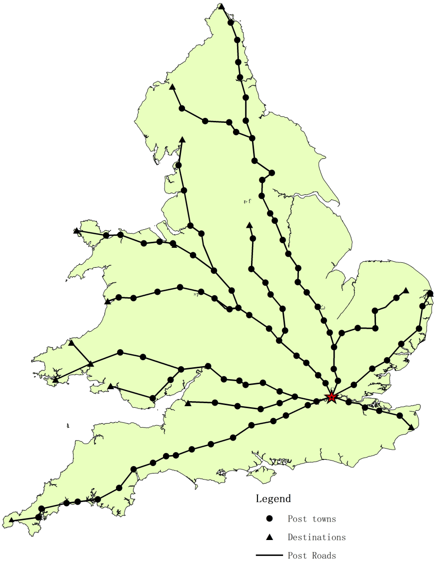
Staggered DID



Constructing the instruments

- Endogeneity: Omitted variables, e.g. lag in structural change.
- Baseline Instruments Relevance
  - ln(M2) $\times$ Historical post towns
  - ln(M2) $\times$ Historical post towns $\times \mathbb{1}$(year>1797)
- ln(M2) by Palma (2018): Variations in the money supply.
- Post towns: Advantages of post towns for banks: safety, information, and the demand from postmen (Dawes and Ward-Perkins, 2000; Heblich and Trew, 2019).
- Sudden unexpected shock following Burgess and Pande (2005): Changes in money supply due to the suspension of convertibility from BoE notes to gold in 1797. A French army landed in Wales and created panic in England.
- The Bank of England expanded credit supply (Michie, 2016) and offset the banking advantages of post towns.

Post towns in 1675



Balance tests

Table 3 Balance tests

Panel A	Time-invariant variable	coefficient	SE
(1)	1 (Coal field)	0.0194	(0.0519)
(2)	1 (Sea port)	-0.0398	(0.0428)
(3)	ln(distance to the nearest sea port)	0.105	(0.112)
(4)	ln(distance to the nearest coast)	0.122	(0.143)
(5)	ln(area)	-0.100	(0.114)
(6)	Average slope (percentage rise)	-0.644	(0.472)
(7)	Oat suitability	-0.610	(1.957)
(8)	Barley suitability	-0.526	(1.634)
(9)	Rye suitability	-0.411	(1.645)
(10)	Wheat suitability	-0.599	(1.647)
Panel B	Time-varying variables	coefficient	SE
(1)	ln (1+num of newspapers within 50 km)	0.103	(0.0903)
(2)	ln (hours to London via turnpike roads)	0.0163	(0.0207)
(3)	ln(population)	-0.113***	(0.0371)
(4)	1(waterway access)	-0.0121	(0.0739)

Notes: In Panel A, I report the results of regressing each time-invariant characteristic on the post town dummy. In Panel B, I report the results of regressing each time-varying characteristic on the interaction of post town dummy and year. The coefficient column reports the coefficient of the main variable. Standard errors are clustered on the registration district level.

2SLS Estimation Results

Table 4 2SLS Estimation

	(1)	(2)	(3)	(4)
		IHS(patents)		
Panel A: 2SLS estimation				
IHS(banks)	0.185**	0.185**	0.190**	0.189**
	(0.0835)	(0.0830)	(0.0825)	(0.0820)
Panel B: First Stage Results				
1(post town) X ln(M2)	0.418***	0.420***	0.620***	0.619***
	(0.0559)	(0.0562)	(0.102)	(0.101)
1(post town) X ln(M2)			-0.495***	-0.486***
X 1(Post-1797)			(0.185)	(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

The size of 2SLS coefficients

- The coefficients estimated by 2SLS are about 1.6 times as large as the coefficients estimated by OLS
- Possible explanations
  1. Measurement error in banking access
  2. Some banks in agricultural areas collected deposits and invested in London
- No evidence of direct violation of the exclusion restriction: KS Statistic=1.069, p=0.646 for the test proposed by D'Haultfœuille, Hoderlein and Sasaki (2023).

