The Long Shadow of a Sudden River

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Abstract

In 1134, a storm created the Zwin, a 15-kilometre-long river that suddenly connected Bruges to the North Sea. But by 1500, this sudden river silted up, becoming unnavigable. I use this natural experiment to show that while it remained open, the Zwin more than tripled Bruges's population. To quantify the shadow this temporary river casts, I then develop a dynamic quantitative spatial model that incorporates merchants and Malthusian dynamics. Because no systematic quantitative data on merchant numbers exists, I construct a novel retrieval-augmented generation large language model to quantify merchant activity from 120 qualitative historical sources in a transparent and verifiable manner. I find that two hundred years after silting up, the Zwin continued to increase Bruges's population by around 10 per cent and had persistent effects on the spatial distribution of population in other nearby cities.

JEL: R12, R13, N9, O18

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Cities are engines of productivity and beacons of opportunity [Glaeser, 2011]. Understanding how the prevailing urban structure was born and the role past shocks have had in shaping this distribution are thus crucial economic questions. These questions can, however, only be answered by considering a very long-run horizon, accounting for complex spatial inter-linkages, and identifying plausibly exogenous shocks to the system. In this paper, I trace the impact of a unique and dramatic natural experiment over hundreds of years, and employ an augmented dynamic quantitative spatial economics model to shed some light on these questions.

In the 12th century, a biblical storm caused a large sea inlet, the Zwin, to form [Glaeser, 2022, Ryckaert, 1989].[1] This new river connected the outskirts of Bruges[2] to the North Sea [Trachet et al., 2015] and the lucrative trade that flowed through it [Glaeser, 2022]. However, by 1500, the Zwin had silted up and was no longer navigable. The sudden appearance and (not quite so sudden) disappearance of the Zwin has previously been qualitatively attributed to Bruges' rise and subsequent fall [Dumolyn and Leloup, 2016, Van Houtte, 1966].

First, taking a reduced form approach, I find that the Zwin increased the population of Bruges whilst navigable by between 174% and 425%. I also find a persistent reduced form effect after the Zwin silted up, a *shadow*, of on average between 78% and 123% higher population over the 1500-1800 period. To generate these estimates, I use updated historic population data based on the Bairoch et al. [1988] dataset, and employ four empirical strategies: difference-in-differences, event-study, synthetic control and take a market access approach. To perform inference in this setting with one treated unit, I follow Conley and Taber [2011] and use information on estimate uncertainty from placebo experiments.

To ask what impact the Zwin had on the entire urban structure of the Low Countries we need to consider the counterfactual world in which the Zwin had not appeared. To do this, I develop a dynamic quantitative spatial economics model adapted to the Medieval and Early Modern European economy. I extend the framework of Allen and Donaldson [2022] to account for two key features of this period: Merchants and Malthusian dynamics. Locations

[1] Technically, a sea inlet is not a river, but for our purposes, the two formations are equivalent and so in this paper from now on I will describe the Zwin as a river.

[2] For simplicity and clarity throughout this paper, I will use the English spelling of cities in the Low Countries. For example, I will use "Bruges" and "Antwerp" rather than their Dutch spellings "Brugge" and "Antwerpen" or French spellings "Bruges" or "Anvers".

interact through costly migration and costly trade, and the past impacts today through historical amenity and productivity spillovers and fertility dynamics. Merchants choose where to locate to maximise profits and directly impact local productivity, and Malthusian dynamics allow a location to grow endogenously without in-migration. To identify model parameters, I use data on populations, wages, and merchant numbers to estimate model-implied regressions. Armed with parameter estimates, I can then invert the model to back out rationalising local fundamentals for each city and estimate the direct impact the Zwin may have had on local fundamentals in Bruges. In this way, I can flexibly allow the Zwin to both impact travel costs and fundamentals in Bruges directly.

To pursue this estimation strategy, I require data on merchant numbers at the city-level across multiple time periods. Quantitative information on merchant numbers is not available in historical records. However, significant qualitative information in primary and secondary sources does exist. To leverage this qualitative information, I develop a retrieval-augmented generation large language model that estimates city-year merchant numbers from 120 qualitative sources. This approach combines the power of a large language model with the transparency, verifiability, and credibility of using cited information from provided sources and documenting the exact reasoning behind each generated estimate.

The estimated model suggests that the Zwin caused Bruges' population to be over 80% larger in 1400, whilst the Zwin was navigable. The model results also suggest that the Zwin cast a shadow. One hundred years after the Zwin silted up, Bruges' population is still over 40% higher than in the counterfactual world where the Zwin had never existed, and two hundred years after it remains 10% higher. I find that, whilst it was navigable, the Zwin had a negative impact on the population of other cities far from Bruges, but a positive impact on cities close by. In its heyday the Zwin caused the population of cities such as Dunkerque, Dover, kortrijk to be up to 20% higher.[3]

This paper contributes to three strands of the literature. First, I contribute to the broad literature on understanding the short and long-run impact of shocks to urban systems and

[3]A limitation of this approach is that I can trace the endogenous long-run impact of the Zwin through its impact on trade and migration, but not on other aspects such as political economy. The period I study is volatile, but the various conflicts are taken as exogenous and are not allowed to vary endogenously with local economic conditions. In addition, in this framework total population across the whole of Europe is fixed, and so necessarily gains in Bruges will lead to losses elsewhere.

the determinants of the spatial distribution of economic activity [Hanlon and Heblich, 2022, Nunn, 2020]. One strand of this literature has considered the impact of past events in determining the observed distribution of economic activity [Lin and Rauch, 2022, Alesina et al., 2013, Davis and Weinstein, 2002, Miguel and Roland, 2011, Jedwab et al., 2019, Bleakley and Lin, 2012, Jedwab et al., 2017, Michaels and Rauch, 2018, Redding and Sturm, 2008, Gibbons et al., 2018, Dell, 2010]. In this paper, I contribute to this debate by showing that shocks can have persistent effects over a long time frame, leveraging a unique natural experiment, long-run data, and a setting-appropriate dynamic quantitative spatial economics model.

Secondly, I contribute to a nascent literature using quantitative economic geography models to understand the spatial impact of historical events [Nagy, 2022, Eckert and Peters, 2022, Ellingsen, 2025, Heblich et al., 2020, Milsom, 2024]. I build on this literature by estimating a model with merchants and Malthusian dynamics in the medieval and early modern European economy. Finally, I contribute to a large literature in history and the humanities on the Zwin and general Bruges scholarship. For an introduction to this topic see Charlier [2011], Dumolyn and Leloup [2016], Gelderblom [2015], Van Houtte [1966], Ryckaert [1989]. I contribute to this literature by providing a quantification of the impact of the Zwin using reduced form and structural methods from economics.

The rest of this paper proceeds as follows: Section 1 describes the historical context and data, 2 details how merchant numbers are estimated, 3 performs the reduced form, and market access based analysis, section 4 sets up the dynamic quantitative spatial economics model and describes the counterfactual results, and finally section 5 concludes.

1 Historical context and data

1.1 Brief historical context

The hydrological, social, and economic history of the Low Countries and, in particular, the area between Bruges and the North Sea is a topic of long and still active academic debate (see, for example, Trachet et al. [2015] for a summary). Although this land appears stable and dry today, prior to modern diking, damming, and canals, it was a considerably more volatile landscape. This was further exacerbated by a series of large tidal transgressions, causing this low landscape to be crisscrossed with rivers, marshes, and routinely flooded areas [Soens et al., 2014]. Much more than today, on this historic landscape, it is possible to imagine a large storm creating a 15km inlet connecting the North Sea to near Bruges — although this must still have been a remarkable event.

Although recent work has also emphasized the role of inclusive institutions and geopolitical events in explaining Bruges' success and decline, it remains clear that without access to the north sea, through the Zwin, Bruges would never have been able to succeed in the way it did between 1200 and 1500 [Charlier, 2011, Dumolyn and Leloup, 2016, Lambert, 2016, Ryckaert, 1989, Charlier, 2005, Dewilde et al., 2018, Glaeser, 2022]. Recent work has also highlighted the role of human activity directed by Bruges, in attempting to keep the Zwin navigable for as long as possible.[4] However, such efforts were completely in vain, as the necessary dredging technology simply didn't exist, and by 1500, the Zwin was no longer navigable to all but small and inconsequential vessels [Dewilde et al., 2018].

It's important to highlight that the study period was a volatile time for Bruges and the Low Countries in general, this geography was subject to many shocks other than just the advent and decline of the Zwin. Undoubtedly, Bruges' institutions, diplomatic position, and outports (Sluis and Damme)[5] among other features, also factored into its success [Gelderblom, 2015, Van Houtte, 1966]. Similarly, political conflict in the late 15th century resulted in merchants being expelled from Bruges (although many briefly returned), almost contemporaneously with the Zwin finally becoming impassable. In this paper, I will not attempt to give a complete analysis of each of these factors but rather focus on the exogenous presence of the Zwin. One limitation of this work is that, due to this, I will bundle

[4] For example, Dumolyn and Leloup [2016] notes: "From about 1400, a pilotage service was organised to lead larger vessels around the sandbanks and in 1456, a signalization system was installed. During the fifteenth century, Bruges also deployed two dredge boats, one of which was aptly named the 'mole'. In the latter fifteenth century, Bruges even invested in major hydraulic works to scourge the Zwin but to no avail; by 1500, the sandbanks in the Zwin estuary had become so large that only small ships could enter and navigate the stream. In 1486, only 73 ships called in at the port of Sluis, while fifteen years later this number had dropped to merely 36".

[5] In this paper, I will consider Bruges and its outports Sluis and Damme as one entity. This is due to the available data and the close connection between the settlements. For example, all goods unloaded at Sluis or Damme had to be sold in the market at Bruges.

together factors influencing Bruges contemporaneously with the Zwin and can only estimate their combined effect. The advantage of using a dynamic quantitative spatial economics model is that I can estimate the impact of the Zwin conditioning both on economic shocks stemming from changes to the urban network, and on other events affecting other periods or geographies, such as the 100 Years' War, the 80 Years' War, the advent of the Dukes of Burgundy, or the fall of Antwerp. This disadvantage is that such events are not allowed to endogenously occur in counterfactual scenarios.

1.2 Data

Europe from 700 to 1800 is an extremely data-scarce environment. Little quantitative information exists at a geographically disaggregated level over this period. However, one series is uniquely detailed — that of city-level population estimates. In this paper, I rely on this data and augment it with information on wages and estimated merchant numbers.

1.2.1 Population estimates

I create a dataset of 697 cities across Europe (not including Russia) from three main sources. I use as my baseline the well known Bairoch et al. [1988] (for examples of uses of this dataset in economics see Bosker et al. [2013], Acemoglu et al. [2005], Glaeser [2022], Duranton and Puga [2020]). I combine this data with that from Chandler [1987] and Buringh [2021]. Where the three data sources overlap but disagree, I take the average over the two that don't disagree. If there is ambiguity, I take the value from Buringh [2021] if it comes with a documented and reasonable source, and otherwise use as my baseline Bairoch et al. [1988]. I then adjust this data in the following ways: I revise the population of Palermo in 1200 following Russell [1972], the population of Italian cities following Malanima [1998], and Cordoba and Palermo in 1000 following Bosker et al. [2013].

