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All Aboard: The Effects of Port Development

Abstract

Seaports facilitate the fast flow of goods across space, but ports also entail local costs borne by host cities. We use the introduction of containerized shipping to explore the effects of port development. At the local level, we find that seaport development increases city population by making a city more attractive, but this market access effect is offset by costs which make the city less attractive. At the aggregate level, we find that the local costs associated with port development are heterogeneous across cities and reduce aggregate welfare gains, which however are still positive and substantial.

JEL-Codes: R400, O330, F600.

Keywords: ports, containerization, quantitative economic geography, endogenous trade costs.

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> Across the planet, the expansion of seaports is becoming tougher (...). Space in the right locations is scarce.
>
> *The Economist*, January 14th, 2023

1 Introduction

Seaports play a vital role in the global trading system, handling over 80% of world merchandise trade in 2018 in terms of volume (UNCTAD, 2019). Efficient, modern facilities that provide ample space for the fast loading and unloading of containers are a precondition for a country to participate in global production networks (Rodrigue, 2016, p. 131). Despite their importance, little is known about the economic effects of ports. What determines which coastal cities become important ports? What are the aggregate gains from port development? Which cities reap the benefits, and which pay the costs of port development?

In this paper, we study these questions by exploiting a major technological shock to port development: containerization, that is, the handling of cargo in standardized boxes. Our analysis sheds light on a novel mechanism that affects i) the economic geography of ports, ii) the gains from port development, and iii) the distribution of these gains. This mechanism is driven by the *local costs of port development*.

Modern port development entails at least two costs that are borne by host cities. First, ports occupy large amounts of land in their host cities. For example, the ports of Antwerpen and Rotterdam occupy more than 30% of the metropolitan area of the city, while in Los Angeles 85% of total truck traffic is accounted for by port related traffic on some highway segments (OECD, 2014, p. 17). The costs associated with space have become particularly salient with recent supply chain disruptions. The overflow of containers in major ports such as Long Beach, California that did not have slack capacity highlights the extent to which many modern ports are space-constrained.[1]

Second, ports may induce large-scale local disamenities such as noise and pollution (Ducruet, Itoh, Polo Martin, Sene, and Sun, 2023). In Hong Kong, more than half of the sulphur dioxide emissions are related to shipping (OECD, 2014, p. 17). As a recent article in The Economist (2023) highlights, the localized land and environmental costs of port development are arguably some of the most pressing current challenges for ports.

In the first part of our analysis, we assemble a unique panel dataset of city populations and shipping flows to document the local effects of port development across the globe. We use the introduction of containerized shipping to explore these effects. To isolate exogenous variation in a city's suitability for containerization, we build on a previous literature that has shown that access to deep water at the port is important for containerization (Brooks, Gendron-Carrier, and Rua,

[1] E.g., https://qz.com/2079345/cargo-ships-containers-are-piling-up-in-long-beach.

2021; Altomonte, Colantone, and Bonacorsi, 2018). We construct a novel measure of 'naturally endowed' depth (as distinct from depth attained by dredging) based on granular data on oceanic depths around a port.

Using this exogenous measure of suitability to containerization, we document three empirical facts. First, we show that cities exogenously more suited to containerization witnessed a boom in shipping flows after the onset of containerization. This fact suggests that containerization increased these cities' market access by lowering their shipping costs. Second, we find that the shipping boom was less pronounced in cities where land is scarce due to geographic constraints. This fact reflects the importance of land costs for port development. Third, we show that the increase in local shipping did not translate into population inflows for the average city: our IV estimates show an effect of increased shipping on population growth that is both economically and statistically insignificant. This fact suggests that the local costs of port development from land or other sources can fully offset the benefits from better market access. The economic geography literature has traditionally focused on only these market access benefits (Donaldson and Hornbeck, 2016; Redding and Turner, 2015).

In the second part of the paper, we develop a general equilibrium model that can be used to quantify the aggregate and distributional impacts of port development. The model adds an endogenous port development decision to an otherwise standard economic geography model of trading cities. Port development is costly for two reasons: it requires scarce local land, and it creates disamenities in the port city. As a result, the model incorporates not only the standard market access effect, but also both types of local port development cost suggested by narrative evidence and our empirical facts. Whether a city ultimately gains in population is the outcome of the trade-off between the market access benefits and the local (land use and disamenity) costs of port development.

We quantify the aggregate and distributional effects of port development by taking the model to the data. We use data on shipping flows, city GDP and population in 1990 to back out cities' unobserved model fundamentals. Armed with these fundamentals, we conduct two counterfactual simulations to shed light on the importance of the local costs of port development.

In our first counterfactual, we simulate the pre-containerization equilibrium in the model by *undoing* the containerization shock. Our estimates suggest that containerization increased world welfare by 3.38%, the ratio of world trade to GDP by 4.2 percentage points, and the median port size relative to city area by 2 percentage points. In a model-based decomposition, we find that the aggregate resource cost of increased land use amounted to 0.28% of world GDP, reducing the welfare gains from containerization by 8%. This result highlights that the local costs of port development are important not only for where port activity is located, but also for how much the world as a whole gained from containerization. We also find an additional welfare gain from cities' endogenous specialization in port- and non-port activities, depending on their comparative advantage. These specialization gains offset 44% of the resource costs of containerization, but they do not compensate for all the costs.

In our second counterfactual, we examine the effects of targeted port development policies. We focus on a setting similar to the 'Maritime Silk Road' project – a large set of port investments undertaken by China in South Asian, African and European ports. Our findings suggest that targeted port development has the potential for large distributional effects triggered by the reallocation of shipping activity. The model predicts a large decline in shipping in Singapore (a non-targeted port which we estimate to lose about 50% of its shipping flows), which is driven by the fact that shipping activity reallocates to nearby, targeted ports. Crucially, this initial shock is amplified by less endogenous port development in Singapore as demand for port services falls. However, despite losing a sizeable fraction of its shipping flows, Singapore gains 1% in GDP, as resources reallocate to Singapore's highly productive non-port activities. This illustrates that, because of the costs of port development, gains and losses in shipping do not translate directly into gains in real GDP. These findings highlight the importance of accounting for the endogenous port development mechanism when quantifying how the gains from targeted port development are distributed across space. More speculatively, they question the wisdom of highly productive, expensive cities such as Hong Kong and Singapore continuing to specialize heavily in port services.

Related literature. A recent, growing literature provides evidence that better trading opportunities lead to local benefits through increasing market access (Donaldson and Hornbeck, 2016; Redding and Turner, 2015), which may induce city development (Bleakley and Lin, 2012; Armenter, Koren, and Nagy, 2014; Nagy, 2022). Some of these studies focus on city development at port locations in particular (Fujita and Mori, 1996; Coşar and Fajgelbaum, 2016; Fajgelbaum and Redding, 2022). We contribute to this literature by showing that trade-induced development can also have substantial local costs. While the potential for transport infrastructure to put a strain on scarce local resources has long been recognized theoretically (Solow and Vickrey, 1971; Solow, 1972; Pines and Sadka, 1985), the effect has not been estimated empirically. This mechanism also relates the paper to the 'Dutch disease' literature, which shows that booming industries can entail significant costs through competing with other (tradable) sectors for local resources (Corden and Neary, 1982; Krugman, 1987; Allcott and Keniston, 2017).[2] Relative to this literature, our setting contains the potential for not only costs but also gains, as booming port activities benefit local tradables through improving market access. Thus, one contribution of our paper is to generalize the predictions from the two literatures that have focused on either the costs or the benefits from booming sectors.

Our paper is also related to the quantitative international trade literature, which has developed

[2]Relatedly, Falvey (1976) discusses how the transportation sector can draw away resources from tradables in particular.

tractable models of cross-country trade with various dimensions of heterogeneity (Anderson, 1979; Eaton and Kortum, 2002; Melitz, 2003). These seminal models characterize trade and the distribution of economic activity as a function of exogenous trade costs. A standard prediction of these models is that the relationship between trade flows and costs follows a gravity equation, which has been documented as one of the strongest empirical regularities in the data (Head and Mayer, 2014). We complement this literature by developing a framework in which trade costs are *endogenous*, in a way that is both tractable and preserves the gravity structure of trade flows. This relates our paper to Fajgelbaum and Schaal (2020) and Santamaría (2022), who consider endogenous road construction in multi-location models of economic geography, as well as Brancaccio, Kalouptsidi, and Papageorgiou (2020), who endogenize trade costs in the non-containerized shipping sector. Unlike these papers, we focus on port development as a source of endogenous shipping costs, and solve for the decentralized equilibrium as opposed to the optimal allocation to quantify the effects of port development on trade, the distribution of population, and welfare.