IV Validity

- Balancing test on post roads Table A3
- Alternative IVs based on money supply: Use linear year variable and other transformations of M2 that are not serially-correlated (Borusyak, Hull, and Jaravel, 2022) Alternative IVs
- Placebo test: Historical post towns without banks vs Without historical post towns PostNoBank
- Post towns but not post roads mattered: Permutation Permu
- Placebo post towns: Straight roads between London and destinations Placebo
- Falsification test: Districts with other post towns but without banks Falsify

Robustness checks

- Different measurement of innovation Table A6
- Specification with time-invariant variables interacted with Year FE and county linear trends Additional controls
- Conley standard errors: cutoffs 50 - 500 km Conley SEs
- Interactive Fixed Effects (Bai, 2009) iFE
- Different transformations of the dependent variable Table A9.1
- Patents with higher Woodcroft Reference Index (Nuvolari & Tartari, 2011) Table A10
- Different aggregation periods of patent statistics Table A11.1
- Effects smaller compared to USA (0.361) Table A11.2
- Alternative subsamples Table A12
- Long differences using subsamples of 1750 and another year Long Differences
- Spillovers Spillovers

1. Introduction

2. Background and data

3. Empirical strategy

4. Identification

5. Mechanisms

6. Concluding remarks

How country banks contributed to innovation (1/2)

1. Country banks and their London agents formed the basis of a national financial market (North and Weingast, 1989) channeling credit from agriculture to industry. I show:
   - The number of country banks that local bankers in a district connected to through London agents increased patenting.
   - The connections to rural areas with abundant credit increased patents in districts that lacked credit.
2. Country banks provided short-term loans to their clients: industrialists and merchants. I show:
   - The increases in banking access mainly increased the number of patents by patentees in the manufacturing sector.
   - The industrialists, the effects of banks were observed for both traditional sectors like clothing and leather, and innovative sectors like paper, printing, and publishing.
   - For merchants who usually involved investments in many industries (Crouzet, 1985), the impacts were restricted to innovative sectors.

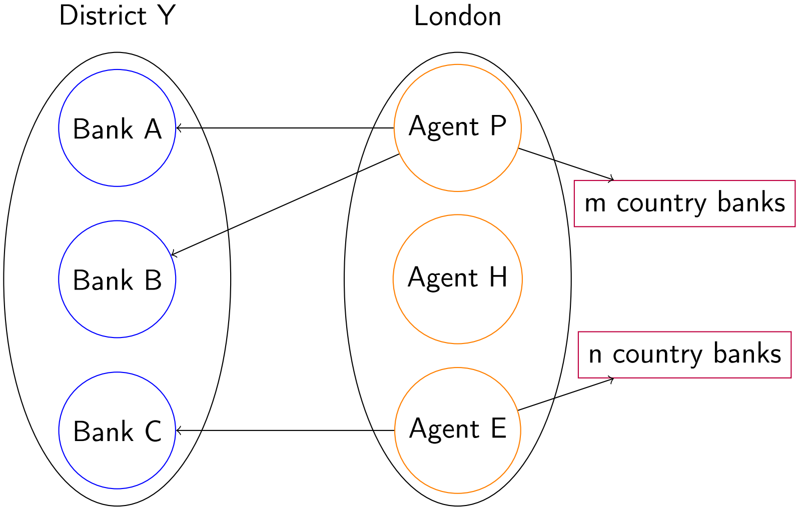
How country banks contributed to innovation (2/2)

3. Country banks alleviated the credit constraints of industrialists by providing short-term credit. I show:
   - The impacts of banks and bank connections were larger in districts that lacked credit when I use agricultural suitability as a proxy for credit adequacy.
   - The impacts of banks and bank connections were larger in counties with higher bankruptcy rates before 1750.
4. Country banks lowered the costs of procuring working capital by providing cash. I show:
   - The impacts of banks as providers of gold coins were larger in periods and regions subject to cash shortage.
5. The provision of working capital enabled industrialists to invest their own funds in innovation and fixed capital investments (Rimmer, 1960; Crouzet, 1972; Balston, 1979; Hudson, 1981).

Mechanism 1: Banks creating a national financial market

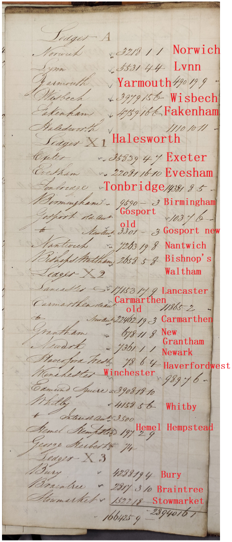
- London was an important market where country banks rediscounted bills (Michie, 2016). Country banks set up agency relationships with London bankers to access the London market (Dawes and Ward-Perkins, 2000).
- London bankers accepted deposits from country banks in areas with surplus funds and could directly provide loans to other country banks in regions that lacked adequate credit (Ackrill and Hannah, 2001)
- Country banks across England and Wales were connected with each other through London (Gilbart, 1849; Michie, 2016).
- The costs of accessing other country banks connected to the same London agent were likely to be lower than accessing banks connected to other London banks.
- Plausibly exogenous variation results from banks' entry and exit in other districts.

