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

Jinlin Wei

University of Warwick

Introduction

Question

- Did the development of country banks in England and Wales increase patenting between 1750 and 1825?

Motivation

- Banks were conservative and not important in providing capital during the English industrialization (Gerschenkron, 1962). However, anecdotal evidence during the Industrial Revolution shows a different picture (Mathias, 1969).
  - There is scope for quantitative evidence to address this question systematically and provide credible causal inference.
- Both recent and historical evidence from the United States shows that better banking access increases innovation (Kerr and Nanda, 2015). How do banks contribute to innovation?

What I have done

- I use a setting where banks generally provided short-term credit, to show that short-term credit increased innovation by alleviating credit constraints.
- 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.
- Construct an instrumental variable based on the existence of historical post-towns following Heblich and Trew (2019).
  - Country banks were more likely to locate in towns with post houses because of safety, information and demand for services from the postal system.
- Increased banking access predicts more patents per capita. Country banks increased patents in the manufacturing sector by lowering the financial costs of industrialists.

Contribution (1/2)

On the role of banks in innovation

- Debt markets serve innovation poorly (Williamson, 1988; Hall and Lerner, 2010). However, recent studies show debt fosters innovation and growth on aggregate (Geelen et al., 2021).
- Empirical evidence from the United States shows that increased credit supply promotes innovation in the late 20th century (Amore et al., 2013; Chava et al., 2013; Nanda and Nicholas, 2014; Cornaggia et al., 2015) and in the Antebellum Period (Mao and Wang, 2022), especially innovative firms that relied heavily on external finance.
- Lower level of bank distress leads to higher innovation during the Great Depression (Nanda and Nicholas, 2014).
- This paper shows that short-term credit provided by banks for the working capital of industrialists enabled industrialists to allocate more funds to innovation.

Contribution (2/2)

On the role of banks during the Industrial Revolution

- Banks provided short-term credit to industrialists and merchants (Pressnell, 1956; Hudson, 1986; Michie, 2016). There is little evidence that banks affected industrialization in the second half of the 18th century (Mokyr, 2009; Kelly et al., 2023). In the 19th century, banking access promoted industrialization (Heblich and Trew, 2019).
- Some banks acted as venture capitalists (Brunt, 2006). There is also contrasting evidence: bankers rejected Matthew Boulton (Postan, 1935) and Richard Arkwright (Fitton, 1989).
- I use granular data to provide novel quantitative evidence about the impacts of banks on innovation during the English industrialization between 1750 and 1820.
- I show that country banks served as the bridge that connected industrialists outside London with the London money market and country banks in other districts.

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: average capital about £10,000 in late 18th century (Pressnell, 1956). Using GDP per capita as the deflator, about 10 - 20 million pounds (Beers et al., 2020).
  - 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 joint-stock banks became legal in 1826 (Michie, 2016).

How Marshall survived the 1793 War

- The flax-spinning 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. in 1792-1793 (Rimmer, 1960; Crouzet, 1972)
- The partnership of Marshall might have gone bankrupt without the overdraft because the deficit of the firm reached £3,042 in April 1793 during its hardest days. They had only £191 in cash.
- Matthew Murray, an engineer that John employed to invent a new flax-spinning machine, patented it in December 1793. John Marshall managed to make a success with the new patent and left 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).
- Addresses, dates of patents and occupations of patentees in England and Wales from Woodcroft (1854).
  - Patent statistics as a measurement of innovation (Sokoloff, 1988; Sullivan, 1989; Moser and Voena, 2012)
  - For robustness, I use a constructed patent quality index that is correlated positively with important inventors and inventions between 1740 and 1840 (Nuvolari and Tartari, 2011). The results are robust for patents of higher quality.
- 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)
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.

1. Introduction

2. Background and data

3. Identification strategy

4. Empirical results

5. Concluding remarks

Identification

$$\ln[1 + (\frac{Patents}{Population})_{i,t+1\ to\ t+5}] = \beta_0 + \beta_1 \times \ln[1 + (\frac{Banks}{Population})_{i,t}] + x_{i,t}^{'}\gamma + \delta_i + \eta_t + \varepsilon_{i,t} \quad (1)$$

- $(\frac{Patents}{Population})_{i,t+1\ to\ t+5}$ measures the number of patents over population (unit: million people) in district i within 5 years after year t (t= 1750, 1755, ...,1820).
- $(\frac{Banks}{Population})_{i,t}$ is the number of surviving country banks over population (unit: million people) 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.