Finally, our paper is related to a large literature studying the effects of transport infrastructure improvements.[3] Within this literature, Brinkman and Lin (2022) is the only other paper we are aware of that shows empirical evidence for the cost side of infrastructure development, focusing on disamenities associated with freeway construction in mid-20th century U.S. cities. Our paper also relates to the growing empirical literature studying the effects of containerization (Hummels, 2007; Bernhofen, El-Sahli, and Kneller, 2016; Gomtsyan, 2016; Coşar and Demir, 2018; Holmes and Singer, 2018; Altomonte et al., 2018; Brooks et al., 2021; Bridgman, 2021) or the role of container shipping networks in world trade (Wong, 2022; Heiland, Moxnes, Ulltveit-Moe, and Zi, 2022; Ganapati, Wong, and Ziv, 2022; Koenig, Pigné, Poncet, Sanch-Maritan, and Duvallet, 2023). Most closely related in this vein is Brooks et al. (2021), who study the reduced-form effects of containerization on local economic outcomes across U.S. counties. Our main contribution to this literature is twofold. First, our paper is the first to highlight that containerization leads to sizeable local and global costs.[4] Second, to the best of our knowledge, ours is the first paper seeking to quantify the aggregate effects of containerization on global trade and welfare through the lens of a general equilibrium economic geography model.

The paper is structured as follows. In the next section, we describe the transshipment cost reductions caused by containerization. Section 3 discusses the main data sources used in the analysis. Section 4 presents three stylized facts about the local effects of containerization, while Section 5 introduces the model. Section 6 takes the model to the data, while Section 7 uses the quantified model to measure the aggregate effects of containerization and to illustrate the effects of targeted

[3]Redding and Turner (2015) provides an overview of recent developments in this literature. Ducruet and Notteboom (2023) reviews the existing port geography literature.

[4]Our result that land-abundant cities see faster shipping growth is consistent with Brooks et al. (2021) who find that containerization led to faster population growth in U.S. counties with initially low land rents.

port development policies similar to the Maritime Silk Road. Finally, Section 8 concludes.

2 Background: containerization reduced transshipment costs

As late as the mid-1950s, transshipment at seaports was a costly and slow procedure as it entailed handling cargo item-by-item – a process called breakbulk shipping (Krugman, 2011). Cargo came in many different sizes and needed to be handled individually, despite the widespread use of machinery introduced pre-containerization (see Panel A of Figure F.1). The San Francisco Port Commission (1971) estimated that it took 7 to 10 days to merely discharge cargo from a ship. According to Bernhofen et al. (2016), two-thirds of a ship's time was spent in port. This led to high costs as the capital utilization of ships was low, and the cost of capital tied up in inventory was high.[5]

U.S. shippers first started placing cargo into containers in the late 1950s. Containerized shipping was initially introduced on domestic routes between U.S. ports, but the technology was rapidly adopted and standardized worldwide over the next two decades (Rua, 2014). Containerized port technology can be seen in its mature form at the Port of Seattle in 1969 in Panel B of Figure F.1 (a mere 10 to 15 years after the photos shown in Panel A were taken). Cargo, packed in standardized containers, is loaded onto and off ships using large, purpose-built cranes situated on the wharf. Large, open areas beside the wharf are used to line up containers.

Containerization substantially reduced transshipment costs for a number of reasons. First, as containers could be handled in a uniform way, loading and unloading times were vastly reduced. The San Francisco Port Commission (1971) estimated that a container ship could be unloaded and loaded in 48 hours or less, a tenth of the previous time spent in port. Similarly, using detailed data on vessel turnaround times for an anonymized port, Kahveci (1999) estimates that the average time ships spent in port fell from 8 days to 11 hours as a result of containerization, a reduction of 94%. Second, the reduction in turnaround time justified investment in much larger vessels (Gilman, 1983). The average size of newly-built container ships increased by 402% between 1960 and 1990.[6] Larger ship sizes made it possible to realize even larger cost reductions through increasing returns to scale in shipping and port handling. Rodrigue (2016, p. 118) estimates that moving from a 2,500 TEU capacity vessel to one with 5,000 TEU reduced costs per container by 50%.

[5] Industry experts estimated that the handling of cargo at the port accounted for a major share of freight costs (Levinson, 2010). As an example, transshipment costs were estimated to account for 49% of the total transport cost on one route from the U.S. to Europe (Eyre, 1964).

[6] These calculations are based on data from the *Miramar Ship Index* (Haworth, 2020). See Appendix D.11 for details.

3 Data

Our analysis builds on a decadal city-level dataset of shipping flows, population, and other economic outcomes for the period 1950-1990. We complement this with GIS data that allows us to calculate geographic characteristics of the cities and ports. We review the main variables used in the analysis below and report summary statistics in Table E.1. Detailed documentation including sources and description of data construction for all the data used in the paper can be found in the Data Appendix (Appendix D).

Shipping flows (Appendix D.1). Crucial to our analysis is a unique dataset of worldwide bilateral ship movements at the port level for the period 1950-1990 from the *Lloyd's Shipping Index*, a unique source that provides a daily list of merchant vessels and their latest inter-port movements. The data we use were constructed by Ducruet, Cuyala, and Hosni (2018) using one week samples from the first week of May for each year. An observation is a ship moving from one port to another at a particular point in time.[7]

These data provide us with rich variation to study the geography of sea-borne trade through the second half of the 20th century. They cover both domestic and international shipping. Moreover, the data cover a long time period spanning the containerization revolution. We are thus able to compare the effects of port activity on cities both before and after the arrival of the new technology. We know of no other data source that has a similar coverage across time and space, especially at such a detailed level of disaggregation. An important limitation, however, is that we do not observe either the value or the volume of shipment but only bilateral ship movements. From these ship movements, we sum the total number of ships passing through each port, which we call *shipping flows*.

City population. As we are interested in the economic effects of containerization, we use data on city population worldwide for locations with more than 100,000 inhabitants from *Villes Géopolis* (Moriconi-Ebrard, 1994) for each decade between 1950-1990 (Geopolis cities, henceforth). The advantage of these data relative to sources such as the more frequently used *UN World Cities* dataset is that a consistent and systematic effort was made to obtain populations for the urban agglomeration of cities (that is, the number of inhabitants living in a city's contiguous built-up area) as opposed to the administrative boundaries that are often reported in country-specific sources. This definition of the city ensures that the port lies within the city boundaries even if it is outside the administrative boundaries of the city. For example, New York (New York) and Elizabeth (New Jersey), which includes the port of Elizabeth, form one 'city' according to this definition.

[7] As such, it is similar to contemporary satellite AIS (Automatic Identification System) data that tracks the precise movements of vessels around the globe. Such AIS data are used in Brancaccio et al. (2020) and Heiland et al. (2022).

We observe population for cities that reached 100,000 inhabitants in any year throughout this period. For most of these cities, we observe population even when the city had fewer than 100,000 inhabitants, potentially leading to sampling bias. To address this, we will show that our results are robust to using the subset of cities that had already attained 100,000 inhabitants in the first sample year, 1950.

Ports were hand-matched from the shipping data to cities based on whether the port was located within the urban agglomeration of a city in the Geopolis dataset, allowing for multiple ports to be assigned to one city (Ducruet et al., 2018). We define port cities in a time-invariant manner; a port city with positive shipping flows in at least one year will be classified as a port city for all years. Of the 2,636 cities in the Geopolis dataset, 553 have at least one port. We label these as *port cities*. The quantitative estimation covers the full set of 2,636 Geopolis cities (port and non-port cities).

Underwater elevation levels (Appendix D.2). We use gridded bathymetric data on underwater elevation levels at a detailed spatial resolution (30 arc seconds, or about 1 kilometer at the equator) from the *General Bathymetric Chart of the Oceans (GEBCO)* to measure sea depth around port cities.

Saiz land scarcity measure (Appendix D.3). To measure cities' land scarcity, we follow the methodology in Saiz (2010), using GIS data that have global coverage: We take a 50 kilometer radius around the centroid of the city, and count all sea cells, all internal water bodies and wetland areas, as well as all cells with a gradient above 15%. These cells, as a share of the total cells, can be used as a proxy for a city's land scarcity, as they cannot be built on.[8]

City-level GDP per capita (Appendix D.4). Data on city-level income levels are needed for the quantitative estimation only. We are not aware of readily available sources of GDP per capita data for cities worldwide. For this reason, we estimate GDP per capita for the last year in our sample (1990) for the full sample of 2,636 worldwide cities in the following way. First, we use estimates of city GDP from the *Canback Global Income Distribution Database* for a subset of our sample (898 cities) for which data are reported for 1990. We extrapolate GDP per capita for the full sample of cities using the linear fit of the GDP per capita data on nightlight luminosity and country fixed effects, building on a growing body of evidence suggesting that income can be reasonably approximated using nightlight luminosity data (Donaldson and Storeygard, 2016).

Google Earth port area (Appendix D.7). To measure the land area of ports, we hand-coded polygons from *Google Earth* that we identified as containing port activities for a random set of 236 port cities in our dataset.

[8] Saiz (2010) argues that this measure (or rather, 1 minus our measure) captures land supply well, as it is positively correlated with rents in his sample.

4 Stylized facts

In this section, we document three stylized facts about the local effects of containerization on port cities. Together, these stylized facts suggest that containerization entailed both costs and benefits for host cities.