The English bank network centred around London



- For example, District Y is connected to (m+n) country banks in other districts. There are 3 banks in city Y. The total number of banks connected is (m+n) for this specific year t.

Agency relationship: The expansion since 1790



- Most of the records about agency relationships of country banks were created in the 1790s
- The number of country banks recorded in the ledgers of Barclays
  - Year 1790: 3
  - Year 1795: 5
  - Year 1800: At least 13
  - Year 1810: At least 26

Source: The 1810 Ledger of Barclays

The impacts of the national bank network

Table 5 The impacts of bank connections on patents

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(banks)	0.115***		0.0861***	0.0106
	(0.0207)		(0.0230)	(0.0277)
IHS(connected banks)		0.0385***	0.0170**	0.0186**
		(0.0076)	(0.0082)	(0.0080)
Observations	8,925	8,925	8,925	3,570
Sample	Full	Full	Full	Post-1790
Time-Varying Controls	Yes	Yes	Yes	Yes
District and Year Fixed Effects	Yes	Yes	Yes	Yes
Within R2	0.0415	0.0377	0.0428	0.0093
Standardized B for connection		0.120	0.0527	0.0604

Notes: Column (1) reports the impacts of banks on patents and column (2) reports the impacts of bank connections on patents. Column (3) reports the impacts of banks and bank connections on patents. Column (4) reports the IV estimates of the impacts of bank connections on 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 on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Mechanism 2: Clients benefiting from banks

- Categorize jobs of patentees into agricultural, manufacturing, traders, other non-trading services, and other occupations using the Primary-Secondary-Tertiary (PST) system (Wrigley, 2010)
- Separate patents into innovative and traditional industries following Squicciarini and Voigtländer (2015).
- The effects of banks on patents are strongly driven by patentees working in the secondary sector, the industrialists
- For robustness, I alternatively categorize patents according to the subjects of the patents (Nuvolari and Tartari, 2011)
- The existence of an active patent market (Bottomley, 2014) and patentees being in other sectors suggest that banks might also have increased the market demand for patents that could be utilized by industrialists

Patents by Industrialists and Merchants

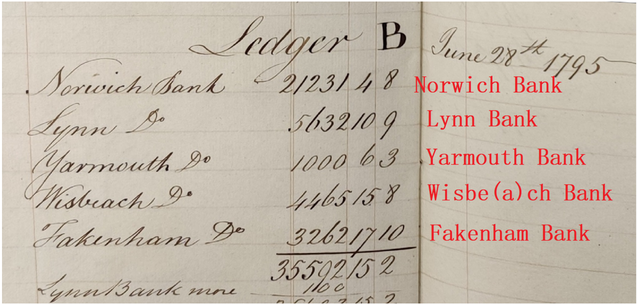
Table 6 Heterogeneous effects on different sectors (by patentee's occupation) Robust

	IHS(patents)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Modern industries					
IHS(banks)	0.0026	0.0728***	0.0215***	0.0258***	-0.0009
	(0.0018)	(0.0167)	(0.0053)	(0.0097)	(0.0007)
Panel B: Traditional industries					
IHS(banks)	0.0008	0.0256**	-0.0024	0.0062	0.0001
	(0.0012)	(0.0090)	(0.0028)	(0.0047)	(0.0004)
Observations	8,925	8,925	8,925	8,925	8,925
Time-Varying Controls	All	All	All	All	All
District & Year FEs	Yes	Yes	Yes	Yes	Yes
Sectors	Agriculture & Mining	Manufacturing	Trading	Non-trading services	Others

Mechanism 3: Exposure to credit constraints

"... —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...."

From Thomas Bland (Norwich) to John Gurney junior (London), 1772



Source: 1795 Bank Ledger of Barclays

Exposure to credit constraints

- Banks in rural areas possessed excess deposits and banks in industrial areas were in need of funds (Joplin, 1837).
- Interest rates from Keller et al. (2021) are negatively correlated with agricultural suitability.
- Interest rates in districts with below-median agriculture suitability are about 1.5% to 2.5% higher than other districts.
- Thus, I use agricultural suitability as a proxy for interest rates.
- I also use bankruptcy rate between 1720 and 1740 from Hoppit (1987) to see if the impacts of banks were different in counties with different bankruptcy rates
- I categorize bank connections into connections to banks in areas suitable for agriculture and those in areas unsuitable for agriculture. I focus on the connections to banks with adequate credit from districts subject to credit constraints.