Constructing the instrument

- Endogeneity: Omitted variables
- Instrument: post towns recorded in Britannia (Ogilby, 1675) $\times$ year Relevance
- Relevance: Advantages of post towns for banks: safety, information and the demand for financial services from post offices (Dawes & Ward-perkins, 2000; Heblich & Trew, 2019).
- Exogeneity assumption: Post towns were not selected based on pre-existing characteristics that predict differential trends in patent growth.
- Exclusion restriction assumption: Post towns only affected patents through the channel of banks.

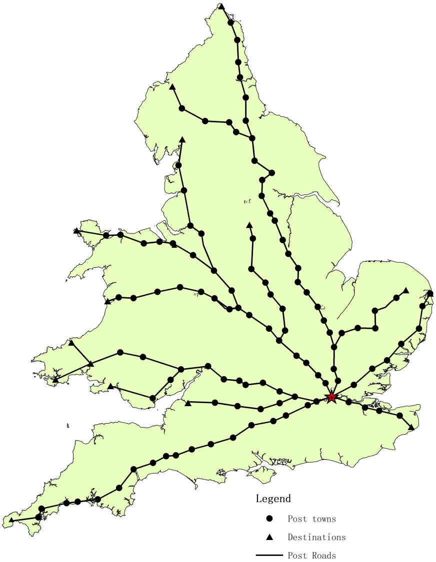
Balance tests

Table 2 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.

Post towns in 1675



Baseline Results

- One standard deviation increase (1.306) in banking access (mean 1.225) ⇒ 15% increase in patents per capita (mean of dependent variable: 0.582)

Table 3 Baseline results

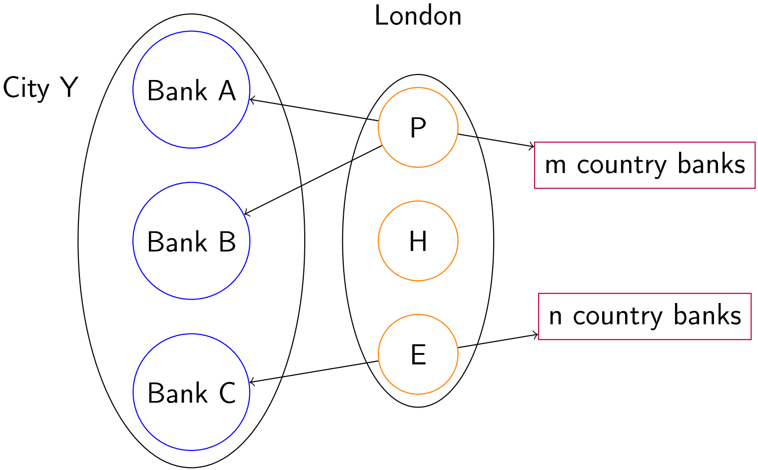
	(1)	(2)	(3)	(4)
		ln(1+patents/pop)		
ln(1+banks/pop)	0.044***	0.049***	0.163*	0.218**
	(0.0145)	(0.0141)	(0.0884)	(0.0881)
Observations	8,925	8,925	8,775	8,775
Model	OLS	OLS	IV	IV
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	None	Yes	None	Yes
Kleibergen-Paap F			50.66	47.55
Standardized B	0.0597	0.0670	0.222	0.297

Notes: Column (1) and (2) report OLS regression estimates of Eq. (1) and column (3) and (4) report the IV estimates. 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.

The English bank network centred around London

- Country banks across England and Wales were connected with each other through London (Gilbart, 1849; Michie, 2016). Their London agents, usually bankers, created a national network.
- 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)
- The costs of accessing other country banks connected to the same London agent were likely to be lower than accessing banks connected other London banks.
- Plausibly exogenous variation results from banks entry and exit in other districts.

The English bank network centred around London



- For example, City 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.

The impacts of the national bank network

Table 4 The impacts of bank connections on patents

	(1)	(2)	(3)	(4)
	ln(1+patents)			
ln(1+banks/pop)	0.0490***		0.0264	
	(0.0141)		(0.0187)	
ln(1+connected banks/pop)		0.0373***	0.0265**	0.132***
		(0.0102)	(0.0135)	(0.0499)
Observations	8,925	8,925	8,925	8,775
Time-Varying Controls	Yes	Yes	Yes	Yes
Fixed Effects	District and Year	District and Year	District and Year	District and Year
Within R2	0.0125	0.0130	0.0135	
Kleibergen-Paap F				57.54
Standardized B for connection		0.0666	0.0473	0.237

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.