4.1 Stylized fact 1: Containerization led to shipping growth in deeper port cities

Section 2 discussed the fact that containerization led to larger ship sizes. This, in turn, required greater depth at the port. Following the previous literature, we think of *naturally endowed* depth as an exogenous cost-shifter that makes it cheaper for a port to reach a desired depth through costly dredging (Brooks et al., 2021; Altomonte et al., 2018). The empirical challenge is that *observed* port depth is a combination of naturally endowed depth and depth attained by dredging. Our solution to this relies on using contemporary, granular data on underwater elevation levels around the port to isolate the naturally endowed component of depth. In particular, we take all sea cells within buffer rings around the geocode of the port and sum the number of cells that are 'very deep,' which we define as depth greater than 30 feet following Brooks et al. (2021). These authors argue that given vessel sizes in the 1950s (pre-containerization), depth beyond 30 feet conferred no advantage to the port. Our baseline measure of port suitability is thus the log of the sum of 'very deep' cells in a buffer ring 3-5 km around the port. The key assumption behind our ability to isolate naturally endowed depth (from depth attained by dredging) is that when ports need to invest in costly dredging, they typically do not dredge entire areas in our buffers, but narrow channels that ships use to navigate to the port. By calculating depth over many sea cells, the vast majority of depth measurements for each port should reflect naturally endowed depth. We test and validate this assumption in Appendix B.2 using nautical maps that show dredged channels.

The following flexible specification allows us to estimate the causal effect of containerization on shipping, driven by exogenously endowed port depth:

$$\begin{aligned} \ln(Ship_{it}) \quad = \quad & \sum_{j=1960}^{1990} \beta_j * Depth_i * \mathbb{1}(Year = j) + \\ & \sum_{j=1960}^{1990} \phi_j * \ln(Pop_{i,1950}) * \mathbb{1}(Year = j) + \alpha_i + \delta_t + \epsilon_{it} \end{aligned} \tag{1}$$

The outcome variable of interest, $\ln(Ship_{it})$, is the log of shipping flows observed in city i at time t.[9] $Depth_i$ is the cross-sectional measure of port suitability defined above. We interact

[9] In practice, we replace the zeros in the data with ones and take the natural logarithm of this adjusted count (see Appendix B.1 for details).

this measure with binary indicators for the decades 1960 – 1990 to estimate the time path of how depth affected shipping flows. Since containerization spread globally towards the end of the 1960s, when international standards for the size of containers were introduced, we would expect depth to positively affect shipping only after 1970. We include the full set of city and year fixed-effects (denoted α_i and δ_t, respectively), and also allow for the initial population in 1950 to have a time-varying effect on shipping. The latter ensures that we do not mistake population convergence patterns, i.e., initially smaller cities experiencing stronger growth, as the effect of containerization. We cluster standard errors at the city level in the baseline to account for the serial correlation of shocks.[10] Each β_j in this specification estimates the increase in shipping caused by having a deeper port in a given year relative to 1950.

Table 1 contains the estimated coefficients. Column (1) presents coefficients for the baseline specification. Consistent with containerization technology being rolled out in the early 1960s across US ports and worldwide later in the decade, we see that deeper ports experienced differential growth in shipping flows only from 1970 onwards, but not in the decade between 1950 and 1960. The effect of depth on shipping is much larger and significantly different from zero for the interaction of depth and each year indicator including and after 1970.

A causal interpretation of the estimated effect of depth relies on the identifying assumption that the time-varying effect of depth is uncorrelated with the error term. The timing of when depth started to matter and the lack of pre-trends provide evidence that this assumption is plausible. The results are also robust to allowing for regional trends (column 2 adds coastline-by-year fixed effects[11]), to allowing for differential trends across more and less land-scarce port cities (column 3 includes the Saiz land scarcity measure interacted with year fixed effects), and differential trends across initially rich and poor countries (column 4 adds country GDP per capita in 1960 interacted with year indicators).

Overall, there is a consistent absence of pre-trends, and a consistent effect of depth on shipping in the years 1970 and after. Based on these results, we introduce a 'containerization' treatment indicator that turns on in years including and after 1970. This yields a single coefficient that estimates the differential effect of depth on shipping after the onset of containerization. Column (5) shows the results. Cities endowed with more depth, and hence more suitable to containerized technologies witnessed disproportionate increases in their shipping flows after containerization. Appendix B.3 discusses additional robustness checks. We note that the coefficient of interest becomes somewhat smaller when we drop North America, which is in line with the United States

[10] We also estimated Conley standard errors, but as these are typically very close to the clustered standard errors, we omit them for readability of the tables.

[11] We define coastlines in the following way. We assign each port to its nearest ocean (e.g., 'Pacific Ocean') or body of water (e.g., 'Great Lakes') and further disaggregate oceans by continent. This yields 22 coastlines worldwide. Examples are 'Mediterranean – Europe' and 'North America – Atlantic.'

being the birthplace and an early adopter of containerization. We now turn to examining whether this containerization-induced shipping boom was heterogeneous across port cities.

4.2 Stylized fact 2: Ports expanded more in response to containerization where land was less scarce

Modern container ports require vast amounts of land. Faster turnaround times can only be achieved by building much larger terminals. Rodrigue (2016, p. 118) names site constraints, and in particular, the large consumption of terminal space as the primary challenge associated with containerization. In this section, we first document the increased land-intensity of containerization in historical and contemporaneous data. Next, we examine how the increased land intensity affected *where* port development took place.

The increased land-intensity of containerized ports. Historical case study evidence from a number of ports shows that successful containerization required substantial geographic expansion of the port. In a 1971 report, alarm bells were rung about the inadequacy of San Francisco's finger piers to accommodate new types of cargo handling; "No pier facilities in the Bay Area today are capable of handling the new space requirements on this scale of new and larger container ships. (...) thus more berthing and backup area is needed" (1971, p. 13). Ports such as the one in San Francisco that were adjacent to a densely built up city struggled (and often ultimately failed) to find the necessary space for container port development (Corbett, 2010, p. 164). In contrast, at ports where containerization succeeded, the port expanded substantially. Using detailed, annual engineering maps and cargo throughput for the Port of Seattle, we find that the area of the port increased fourfold, while the land intensity of the port (i.e., the area of the port relative to throughput) almost doubled between 1961-1973, the period when the port containerized[12]

The land intensity of containerized terminals is also evident in contemporaneous data from *Google Earth*. Table E.2 shows that ports that handle more containerized cargo are typically larger. This is true when controlling for the total volume of traffic, and the results are also robust to the addition of other controls for cargo composition, and host country characteristics.

Port development took place where land was less scarce. The land-intensity of containerization documented above suggests the technology was better suited to locations where land for the expansion of the port was more readily available. To test this, we examine whether shipping increased more in cities where land was less scarce by allowing for heterogeneous effects with respect to land scarcity in regression equation (1):

[12]See Appendix A for further historical evidence and Appendix D.6 for a discussion of Seattle's containerization, respectively.

$$\begin{aligned}\ln(Ship_{it}) \quad = \quad & \beta * Depth_i * \mathbb{1}(Year \geq 1970) + \gamma * Depth_i * LandScarcity_i * \mathbb{1}(Year \geq 1970) \\ & + \eta * LandScarcity_i * \mathbb{1}(Year \geq 1970) + \sum_{j=1960}^{1990} \phi_j * \ln(Pop_{i,1950}) * \mathbb{1}(Year = j) \\ & + \alpha_i + \delta_t + \epsilon_{it} \qquad (2)\end{aligned}$$

where $LandScarcity_i$ measures the share of land in city i that cannot be built on, as defined in Section 3, and all other variables are as defined above. We have defined the measure such that higher values correspond to a city with more land scarcity. The coefficient of interest is γ—the interaction between our depth measure and the land scarcity measure (interacted with the 'containerization' treatment variable that turns on in 1970). Note that this is a fully saturated specification: We allow both depth and the land scarcity measure to have their own time trend break in 1970.

We plot the marginal effect of depth at different values of the land scarcity measure in Figure 1 (the corresponding estimates are presented in Table E.3). Consistent with an important role for land scarcity in determining the location of port development, the coefficient of interest, γ, is negative, large and statistically different from zero (coefficient -0.707, s.e. 0.323). Cities with exogenously deeper ports witnessed increased shipping flows after 1970, but disproportionately more so in cities where land was less scarce. Appendix B.3 discusses further robustness checks. This includes examining whether the Saiz land scarcity measure may be mismeasured due to land reclamation, which we find no evidence of.

A second test of whether the increased land requirements of port development affected the location of ports comes from examining how the location of ports changed *within* cities over time. Figure F.2 shows that, over time (1953 – 2017), ports systematically moved *within city* to the outskirts, where land is typically less scarce. This came about as a combination of existing ports expanding outwards from the city center (by about one kilometer, on average), as well as new terminals being set up further from the city center (which were nine kilometers further form the city center, on average).

Taking the findings of this section together, we conclude that there is wide-ranging evidence for the increased land-intensity of containerization. This feature of the new technology mattered for where port development took place, both *across* and *within* cities.