Exposure to credit constraints

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

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(bank)	0.155***	0.156***	0.0797***	0.0808***
	(0.0274)	(0.0275)	(0.0235)	(0.0236)
IHS(bank) X 1(Agri-Suitable)	-0.0831**	-0.0859**		
	(0.0335)	(0.0334)		
IHS(bank) X 1(High-Bankruptcy)			0.0693*	0.0671*
			(0.0135)	(0.0127)
	(5)	(6)	(7)	(8)
IHS(connected bank)	0.0553***	0.0559***	0.0254**	0.0258**
	(0.0111)	(0.0111)	(0.0102)	(0.0102)
IHS(connected bank) X 1(Agri-Suitable)	-0.0335***	-0.0348***		
	(0.0128)	(0.0128)		
IHS(connected bank) X 1(High Bankruptcy)			0.0267*	0.0258*
			(0.0138)	(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

Exposure to credit constraints

Table 7.2 The impacts of different bank connections

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(Agri banks connected to	0.0706*	0.0701	0.0706**	0.0701**
Non-agri areas)	(0.0427)	(0.0428)	(0.0326)	(0.0324)
IHS(Agri banks connected to	-0.0586	-0.0590	-0.0586	-0.0590
Agri areas)	(0.0492)	(0.0493)	(0.0432)	(0.0432)
IHS(Non-agri banks	-0.0013	-0.0000	-0.0013	-0.0000
connected to Non-agri areas)	(0.0399)	(0.0400)	(0.0353)	(0.0351)
IHS(Non-agri banks	0.0167	0.0156	0.0167	0.0156
connected to Agri areas)	(0.0468)	(0.0469)	(0.0445)	(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

Mechanism 4: Banks Providing Cash

- The Royal Mint failed to provide adequate currency for the country in the 18th century (Pressnell, 1956: p. 14). Country banks provided their customers with means of payment, including coins and notes.
- The creation of notes and bills smaller than 1 pound was banned on June 24th, 1775. The number increased to 5 pounds later.
- A letter from a Newbury bank to London to collect 1,000 pounds in 1789: *'... in the words of our Mr. Vincent, such as are call'd Shiners ...'*.
- Impacts weaker in areas with good access to the London money market.
- Focus on the subsample before 1795 because the Act was suspended in 1797.

Exposure to Cash Shortage

Table 8 The impacts of banks as providers of means of payment

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(bank)	-0.0296	0.1089	-0.0414	-0.0395
	(0.0863)	(0.1203)	(0.0867)	(0.0906)
IHS(bank) X 1(Post 1775)	0.1930**	0.1793**	0.2134***	0.2230***
	(0.0779)	(0.0779)	(0.0768)	(0.0795)
IHS(bank) X 1(Post 1775)			-0.8224***	-0.4230***
X 1(Near London)			(0.0911)	(0.1591)
Observations	4,760	2,380	4,760	4,760
Year	[1755,1790]	[1765,1780]	[1755,1790]	[1755,1790]
Near London			48 km	100 km
Within R2	0.0346	0.0431	0.0391	0.0383
Time-Varying Controls	All	All	All	All

Notes: Columns (1) and (2) report the effects of banks as specialized cash providers before and after small-value notes were banned. In column (1) I restrict the time window to the period between 1755 and 1790. I further refine the periods to 1765 to 1780 in column (2). In columns (3) and (4), I test whether the impacts of banks as money providers after 1775 were weakened by the proximity to the London money market. Standard errors clustered on the registration district level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels

Conclusions

- Better banking access spurred innovation in England and Wales between 1750 and 1825, during the Industrial Revolution.
- Increases in banking access explain 38% of the increase in patenting between 1750 and 1825.
- Banks provided short-term credit to industrialists and merchants to alleviate their credit constraints, so they could spend more of their own internal funds on innovation and avoid bankruptcy.
- Banks not only served as local financial intermediaries. They were also bridges to the London money market and to country banks in other districts.