Mechanisms: Heterogeneous effects across sectors

- Categorize jobs of patentees into agricultural, manufacturing, traders, other non-trading services, and other occupations using the Primary-Secondary-Tertiary (PST) system (Wrigley, 2010)
- The effects of banks on patents are confined to patentees working in the secondary sector
- The coefficient in column (2) is significantly different from the coefficients in column (1), (3), (4) and (5)
- For robustness, I alternatively categorize patents according to the subjects of the patents (Nuvolari and Tartari, 2011)

Mechanisms: Patents by Industrialists

Table 5 Heterogeneous effects on different sectors (by patentee's occupation) Robust

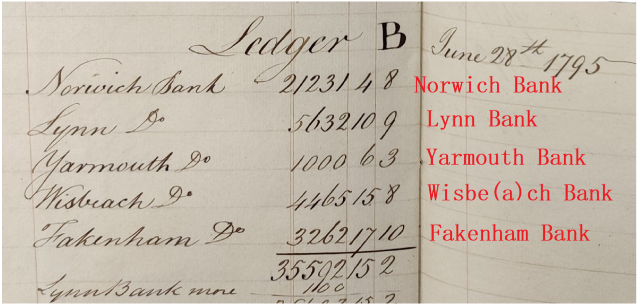
	ln(1+patents/pop)				
	(1)	(2)	(3)	(4)	(5)
ln(1+banks/pop)	0.00515	0.0393***	0.00495	0.0129	-0.00114
	(0.00317)	(0.0115)	(0.00495)	(0.00931)	(0.00100)
Observations	8,925	8,925	8,925	8,925	8,925
Time-Varying Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year
Sectors	Agriculture & Mining	Manufacturing	Trading	Non-trading services	Others
p-value against (2)	0.0040		0.0029	0.0442	0.0005

Notes: This table reports OLS regression estimates of Eq. (1) while the dependent variable is the natural logarithm of one plus the total number of patents acquired by patentees from different sectors in a district in year t+1 to year t+5 over the population in the district. The unit of population is million people. Column (1) reports the result of patents whose patentees were from agriculture and mining. Column (2) reports the result of patents whose patentees were from the manufacturing sector. Column (3) reports the result of patents acquired by traders, column (4) reports the result of non-trading services and column (5) are other occupations. Standard errors are clustered on the registration district level. The results do not change significantly when I cluster standard errors at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

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 the 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.

Exposure to credit constraints

Table 6 Heterogeneous effects of banks in districts with different agricultural suitability

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.0792***	0.0724***		
	(0.0206)	(0.0201)		
ln(1+banks/pop) X 1(Agri-Suitable)	-0.0639***	-0.0415*		
	(0.0243)	(0.0238)		
ln(1+connected banks/pop)			0.0695***	0.0667***
			(0.0144)	(0.0138)
ln(1+connected banks/pop) X 1(Agri-Suitable)			-0.0525***	-0.0414***
			(0.0175)	(0.0170)
Observations	8,925	8,925	8,925	8,925
Time-Varying Controls	None	Yes	None	Yes

Notes: Column (1) and (2) report the different effects of banks in districts with different agricultural suitability. I define a district suitable for agriculture if the crop suitability is higher than the median of crop suitability for more than 2 crops among oat, barley, wheat and rye. In column (1) I include only district and year fixed effects and in column (2) I add time-varying 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

Discussions about 2SLS

- Why the IV is relevant to banks Relevance
- Balancing test on post roads Table A3
- Historical post towns without banks OnlyPost
- Permutation test Permutation
- Refined IV Refined
- IV based on money supply M2
- Placebo post towns: Straight roads between London and destinations Placebo
- Falsification test: Districts without banks Falsify

Robustness checks

- Specification with time-invariant variables interacted with Year FE and county linear trends Additional controls
- Conley standard errors Conley SEs
- Interactive Fixed Effects (Bai, 2009) iFE
- Different transformations of the dependent variable Table A9.1
- Different measurement of innovation Table A9.2
- Patents with higher quality as measured by Woodcroft Reference Index (Nuvolari & Tartari, 2011) Table A10
- Different aggregation periods of patent statistics Table A11.1
- Comparison to other papers Table A11.2
- Alternative subsamples Table A12
- Long differences using subsamples of 1750 and another year Long Differences
- Different definition of the manufacturing sector Subjects
- Bank entry: Staggered DID Bank Entry
- Spillovers Spillovers

Conclusions

1. Better banking access stimulated innovation in England and Wales during the First Industrial Revolution.
2. Increases in banking access explain 12% of the increases in patenting between 1750 and 1825, the effects are not negligible.
3. Banks increased patents by lowering the financial costs of industrialists. Short-term credit provided for working capital freed funds for innovation and increased patents in England.