4.3 Stylized fact 3: The increase in shipping did not translate into population growth

To document the long-run effect of containerization-induced port development on population, we estimate the following long-differenced specification:

$$\Delta \ln(Pop_i) = \beta * \Delta \ln(Ship_i) + \phi * \ln(Pop_{i,1950}) + \epsilon_i \tag{3}$$

where $\Delta \ln(Pop_i)$ and $\Delta \ln(Ship_i)$ are the change in the natural logarithm of population and shipping flows between 1950 and 1990, respectively. The identification challenge is that the shipping flows of a city are endogenous. Our main worry is reverse causality: fast growing cities will witness increases in their shipping flows. Our solution is to isolate exogenous variation in shipping using a city's suitability for containerization based on its natural depth. We control for initial population levels to account for population convergence.

Table 2 contains the baseline regression results. Both the estimated OLS and 2SLS coefficients on shipping are small and statistically indistinguishable from zero (OLS coefficient 0.013, s.e. 0.009; 2SLS coefficient 0.006, s.e. 0.073). To assess magnitudes, we report the standardized 'beta' coefficients for our effects of interest in italics underneath the estimated regression coefficients. A one standard deviation increase in the growth of shipping flows between 1950 and 1990 leads to a 0.02 standard deviation increase in population growth over the same time horizon based on the 2SLS estimate. Columns (3) and (4) show the first stage and reduced form, respectively. These help illuminate what drives the small and insignificant effect. While the first stage coefficient is highly significant and the Kleibergen-Paap F-statistic is reasonable (9.98), there is no reduced form relationship between depth and population (the reduced form coefficient is 0.002, s.e. 0.020).

Table E.4 shows the panel specification allowing us to utilize the full decadal variation in the data.[13] Two important points emerge. First, the results are very similar to the long-differenced specification. The 2SLS coefficient remains small in magnitude and statistically indistinguishable from zero. The first stage is strong (the Kleibergen-Paap F-statistic is 21.13), and the reduced form is small and statistically insignificant. Second, column (5) shows the full time path of effects for the reduced form. These make clear that the statistically insignificant coefficient in the 2SLS estimate does not stem from the fact that population is sluggish to adjust. The time path of the coefficients shows no discernible trend, and there is no clear difference in population growth post-containerization for deeper ports. All of the coefficients are estimated to be very close to zero (the one 'furthest' away from zero is 0.007), the coefficients are never close to statistical significance, and in two of the five decades, the estimated effect is negative, suggesting that, if anything, deeper ports were growing at a slower rate than shallower ones some of the time.

These results are in contrast to Brooks et al. (2021) who find a positive effect of containerization on county population growth in the United States. A direct comparison is not possible as our sample only contains 40 U.S. cities and the 2SLS estimate on this subsample yields a Kleibergen-

[13] The specification is $\ln(Pop_{it}) = \beta * \ln(Ship_{it}) + \sum_{j=1960}^{1990} \phi_j * \ln(Pop_{i,1950}) * \mathbb{1}(Year = j) + \alpha_i + \delta_t + \epsilon_{it}$, where $\ln(Pop_{it})$ is the natural logarithm of population in city i at time t, and all other variables are as previously defined.

Paap F-statistic below 1. However, dropping North America leads to a negative (though statistically insignificant) point estimate (Figure F.3), suggesting that North American cities may have had a larger than average population response to containerization.

We subject the 2SLS panel specification to the same set of robustness checks conducted above (Table E.5 and Appendix B.3). The coefficient is consistently small and indistinguishable from zero. In summary, these results show that we cannot reject that the effect of increased port activity on population was zero. Given that increased trade through a city tends to increase population through the standard market access effect (Donaldson and Hornbeck, 2016; Redding and Turner, 2015), this finding suggests a role for countervailing force. One potential channel may be the one working through the increased land-intensity of containerized ports. The results from Stylized fact 2 suggest these are empirically relevant and large enough to affect the economic geography of ports. In the next section, we build a model that incorporates this mechanism, thereby capturing both the benefits and the costs of port development.

5 A model of cities and endogenous port development

In this section, we present a flexible general equilibrium model that is consistent with the three stylized facts and allows us to estimate the aggregate and distributional effects of port development. The model captures the standard positive effects from market access, but also allows for two types of negative effects: the increased land use and the negative amenity externalities associated with port development.

5.1 Setup

The world consists of $S > 0$ cities, indexed by r or s. An exogenously given subset of cities are port cities, while the rest are non-port cities. We make the Armington assumption that each city produces one variety of a differentiated final good that we also index by r or s (Anderson, 1979). Each city belongs to one country, and each country is inhabited by an exogenous mass of workers who choose the city in which they want to live. We do not allow for mobility across countries but allow for mobility across cities within a country, subject to frictions.

5.1.1 Workers

Each worker owns one unit of labor that she supplies in her city of residence. The utility of a worker j who chooses to live in city r is given by

$$u_j(r) = \left[\sum_{s=1}^{S} q_j(r,s)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} a(r)\, b_j(r) \tag{4}$$

where $q_j(r,s)$ is the worker's consumption of the good made in city s, $a(r)$ is the level of amenities in city r, and $b_j(r)$ is an idiosyncratic city taste shifter. $\sigma > 1$ is the elasticity of substitution across goods.

The dispersion of $b_j(r)$ represents the severity of cross-city mobility frictions that workers face, similar to Kennan and Walker (2011) and Monte, Redding, and Rossi-Hansberg (2018). For tractability, we assume that $b_j(r)$ is drawn from a Fréchet distribution with shape parameter $1/\eta$ and a scale parameter normalized to one. Hence, a larger value of η corresponds to more severe frictions to mobility.

We also capture the fact that port activity might induce disamenities such as noise and pollution. In particular, we assume

$$a(r) = \bar{a}(r)\left[1 + Shipping(r)\right]^{-\rho} \tag{5}$$

where $\bar{a}(r)$ is the city's fundamental, exogenous amenity level, $Shipping(r)$ is the total amount of shipping flowing through the port of city r, and $\rho > 0$. In non-port cities, by definition, $Shipping(r) = 0$, implying $a(r) = \bar{a}(r)$. In port cities, fundamental amenities $\bar{a}(r)$ are lowered by the term $[1 + Shipping(r)]^{-\rho}$, implying that a larger volume of shipping is associated with more disamenities. The extent to which this is the case is disciplined by the value of parameter ρ.

5.1.2 Landlords

Each city r is also inhabited by a positive mass of immobile landlords who own the exogenously given stock of land available in the city.[14] We normalize the stock of land available in each city to one.[15] Landlords have the same preferences over goods as workers. They do not work but finance their consumption from the revenues they collect from their stock of land.

Each landlord is small relative to the total mass of landlords in the city and hence thinks that she cannot influence prices. Yet the mass of landlords is small enough that the population of each city can be approximated well with the mass of workers who choose to reside in the city.

In non-port cities, landlords rent out their land to firms that produce the city-specific good. In port cities, landlords allocate their land between what they rent out to firms for production and what they use for transshipment services at the port. The more land they use for transshipment services, the more the cost of transshipping a unit of a good decreases. At the same time, more land for

[14]The assumption about the elasticity of land supply merits further discussion. A perfectly elastic land supply would not yield a land use cost of port development as cities would respond to containerization by expanding their stock of land. As we find empirical evidence in support of sizeable local costs from containerization (Section 4), we need to move away from the case of perfectly elastic land supply. To retain the tractability of the model, we assume that land supply is perfectly inelastic and leave the case of imperfectly elastic supply for future research.

[15]We could allow the stock of available land to vary across cities. This more general setup is isomorphic to our current model, except that, instead of productivity in the city-specific good sector, a combination of the stock of land and productivity enters the model's equilibrium conditions. In other words, the city productivity levels we identify from our current model reflect not only productivity per se, but also the stock of available land. This fact, however, does not affect our quantitative results as we keep productivity levels fixed in our model simulations.

transshipment necessarily implies less land available for production. In other words, the model implies a resource cost of land use that can influence the spatial allocation of port development across port cities, consistent with Stylized fact 2.

Port city landlords can charge a price for the transshipment service they provide. Competition among landlords drives down this price to marginal cost. Hence, profits from transshipment services are zero in equilibrium.[16]

5.1.3 Production

Firms can freely enter the production of the city-specific good. Hence, they take all prices as given and make zero profits. Production requires labor and land. The representative firm operating in city r faces the production function

$$q(r) = \tilde{A}(r)\, n(r)^{\gamma} (1 - F(r))^{1-\gamma}$$

where $q(r)$ denotes the firm's output, $\tilde{A}(r)$ is total factor productivity in the city, $n(r)$ is the amount of labor employed by the firm, and $F(r)$ is the share of land that landlords in the city allocate to transshipment services (thus, $F(r) = 0$ in non-port cities). Hence, $1 - F(r)$ is the remainder of land that landlords rent out to firms for production, and γ and $1 - \gamma$ correspond to the expenditure shares on labor and land, respectively.

We incorporate agglomeration economies by allowing total factor productivity to depend on the population of the city, $N(r)$:

$$\tilde{A}(r) = A(r)\, N(r)^{\alpha}$$

where $A(r)$ is the exogenous fundamental productivity of the city, and $\alpha \in [0, 1-\gamma]$ is a parameter that captures the strength of agglomeration economies.[17] The representative firm does not internalize the effect that its employment decision has on local population. Hence, it takes $N(r)$ as given.