Of particular importance in my setting, it is well known that the Bairoch et al. [1988] estimate for Bruges in 1400 is a significant overestimate [Bosker et al., 2013]. Bruges' population in 1400 is a particularly important data point for this project, but one that is difficult to pin down due to rapid growth and periodic famines [Espeel, 2016] in this period. I follow an authoritative modern source Stabel et al. [2018] which estimates a population of around 60,000 at the end of the 13th century in Bruges (around half of the estimate provided by Bairoch et al. [1988]). This estimate is based on earlier work by Prevenier [1975], who uses data on draft lists for the city militia. Such draft lists are informative, as craft guilds and merchants had to deliver a certain proportion of their population to the city militia. Stabel et al. [2018] then add to this an estimate of the number of non-guild or otherwise exempt persons based on a conservative estimate of the proportion of the population such a group would normally consist of. If I instead naively used the estimated population given in Bairoch et al. [1988], the estimated impacts of the Zwin would have been much larger.

1.2.2 Wages

I use information from Allen [2001] who provide wage estimates in 17 European cities from 1500 to 1800, each 100 years. Wages pertain to the purchasing power of local building craftsmen, a common and fairly homogeneous group of workers who Allen [2001] argues is representative of broader wage patterns. Allen [2001] denotes nominal wages in grams of silver to allow international comparison. For four city-year cells wages are missing, I fill this gaps by simple linear interpolation.

2 Estimating merchant activity from qualitative data

There exists little to no precise quantitative information on merchant activity in the Low Countries and surrounding area from 1000 to 1800 [Puttevils, 2012] (due to the complete lack of merchant activity prior to 1000, here I focus on years post-1000). This is perhaps unsurprising as merchant populations were transitive and often seasonal. For example, in a rare piece of quantitative information in 1438, the mayor of Bruges, Nicolar Despars, describes the number of merchants taking part in a procession to mark the arrival of the Duke of Burgundy [Murray, 2005]. He mentions 136 Hansards, 150 Italians, and 48 Spanish merchants. However, this is likely to be an incomplete list, and as the procession took place in December at the low point for merchant activity, it is a significant underestimate. Another example comes from the money changer Collard de Marke, whose records suggest over 400 Flemish and 500 foreign merchants were present in Bruges in the 1360s [Murray, 2005]. However, it's unclear whether this information pertains to a single year or covers many, or whether these merchants merely passed through or were permanent residents. Nor is it known what proportion of the relevant merchant population one could expect to see on Marke's books. As these examples indicate, although little quantitative information exists, there is a large qualitative literature on this subject, and a comprehensive bibliography including over 120 sources is available in the online appendix.

To leverage the volume of available qualitative information I construct a retrieval-augmented-generation large language model and feed in these sources (articles, books, PhD theses, as well as general information from Wikipedia pages). This approach brings more transparency, verifiability, and credibility to the otherwise black box of a large-language model. It brings transparency because every estimate is backed up by citations from known sources. It brings verifiability because the reasoning and logic behind each estimate are clearly elucidated. It brings credibility because the input information is from known and reputable sources. I use this model to estimate the merchant population in each of the 17 cities I have wage information for, every century from 1000 to 1800.

Retrieval-augmented-generation is an approach used to improve the performance of large language models (LLM) in some specific task [Lewis et al., 2020]. With RAG an LLM is constrained to generate an answer based primarily on retrieved documents which the user specifies. In this way the LLM can be augmented to perform tasks that require information not available online (such as company-specific records) or, as in this case, encourage an LLM to stick to only relevant information from reputable sources. Using a RAG approach has been shown to greatly reduce LLM hallucinations [Njeh et al., 2024, Li et al., 2024]. For our use case, a RAG approach is particularly attractive because it somewhat opens the black-box of the LLM model by being explicit about the main sources used to generate responses. We are able to construct referenced reasoning behind each city-year merchant estimate, allowing the reader to transparently see where each number comes from and therefore come to their own conclusions regarding accuracy.

How this works in general is that RAG LLM models introduce an information-retrieval component into the process of searching through external data sources rather than relying only on pre-trained knowledge that a normal LLM uses. The RAG LLM will first perform a search through all the provided sources for text relevant to the user query and collect such relevant text. This first step can involve multiple sub-queries or retrieval rounds to improve the quality of the collected information. In a second step the model then sends a prompt to a general generative AI model requesting an answer to the initial user-provided question in the context of the retrieved results from the first step. This second prompt provides a referenced answer where explicit reasoning is given, and the main sources used to construct this reasoning are cited.

This approach, as well as recovering hopefully more accurate numbers, has the advantage that the LLM is forced to justify every estimate it makes, citing its sources, and describing its logic. Here I provide two examples of the output. The full output and source list are provided in the online appendix.

Output example one (relatively high information setting): Amsterdam in 1600. Sources used: Gelderblom and Grafe [2007], Lilienfeld, Gelderblom and Jonker [2004], Puttevils [2012], Soens [2009]. Verbatim output from the RAG LLM:

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Estimated Merchants: 250-450


Justification:
1. Gelderblom & Grafe (2007, appendix) report 21 English merchants
    present ca. 1600 (using 1607 as proxy), providing a concrete
   floor for one foreign nation in Amsterdam.
2. The same appendix mentions separate counts/estimates for
   Portuguese (Vlessing) and for Flemish and Dutch merchants (
   Gelderblom), implying multiple additional sizable groups beyond
    the English; even conservatively assigning only 20 to 50
   merchants to a few such groups yields roughly 80 to 200 foreign
    merchants.
3. Puttevils (2012) documents 1,089 merchants registering as
   citizens in Antwerp between 1533 and 1608, evidencing a very
   large regional pool of long-distance traders in the Low
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Countries; it is reasonable that Amsterdam by 1600 hosted at
least as many domestic (Dutch/Flemish) international merchants
as its foreign contingent, pushing the total into the low
hundreds.
4. As a scale benchmark, the 1767 Naamregister lists 106
permanently resident French merchants in Amsterdam (mid-18th
century); while later, it shows single-nation communities could
 number ~100, supporting an overall merchant community in the
few hundreds when aggregating multiple nationalities plus
native Amsterdam merchants in 1600.
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Output example two (relatively low information setting): Milan in 1100. Sources used: Mainoni [2015], Lilienfeld, Puttevils [2012]. Verbatim output from the RAG LLM:

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Estimated Merchants: 50-90

Justification:
1. Quantitative anchor: by the end of the 14th century, the
Milanese corporation of 'merchants who have fine wools worked'
alone counted about 300 firms, implying a very large late-
medieval international-trading community even within a single
sector (Patrizia Mainoni, Economy of Renaissance Milan).
2. Trend signal: the text notes Lombard production in the 14th
century was lower than in the 13th, implying that the 13th
century was a peak relative to the 14th; the year 1100 (early
12th century) precedes this expansion and therefore should have
 substantially fewer international merchants than either the 13
th or late 14th centuries.
3. Institutional development: large Milanese merchant-banking
houses (e.g., Borromeo) are highlighted only for the 15th
century, indicating that the robust, specialized long-distance
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merchant milieu developed after 1100.

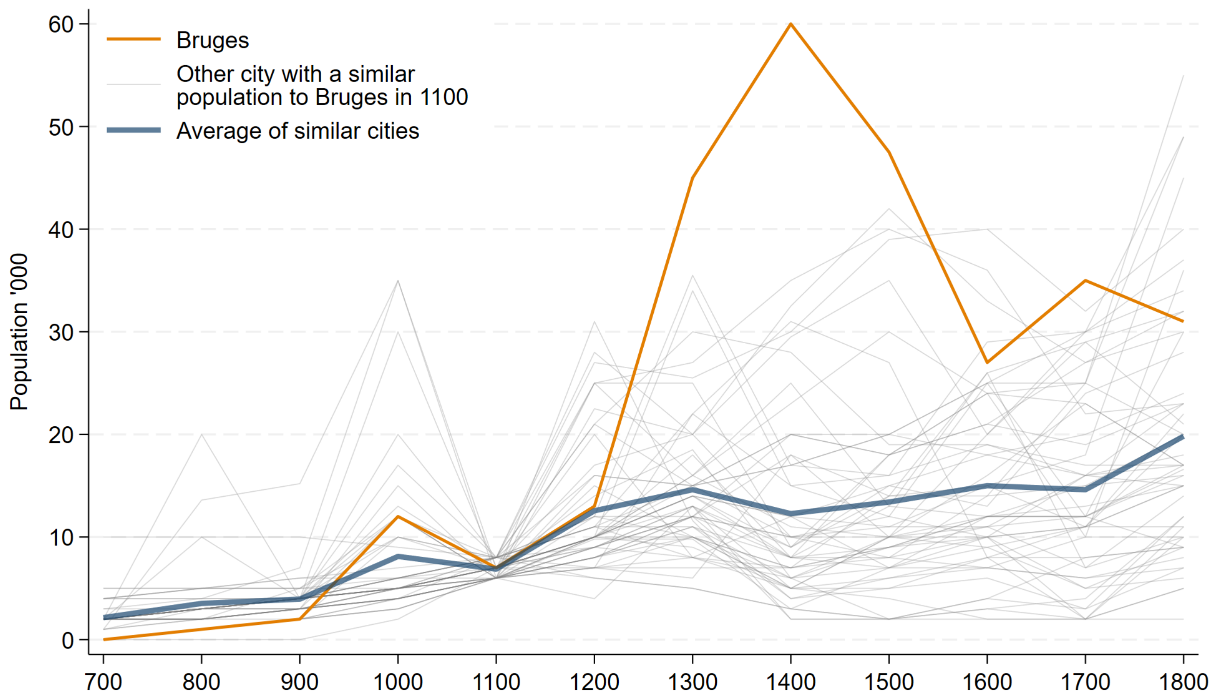
4. Scaling logic: taking the late–14th benchmark of ~300 firms in just one high–end textile guild and conservatively inferring the total international merchant community then to be at least 2x that across sectors (greater than 600), an early 12th century community at roughly 10 to 15% of that mature scale (reflecting the earlier stage of the commercial revolution and less sectoral specialization) yields approximately 60 to 90 international merchants; rounded to a range of 50 to 90.

3 The reduced form impact of the Zwin on the population of Bruges

Before attempting any formal econometrics, I simply plot the raw data. Figure 1 shows the population of Bruges against that of similar cities from 700 to 1800. Similar cities are defined simply as those having a population similar to Bruges in 1100. Figure 1 shows a large population spike for Bruges (plotted in orange) during the period that the Zwin is navigable, far in excess of any other similar city (other cities are plotted in gray, and the average over such cities in blue). Out of all of the 697 cities in my full sample the population of Bruges increased by more than any other city between 1200 and 1400, and decreased more than all but one city between 1400 and 1600.[6] Despite the large decrease after 1400 figure 1 already hints at a lingering positive impact of the Zwin on the population of Bruges. Of course, figures such as figure 1 capture all changes in Bruges, not just the impact of the Zwin. The impact of events such as the Zwin cannot be separately identified from other location-specific shocks that occurred in this time period. However, given the scale of the uncovered effects, it is unlikely that any other event could explain a large proportion of the pattern shown in Figure 1.

[6]The one city who's population fell faster was Gent, popularly known as the factory of Bruges, where much of the Flemmish cloth was produced that was subsequently sold at Bruges.

Figure 1 Plotting the raw city-level population data



Notes: This figure plots the raw population data over time for Bruges (in orange) and each of 55 European cities that have a similar population to Bruges in 1100 (in thin gray). The (unweighted) average over these similar cities is given in thick blue.