Data source

Table A1 Data sources back

data	source	notes
Patents	Woodcroft (1854)	correct errors in texts digitized by Google, geocode locations, and map into districts
Country banks	Dawes & Ward-Perkins (2000)	digitize, geocode locations and map into registration districts
Post towns	Ogilby (1675)	
Population	Great Britain Historical GIS Project & Wrigley (2007)	extrapolation
Newspapers	Richard Heaton's Index to Digitalised British and Irish newspapers (2015)	
Turnpike road network	Rosevear, Satchell, Bogart, Sugden & Shaw Taylor (2017)	
Canals	The Cambridge Group for the History of Population and Social Structure	One map in 1820 and retrieved other earlier maps according to https://www.canalmuseum.org.uk/h
Crop suitability	Global Agro-ecological Zones by FAO	
Slope	SRTM data by NASA (resolution: 90 metres)	
sea port	Alvarez-Palau, Dunn, Bogart, Satchell, & Shaw-Taylor (2019)	
map of English registration district (and coast)	Satchell, Kitson, Newton, Shaw-Taylor & Wrigley (2018)	merged to one polygon to draw the coastline
Woodcroft Reference Index	Nuvolari & Tartari (2011)	
Taxonomy according to subjects	Nuvolari & Tartari (2011)	
PST system	Wrigley (2010)	
Crop price changes	Keller, Shiue & Wang (2021)	

Relevance: post town and country banks

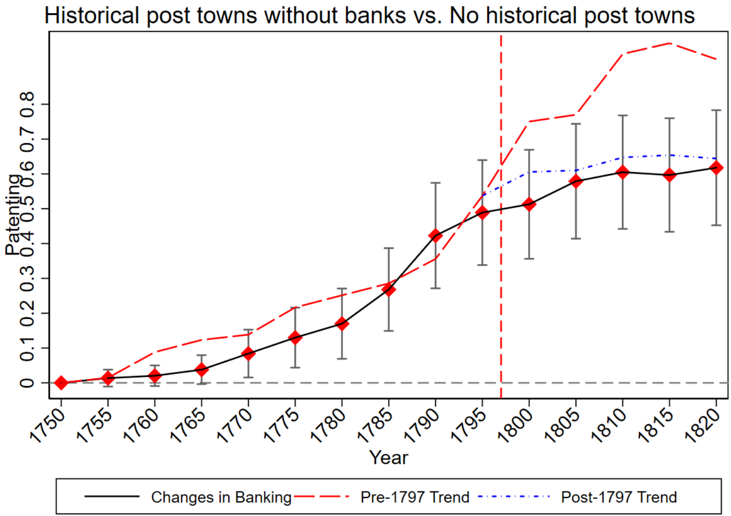
Table A2 The relationship between post town status and banks

	first year with banks		1 (banks in 1825)	
	(1)	(2)	(3)	(4)
1(post town)	-9.168***	-8.600***	-0.249***	-0.205***
	(1.697)	(1.609)	(0.0504)	(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.

Different financial access growth in districts with and without post towns

back



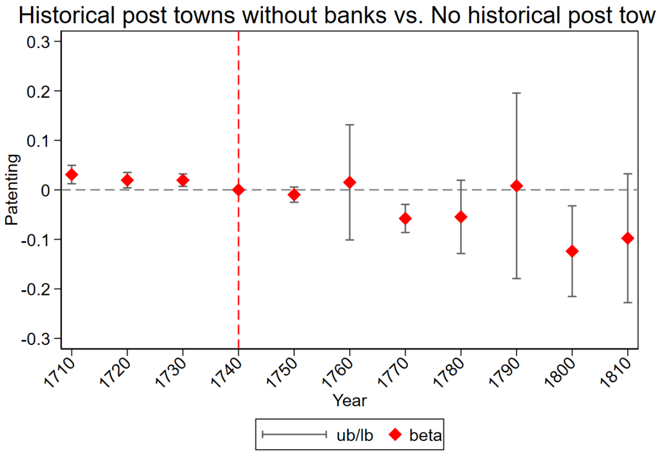
Validity of the instrument

Table A3 Robustness checks: balance tests on post roads

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

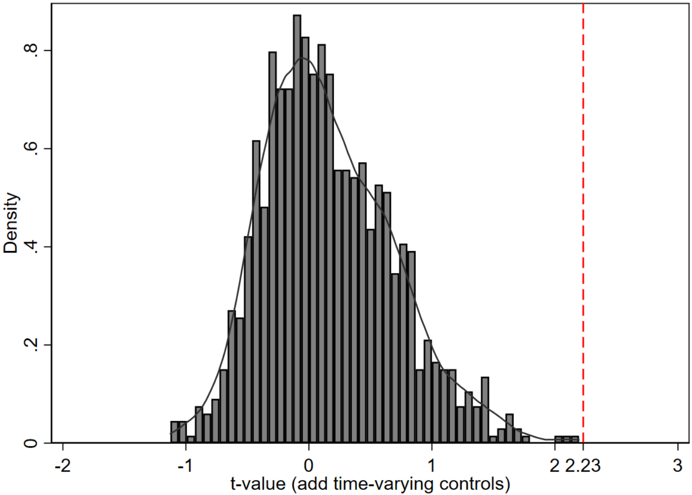
Notes: In this table, I do balance tests across districts on post roads. In Panel A, I report the results of regressing pre-existing time-invariant characteristic on the post town dummy. Panel A shows the differences in pre-existing characteristics across districts with and without post towns. In Panel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