5.1.4 Shipping and port development

Firms in city r can ship their product to any destination $s \in S$. Shipping is, however, subject to iceberg costs: if a firm i from city r wants to ship its product over a route $\bar{\rho}$ that connects r with s, then it needs to ship $T(\bar{\rho}, i)$ units of the product such that one unit arrives at s. Shipping

[16] In Section 7.1, we show that the effects of containerization remain similar in an alternative framework in which landlords have market power and thus can make profits. We provide a detailed description of this alternative framework in Appendix C.7.

[17] We make the assumption $\alpha \leq 1 - \gamma$ to guarantee that agglomeration forces are not overwhelmingly strong in the model. Estimates of the land share, $1 - \gamma$, tend to be substantially above estimates of agglomeration externalities α. In particular, our calibration involves setting α to 0.06 (a standard value used in the literature) and $1 - \gamma$ to 0.16 based on Desmet and Rappaport (2017).

costs consist of a component common across firms $\bar{T}(\bar{\rho})$, as well as a firm-specific idiosyncratic component $\epsilon(\bar{\rho}, i)$ that is distributed i.i.d. across firms and shipping routes:[18]

$$T(\bar{\rho}, i) = \bar{T}(\bar{\rho})\,\epsilon(\bar{\rho}, i)$$

For tractability, we assume that $\epsilon(\bar{\rho}, i)$ is drawn from a Weibull distribution with shape parameter θ and a scale parameter normalized to one. Firms only learn the realizations of their idiosyncratic cost shifters after making their production decisions. Therefore, they make these decisions based on the expected value of shipping costs,

$$\mathbf{E}[T(\bar{\rho}, i)] = \bar{T}(\bar{\rho})\,\mathbf{E}[\epsilon(\bar{\rho}, i)] = \bar{T}(\bar{\rho})\,\Gamma\left(\frac{\theta+1}{\theta}\right).$$

After learning $\epsilon(\bar{\rho}, i)$, they choose the route that minimizes their total shipping costs.

Certain shipping routes involve land shipping only (*land-only*), while others involve a combination of land and sea shipping through a set of ports (*land-and-sea*). Land-only shipping is only available between cities that are directly connected by land. The common cost of land-only shipping between cities r and s is an increasing function of the minimum overland distance between the two cities, $d(r, s)$:

$$\bar{T}(\bar{\rho}) = 1 + \phi_{\varsigma}(d(r, s))$$

The cost of land-and-sea shipping depends on the set of ports en route. In particular, the common cost of shipping from r to s through port cities $p_0, ..., p_M$ takes the form

$$\bar{T}(\bar{\rho}) = [1 + \phi_{\varsigma}(d(r, p_0))]\,[1 + \phi_{\varsigma}(d(p_M, s))] \prod_{m=0}^{M-1} [1 + \phi_{\tau}(d(p_m, p_{m+1}))] \prod_{m=0}^{M} [1 + O(p_m)]$$

where $\phi_{\varsigma}(d(r, p_0))$ corresponds to the overland shipping cost between the origin and the first port en route p_0, and $\phi_{\varsigma}(d(p_M, s))$ corresponds to the overland shipping cost between the last port en route p_M and the destination. $\phi_{\tau}(d(p_m, p_{m+1}))$ denotes the sea shipping cost between ports p_m and p_{m+1}, a function of the minimum sea distance between the two ports, $d(p_m, p_{m+1})$. Finally, $O(p_m)$ denotes the price that the firm needs to pay for transshipment services in port city p_m.[19]

Transshipment costs are central to our analysis as these are the costs that port city landlords

[18] The assumption of idiosyncratic shipping cost shifters follows Allen and Atkin (2022) and Allen and Arkolakis (2019), and allows us to tractably characterize shipping flows with a large number of cities. In the alternative case with no idiosyncratic shifters, applied in Allen and Arkolakis (2014) and Nagy (2022), finding optimal shipping flows is computationally more demanding.

[19] Note that this formulation does not allow for land shipping between two subsequent ports along the route. In practice, this is extremely unlikely to arise as land shipping is substantially more expensive than sea shipping.

can lower through *port development*, that is, through allocating more land to the port. In particular, we assume that the landlord's cost of handling one unit of a good at port p_m equals

$$[\nu(p_m) + \psi(F(p_m))]\, Shipping(p_m)^{\lambda}$$

where $\nu(p_m)$ is an exogenous cost shifter capturing the fundamental efficiency of port p_m, $\psi(F(p_m))$ is a non-negative, strictly decreasing and strictly convex function of $F(p_m)$, the share of land allocated to the port, and $Shipping(p_m)^{\lambda}$ captures congestion externalities arising from the fact that handling one unit of cargo becomes more costly as the total amount of shipping, $Shipping(p_m)$, increases for a given port size.[20] As each port city landlord is atomistic, she takes the price of transshipment services $O(p_m)$ and the total port-level shipping $Shipping(p_m)$ as given when choosing $F(p_m)$. Moreover, perfect competition among port city landlords ensures that the price of transshipment services is driven down to marginal cost and therefore

$$O(p_m) = [\nu(p_m) + \psi(F(p_m))]\, Shipping(p_m)^{\lambda} \tag{6}$$

in equilibrium.

One concern is that, according to our formulation, land is required for transshipment services while labor is not. In reality, ports employ labor. To address this concern, Appendix C.6 presents an extension of our model in which a combination of land and labor must be employed in transshipment. This appendix also shows that the model with transshipment labor, although more complex in its structure, delivers qualitative predictions that are extremely similar to the predictions of our baseline model.

5.1.5 Equilibrium

In equilibrium, workers choose their consumption of goods and residence to maximize their utility, taking prices and wages as given. Landlords choose their consumption and land use to maximize their utility, taking prices, land rents and shipping flows as given. Firms choose their production of goods, employment and land use to maximize their profits, taking prices, land rents and wages as given. Competition drives profits from production and profits from transshipment services down to zero. Markets for goods, land and labor clear in each city, and markets for transshipment services clear in each port city. Appendix C.1 provides a formal definition and characterization of the equilibrium.

[20] To be precise, $Shipping(p_m)$ is defined as the dollar amount of shipping flowing through port p_m, excluding the price of transshipment services at p_m. We exclude the price of transshipment services from the definition of $Shipping(p_m)$ as it simplifies the procedure of taking the model to the data.

5.2 City populations in the model

What determines the population of cities in equilibrium? The model delivers the following structural equation for the equilibrium population of city r, $N(r)$:

$$N(r)^{[1+\eta\sigma+(1-\gamma-\alpha)(\sigma-1)]\frac{\sigma-1}{2\sigma-1}} = \gamma^{\sigma-1}\tilde{a}(r)^{\frac{\sigma(\sigma-1)}{2\sigma-1}} A(r)^{\frac{(\sigma-1)^2}{2\sigma-1}} (1-F(r))^{(1-\gamma)\frac{(\sigma-1)^2}{2\sigma-1}} MA(r) \quad (7)$$

where $MA(r)$ is the *market access* of city r, given by

$$MA(r) = \sum_{s=1}^{S} \frac{\tilde{a}(s)^{\frac{(\sigma-1)^2}{2\sigma-1}} A(s)^{\frac{\sigma(\sigma-1)}{2\sigma-1}} (1-F(s))^{(1-\gamma)\frac{\sigma(\sigma-1)}{2\sigma-1}} N(s)^{[1-\eta(\sigma-1)-(1-\gamma-\alpha)\sigma]\frac{\sigma-1}{2\sigma-1}}}{\mathbf{E}[T(r,s)]^{\sigma-1}} \quad (8)$$

and $\tilde{a}(r)$ can be obtained by scaling amenities $a(r)$ according to

$$\tilde{a}(r) = \aleph_c a(r)$$

where the endogenous country-specific scaling factor $\aleph_c$ adjusts such that the exogenously given population of country c equals the sum of the populations of its cities.

Equation (7) implies that the population of city r is increasing in four objects: (1) re-scaled city amenities $\tilde{a}(r)$; (2) fundamental city productivity $A(r)$; (3) the share of land allocated to production, $1-F(r)$; (4) and the city's market access, $MA(r)$.

How is the population of a port city affected by the development of its port? The following proposition shows that the net effect on population is the outcome of three opposing forces: the *market access effect* that increases the population of the city, and the *land use* and *disamenity effects* that lead to a decrease in the city's population.

Proposition 1. *An increase in the share of land allocated to the port in city r, $F(r)$, decreases shipping costs $\mathbf{E}[T(r,s)]$, thus increasing $MA(r)$. Everything else fixed, an increase in $MA(r)$ increases the population of the city (market access effect). Holding $MA(r)$ fixed, an increase in $F(r)$ decreases the share of land that can be used for production, $1-F(r)$, thus decreasing the population of the city (land use effect). Finally, an increase in $F(r)$ increases shipping flows, thus lowering amenities $\tilde{a}(r)$ and, everything else fixed, city population (disamenity effect).*

Proof. These results follow directly from equation (7). □

Proposition 1 sheds light on the fact that, to measure the net effect of port development, it is essential to consider both its benefits and its costs. On the one hand, port development lowers shipping costs. On the other hand, it requires scarce local land that needs to be reallocated from other productive uses, while also making the city a less desirable place to live. The presence of these opposing forces makes the model consistent with Stylized fact 3, that is, the fact that port cities' population remained constant in the data, despite the port development induced by containerization.