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

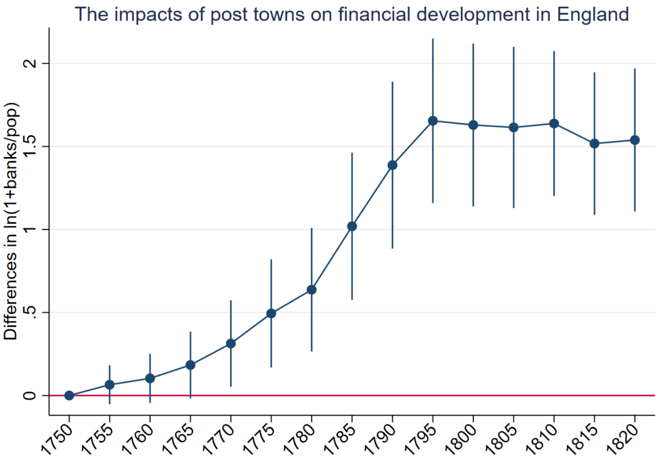
Table A2 The relationship between post town status and banks

	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



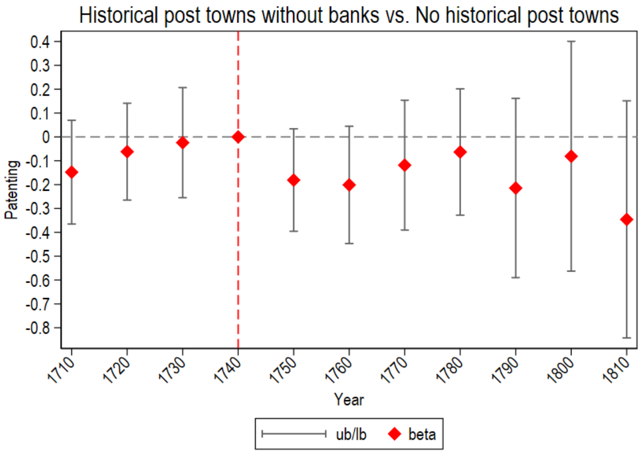
Validity of the instrument

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

Historical Post Towns without Banks



back

Permutation tests

Figure 3_1.png

Figure 3_2.png

back

2SLS results using different instruments

Table A4.1 2SLS results back

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.218**	0.183**	0.191**	0.184*
	(0.0881)	(0.0921)	(0.0971)	(0.106)
First Stage Dependent variable: ln(1+bank/pop)				
1(post town)*year	0.0280***	0.0281***	0.0273***	0.0253***
	(0.0041)	(0.0043)	(0.0043)	(0.0044)
Observations	8,775	8,820	8,820	8,820
Sample to construct IV	all post towns	Drop non-border towns	Drop detours	Population $\leq$ 5k
Time-varying Controls	Yes	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Clustering	District	District	District	District
Kleibergen-Paap F statistic	47.55	43.80	40.49	32.67

Different IV

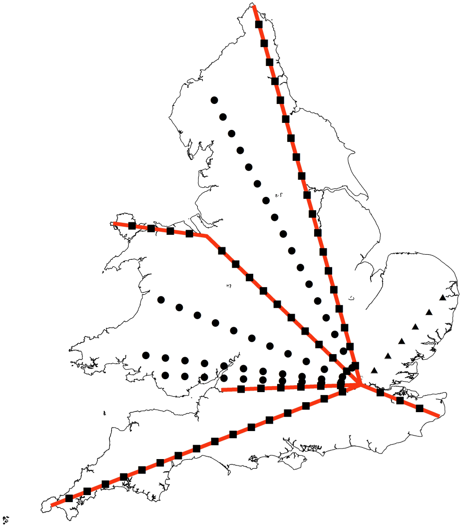
- Use M2 data from Palma (2018) and create five-year moving average of the natural logarithm of M2. IV=1(post town) X ln(M2)

Table A4.2 IV Based on Money Supply back

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.044***	0.049***	0.173*	0.232**
	(0.0145)	(0.0141)	(0.0884)	(0.0881)
Observations	8,925	8,925	8,775	8,775
Model	OLS	OLS	IV	IV
Fixed Effects	District, Year	District, Year	District, Year	District. Year
Time-Varying Controls	None	Yes	None	Yes
Kleibergen-Paap F statistic			44.616	41.86
Standardized B	0.0597	0.0670	0.236	0.316

Notes: Column (1) and (2) report OLS regression estimates of Eq. (1) and column (3) and (4) report the IV estimates. 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.