Placebo: Historical Post Towns without Banks



back

Permutation tests



back

Robustness: Alternative IVs

Table A4.1 2SLS Estimation Using Alternative IVs back

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(banks)	0.185**	0.184**	0.190**	0.188**
	(0.0830)	(0.0822)	(0.0829)	(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**	0.239**	0.209**	0.209**
	(0.109)	(0.109)	(0.102)	(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*	0.458	0.235**	0.235**
	(0.269)	(0.278)	(0.105)	(0.105)
Time variation	Δ 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

Robustness: Alternative IVs

Table A4.1 2SLS Estimation Using Alternative IVs (continued) back

	(13)	(14)	(15)	(16)
	IHS(patents)			
IHS(banks)	0.251**	0.247**	0.188**	0.187**
	(0.105)	(0.105)	(0.0819)	(0.0812)
Time variation	Coins Circulated		Coins Circulated	
Post-1797 Interaction	No	No	Yes	Yes
Kleibergen-Paap F	36.62	36.94	29.20	29.35
Hansen p-value			0.348	0.373
	(17)	(18)		
IHS(banks)	0.223**	0.223**		
	(0.104)	(0.105)		
Time variation	American metals			
Post-1797 Interaction	No	No		
Kleibergen-Paap F	41.99	41.79		
Observations	6,435	6,435		
Time-Varying Controls	Population	All		

2SLS results using different instruments

Table A4.2 2SLS results back

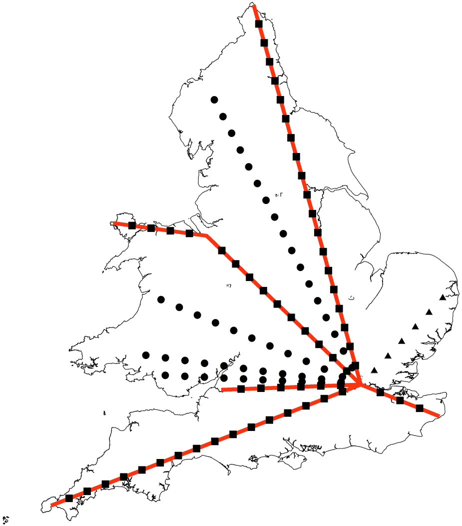
	(1)	(2)	(3)	(4)	(5)
	IHS(Patents)				
Panel A: Baseline IV					
IHS(Banks)	0.187**	0.186**	0.132*	0.138*	0.148*
	(0.0840)	(0.0834)	(0.0736)	(0.0769)	(0.0894)
Kleibergen-Paap F statistic	55.83	55.90	55.89	51.71	38.83
Panel B: IV based on linear year					
IHS(Banks)	0.185**	0.184**	0.129*	0.135*	0.139
	(0.0830)	(0.0822)	(0.0718)	(0.0754)	(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 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

First Stage Results

Table A4.3 The First Stage results of 2SLS back

	(1)	(2)	(3)	(4)	(5)
			IHS(Patents)		
Panel A: Baseline IV					
1(post town) *ln(M2)	0.440***	0.443***	0.473***	0.459***	0.406***
	(0.0589)	(0.0593)	(0.0633)	(0.0638)	(0.0651)
Panel B: IV based on linear year					
1(post town) *year/10	0.109***	0.110***	0.117***	0.113***	0.098***
	(0.0143)	(0.0144)	(0.0154)	(0.0155)	(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

Placebo post towns



Placebo tests

Table A5.1 Placebo tests back

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(banks)	-0.148	-0.183	-2.054	4.677
	(0.400)	(0.430)	(8.191)	(44.58)
First Stage				
1(Placebo post town)*year/100	0.208	0.196	0.045	-0.019
	(0.150)	(0.150)	(0.175)	(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	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year

Notes: This table reports IV estimation results using instruments constructed based on placebo post towns. Column (1) 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.

Falsification tests

Table A5.2 Falsification tests back

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

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.