6 Taking the model to the data

Taking the model to the data consists of three steps. First, we calculate inland and sea shipping costs across cities and choose a functional form for endogenous transshipment costs. Second, we choose the values of the model's seven structural parameters. Finally, we back out the values of unobserved city fundamentals that rationalize the post-containerization data.

6.1 Calculating shipping costs

To calculate the shipping costs across all potential routes, we need to specify each possible component: i) the cost of shipping overland; ii) the cost of sea shipping; and iii) the cost of transshipment at seaports. Following Allen and Arkolakis (2014), we assume that overland shipping costs ϕ_ς and sea shipping costs ϕ_τ take the form

$$\phi_\varsigma(d) = e^{t_\varsigma d} \qquad\qquad \phi_\tau(d) = e^{t_\tau d}$$

where d is (point-to-point) distance traveled. We take the values of t_ς and t_τ from the road and sea shipping cost elasticities estimated by Allen and Arkolakis (2014).

Next, we specify endogenous transshipment costs as a function of the share of land allocated to transshipment services (*port share*, F), $\psi(F)$. Our goal is to keep the functional form of ψ numerically tractable and to satisfy our theoretical restrictions. One simple function that satisfies both is

$$\psi'(F) = 1 - F^{-\beta} \tag{9}$$

where we restrict $\beta > 0$ to guarantee $\psi' < 0$.

Given that β drives the relationship between the value of shipping flows and the port share (see equation C.5 in Appendix C.2), we calibrate it to match the correlation between these two variables in the data. Under higher values of β, the endogenous port development mechanism plays a stronger role in the model. Hence, everything else fixed, landlords have an incentive to increase the port share further if β is high. Thus, we expect a stronger correlation between shipping and port share under higher values of β. This is precisely what we find. Figure F.4 plots the values of the correlation for a range of β between 0.020 and 0.046. Within this range, $\beta = 0.031$ is the one that implies the correlation found in the data, 0.474 (see Appendix D.5 for details).

Finally, we capture the additional costs of cross-country trade, such as tariffs, quotas and red-tape barriers, by multiplying the overall shipping cost between any two cities that are not in the same country by a constant $B > 1$. We choose the value of B such that the model replicates the ratio of international trade to world GDP in 1990. This procedure yields $B = 2.1$.

6.2 Choosing the values of structural parameters

On the production side, we take the estimate of the strength of agglomeration externalities, $\alpha = 0.06$, from Ciccone and Hall (1996). The expenditure shares on labor and land equal γ and $1-\gamma$, respectively. We base our benchmark value of γ on Desmet and Rappaport (2017), who estimate a value of 0.10 for the difference between the land share and the agglomeration elasticity in the United States between 1960 and 2000, a period that corresponds to our sample period. Given we set $\alpha = 0.06$, this suggests choosing $\gamma = 0.84$. Another advantage of using this land share estimate is that it also accounts for the share of land embedded in housing, which is absent from our model but could matter for the quantitative results.

On the consumption side, we have three structural parameters: the migration elasticity, which we set to $\eta = 0.15$ based on Kennan and Walker (2011); the elasticity of substitution across tradable final goods, which we set to $\sigma = 4$ based on Bernard, Eaton, Jensen, and Kortum (2003); and the elasticity of port city disamenities with respect to shipping, which we set to $\rho = 0.005$ based on the estimated economic cost of pollution for Los Angeles from Marquez and Vallianatos (2012); see section C.9 for details.

Finally, there are two structural parameters that influence the shipping technology. One is the dispersion of idiosyncratic shipping costs, which – together with the functional form of these costs – we take from Allen and Arkolakis (2019), setting $\theta = 203$. Another is the elasticity of transshipment costs to total shipping at the port (congestion externalities), which we take from the empirical estimates of Abe and Wilson (2009), setting $\lambda = 0.074$.

6.3 Recovering post-containerization fundamentals

We use observed data on city populations, shipping flows and city-level GDP per capita together with the structure of the model to find the set of fundamental city amenities $\bar{a}(r)$, productivities $A(r)$ and exogenous transshipment costs $\nu(r)$ that rationalize the data.

As city-level GDP data are only available for 1990, we choose to back out the model fundamentals based on the 1990 distribution of population, shipping and GDP. Hence, the aggregate effect of containerization can be assessed by comparing the counterfactual equilibrium (pre-containerization) to our 1990 equilibrium (post-containerization).

We transform the number of ships observed in the data in port city r in 1990, $Ship(r)$, into the value of shipments, $Shipping(r)$, according to

$$Shipping(r) = V \cdot Ship(r)$$

where we choose V to match the ratio of shipping to world GDP. The rationale behind choosing this particular moment is that it can be calculated as a simple linear function of V:

$$\frac{\sum_r Shipping\,(r)}{\sum_r GDP\,(r)} = V \cdot \frac{\sum_r Ship\,(r)}{\sum_r GDP\,(r)}$$

where $Ship\,(r)$ and $GDP\,(r)$ are both observable in the data. This procedure gives us a value of $V = 364$.[21]

Using city-level GDP data, we can obtain wages as

$$w\,(r) = \gamma \frac{GDP\,(r)}{N\,(r)}$$

according to the model, where the structural parameter γ is calibrated to 0.84.

Once population $N\,(r)$ and wages $w\,(r)$ are available for each city and the value of shipments, $Shipping\,(r)$, is available for each port city, the equilibrium conditions of the model can be inverted to back out city amenities up to a country-level scale, $\tilde{a}\,(r)$, fundamental city productivities $A\,(r)$, and each port city's exogenous transshipment costs $\nu\,(r)$. We provide the details of this inversion procedure in Appendix C.3. The complex structure of the model does not allow us to prove that the inversion procedure identifies a unique set of $\tilde{a}\,(r)\,, A\,(r)$ and $\nu\,(r)$. Nonetheless, we have experimented with various different initial guesses, and the inversion algorithm converges to the same fixed point, suggesting that the vector of city-specific fundamentals that rationalize the data is likely unique.

7 Counterfactuals

We conduct two counterfactuals in the model. The first counterfactual is backward-looking and 'rolls back' containerization. This allows us to estimate the aggregate effects of containerization. The second counterfactual is forward-looking and studies the port development undertaken by the Chinese government as part of their 'Belt and Road Initiative.' This allows us to illustrate the effects of targeted port development policy on targeted and untargeted cities, as well as aggregate welfare. Appendix C.4 discusses how we numerically solve for counterfactual equilibria in the model.

7.1 Rolling back containerization

In our first counterfactual, we compare the post-containerization (1990) equilibrium of the model to a counterfactual equilibrium in which containerization did not arise. When simulating the counterfactual, we account for the technological aspects of containerization in seaports that we document

[21] As not all our port cities have positive shipping flows in 1990 but the model cannot rationalize zero shipping flows under finite positive values of city-specific fundamentals, we change $Ship\,(r)$ from zero to one in these cities.

in Sections 2 and 4.1: lower costs, particularly in deep ports. This requires us to change the values of two model fundamentals relative to the post-containerization equilibrium.

First, we capture the fact that *depth* was not relevant for transshipment prior to containerization. To this end, we offset the relationship between exogenous transshipment costs and depth in the counterfactual. We first run the regression

$$\log \nu(r) = \omega_0 - \omega_1 * Depth(r) + \varepsilon(r)$$

on our sample of port cities, where $\nu(r)$ is the exogenous transshipment cost of city r recovered in Section 6.3, and $Depth(r)$ is the depth measure, defined in Section 4. In line with the fact that depth lowers transshipment costs after containerization, we find $\widehat{\omega_1} = 0.048$ (s.e. 0.025, p-value 0.053). Next, we undo this dependence of exogenous transshipment costs on depth by adding $\widehat{\omega_1} * Depth(r)$ to $\log \nu(r)$.

Second, we incorporate the overall *reduction in transshipment costs* due to containerization by increasing exogenous transshipment costs $\nu(r)$ uniformly across ports. More precisely, we increase $\log \nu(r)$ by the same number ν_{CF} at each port to match the estimated average change in the sum of exogenous *and* endogenous transshipment costs as a result of containerization.

We estimate that containerization reduced transshipment costs 25% by 1990 based on the following procedure. Rodrigue (2016, p. 117) estimates that containerization led to an overall 70% to 85% reduction in maritime transport costs by 2010; "While before containerization maritime transport costs could account for between 5 and 10 percent of the retail price, this share has been reduced to about 1.5 percent, depending on the goods being transported." A reduction from 5% to 1.5% of retail price equals a 70% cost reduction ($= 1 - 1.5/5$); similarly, a reduction from 10% to 1.5% equals an 85% cost reduction. We estimate that 36% of the total cost reduction took place up to 1990, by assuming that cost reductions are proportionate to ship size increases. These calculations are based on data from the *Miramar Ship Index* (Haworth, 2020); see Appendix D.11 for details. Using the more conservative estimate of 70%, this gives us a 25% decrease in average transshipment costs. Naturally, higher values of ν_{CF} yield a larger change in transshipment costs, suggesting that there should be a unique ν_{CF} at which we meet our 25% target. This procedure identifies $\nu_{CF} = 0.227$.