In the remainder of this section, I provide reduced form evidence of the impact of the Zwin on Bruges whilst it was navigable and in the centuries after it silted up. To do this, I use four different empirical strategies: two-way fixed effects, event study, synthetic control, and finally, a market access approach. In subsection 3.5 I show that results across methodologies are qualitatively similar and match those shown in figure 1 — the Zwin had a large impact on the population of Bruges whilst navigable and a muted, albeit still quantitatively important effect even long after it silted up.

3.1 Two-way fixed effects

To more formally assess the impact of the Zwin on Bruges whilst it was navigable, I perform a two-way fixed effects analysis estimating specifications of the form given in equation 1. The variable Zwin_{it} takes the value one if the Zwin is navigable in location i in period t, and therefore only takes the value one between 1200 and 1400 (inclusive) in Bruges. The dummy variables PreZwin_{it} and PostZwin_{it} take the value one in Bruges for the years before

1200 and after 1400 respectively.[7] City and year fixed effects are denoted by γ_i and τ_t, and idiosyncratic errors by ε_{it}.

$$\text{Pop}_{it} = \beta_{\text{pre}} \cdot \text{PreZwin}_{it} + \beta_{\text{Zwin}} \cdot \text{Zwin}_{it} + \beta_{\text{post}} \cdot \text{PostZwin} + \gamma_i + \tau_t + \varepsilon_{it} \tag{1}$$

This two-way fixed effects specification relies on the perennial parallel trends assumption to make causal claims (as well as no contemporaneous shocks as discussed above). To increase the reasonableness of this assumption, I consider two alternative control groups. First, I consider cities with a similar population to Bruges in 1100 — exactly those cities displayed in figure 1. Second, I consider 11 cities close to the coast near Bruges, where plausibly the Zwin could have appeared instead of appearing in Bruges. This sample aims to leverage the randomness of the Zwin specifically, by comparing the trajectory of Bruges to other cities that could plausibly been shocked. I also consider a sample of cities within 500km of Bruges (as the crow flies) to facilitate comparison across empirical approaches.

In panel [A] of table 1, I show the estimated beta coefficients from equation 1 on the whole sample and the three sub-samples discussed above. The impact of the Zwin when it was navigable and the period after it silted up is qualitatively similar across each sample and specification. This result suggests that, during the period it was navigable, the Zwin increased the population of Bruges by between 26.7 and 31.4 thousand. Turning to the impact of the Zwin in the centuries after it silted up, that is the size of the shadow the Zwin cast over Bruges — I also estimate large impacts of between 12.1 and 27.1 thousand.

To put the magnitude of these estimates into context, I compare the level effects to the average population among cities in a given comparison group. For transparency, here I simply consider the implied comparison group consisting of other cities in each sample. Panel [B] of table 1 gives the magnitude of the effect on the population of Bruges as a multiple of the average in the implied control group. For example, column (5) indicates that the impact of the Zwin on the population of Bruges, whilst it was navigable, was to increase it by, on average, 4.41 times the average population of cities within 500km of Bruges (not including Bruges) during that period. The analogous average effect of the Zwin on Bruges

[7] In the two way fixed effects specification coefficients on all three variables will not be identified due to multicollinearity, it this case I take pre-Zwin as the baseline omitted category.

in the centuries after it silted up is estimated to be to increase its population by on average 0.87 times the average population of cities within 500km of Bruges in this period. I discuss inference in this setting with one treated unit in the next sub-section.

Table 1 Direct Impact of the Zwin on Bruges' Population

	(1) All Sample	(2) All Sample	(3) Similar 1100 Population Sample	(4) Possible Alternative Rivers Sample	(5) Within 500km Sample
[A] Coefficient Estimates					
Zwin Navigable	31.28^{***}	30.73^{***}	26.65^{***}	31.44^{***}	30.19^{***}
	(0.464)	(0.273)	(0.886)	(10.99)	(11.58)
Post Zwin	27.07^{***}	18.17^{***}	18.93^{***}	12.07^{*}	15.25^{**}
	(0.464)	(0.973)	(1.582)	(6.649)	(7.172)
[B] Magnitude					
Zwin Navigable	4.45	4.38	2.02	7.96	4.41
Post Zwin	1.76	1.18	1.14	0.63	0.87
Year FE		X	X	X	X
City FE		X	X	X	X
# Cities	697	697	56	12	182
Observations	8364	8364	672	144	2184
R2	0.00165	0.441	0.449	0.727	0.354

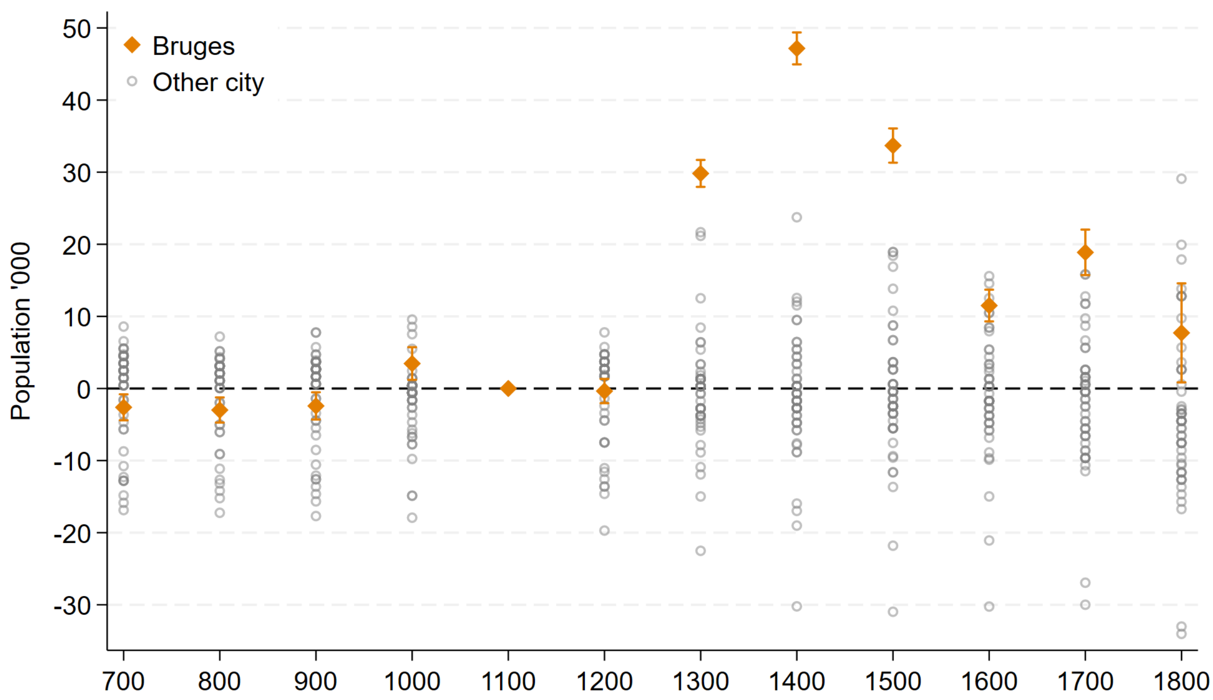
Notes: This table reports results from estimating the impact of the Zwin being navigable in Bruges. In panel [A] I show the regression results. In column one, I report raw estimates with no controls. In column two, I include city and time fixed effects, therefore performing a two-way fixed effects analysis. In column three, I restrict the sample to the 55 European cities that have a population similar to Bruges in 1100 (and Bruges itself). In column four, I further restrict the sample to only include 11 cities that could plausibly have been shocked instead of Bruges. In all specifications, standard errors are clustered at the city level. In panel [B], I convert these regression estimates into relative magnitudes. Panel [B] gives the magnitude of the effect on the population of Bruges as a multiple of the average in the implied control group. For example, column (5) indicates that the impact of the Zwin on the population of Bruges, whilst it was navigable, was to increase it by, on average, 4.41 times the average population of cities within 500km of Bruges (not including Bruges) during that period.

3.2 Event study

Identification in the two-way fixed effects specification relies on the parallel (post) trends assumption. To probe the validity of this assumption, I consider the parallel-ness of pre-trends and provide year-specific estimates using an event study approach. Figure 2 shows the corresponding event study plot on the sample of 56 cities with a similar population to Bruges in 1100 (as in figure 1). In orange (with corresponding orange 95% confidence intervals), I plot the event study coefficients for Bruges relative to 1100. Figure 2 mirrors that of 1, showing no real pre-trends to speak of, and a large impact of the Zwin. Figure 2 also gives some indicative evidence that the impact of the Zwin continued long after it became impassible, with positive coefficients in all subsequent years.

Figure 2 also shows placebo estimates from each of the 55 cities in my sample with a similar population to Bruges in 1100. To generate these coefficients, I estimate the same event study specification but suppose that each of the 55 alternative cities had been "treated" by the Zwin as opposed to Bruges. These estimates act as a placebo, as we would not expect as large an impact in these locations. As the Bruges coefficients are much in excess of any of the placebo coefficients in many periods, I take this as strong evidence that the impact of the Zwin, as opposed to noise, is being picked up. This exercise also suggests that no contemporaneous shock in any other city is anywhere near the same magnitude as that of the Zwin, implying once again that it's unlikely such a shock affected Bruges. However, we cannot rule it out, and it's possible that some of the impact attributed to the Zwin is due to an alternative contemporaneous shock.

Figure 2 Event study with placebos



Notes: This figure plots the event study coefficients for Bruges in orange (diamonds) with corresponding 95% confidence intervals indicated by vertical bars and calculated by clustering standard errors at the city level. In gray hollow circles, I plot the analogous event study estimated for each of 55 placebo cities, which had a similar population to Bruges in 1100.