Robustness checks

Table A6 Robustness checks with alternative measurements of innovation back

	(1)	(2)	(3)	(4)	(5)	(6)
	IHS(patents)					
	OLS				IV	
IHS(banks)	0.108***	0.109***	0.156***	0.104***	0.170*	0.169**
	(0.0201)	(0.0201)	(0.0366)	(0.0358)	(0.0795)	(0.0788)
Observations	8,925	8,925	8,925	8,925	8,775	8,775
Within R2	0.0422	0.0429	0.0978	0.164		
KPF					58.18	58.43
Time-Varying Controls	Pop	All	Pop	All	Pop	All
Bank Cohort FE X Year FE	No	No	Yes	Yes	No	No
Fixed Controls X Year FE	No	No	No	Yes	No	No
County Linear Trends	No	No	No	Yes	No	No
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Standardized B	0.155	0.156	0.224	0.148	0.242	0.239

Interactive Fixed Effects

$$X_{it} = \tau_i + \theta_t + \sum_{k=1}^{r} a_k \lambda_{ik} + \sum_{k=1}^{r} b_k F_{kt} + \sum_{k=1}^{r} c_k \lambda_{ik} F_{kt} + \pi_i' G_t + \eta_{it},$$

Table A7 Interactive Fixed Effects back

	(1)	(2)	(3)	(4)
		ln(1+patents/pop)		
Panel A: Interaction Dimension=1				
ln(1+banks/pop)	0.0602***	0.0588***	0.0737*	0.0565***
	(0.0185)	(0.0185)	(0.0379)	(0.0206)
Panel B: Interaction Dimensions=2				
ln(1+banks/pop)	0.0544***	0.0529***	0.0568	0.0538**
	(0.0186)	(0.0187)	(0.0414)	(0.0215)
Observations	8,925	8,925	8,925	8,925
Fixed Effects	District, Year	District, Year	District, Year	District. Year
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

Robustness checks: controls and different clusters

Table A8.1 Robustness: additional controls and standard errors clustered on the county level

	(1)	(2)	(3)	(4)	(5)	(6)
	IHS(patents)					
IHS(banks)	0.0468**	0.0444**	0.115***	0.115***	0.0468**	0.0444***
	(0.0195)	(0.0199)	(0.0311)	(0.0308)	(0.0193)	(0.0202)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Within R2	0.280	0.297	0.0409	0.0415	0.280	0.297
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	All	All	Pop	All	All	All
County Linear Trends	Yes	Yes	No	No	Yes	Yes
Time invariant controls X Year FE	No	Yes	No	No	No	Yes
Cluster	District	District	County	County	County	County

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

Robustness checks: Conley standard errors

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***	0.115***	0.115***	0.115***	0.115***	0.115***
	(0.0146)	(0.0166)	(0.0179)	(0.0177)	(0.0172)	(0.0171)
Panel B: With all time-varying controls						
IHS(Banks)	0.115***	0.115***	0.115***	0.115***	0.115***	0.115***
	(0.0145)	(0.0164)	(0.0177)	(0.0174)	(0.0170)	(0.0170)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Fixed Effects	District and Year	District and Year	District and Year	District and Year	District and Year	District and Year

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

Robustness checks

Table A9.1 Robustness checks with different models

	ln(1+patents)		1(patent>0)		N(patents)		IHS(patents)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IHS(banks)	0.0897***	0.0898***	0.0716***	0.0716***	0.152**	0.150**	0.116*	0.112
	(0.0165)	(0.0164)	(0.0114)	(0.0114)	(0.0624)	(0.0623)	(0.0685)	(0.0691)
Observations	8,925	8,925	8,925	8,925	5,325	5,325	5,325	5,325
Model	Hyperbolic sine	Hyperbolic sine	Binary	Binary	Poisson	Poisson	PPML	PPML
Time-varying Controls	Pop	All	Pop	All	Pop	All	Pop	All
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year

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 Poisoon pseudo-likelihood Model and the dependent variable is the inverse hyperbolic transformation 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. back

Robustness checks

Table A9.2 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***	0.0490***	0.220**	0.218**		
	(0.0141)	(0.0141)	(0.0883)	(0.0881)		
1(post town)*year/10					0.278***	0.280***
					(0.0402)	(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, Year	District, Year	District, Year	District, Year	District, Year	District, Year

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

Robustness checks

Table A10 Robustness: Patents of high quality

	(1)	(2)	(3)	(4)
	IHS(patents)			
IHS(banks)	0.0511***	0.0511***	0.0436***	0.0140*
	(0.0134)	(0.0134)	(0.0127)	(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
Fixed Effects	District, Year	District, Year	District, Year	District, Year