Placebo post towns



Placebo tests

Table A5.1 Placebo tests back

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	-0.393	-0.239	-0.598	-1.113
	(0.333)	(0.353)	(1.030)	(3.267)
First Stage				
1(Placebo post town)*year/100	0.897**	0.714	0.398	0.210
	(0.435)	(0.439)	(0.552)	(0.576)
Observations	8,775	8,775	8,775	8,775
Destination sets	Baseline	Baseline	Drop non-border destinations	Strategic destinations
KP F Statistics	4.246	2.641	0.521	0.133
Time-Varying Controls	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year

Notes: This table reports IV estimation results using instruments constructed based on placebo post towns. Column (1) 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)
	ln(1+patents/pop)			
1(all post town)*year	-0.753***	-0.520*	-0.353*	
	(0.298)	(0.274)	(0.213)	
1(post town)*year				-0.431
				(0.339)
1(minor post town)*year				-0.605*
				(0.338)
1(post town after 1750)*year				-0.442
				(0.443)
Observations	2,925	2,925	6,565	2,925
Subsample	Never banks	Never banks	No banks	Never banks
Time-Varying Controls	None	Yes	Yes	Yes
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: controls and different clusters

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

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents/pop)					
ln(1+banks/pop)	0.0451***	0.0439***	0.0437**	0.0490***	0.0451***	0.0439***
	(0.0140)	(0.0139)	(0.0178)	(0.0159)	(0.0145)	(0.0152)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Within R2	0.0537	0.0663	0.00204	0.0125	0.0537	0.0663
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	Yes	Yes	No	Yes	Yes	Yes
Time invariant controls X Year FE	Yes	Yes	No	No	Yes	Yes
County Linear Trends	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 A7.2 Conley standard errors

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

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

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 A8 Interactive Fixed Effects

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
ln(1+banks/pop)	0.049***	0.051***	0.056***	0.056***
	(0.0166)	(0.0162)	(0.0181)	(0.0173)
Observations	8,925	8,925	8,925	8,925
Interactive Dim	1	1	2	2
Model	iFE	iFE	iFE	iFE
Fixed Effects	District, Year	District, Year	District, Year	District. Year
Time-Varying Controls	None	Yes	None	Yes

Notes: This table reports the OLS estimates of using interactive 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. back

Robustness checks

Table A9.1 Robustness checks with different models

	IHS(patents/pop)		1(patent>0)		N(patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+banks/pop)	0.0509***	0.0571***	0.0107***	0.0120***	0.0398*	0.0480**
	(0.0166)	(0.0162)	(0.00316)	(0.00308)	(0.0224)	(0.0224)
Observations	8,925	8,925	8,925	8,925	5,325	5,325
Model	Hyperbolic sine	Hyperbolic sine	Binary	Binary	Poisson	Poisson
Time-varying Controls	No	Yes	No	Yes	No	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year

Notes: Notes: In Column (1) & (2), the dependent variable IHS(patent/pop) denotes the inverse hyperbolic sine transformation of the variable patent/pop. 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. 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 measurements of innovation

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

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

Robustness checks

Table A9.3 Robustness checks with different measures of banking access and innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1+patents)				ln(1+banks)	
	OLS		IV		First Stage	
ln(1+banks)	0.118***	0.118***	0.129	0.191**		
	(0.0231)	(0.0217)	(0.0928)	(0.0865)		
1(post town)*year/100					0.831***	0.844***
					(0.111)	(0.111)
Observations	8,925	8,925	8,775	8,775	8,775	8,775
Within R2	0.0164	0.0426				
KPF			56.43	57.61		
Time-Varying Controls	None	Yes	None	Yes	None	Yes
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: considering patent quality back