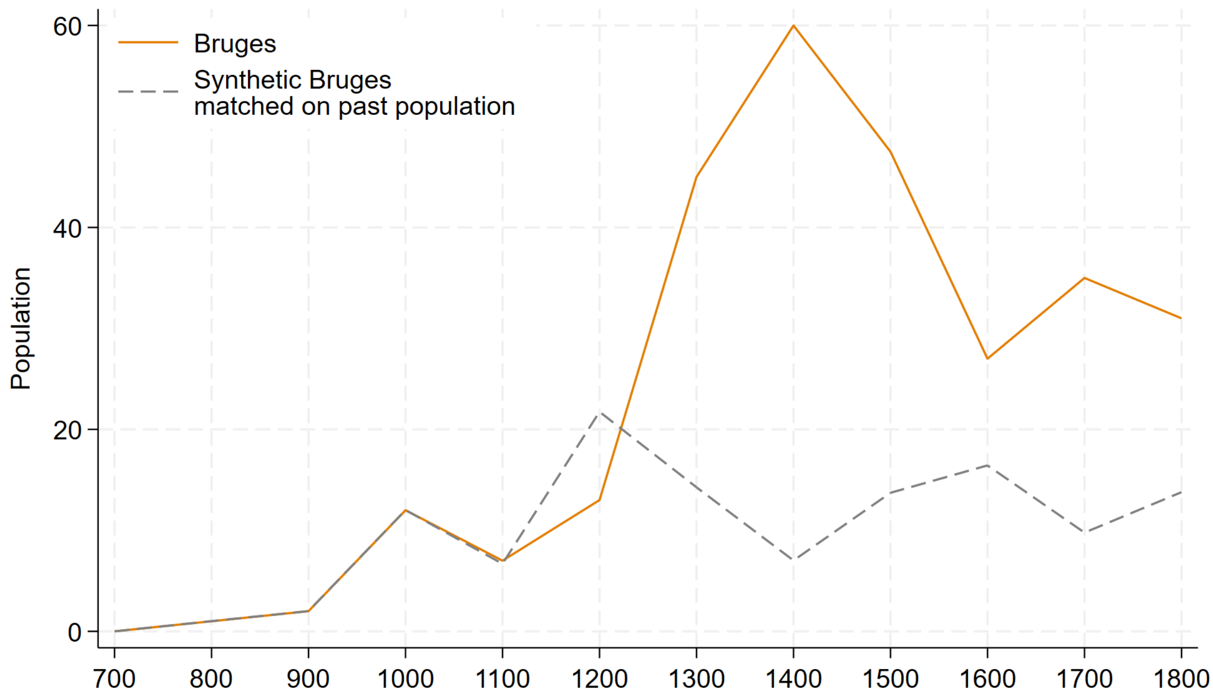
Inference in this setting is complicated by the fact that there is only one treated unit. Conley and Taber [2011] and others show that in this case, although estimates will be unbiased they will not be consistent, leading to incorrect inference. Intuitively, this is because the noise term associated with the treated group does not tend to zero as the size of this group is fixed and small (in my case, one). To overcome this, Conley and Taber [2011] suggests using control units and placebo experiments to estimate the magnitude of this noise. The event-study approach adopted here is an intuitive way of achieving this. The variability across placebo estimates allows me to quantify uncertainty in my main estimates under a homogeneity assumption following Conley and Taber [2011]. This procedure gives reassurance of the strong statistical significance of these results, especially during the period in which the Zwin was navigable.

One lingering concern highlighted by Ferman and Pinto [2019] is that of heteroskedasticity preventing the comparability of noise estimates in the control and treated group. As Ferman and Pinto [2019] highlights, this is a particular concern if groups are of different sizes; however, in my case, all groups are the same size. In the absence of any economic reason as to why we would expect heterogeneity, and the strength of the significance shown in figure 2, I opt to use the intuitive approach of Conley and Taber [2011] to this inference problem as discussed.

3.3 Synthetic control

This setting, with one treated unit, is particularly well suited to a synthetic control approach. I construct a synthetic Bruges matching on previous population in 700, 800, 900, 1000, and 1100, as well as elevation, latitude, longitude, and population growth from 700 to 900. Figure 3 plots the actual against the synthetic Bruges, where the synthetic Bruges is a combination of other cities. All 696 other cities in my data are included in the donor pool, the synthetic control gives weight to: Veliko Tarnovo (48.6%), Granada (4.4%), Burgos (5.7%), Badajoz (0.4%), and 409 cities are given the minimum 0.1% weight. Mirroring the analysis above, figure 3 shows a large impact of the Zwin during the period in which it is navigable as well as a muted but still large effect in the centuries after it silted up. Figure 8 in the appendix then shows inference in the synthetic control setting — permuting the synthetic control procedure over all cities with a similar population to Bruges in 1100 — showing that the whilst-navigable estimates are highly significant.

Figure 3 Synthetic control results: Bruges



Notes: This figure shows the population of Bruges and its estimated synthetic control. The solid gray line is the baseline synthetic control that matches on pre-1200 population, the dashed gray line does not match on past population.

The evidence presented so far in this section suggests that the Zwin had a large impact on the population of Bruges whilst it was navigable and for hundreds of years after it silted up. However, one should be cautious in causally interpreting the entire effect uncovered to the Zwin. This is for three main reasons. First, contemporaneous shocks cannot be ruled out, and although it seems improbable that they account for a significant proportion of the estimated impact, it is eminently plausible that they account for some proportion. Second, over such a long time period with one treated unit, the parallel (post) trends assumption becomes increasingly strained. Evidence from using similar locations or alternative Zwin sites gives some reassurance, but this remains a concern. Lastly, and crucially, the Zwin not only impacts Bruges. For example, cities well connected to Bruges (but not in competition for seaborne trade), gained by being able to trade with the increasingly rich and large hub of Bruges. These spillover effects will contaminate control cities in the analysis performed in this section. Again, it seems unlikely that this is sufficient to completely overturn the conclusions reached, but it could bias them. To overcome the issue of spillover effects contaminating control cities, estimate heterogeneous impacts, and side-step the contemporaneous shocks critique, I turn now to a market access approach.

3.4 A market access approach

The market access approach estimates the impact of the arrival (and silting up) of the Zwin on each location's market access, which is then related to each location's population. In this way, it uses the direct variation caused by the Zwin. There is a long and well-developed literature showing a strong empirical link in various settings between local economic activity and market access (see, for example, Donaldson and Hornbeck [2016], Redding and Sturm [2008], Jedwab and Storeygard [2022]) backed up by theory showing the generality of the market access approach [Allen et al., 2020b].

The market access approach is intuitively attractive as it directly uses the plausibly exogenous variation in transport costs generated by Zwin. It is exactly for this reason that it can help overcome the two main critiques of the previous designs: spillovers and contemporaneous shocks. By specifying the empirical nature of the shock, and linking it via theory to outcomes, I trade off leveraging more precise variation caused by the Zwin with adding greater structure to the data.

The market access a given location i enjoys is given by $MA_i = \sum_j \tau_{ij}^{-\theta} L_j MA_j^{-1}$. The cost of travel between i and j is given by $\tau_{ij}^{-\theta}$, where τ_{ij} is the iceberg migration cost between i and j such that $\tau_{ij} \geq 1$. The elasticity of migration with respect to the iceberg migration cost is given by θ. A location will have higher market access if it is close to (low τ_{ij}^{θ}) many large markets (large L_j) which themselves do not have many alternative trading partners (low MA_j).

I parameterise bilateral iceberg costs as depending on the travel time between each of city in my sample. To do this, I first construct a cost surface over the land, river, and sea routes of Europe by splitting the map of Europe into 2km pixels and calculating the cost of traversing each pixel as the inverse of travel time. Travel time across the sea is normalized to 1. Using Cogs (the most commonly available ship in the Middle Ages before Caravels), this is calibrated to 15km/h on average. Travel time in rivers is calibrated to 1.25, i.e., it takes 25% longer to travel on a river than in the open sea. Travel on land is calibrated to 3 on flat land, corresponding to 5km/h. It increases with terrain ruggedness such that speed relative to ocean travel $= 2 + \exp(0.002 \times \text{Ruggedness})$. Over the most rugged terrain, this corresponds to a speed of around 500 meters an hour. Figure 4 displays the resulting cost surface, which is given by 1/cell speed and is in units of 15km/h — therefore, one can divide the resulting cost output by 15 to get travel times in hours per pixel. Pixels in figure 4 are on average 0.85km long, so to convert this to km per hour, I finally multiplying by 0.85.

Figure 4 Estimated cost surface

Notes: This figure shows the cost surface and location of cities in my sample. Darker colors indicate lower costs of travel.

The least cost path to and from each city is then calculated over the cost surface using Dijkstra's algorithm. Figure 9 in the appendix shows some example least cost paths. I calculate such travel costs in two scenarios, one without the Zwin and one with the Zwin. This process calculates two pair-wise travel time matrices $T^{NZ} = \{t_{ij}^{NW}\}$ and $T^{Z} = \{t_{ij}^{Z}\}$. I then parameterise iceberg travel costs to be a log-linear function of travel times such that $\tau_{ij}^{-\theta} = t_{ij}^{-\kappa\theta}$. In the absence of data on bilateral trade flows in my setting, I turn to the literature for plausible estimates. Estimates of $\kappa \cdot \theta$ covering my historical setting are hard to come by. For simplicity, in this section, I will use the value -1.[8] Given data on $\tau_{ij}^{-\theta}$ and L_j, market access terms can then be calculated via a simple iterative algorithm which has a unique solution (up to scale) [Donaldson and Hornbeck, 2016]. In this manner, I can estimate market access terms for each city in each period with and without the Zwin: $\{MA_{it}^{Z}, MA_{it}^{NZ}\}$. To focus on the most affected locations, I use a sample of 182 cities that are within 500km of Bruges.

I am interested in the impact of the changes in market access due to the Zwin, whilst the Zwin was navigable, but also in the period before it appeared and after it disappeared. To do this, I use the above procedure to estimate the city-level average change in market access caused by the Zwin during its period of navigability: $\mathrm{MA}_i^{\mathrm{Zwin}} = 3^{-1}\left(\sum_{y=1200}^{1400} \mathrm{MA}_{iy}^{Z} - \mathrm{MA}_{iy}^{NZ}\right)$, using this quantity I then estimate the following regression.

$$\mathrm{Pop}_{it} = \sum_{y=700}^{1800} \beta_y \cdot \mathbb{1}_{[y=t]} \cdot \mathrm{MA}_i^{\mathrm{Zwin}} + \gamma_i + \tau_t + \varepsilon_{it} \tag{2}$$

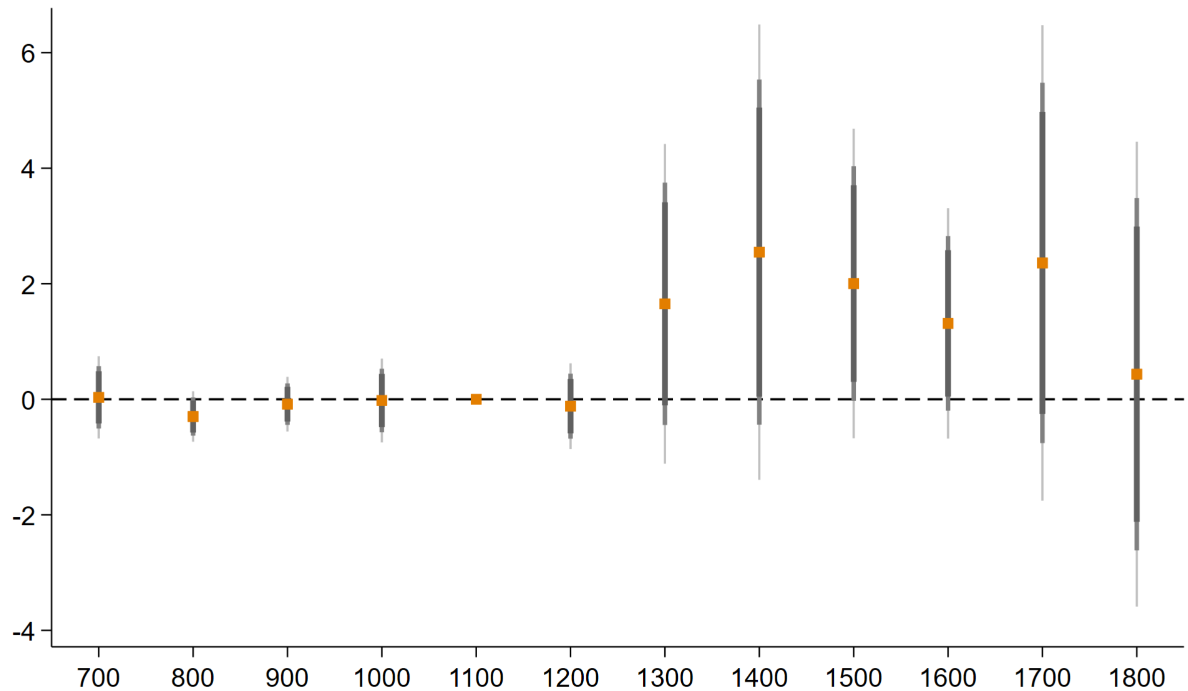
The estimated coefficients $\widehat{\beta}_y$ then give the impact of the change in market access due to the Zwin whilst it was navigable on the local population in year y. For $y < 1200$, this gives an anticipation effect which should be zero in the absence of the Zwin selecting where to suddenly appear. For $1100 < y < 1500$, this gives a contemporaneous effect of the Zwin whilst navigable. Finally, for $y > 1500$ this gives the shadow effect of the lingering impact of the Zwin after it silted up.