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

Robustness checks

Table A11.1 Robustness: patent counts within a 3-year or a 10-year window

	IHS(patents)							
	Window: 3 years				Window: 10 years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IHS(banks)	0.0773***	0.0775***	0.103***	0.0733***	0.187***	0.187***	0.295***	0.226***
	(0.0162)	(0.0161)	(0.0270)	(0.0258)	(0.0289)	(0.0289)	(0.0603)	(0.0617)
Observations	14,875	14,875	14,875	14,875	4,165	4,165	4,165	4,165
Time-varying Controls	Pop	All	All	All	Pop	All	All	All
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Bank Cohort FE X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Time-invariant controls X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes	No	No	No	Yes

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

Robustness checks

Table A11.2 Comparison of coefficients to Mao & Wang (2021)

	(1)	(2)	(3)	(4)
	ln(1+patents)			
ln(1+banks)	0.0805***	0.0800***	0.111***	0.0803***
	(0.0180)	(0.0169)	(0.0294)	(0.0276)
Observations	14,875	14,875	14,875	14,875
Within R2	0.0109	0.0325	0.117	0.173
Fixed Effects	District and Year	District and Year	District and Year	District and Year
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 settng is similar to county-level analysis in Table 6 of Mao & Wang (2021). I add only district and year fixed effects in column (1), time-varying controls in column (2), interaction of 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.

back

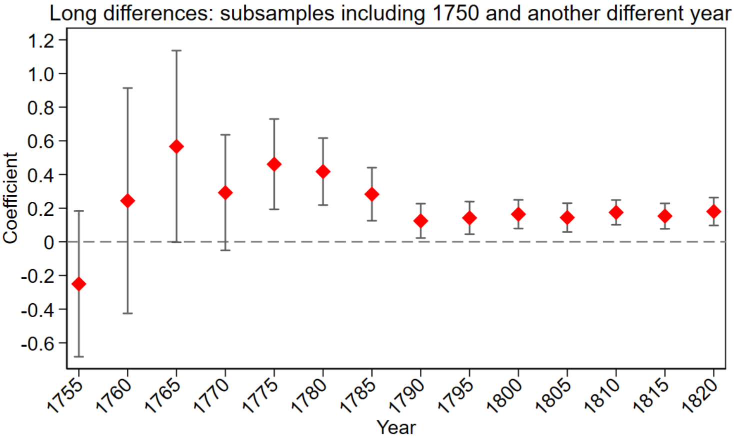
Robustness checks

Table A12 Robustness checks: Restricted samples

	IHS(patents)							
	districts with banks				districts with patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IHS(banks)	0.136***	0.137***	0.163***	0.105***	0.112***	0.113***	0.195***	0.105**
	(0.0236)	(0.0236)	(0.0389)	(0.0390)	(0.0277)	(0.0277)	(0.0516)	(0.0509)
Observations	6,000	6,000	6,000	6,000	5,325	5,325	5,325	5,325
Time-varying Controls	Pop	All	All	All	Pop	All	All	All
District & Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Cohort FE X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes	No	No	No	Yes
Time-invariant controls X Year FE	No	No	No	Yes	No	No	No	Yes

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

Long differences back



Mechanisms: Heterogeneous effects across sectors

Table A13 Heterogeneous effects on different sectors (by the industry of patents) back

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

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the inverse hyperbolic sine transformation 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.

Spillover Effects

- Heblich and Trew (2019) argued that the impacts of banks on industrialization were local.

Table A14 Spillover effects of banks in neighbouring districts back

	(1)	(2)	(3)
		IHS(patents)	
IHS(banks)	0.115***	0.114***	
	(0.0207)	(0.0205)	
IHS(neighbour banks)		-0.051***	-0.052***
		(0.0161)	(0.0164)
Observations	8,925	8,925	8,925
R2	0.0415	0.0461	0.0304
Fixed Effects	District, Year	District, Year	District, Year
Time-Varying Controls	Yes	Yes	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. 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.

Qualitative evidence from biographies: other possibilities

- Direct sponsorship
  - James Backhouse, a Darlington banker, sponsored John Kendrew and Thomas Porthouse to invent a flax-spinning machine in 1787 and set up a small factory in the 1780s and 1790s (Cookson, 2003).
  - The funds from the Gurneys in East Anglia flowed to Barclays and other London bankers, then to the Backhouses (Ackrill and Hannah, 2001)
  - John Marshall bought the copyright of the flax-spinning machine from John Kendrew and Thomas Porthouse (Beresford, 2004). Matthew Murray, an employee of Marshall, improved the machine and created 2 patents in 1790 and 1793.
- Partnership
  - Richard Moody, a Southampton banker and brewer, formed a partnership with Walter Taylor, a nautical instrument inventor, in the 1780s (Dykes, 1999). Walter Taylor achieved a patent for a brewery process in 1786.