Note that, in our counterfactual, we focus on estimating the effects containerization had by reducing transshipment costs at seaports. In reality, containerization had broader effects on transport costs. Most importantly, it arguably also reduced overland transport costs as intermodal transshipping between trucks and railways became cheaper. To address this, Appendix C.8 investigates how adding an additional inland cost increase to our counterfactual simulation changes the results.

The aggregate effects of containerization. We estimate that aggregate world welfare increased by

3.38% as a result of containerization. We define the change in aggregate world welfare as the average of changes in country-level welfare between the counterfactual and the 1990 equilibrium, weighted by country population. Within each country, labor mobility equalizes welfare across cities, as in Redding (2016). However, we do not allow for mobility across countries, hence different countries experience different welfare effects.

Consistent with Stylized fact 1, we find that containerization led to a boom in shipping flows. More precisely, containerization increased the international trade to world GDP ratio by 4.2 percentage points from the counterfactual to the 1990 equilibrium. As a reference point, the trade to world GDP ratio increased by 15 percentage points between 1960 and 1990. This suggests that containerization was responsible for about *one quarter* of the overall increase in trade to world GDP during these three decades.

The fraction of land occupied by ports (i.e., the port share) increases in most port cities from the counterfactual to the 1990 equilibrium. Port shares become larger since the reduction in trade costs leads to increased demand for shipping, encouraging more investment in port development. Figure F.5 presents the full distribution of port share changes across cities. The median change is 2 percentage points, while the 5th percentile is -2 pp and the 95th percentile is 34 pp.

How large was the cost of increased land use due to containerization? To answer this question, we conduct a decomposition that exploits the fact that the welfare gains from containerization stem from a combination of three factors in the model. First, containerization lowers shipping costs, thus increasing welfare. Second, containerization increases port city land use, which we label the *resource costs* of containerization. Finally, containerization might yield gains from increased specialization of cities in port or non-port activities, which we label as the *specialization gains* from containerization.

To assess the quantitative importance of each of these margins, we develop two alternative models that we label as 'Benchmark 1' and 'Benchmark 2.' In 'Benchmark 1,' port development yields transshipment cost reductions but does not require land use. In 'Benchmark 2,' land needs to be used to reduce transshipment costs, but we restrict land use to be identical across port cities (and equal to the mean port share in our baseline). We provide a detailed description of each benchmark model and their quantitative estimation in Appendix C.5.

As Benchmark 2 only differs from Benchmark 1 in land being used for port activities, a comparison between these two models reveals the resource costs of increased land use due to containerization. As our baseline model only differs from Benchmark 2 in the potential specialization of port cities in port or non-port activities (through each city choosing the allocation of land between the two), a comparison between these two models reveals the endogenous specialization gains from containerization.

We find that containerization leads to welfare gains of 3.54% in Benchmark 1. In Benchmark

2, the gains from containerization reduce to 3.26%. The difference between Benchmark 1 and Benchmark 2, 0.28 percentage points, captures the resource costs of containerization. These costs are sizeable: they account for as much as 8% of the gains from the shipping cost reduction. Finally, the difference between Benchmark 2 and our baseline model, 0.12 percentage points, captures the specialization gains from containerization. Note that these gains are able to offset about 44% of the resource costs of containerization, but they do not fully compensate for all the costs.

In Appendix C.8, we show that the aggregate effects of containerization implied by the model are robust to different values of the containerization shock and some alternative modeling choices. These alternative specifications include different values of transshipment cost shape parameter β, different changes in exogenous transshipment costs, and a model in which landlords make profits from the provision of transshipment services.

7.2 The effects of targeted port development

In our second counterfactual, we study a large-scale port development policy similar to the Chinese government's Maritime Silk Road project, which is part of the 'Belt and Road Initiative.' The simulation we conduct is *similar* to the Maritime Silk Road project, as we analyze effects relative to the 1990 equilibrium, not today. Moreover, the absence of specific details on the size of the actual investments precludes us from matching exactly what the project entails. In particular, we study the effects of a 10% reduction in exogenous transshipment costs in 24 port cities in Asia, Africa and Europe targeted by Chinese investment (see Figure F.6 for the set of targeted ports).We take the targeted ports from OECD (2018) and choose the decrease in exogenous transshipment costs, $\nu(r)$, to be 10% to illustrate the effects of a sizeable, but not dramatic decrease in costs. We keep all other fundamentals of the model fixed at their levels recovered in Section 6.

Table 4 examines the effects of this policy on treated and untreated port cities, and inland cities. We compare the effects generated by our model ('Baseline') to those of a more standard model ('Benchmark 1' – introduced in Section 7.1).

Targeted port cities see a significant and large increase in shipping activities, primarily at the expense of non-targeted port cities in the same country (column 1). This local reallocation of shipping is more pronounced in the baseline model than in Benchmark 1 (column 5). To see why this is the case, in columns (2) and (6) we examine the effect on port costs (the sum of exogenous and endogenous transshipment costs, $\nu(r) + \psi(F(r))$). In Benchmark 1, endogenous transshipment costs are absent, implying that targeted port cities see an exact 10% (0.105 log point) decline in their transshipment costs, while non-targeted cities see no effect. By contrast, in the baseline model, the direct effect of the policy is amplified by an endogenous reallocation of land within the city. This results in a decline in endogenous transshipment costs in targeted ports (where more land is allocated to the port) and an increase in endogenous transshipment costs in non-targeted ports (where less land is allocated to the port). This endogenous response to the policy leads to increasing returns from port development, drawing additional shipping into targeted cities and away from non-targeted ones. Table E.10 shows the results remain similar if we include country fixed effects.

We also study the effects on cities' market access (as defined by equation 8) and population across both models. The effect on market access is similar in both simulations. In terms of population responses, however, the similar improvement in market access results in strikingly different population responses – highlighting the local costs of port development at work in our model. In the baseline (column 4), endogenous port development in targeted port cities moves people out of the city through increased land use and disamenities, primarily to non-targeted port cities. In contrast, in Benchmark 1 (column 8), targeted ports gain population.

We examine how targeted port development redistributes shipping and real GDP across regions of the world in Figure 2. We find the most dramatic distributional effects in Asia. Strikingly, we see a dramatic reallocation of shipping to China and away from Singapore (which we estimate loses almost 50% of its shipping flows).[22] Neither countries have targeted ports in this simulation. While these effects are also present in the benchmark model, they are far more muted.

In our model, the initial reallocation of shipping is amplified by increasing returns to port development. As shipping moves away from Singapore towards targeted ports, incentives to develop the port of Singapore decrease, which ultimately leads the city to cut back substantially on its port activities by reallocating land away from the port. However, Singapore sees a more than 1% gain in real GDP in our baseline model, as the city's declining port frees up land that can be used profitably outside the shipping sector. This is particularly true in the case of Singapore, where the non-port sector is very productive (at the 98th percentile of the world productivity distribution according to our model). Of course, the economic benefits from dismantling a port may be not the only factor considered by decision-makers in reality: governments' objective functions may include geopolitical advantages from maintaining a central position in the global shipping network. In our analysis, we focus on the economic effects and do not consider these additional factors. As the example of Singapore illustrates, endogenous port development has the potential to substantially amplify changes in shipping and real GDP in our baseline model relative to a standard trade model such as Benchmark 1.

8 Conclusion

The containerization shock studied in this paper allows us to shed light on the economic effects of port development. Our findings suggest that the land-intensive nature of port development is an empirically strong force that matters for the local, aggregate and distributional effects of port de-

[22]It should be noted, however, that China's percentage change in shipping does not correspond to a dramatic absolute change, as China had relatively little shipping back in 1990.

velopment. Recent disruptions to supply chains due to the COVID-19 pandemic have highlighted some of the consequences of these forces. The containers flowing out of the port of Long Beach in 2022 due to a lack of storage space suggest that many ports operate with very little slack capacity, limiting their ability to adjust to shocks. Our analysis suggests that the scarcity of land around many of the world's major ports is an important driving force. In light of this, our findings raise the question of whether ports today are located optimally. Should highly productive cities such as Los Angeles or Singapore continue to specialize heavily in port activities? We leave the exploration of this normative question for future research.