Figure 5 shows the estimated $\widehat{\beta}_y$ with corresponding 90, 95, and 99 percent confidence intervals where for interpretability, $\mathrm{MA}_i^{\mathrm{Zwin}}$ is measured in standard deviations. Reassuringly, Figure 5 shows precisely estimated zeros for periods before the Zwin appeared. Although often marginally significant, coefficients are clearly larger and positive in the post-Zwin

[8] In section 4 I will relax this assumption.

period and show evidence of a large contemporaneous impact and shadow effect. Converting these standard deviation effects into aggregate impacts, I find that the impact peaked in Bruges in 1400 at over 20,000 before decreasing to 10,000 or so in 1600.

Figure 5 Impact of Zwin-induced changes in market access over time SD



Notes: This figure shows the estimated coefficients β_y coefficients from the following regression $\text{Pop}_{it} = \sum_{y=700}^{1800} \beta_y \cdot \mathbb{1}_{[y=t]} \cdot \text{MA}_i^{\text{Zwin}} + \gamma_i + \tau_t + \varepsilon_{it}$ where MA_i^{Zwin} is the average difference in market access due to the reduction in transport costs caused by the Zwin from 1200 to 1400 measured in standard deviations. 90%, 95%, and 99% confidence intervals are plotted in increasingly thin whiskers.

The market access approach overcomes some deficiencies in the purely reduced form analysis but retains one potentially crucial drawback. In either the Zwin or no-Zwin scenario, I implicitly make the assumption that the underlying population distribution remains the same. That is, the counterfactual population in the no-Zwin scenario is not allowed to adjust. In order to estimate a counterfactual population distribution, I need to add more structure to the data and employ a dynamic quantitative spatial economics model. This is done in section 4.

3.5 Combining estimates

Through various approaches in this section, I have provided evidence of the large impact the Zwin had on Bruges whilst it was navigable, as well as the persistent impact it still had centuries after the Zwin silted up. Using the consistent "within 500km" sample table 2 compares results across specifications. Although numbers differ, qualitative results are consistent and can be summarised as: (1) The Zwin increased the population of Bruges significantly, while it was navigable by 12,000 to 30,000 inhabitants. (2) The Zwin cast a long and deep shadow, increasing the population of Bruges in subsequent centuries by on average between 14,000 and 22,000 inhabitants.

Table 2 Summary of Reduced Form Estimates of the Impact of the Zwin on the Population of Bruges

	Average Impact 1200-1400		Average Impact 1500-1800	
	'000	%	'000	%
TWFE	30.19	425	15.25	86
Event Study	25.54	360	17.95	101
Synthetic Control	24.99	352	21.70	123
Market Access	12.33	174	13.85	78
Bruges population in 1100 = 7,000				
Average within sample population 1200-1400 = 7,100				
Average within sample population 1400-1800 = 17,700				

Notes: This table combines average estimates of the impact of the Zwin whilst it was navigable and after it silted up on the population of Bruges for each of the four different methodologies pursued. Estimates given in columns one and three are in thousands, whereas those in columns two and four as given as a percent of the baseline population — in each case, the estimated additional impact of the Zwin is shown.

4 A dynamic quantitative spatial economics model with Malthusian dynamics and endogenous merchants

I now extend my analysis to consider the impact the Zwin had on the spatial distribution of economic activity across the whole of the Low Countries, both when it was navigable and after it had become impassable, allowing for endogenous reactions. To do this, I need to estimate the counterfactual spatial distribution of population and economic activity.

I develop and estimate a quantitative spatial economics model building on Allen and Donaldson [2022] by including two key features of the European medieval and early modern economy: Merchants and Malthusian dynamics. Merchants facilitated trade and heralded the commercial revolution in Europe, whereby a new merchant class was born. Nowhere in Europe (with the potential exception of the northern Italian cities) was this process more pronounced than in the Low Countries. Merchants were a highly mobile group, and as a result, could be found at a much greater spatial concentration than the general population. Therefore, the spatial distribution of merchants is likely to be more sensitive to shocks inducing equilibrium switching, relative to that of the general population. As merchants bring trade and lower transaction costs within a city, and individuals exhibit higher costs to migration, the sudden movement of the merchant population away from a location could spell ruination for those who remain.

Malthusian dynamics are also a crucial, although controversial, feature of the European medieval and early modern economy [Crafts and Mills, 2009, Galor and Weil, 2000]. In this model I take the view that Malthusian dynamics are present, but not necessarily binding and allow local births per existing population to be an increasing function of local real wages. This effectively increases the elasticity of population growth with respect to (real) wage growth, and allows a given location to grow without neighbouring locations to shrink.

The advantage of leveraging this framework is that I can study the impact of the Zwin holding fixed all other shocks facing cities during this period, and trace out its impact across both time and space, allowing for the endogenous and dynamic responses of individuals' location choice, goods trade, prices, and merchant activity. The model also admits the potential for multiple long-run spatial equilibria whereby shocks can cause permanent changes to the distribution of economic activity. The disadvantage is that I have to impose considerable structure on the data, and shut down endogenous political economy responses.

4.1 Model set up

In this sub-section I describe the main components of the model and relegate technical details to the appendix section A. The base of the model follows a simplified version of Allen and Donaldson [2022], where I simplifying the Allen et al. [2020a] by assuming agents are myopic. There are arbitrarily many locations $i \in N$ (cities) and $t \in \mathcal{T}$ time periods. Cities are connected, and goods and individuals are allowed to move (with some cost) between them. History impacts the future through dynamic agglomeration effects in productivity and amenities. Intuitively infrastructure built some time ago might enhance (or decrease) productivity today. History also impacts the future through fertility dynamics: the current population will depend on how many births there were in the previous period.

Firms

Each location i emits a unique good in an Armington fashion. A continuum of firms ω in i produce this homogeneous good ($q_{it}(\omega)$) under perfect competition and CRTS using labor ($l_i(\omega)$) as the only factor of production.

$$q_{it}(\omega) = A_{it} l_{it}(\omega), \qquad A_{it} = \tilde{A}_{it} L_{it}^{\alpha_1} L_{it-1}^{\alpha_2} \tag{3}$$

Where $\tilde{A}_{it}$ is exogenous productivity and L_{it} is the total number of workers. α_1 captures aggregate contemporaneous spillovers, α_2 captures aggregate historical productivity spillovers. Intuitively α_1 captures what is more traditionally thought of as agglomeration forces, whereas α_2 captures factors like historical infrastructure that remain productive in the next period.

Households

Households have constant elasticity of substitution preferences over differentiated location-specific goods with the elasticity of substitution σ, therefore, consumption welfare is captured by local real wages (w_{it}/P_{it}). A location also generates utility for individuals in the form of local amenities (u_{it}), and therefore location-time specific welfare is given by W_{it} in equation 4.

$$W_{it} = u_{it} \frac{w_{it}}{P_{it}}, \qquad u_{it} = \bar{u}_{it} L_{it}^{\beta_1} L_{it-1}^{\beta_2} \tag{4}$$

Where $\bar{u}_{it}$ is exogenous amenity and β_1, β_2 are analogous to α_1, α_2. For example, β_1 captures contemporaneous congestion forces, i.e., from non-tradeables or land, and β_2 captures the impact of durable infrastructure on amenities, such as existing housing, aqueducts, sanitation, etc.

Trade

Bilateral trade from locations i to j incurs exogenous, symmetric, iceberg trade costs denoted by τ_{ijt}. Iceberg trade costs and CES demand generate the familiar gravity equation in trade.

$$X_{ijt} = \tau_{ijt}^{1-\sigma} \left(\frac{w_{it}}{A_{it}}\right)^{1-\sigma} P_{jt}^{\sigma-1} w_{jt} L_{jt}, \qquad P_{it} = \left(\sum_{k=1}^{N} \left(\tau_{kit} \frac{w_{kt}}{A_{kt}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{5}$$

Total trade flows X_{ijt} are decreasing in the factory gate price at i, the iceberg trade costs between i and j and increasing in the real income of j. Prices are given by the usual CES price aggregator.

Migration

Individuals decide where to move to maximize utility given in equation 4 subject to symmetric iceberg moving costs μ_{ijt} and some idiosyncratic preference ε_{jt} which is drawn from a Fréchet distribution with dispersion parameter θ. Given this distributional assumption, migration will also follow a gravity structure, and the number of people moving from i to j in period t will be given by equation 6. Where B_{it} is the number of people born in location i in period t who can then migrate from that location.

$$L_{ijt} = \mu_{ijt}^{-\theta} \Pi_{it}^{-\theta} W_{jt}^{\theta} B_{it} \tag{6}$$

Where $\Pi_{it} = \left(\sum_k \mu_{ikt}^{-\theta} W_{kt}^{\theta}\right)^{1/\theta}$, is a measure of labor market access.

Malthusian Dynamics

In standard dynamic quantitative spatial economics models births are equal to the previous population, $B_{it} = L_{it-1}$, in this model I relax this by allowing explicit Malthusian dynamics. I allow births to respond to real wages such that $B_{it} = L_{it-1}\left(\frac{w_{it-1}}{P_{it-1}}\right)^{\rho}$ where $\rho \geq 0$. If $\rho = 0$ we are back in the standard case. If $\rho > 0$ then Malthusian dynamics are at play whereby birth rates increase in prosperity. This mechanism effectively increases the elasticity of population with respect to (real) wage shocks. Previously, if a location become more prosperous its population may only slowly respond as individuals need to overcome costly migration costs to relocate there — now this population growth can happen also without migration.

Merchants

I incorporate merchants by modelling them as a distinct set of agents. Merchants choose where to locate to maximise profits, subject to idiosyncratic preferences which may reflect individual taste (merchants are, after all, also people with preferences), but also individual connections and knowledge. I model merchant income in a location i in period t as some constant fraction α^M of the total trade T_{it} in that location.

$$\pi_{it}^M = \alpha^M A_{it}^M T_{it} \tag{7}$$

Merchant location-specific productivity, A_{it}^M, is a function of the number of merchants in a location and some exogenous component $A_{it}^M = \bar{A}_{it}^M \cdot M_{it}^\lambda$. The parameter λ reflects the strength of merchant-specific agglomeration economies. On the one hand, more merchants in a location mean that the "pie" needs to be split more ways, and so one may expect λ to be negative. On the other hand, merchants trade among themselves, and so λ could be positive. Merchants have idiosyncratic location-specific preferences drawn from a type two extreme value distribution with dispersion parameter ϕ. From properties of the type two extreme value distribution, we can therefore write the number of merchants (normalising total Merchant mass to one) in any given location as follows.

$$M_{it} = \left(A_{it}^M T_{it}\right)^\phi \left(\sum_j \left(A_{jt}^M T_{jt}\right)^\phi\right)^{-1} \tag{8}$$

Merchants also interact with the local community by increasing local productivity. We can now separate the previously considered exogenous productivity component $\tilde{A}_{it}$ into that due to merchants, M_{it}^χ, and that purely exogenous, $\bar{A}_{it}$, giving the following expression for local productivity: $A_{it} = \bar{A}_{it} M_{it}^\chi L_{it}^{\alpha_1} L_{it-1}^{\alpha_2}$. The coefficient χ dictates the strength of the link between the merchant and the real economy. Intuitively, the presence of merchants oils the machine of commerce, allowing goods to be produced and traded more efficiently.