	(1)	(2)	(3)	(4)
	ln(1+ patents/pop)			
ln(1+banks/pop)	0.0318**	0.0374***	0.0189*	0.0227**
	(0.0130)	(0.0125)	(0.0098)	(0.0096)
Observations	8,925	8,925	8,925	8,925
Patents	WRI$\geq$ 2		adjusted WRI above median	
Time-Varying Controls	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time invariant controls X Year FE	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes

Notes: The dependent variable is constructed based on the counts of patents with high Woodcroft Reference Index proposed by Nuvolari & Tartari (2011). In column (1) and (2), I include patents with WRI index larger than or equal to 2. In column (3) and (4), I include patents with the above-median adjusted WRI index. I add only district and year fixed effects in columns (1) and (3), time-varying controls in columns (2) and (4). 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 A11.1 Robustness: patent counts within a 3-year or a 10-year window

	ln(1+patents/pop)							
	Window: 3 years				Window: 10 years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(1+banks/pop)	0.0272***	0.0308***	0.0308***	0.0295***	0.0847***	0.0907***	0.0840***	0.0795***
	(0.0102)	(0.00985)	(0.00985)	(0.00969)	(0.0222)	(0.0220)	(0.0218)	(0.0220)
Observations	14,280	14,280	14,280	14,280	4,165	4,165	4,165	4,165
Time-varying Controls	None	Yes	Yes	Yes	None	Yes	Yes	Yes
Fixed Effects	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year	District, Year
Time-invariant controls X Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County Linear Trends	No	No	No	Yes	No	No	No	Yes

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

Notes: I count patents 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 time-invariant variables and year fixed effects in column (3) and county linear trends in column (4). Standard errors are clustered on the registration district level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively. back

Robustness checks

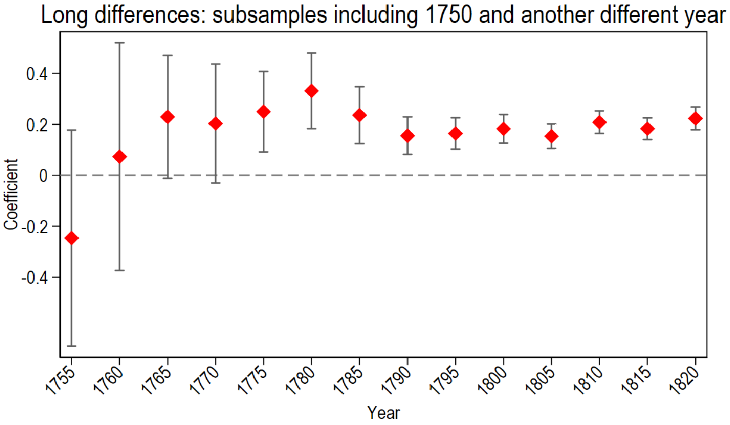
Table A12 Robustness checks: Restricted samples

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

	ln(1+patents/pop)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+banks/pop)	0.00856	0.0414***	0.0439***	0.0458***	0.0432***	0.0447***
	(0.00611)	(0.0124)	(0.0129)	(0.0130)	(0.0134)	(0.0135)
Observations	8,925	8,925	8,925	8,925	8,925	8,925
Time-Varying Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, 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 natural logarithm of one plus the total number of patents in different sectors in a district in year t+1 to year t+5 per million people. 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.

Bank Entry

Table A14 The impacts of bank entry on patents back

	(1)	(2)	(3)	(4)
	ln(1+patents/pop)			
1(banks)	0.305***	0.321***		
	(0.095)	(0.103)		
1(bank entry)			0.183***	0.175***
			(0.0672)	(0.0669)
Observations	8,925	8,925	8,925	8,925
Model	Staggered DID		OLS	
Fixed Effects	District, Year	District, Year	District, Year	District, Year
Time-Varying Controls	None	Yes	None	Yes

Notes: Column (1) and (2) report Staggered DID estimates of the impacts of having a bank on patenting following Callaway and Sant'Anna (2021). A district is regarded as 'treated', having a bank, after the first bank was established in this district. Column (3) and (4) report how bank entry in each period affects patenting. 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.

Spillover Effects

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

Table A15 Spillover effects of banks in neighbouring districts back

	(1)	(2)	(3)
		ln(1+patents/pop)	
ln(1+ banks/pop)	0.049***	0.049***	
	(0.0141)	(0.0127)	
ln(1+neighbour banks/pop)		-0.037***	-0.037***
		(0.0127)	(0.0127)
Observations	8,925	8,925	8,925
R2	0.0125	0.0141	0.0115
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.