Spatial equilibrium.

Equilibrium is characterised by goods and labour markets clearing in each location. The dynamic equilibrium of this model is described in the appendix section A. The model can be solved via a simple iterative algorithm [Donaldson and Hornbeck, 2016].

4.2 Estimating model parameters

To estimate model parameters, exogenous fundamentals, and the impact of the Zwin on travel costs and productivity, I use a five-step procedure. In step one, I use the cost surface and calibrated parameters to estimate travel costs. In step two, I use estimated travel costs and population data to calculate market access terms. In step three, I use model-implied regressions to estimate model parameters having calibrated σ, θ, and ρ from the literature and using some symmetry assumption. In step four, I use the estimated model parameters and data to back out the rationalising location fundamentals. As I only have one data series (population) for each location in each time period, I can only recover a bundle of local fundamentals. In step five, I estimate the effect of the Zwin on these location fundamentals. This procedure recovers all exogenous variables in the world with and without the Zwin (under assumptions elucidated below), as well as setting-specific parameter values — allowing me to estimate the path population in each city in the counterfactual world in which the Zwin never existed.

4.2.1 Step 1: Calibrate migration and trade costs.

I parameterize the iceberg migration and trade costs as functions of the distance between each location, which I denote by t_{ijt}.

$$\tau_{ij}^{1-\sigma} = f_{\tau}\left(t_{ijt}\right) \qquad \mu_{ij}^{-\theta} = f_{\mu}\left(t_{ijt}\right) \tag{9}$$

In the absence of city-to-city trade or migration data I am unable to estimate f_{τ} or f_{μ} and so instead opt for a simple linear parameterization: $f_{\xi}(t_{ijt}) = t_{ijt}^{-\kappa_{\xi}}$ for $\xi = \{\tau, \mu\}$ where

κ_ξ can then be calibrated. Over the time period studied cross-land transport technology changed little in the Low Countries (my sample ends in 1800 before the advent of railways in Belgium or the Netherlands, the first of which was inaugurated on May 5, 1835), and the main thoroughfares remain relatively unchanged.[9] Bilateral travel times are thus estimated using the least cost path across the generated cost surface as discussed in section 3.4. The only time variation comes from whether or not the Zwin is navigable. Estimates of κ_τ and κ_μ in a comparable setting are understandably hard to come by, I take as my baseline $\hat{\kappa}_\tau = 2.24$ and $\hat{\kappa}_\mu = 1.15$ from Ellingsen [2025] who uses migration and trade data from Latin America around 1800.

4.2.2 Step 2: Find market access terms.

Having calculated transport costs, I can calculate labor market access terms using available population data. To do this, I follow the same procedure as in subsection 3.4. The theory demands two market access terms, labor market access and goods market access. However, due to the lack of systematic wage or production data, I am not able to calculate goods market access empirically, although it can still be computed for counterfactual scenarios. Due to this, when estimating model parameters, I will assume that labor and trade market access are up-to-scale equal, which is often close to what is found in empirical applications.

4.2.3 Step 3: Use model-implied regressions to estimate parameters

Solving the model, we can derive the following series of equations, assuming market access terms are equal, see the appendix for full derivations. The components c_{ij} of the matrix of

[9] There were of course some innovations on the margins, especially into the 17th centaury with the advent of stage coaches, turnpike-esque systems of improved roads, and increased canal activity. Although these late additions could have significant impacts on travel time, they pale in comparison to the impact of the railroad and motorised transport. For example, although stage coaches in the mid to late 1700s could travel between Bruges and Brussels in a day — twice as fast as horseback travel 100 years before — even early trains in 1900 could do the same journey in a matter of hours.

coefficients C are all known combinations of structural parameters.

$$\ln(L_{it}) = c_{11} \cdot \ln(MA_{it}) + c_{12} \cdot \ln(L_{it-1}) + v_{it}$$
$$\ln(w_{it}) = c_{21} \cdot \ln(MA_{it}) + c_{22} \cdot \ln(L_{it-1}) + e_{it}$$

To these two equations, I add the expression relating merchant numbers to output $\ln(M_{it}) = \phi \ln(Y_{it}) + \varepsilon_{it}$. The five estimated coefficients, $\hat{\phi}, \hat{c}_{11}, \hat{c}_{12}, \hat{c}_{21}, \hat{c}_{22}$, then allow me to back out the six structural parameters $\alpha_1, \alpha_2, \beta_1, \beta_2, \phi, \chi$ with one additional constraint. I choose to impose symmetry between the β coefficients, and thus that $\beta_1 = \beta_2$.

To estimate this series of three equations, I require data on merchants, market access, population, wages, and output $Y_{it} = L_{it} w_{it}$. As discussed in the data sub-section 1.2, these variables are available for different cities in different periods, and for each equation, I use the maximum available information.

First, I report the results from estimating each equation separately, including city and year fixed effects in table 3. The reduced form effects are intuitive. Higher market access is associated with larger populations and higher wages. Similarly, greater city income draws in more merchants.

Table 3 Parameter Estimation Reduced Form Regression Results

	(1) Log Pop	(2) Log Wage	(3) Log Merchants
$\ln(MA_{it})$	3.28***	1.83***	
	(0.19)	(0.57)	
$\ln(L_{it-1})$	0.41***	0.02	
	(0.02)	(0.07)	
$\ln(Y_{it})$			0.50***
			(0.08)
Observations	6292	64	68
R-squared	0.854	0.789	0.772
Cities (unique)	687	16	17
Period range	800–1800	1500–1800	1500–1800
Fixed effects	City-Year	City-Year	City-Year
SEs	Clustered by city	Robust	Robust

Notes: This table shows the reduced form parameter estimates. Each column corresponds to a separate regression estimated on the largest available sample indicated below. In column one, I regress log population on log market access and lagged log population using data from 687 cities across Europe. Standard errors are clustered at the city level. In column two, I regress log (nominal) wage on market access and lagged log population for 16 cities in 1500, 1600, 1700, and 1800. Due to the small number of cities, standard errors are not clustered but rather heteroskedasticity robust. Finally, in column three, I regress log merchants on log output (given by $Y_{it} = w_{it}L_{it}$) for a sample of 17 cities in 1500, 1600, 1700, and 1800 again with robust standard errors.

I then estimate this system jointly and back out the structural parameters; standard errors are calculated using the delta method, and the whole procedure is block-bootstrapped. In order to find structural parameters from the reduced form coefficients, I must first calibrate σ and θ. To do this, I use values typically found in the literature and take $\sigma = 5$ from Simonovska and Waugh [2014] and $\theta = 3.18$ from Bryan and Morten [2019]. Finally, to back out six parameters from five coefficients, I need to make one additional assumption and choose to impose symmetry in the β parameters: $\beta_1 = -\beta_2$ as this is close to what is found in Allen and Donaldson [2022]. Finally, I enforce the convergence criteria that $\phi\chi < \iota \times (\sigma/(\sigma - 1))$ where ι is some user-defined parameter to bound parameters away from non-convergence. I choose $\iota = 0.9$ and enforce this condition by varying χ.

Table 4 presents the resulting parameter estimates and corresponding standard errors from 500 bootstrap replications. Note that the freely estimated value of χ was 2.605, which lies outside the permissible range.

Table 4 Parameter Estimates

α_1	-1.157
	(0.046)
α_2	0.288
	(0.015)
β_1	-0.176
	(0.129)
β_2	0.176
	(0.129)
χ	2.3
	(0.458)
ϕ	0.503
	(0.090)
σ	5.00
θ	3.18
Bootstrap reps	500

Finally, I calibrate the strength of Malthusian forces: $\rho = 0.1$.

4.2.4 Step 4: Invert the model to back out location fundamentals

Armed with parameter estimates and data I can invert the model to back out underlying fundamentals. However, as I only have wage and merchant data for a subset of cities, I am not able to separately identify productivity, amenity, and merchant productivity fundamentals. Instead, I assume that productivity and merchant productivity fundamentals are constant. This allows me to back out some remaining fundemantal which operates as amenities in the model but will, in practice, capture some bundle.

4.2.5 Step 5: Estimate the counterfactual path of fundamental productivities in the absence of the Zwin.

The Zwin directly effects transport costs to and from Bruges to all other locations. In addition, by potentially influencing merchant activity, it can also indirectly impact local productivity. However, I also allow the Zwin to affect the local fundamentals of Bruges directly. I estimate the Zwins' impact using a dummy variable, including city and period fixed effects. This approach will attribute all within-city deviations from linear city-specific time trends and year fixed effects in local fundamentals to the Zwin, and allows me to generate a no-Zwin counterfactual path for fundamentals.

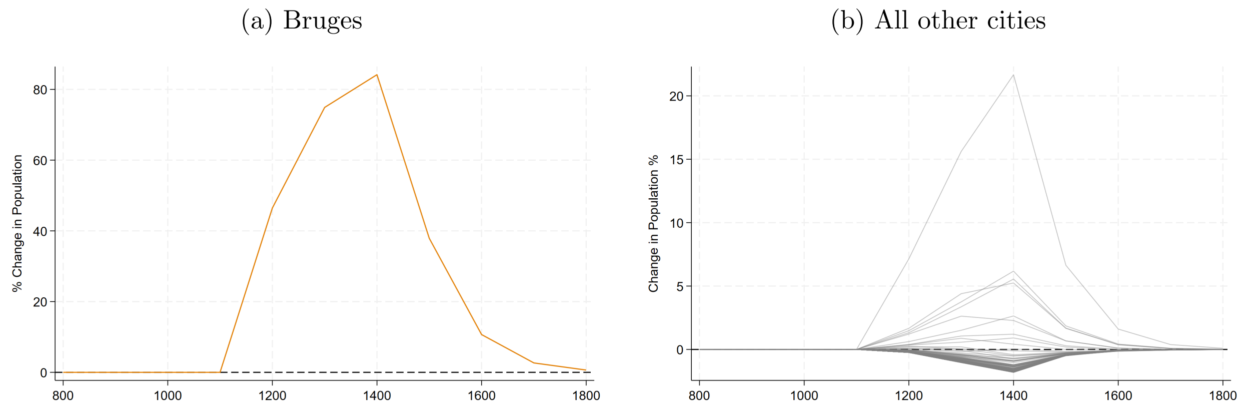
4.3 Counterfactual results

Having estimated a no-Zwin counterfactual path for local fundamentals, and calculated the no-Zwin counterfactual trade and migration costs, I can use these inputs, the structure of the model, and the estimated model parameters, to trace out the no-Zwin counterfactual population in each city. Figures 6 and 7 show the results from this exercise. Figure 6 shows the impact of the Zwin on city populations over time. On the left-hand side, I show the impact on Bruges itself. One can see a clear and large effect; at its peak Bruges was over 80% more populous due to the Zwin. The reduced form results from section 3 suggested that the Zwin caused the population of Bruges to be between 174% and 425% larger whilst it was navigable — a comparable but higher magnitude.

The model allows me to consider the potentially heterogeneous impact of the Zwin on all cities within the urban system surrounding Bruges. The right-hand panel of figure 6 shows the percentage change in population caused by the Zwin in each of the remaining cities in my sample. Comparing the y-axis of this graph to that of the top left graph one can see a considerable change in the magnitude of the effect; however for many locations it remains economically meaningful. This figure highlights that some locations (other than Bruges) gained significantly more than others. Note that the total population is normalised to 1 in each period — so gains will always be countered by losses elsewhere.

Figure 6 also allows me to consider the impact of the Zwin in the centuries after it silted up. The model is a discretized version of reality within which the positive impacts of the Zwin on Bruges disappear sharply just after 1400. Under this interpretation, 1600 indicates 200 years after the Zwin silted up. The model suggests that Bruges' population remained over 40% higher than it would have been 100 years after the Zwin disappeared, and 10% higher than it otherwise would have been, even 200 years after the Zwin disappeared. Although smaller in magnitude, some other cities also still felt positive impacts this far after the last ships had used the Zwin estuary.

Figure 6 The model implied impact of the Zwin

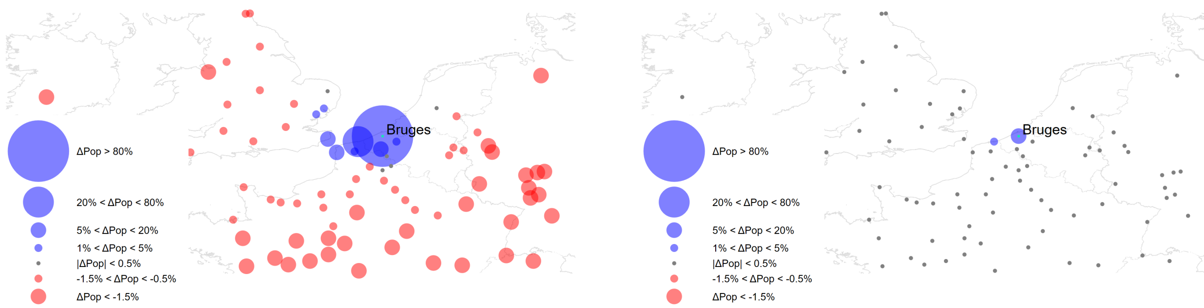


Notes: These figures show the counterfactual results of the additional impact of the Zwin on population. The left-hand-side panel shows the impact for Bruges, whereas the right-hand-side panel shows the impact for all other cities in my sample.

Figure 7 turns to consider the geographic spread of the Zwins' impact across the area immediately surrounding Bruges. It shows the relative change in population in percentage terms for each city due to the Zwin. The left-hand panel shows the impact in 1400, the last period in which the Zwin was navigable, whereas the right-hand panel shows the impact in 1600, some 200 years after the Zwin had silted up. The geographic spread of effects is intuitive; areas close to Bruges saw larger positive impacts as the impact of Bruges's larger market spread out. The right-hand panel shows the remaining impact of the Zwin 200 years after it had silted up. The impact is considerably more muted, with a noticeable positive effect on Bruges and very close cities only.

Figure 7 The model implied impact of the Zwin over space

(a) Last period the Zwin was navigable (b) 200 Years after the Zwin disappeared



Notes: These figures show the counterfactual results of the additional impact of the Zwin on population over space, focusing on the area directly around Bruges. The left-hand-side panel shows the impact in the last period in which the Zwin was navigable, and the right-hand-side panel shows the impact 200 years after it disappeared.

5 Conclusion

In 1134, a large storm caused a sudden river to appear. This unique historical experiment allows us to look at the contemporaneous and long-run impact of a temporary shock to location fundamentals. Combining historical and novel data, a range of reduced-form empirical strategies, and a dynamic quantitative spatial model tailored to the Medieval and Early Modern European economy, I have shown that the Zwin had large and long-lasting impacts not only on Bruges but also on the broader urban structure of the Low Countries.

Empirically, I find that Bruges' population grew by up to 400% during the navigable period of the Zwin, and remained significantly larger by over 10% two hundred years after the river became impassable. The effects, though smaller, extended to nearby cities as well. These results are robust across a range of empirical strategies, including difference-in-differences, event studies, synthetic control, and market access regressions.

While this study focuses on a particular case, the approach and findings have broader relevance. Many regions today continue to experience shocks—climate-related, technological, or political—that may temporarily alter their connectivity or productivity. Ultimately, this paper shows that history leaves a long shadow; temporary events, if large enough, can alter the economic map for centuries to come.

Appendix

A Model details

The model description results in three gravity-esque equations dictating migration, trade, and merchant activity across space, as well as the Malthusian equation determining Births.

$$L_{ijt} = \mu_{ijt}^{-\theta} W_{jt}^{\theta} \left(\sum_k \mu_{ikt}^{-\theta} W_{kt}^{\theta} \right)^{-1} B_{it-1} \tag{10}$$

$$X_{ijt} = \tau_{ijt}^{1-\sigma} w_{it}^{1-\sigma} A_{it}^{\sigma-1} \left(\sum_k \tau_{ikt}^{1-\sigma} w_{kt}^{1-\sigma} A_{kt}^{\sigma-1} \right)^{-1} E_{jt} \tag{11}$$

$$M_{it} = \left(A_{it}^{M} T_{it}\right)^{\phi} \left(\sum_j \left(A_{jt}^{M} T_{jt}\right)^{\phi} \right)^{-1} \tag{12}$$

$$B_{it} = L_{it-1} \left(\frac{w_{it-1}}{P_{it-1}} \right)^{\rho} \tag{13}$$

Market clearing in the goods market implies that total expenditure in a given location is equal to total income, which in turn equals the sum of all imports (and own consumption) which is total trade, $E_{it} = Y_{it} = \sum_j X_{ijt} = T_{it}$. As labor is the only factor of production, local income is, in turn, given by the wage bill $Y_{it} = w_{it} L_{it}$. Labor market clearing, in turn, implies that the population of a given location is equal to the sum of in-migrants (including those who stay), $L_{jt} = \sum_i L_{ijt}$. Focusing first on the trade side, using the market-clearing condition and symmetry of trade costs we can write the following:

$$w_{it} L_{it} = Y_{it} = \sum_j X_{ijt} = \left(\frac{w_{it}}{A_{it}} \right)^{1-\sigma} \sum_j \tau_{ijt}^{1-\sigma} P_{jt}^{\sigma-1} w_{jt} L_{jt} = \left(\frac{w_{it}}{A_{it}} \right)^{1-\sigma} \mathrm{FMA}_{it}.$$

Where $\mathrm{FMA}_{it} = \sum_j \tau_{ijt}^{1-\sigma} P_{jt}^{\sigma-1} Y_{jt}$ is firm market access. Define consumer market access as $\mathrm{CMA}_{it} = P_{it}^{1-\sigma} = \sum_j \tau_{ijt}^{1-\sigma} \left(w_{jt}/A_{jt}\right)^{1-\sigma}$. Then given the above we can write $\mathrm{FMA}_{it} = \sum_j \tau_{ijt}^{1-\sigma} \mathrm{CMA}_{jt}^{-1} Y_{jt}$ and $\mathrm{CMA}_{it} = \sum_j \tau_{ijt}^{1-\sigma} \mathrm{FMA}_{jt}^{-1} Y_{jt}$. Following Donaldson and Hornbeck [2016], the only solution to this system of equations is for $\mathrm{CMA}_{it} \propto \mathrm{FMA}_{it}$, call this up to scale solution trade market access: $\mathrm{TMA}_{it} = \sum_j \tau_{ijt}^{1-\sigma} Y_{jt} \mathrm{TMA}_{jt}^{-1}$.

Turning to the labor side we have the following.

$$L_{jt} = \sum_i L_{ijt} = W_{jt}^{\theta} \sum_i \mu_{ijt}^{-\theta} \Pi_{it}^{-\theta} B_{it} = W_{jt}^{\theta} \text{LMA}_{jt}$$

Where labor market access is defined as $\text{LMA}_{jt} = \sum_i \mu_{ijt}^{-\theta} \Pi_{it}^{-\theta} B_{it}$. Define worker market access as $\text{WMA}_{jt} = \Pi_{jt}^{\theta} = \sum_i \mu_{ijt}^{-\theta} W_{it}^{\theta}$. Then we have $\text{WMA}_{jt} = \sum_i \mu_{ijt}^{-\theta} L_{it} \text{LMA}_{it}^{-1}$ and $\text{LMA}_{jt} = \sum_i \mu_{ijt}^{-\theta} B_{it} \text{WMA}_{it}^{-1}$, so although the exact same recursion result cannot be imposed, we can still write the expression in terms of one market access quantity: $\text{LMA}_{jt} = \sum_i \mu_{ijt}^{-\theta} B_{it} \left(\sum_k \mu_{ikt}^{-\theta} L_{kt} \text{LMA}_{kt}^{-1}\right)^{-1}$.

Bringing this all together, we can write the following series of equations that jointly determine local population and wages.

$$L_{it} = \left(\bar{u}_{it} L_{it}^{\beta_1} L_{it-1}^{\beta_2} w_{it} \text{TMA}_{it}^{-1/(1-\sigma)}\right)^{\theta} \text{LMA}_{it} \tag{14}$$

$$w_{it} L_{it} = w_{it}^{1-\sigma} \left(\bar{A}_{it} M_{it}^{\chi} L_{it}^{\alpha_1} L_{it-1}^{\alpha_2}\right)^{\sigma-1} \text{TMA}_{it} \tag{15}$$

From these two expressions and the equation determining merchant numbers, we can solve for the endogenous variables M_{it}, L_{it}, w_{it} as a function of market access terms, $\text{TMA}_{it}, \text{LMA}_{it}$, predetermined population L_{it-1}, and model parameters, $\alpha_1, \alpha_2, \beta_1, \beta_2, \theta, \sigma, \chi, \phi$. First note we can write the spatial distribution of population as.

$$L_{it} = \bar{u}_{it}^{\frac{\theta}{1-\beta_1\theta}} L_{it-1}^{\frac{\beta_2\theta}{1-\beta_1\theta}} \text{LMA}_{it}^{\frac{1}{1-\beta_1\theta}} w_{it}^{\frac{\theta}{1-\beta_1\theta}} \text{TMA}_{it}^{\frac{-\theta}{(1-\sigma)(1-\beta_1\theta)}} \tag{16}$$

Similarly, after some algebra, we find that the expression determining the spatial distribution of wages can be combined with that determining the distribution of merchants to find the following.

$$w_{it} = L_{it}^{\frac{(\phi\chi+\alpha_1)(\sigma-1)-(1-\phi\lambda)}{1-\phi\lambda}x} L_{it-1}^{(\alpha_2(\sigma-1)-1)x} \bar{A}_{it}^{(\sigma-1)x} (\bar{A}_{it}^{M})^{\frac{\phi\chi(\sigma-1)}{1-\phi\lambda}x} \Omega_t^{\frac{\phi(\sigma-1)}{1-\phi\lambda}x} \text{TMA}_{it}^{x} \tag{17}$$

Where $x = \frac{1-\phi\lambda}{\phi\chi(1-\sigma)+\sigma(1-\phi\lambda)}$, and $\Omega_t = \sum_j \left(A_{jt}^M T_{jt}\right)^{\phi}$ can be normalised to one in each period. Subbing equations 16 and 17 into each other we can find expressions for L_{it} and w_{it} in terms of market access terms and exogenous fundamentals or previous population. We can write

$L_{it} = \text{LMA}_{it}^{a_{11}} \cdot \text{TMA}_{it}^{a_{12}} \cdot L_{it-1}^{a_{13}} \cdot F_{it}^{L}$ and $w_{it} = \text{LMA}_{it}^{a_{21}} \cdot \text{TMA}_{it}^{a_{22}} \cdot L_{it-1}^{a_{23}} \cdot F_{it}^{w}$ where F_{it}^{L} and F_{it}^{w} group together exogenous terms. This system can be written as a log-linear system in matrix form as follows.

$$\begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} \ln(L_{it}) \\ \ln(w_{it}) \end{pmatrix} = \begin{pmatrix} b_{13} & b_{14} & b_{15} \\ b_{23} & b_{24} & b_{25} \end{pmatrix} \begin{pmatrix} \ln(LMA_{it}) \\ \ln(TMA_{it}) \\ \ln(L_{it-1}) \end{pmatrix} \tag{18}$$

Where $b_{11} = 1,\ b_{12} = \frac{-\theta}{1-\beta_1\theta},\ b_{13} = \frac{1}{1-\beta_1\theta},\ b_{14} = \frac{-\theta}{(1-\sigma)(1-\beta_1\theta)},\ b_{15} = \frac{\beta_2\theta}{1-\beta_1\theta}$ and $b_{21} = -x\frac{(\phi\chi+\alpha_1)(\sigma-1)-(1-\phi\lambda)}{1-\phi\lambda},\ b_{22} = 1,\ b_{23} = 0,\ b_{24} = x,\ b_{25} = (\alpha_2(\sigma-1)-1)x$. Therefore, the a coefficients can be found as follows.

$$\begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}^{-1} \begin{pmatrix} b_{13} & b_{14} & b_{15} \\ b_{23} & b_{24} & b_{25} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{pmatrix}$$

Substituting these expressions into the market access terms we arrive at the following expressions, where $K_{jt} = F_{jt}^{L} \cdot F_{jt}^{w}$.

$$\text{LMA}_{it} = \sum_j \mu_{ijt}^{-\theta} \cdot \cdot L_{jt-1} \cdot \left(\sum_k \mu_{ikt}^{-\theta} \cdot L_{kt} \cdot \text{LMA}_{kt}^{-1} \right)^{-1} \tag{19}$$

$$\text{TMA}_{it} = \sum_j \tau_{ijt}^{1-\sigma} \cdot K_{jt} \cdot \text{TMA}_{jt}^{a_{22}+a_{12}-1} \cdot \text{LMA}_{jt}^{a_{21}+a_{11}} \cdot L_{jt-1}^{a_{23}+a_{13}} \tag{20}$$

We can use a similar approach to find K_{jt}. Denote the vector of exogenous variables from equations 16 and 17 as $D = \left(\frac{\theta}{1-\beta_1\theta} \ln\left(\bar{u}_{it}\right),\ (\sigma-1)x\ln\left(\bar{A}_{it}\right) + \frac{x\phi\chi(\sigma-1)}{1-\phi\lambda} \ln\left(\bar{A}_{it}^{M}\right) \right)'$. Then we have the following.

$$\ln(K_{it}) = (1,1) \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}^{-1} D = \frac{1}{1-b_{12}b_{21}} \left(d_1(1-b_{21}) + d_2(1-b_{12})\right) \tag{21}$$

A.1 Identifying structural parameters

We can estimate the following reduced form expressions where market access terms have been assumption to be equal and therefore collapse into one term.

$$\ln(L_{it}) = c_{11} \cdot \ln(MA_{it}) + c_{12} \cdot \ln(L_{it-1}) + v_{it}$$
$$\ln(w_{it}) = c_{21} \cdot \ln(MA_{it}) + c_{22} \cdot \ln(L_{it-1}) + e_{it}$$

First, note that within the matrix notation described above, we therefore have that

$$c_1 = a_{11} + a_{12}, \qquad c_2 = a_{13}, \qquad c_3 = a_{21} + a_{22}, \qquad c_4 = a_{23}.$$

I make two identifying assumptions: $\lambda = 0, \beta_1 = -\beta_2$. Then, again remaining within the above matrix notation, we can find an expression for the elements of the A matrix:

$$A = \frac{1}{D} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} b_{13} & b_{14} & b_{15} \\ 0 & x & b_{25} \end{bmatrix},$$

where $D = 1 - b_{12}b_{21}$. This implies the following expressions.

$$c_1 = \frac{b_{13} + b_{14} - b_{12}x}{D}, \qquad c_2 = \frac{b_{15} - b_{12}b_{25}}{D}, \tag{22}$$
$$c_3 = \frac{-b_{21}(b_{13} + b_{14}) + x}{D}, \qquad c_4 = \frac{-b_{21}b_{15} + b_{25}}{D}. \tag{23}$$

Let us at this stage introduce some helpful notation:

$$K := \frac{1}{1 - \beta_1\theta}, \qquad T := 1 - \frac{\theta}{1 - \sigma}, \qquad D = 1 - b_{12}b_{21} = 1 + \theta K\, b_{21}.$$

Using this notation we can write $b_{12} = -\theta K, b_{13} = K, b_{14} = -\frac{\theta K}{1-\sigma} = K\,(T - 1), b_{13} + b_{14} = KT, b_{15} = (1 + \beta_1\theta)K = (1 - \frac{1}{K})K = 1 - K$. Substituting these into (22)–(23) yields

$$c_1 D = K\,(T + \theta x), \qquad c_3 D = x - b_{21}\,KT, \tag{24}$$
$$c_2 D = 1 - K + \theta K\, b_{25}, \qquad c_4 D = -b_{21}(1 - K) + b_{25}. \tag{25}$$

Step 1: Identify K and (β_1, β_2) from (c_2, c_4).

Eliminate b_{25} from (25). From $c_4 D = -b_{21}(1-K) + b_{25}$ we have $b_{25} = c_4 D + b_{21}(1-K)$. Substitute into $c_2 D$:

$$c_2 D = (1-K) + \theta K\big[c_4 D + b_{21}(1-K)\big] = 1 - K + \theta K c_4 D + \theta K b_{21}(1-K).$$

Using $D = 1 + \theta K b_{21}$, the right-hand side factors to $(1-K)D + \theta K c_4 D$, so dividing by $D \neq 0$ gives $c_2 - \theta K c_4 = 1 - K$. Solving for K yields $K = \frac{1-c_2}{1-\theta c_4}$. Therefore $\beta_1 = \frac{1-\frac{1}{K}}{\theta}$.

Step 2: Identify b_{21}, then D and x from (c_1, c_3).

From (24) we have that $c_1 D = K(T + \theta x)$, $c_3 D = x - b_{21} K T$, and $D = 1 + \theta K b_{21}$. Solve the first for x and substitute into the second, then collect in b_{21} to find $x = \frac{c_1 D/K - T}{\theta}$ which implies the following.

$$b_{21} = \frac{-T - \theta c_3 + \frac{c_1}{K}}{\theta K c_3 - c_1 + KT}$$

This gives us $D = 1 + \theta K b_{21}$, and $x = \frac{c_1 D/K - T}{\theta}$.

Step 3: Identify b_{25} and α_2.

Returning to (25), we can use the derived expression for b_{25} to find $b_{25} = c_4 D + b_{21}(K-1)$, then since $b_{25} = \big[\alpha_2(\sigma - 1) - 1\big]x$, we obtain $\alpha_2 = \frac{b_{25}/x + 1}{\sigma - 1}$.

Step 4: Identify χ from x with $\lambda = 0$.

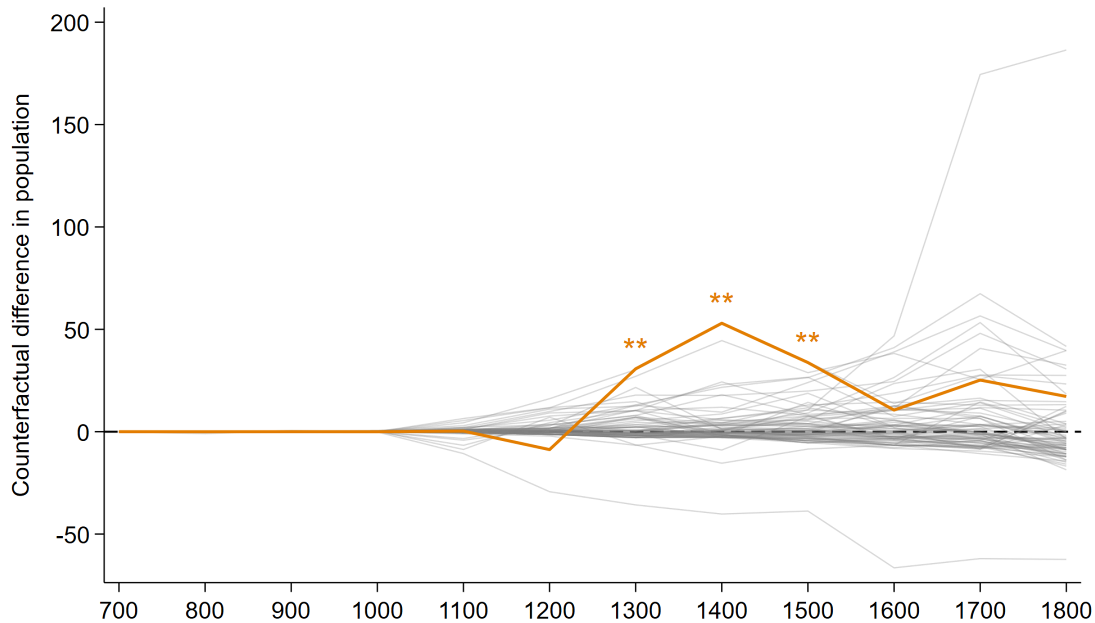
Maintaining our assumption that $\lambda = 0$, then from the definition of x and given that ϕ is known from an auxillary regression we find: $\chi = \frac{1/x - \sigma}{\phi(1-\sigma)}$.

Step 5: Identify α_1.

From the definition of b_{21} with $\lambda = 0$, we have that $\phi\chi + \alpha_1)(\sigma - 1) = 1 - \frac{b_{21}}{x}$ and therefore, $\alpha_1 = \frac{1 - \frac{b_{21}}{x}}{\sigma - 1} - \phi\chi$.

B Additional tables and figures

Figure 8 Synthetic control results: Inference



Notes: This figure plots the difference between actual and counterfactual populations for each of the 76 cities in the sample of cities with a similar population to Bruges in 1100. Counterfactual populations are calculated via a synthetic control procedure for each city as described in the text. The population difference for Bruges in given in orange and stars indicate significance at the usual levels.

Figure 9 Example Least Cost Paths

(a) Aachen to Cordoba | (b) Dundee to Milan

Notes: These figures show example calculated least cost paths between cities using the cost surface described in the main text.

C Details on ChatGPTs sources and analysis

ChatGPT provided a full account of its reasoning behind each quantitative merchant number provided, including references. You can find this full, 237 page, description here.

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