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A Tables

Table 1: Depth predicts shipping flows, but only after 1960 (Stylized fact 1)

	Dependent variable: ln(Ship)				
Independent variables	(1)	(2)	(3)	(4)	(5)
Depth × post 1970					0.247*** *0.131**** (0.059)
Depth × 1960	-0.051 (0.063)	0.029 (0.069)	0.050 (0.066)	-0.055 (0.068)	
Depth × 1970	0.222*** (0.069)	0.233*** (0.077)	0.278*** (0.082)	0.213*** (0.071)	
Depth × 1980	0.188** (0.079)	0.212** (0.085)	0.291*** (0.090)	0.192** (0.081)	
Depth × 1990	0.255*** (0.086)	0.222** (0.087)	0.312*** (0.099)	0.283*** (0.087)	
Observations	2765	2765	2765	2360	2765
R-squared	0.126	0.248	0.131	0.142	0.126
Number of cities	553	553	553	472	553
Year FE	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓
Population 1950 × Year	✓	✓	✓	✓	✓
Coastline × Year FE	×	✓	×	×	×
Land scarcity × Year	×	×	✓	×	×
GDP pc (country) × Year	×	×	×	✓	×

Notes: 'Depth' indicates the port suitability measure. It is interacted with decade dummies or an indicator variable for decades including and after 1970, as indicated. Standardized coefficient in italics underneath the baseline coefficient. Standard errors clustered at the city level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: The local causal effect of shipping on population (Stylized fact 3)

	Δln(Pop)	Δln(Pop)	Δ ln(Ship)	Δln(Pop)
Independent variables	(1)	(2)	(3)	(4)
Δln(Ship)	0.013	0.006		
	0.052	*0.022*		
	(0.009)	(0.073)		
Depth			0.272***	0.002
			*0.134****	*0.003*
			(0.086)	(0.020)
Observations	531	531	531	531
Specification	OLS	2SLS	FS	RF
KP F-stat		9.98		

Notes: 'Depth' indicates the port suitability measure. Standardized coefficients in italics underneath the baseline coefficients. All regressions control for population in 1950. Column (2) uses depth as IV for shipping. Notation for specification as follows: 'FS' refers to the first stage, 'RF' to the reduced form. Standard errors clustered at the city level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Taking the model to the data – summary

Parameter	Description	Target
Step 1: Calculating shipping costs		
t_{ς} = 0.5636	Overland cost elasticity w.r.t. distance	Allen and Arkolakis (2014)
t_{τ} = 0.0779	Sea cost elasticity w.r.t. distance	Allen and Arkolakis (2014)
β = 0.031	Endogenous transshipment cost parameter	Correlation between shipping flows and port share in 1990
B = 2.1	Border trade cost	Ratio of international trade to world GDP in 1990
Step 2: Choosing the values of structural parameters		
α = 0.06	Agglomeration externalities	Ciccone and Hall (1996)
γ = 0.84	Non-land share in production	Desmet and Rappaport (2017)
η = 0.15	Migration elasticity	Kennan and Walker (2011)
σ = 4	Elasticity of substitution across tradables	Bernard et al. (2003)
ρ = 0.005	Disamenities	Port disamenities in Los Angeles (see Appendix C.9)
θ = 203	Idiosyncratic shipping cost dispersion	Allen and Arkolakis (2019)
λ = 0.074	Congestion externalities in ports	Abe and Wilson (2009)
Step 3: Recovering post-containerization fundamentals		
$\bar{a}(r)$	Fundamental city amenities	Population, GDP and shipping by city in 1990
$A(r)$	Fundamental city productivity	
$\nu(r)$	Exogenous transshipment costs	

Table 4: The effects of targeted port development: The Maritime Silk Road

	Baseline				Benchmark 1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ ln(Ship)	Δ ln(Port cost)	Δ ln(Market access)	Δ ln(Population)	Δ ln(Ship)	Δ ln(Port cost)	Δ ln(Market access)	Δ ln(Population)
Treated port city	0.78637***	-0.14993***	0.02936***	-0.02210***	0.60754***	-0.10536	0.02722***	0.00505**
	(0.12006)	(0.03158)	(0.00558)	(0.00598)	(0.09078)	0	(0.00583)	(0.00241)
Untreated port city in treated country	-0.41470***	0.01513**	0.01348***	0.01097***	-0.29817***	0	0.01526***	-0.00234
	(0.08222)	(0.00705)	(0.00285)	(0.00415)	(0.04999)	0	(0.00283)	(0.00218)
Port city in untreated country	0.01047	-0.00209	0.00076**	-0.00132	0.00292***	0	0.00084***	0.00021***
	(0.01109)	(0.00799)	(0.00031)	(0.00097)	(0.00034)	0	(0.00004)	(0.00003)
Inland city in treated country			0.02072***	0.00227***			0.02019***	-0.00013
			(0.00123)	(0.00066)			(0.00122)	(0.00023)
Inland city in untreated country			0.00041***	0.00004			0.00041***	-0.00003***
			(0.00006)	(0.00003)			(0.00005)	(0.00001)
Observations	553	544	2636	2636	553	553	2636	2636
R-squared	0.192	0.029	0.444	0.033	0.430	1.000	0.465	0.025

Notes: The regressors are dummy variables that divide the cities into 5 mutually exclusive groups as indicated, the regression is estimated without the constant. 'Treated port' indicates the 24 treated ports of the Maritime Silk Road counterfactual. 'Treated country' indicates countries that have at least one treated port. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B Figures

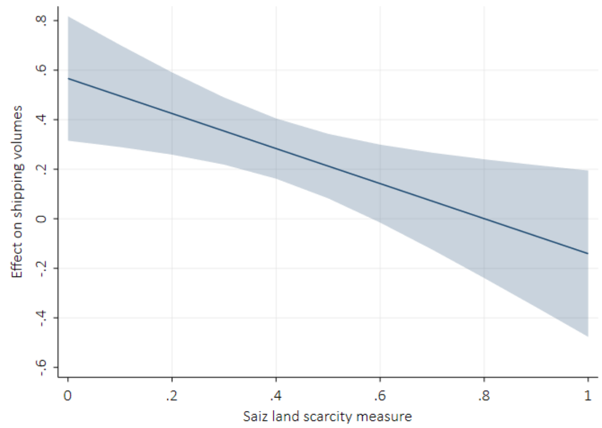
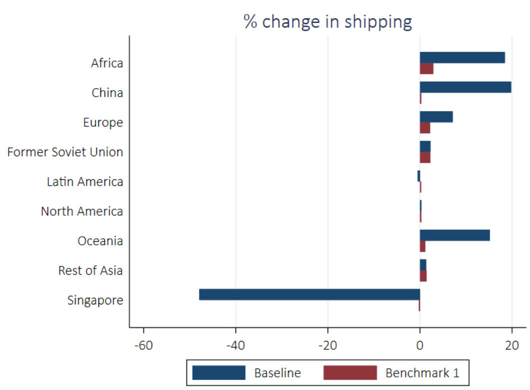
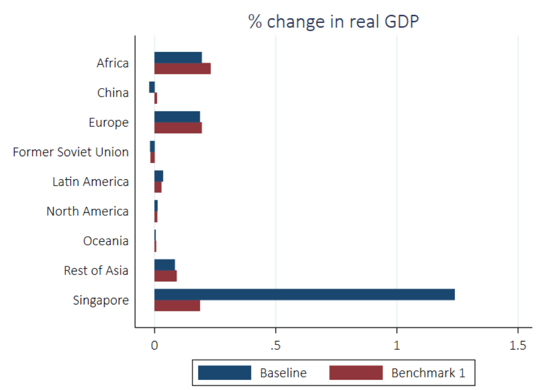


Figure 1: Containerization increased shipping more where land is less scarce (Stylized fact 2)

Notes: This figure shows the estimated γ coefficient from equation (2) evaluated at different values of the Saiz land scarcity measure.



(a) Change in shipping, percent



(b) Change in real GDP, percent

Figure 2: Simulated changes across regions, Maritime Silk Road

Notes: Panel A (B) shows the change in total shipping (total real GDP) of each region between the 1990 equilibrium and the Maritime Silk Road counterfactual. When delineating these regions, we roughly follow the world's continents. An exception is 'Rest of Asia,' which is Asia except China, Singapore, and the former Soviet Union. We treat China separately as we are naturally interested in the effects that this Chinese government policy has on China itself. We treat Singapore separately as we find strikingly large effects on this port city, which we discuss in the text.

Online Appendix

All aboard: The effects of port development

César Ducruet Réka Juhász Dávid Krisztián Nagy Claudia Steinwender

A Historical evidence: The cost-space trade-off in port development

Adapting ports to containerized technology required a substantial increase in the space devoted to the port. The faster turnaround times which reduced transshipment costs could only be achieved by building much larger terminals. This space-cost trade-off was not a novel aspect of containerization. Prior developments in port technology followed a similar pattern. To understand the land-intensity of containerization, it is helpful to review the factors that drive this trade-off in more detail.

Historically, breakbulk ports had used narrow "finger-piers" which made it possible for many ships to dock at the port simultaneously. With slow loading and unloading times, ports needed to be able to accommodate many ships at the same time.

Even before containerization, small continuous technological improvements such as the use of cranes, lift machines, tractors, trailers and belts led to a decrease in loading and unloading times (Port of New Orleans, 1951, p. 22). These improvements highlighted an important trade-off between space and speed. If cargo was unloaded faster, it piled up at the wharf. Increases in turnaround times could only be realized by allocating more space at the pier. As a result, modernizing ports were developing new wharf designs to realize the gains from increased turnaround times. For example, the New York Port Authority invested in reconstructing piers at its Hoboken, Brooklyn and Newark terminals with much wider piers allowing for more efficient turnaround times. In 1955, the Port Authority describes the most modern wharf designs as follows; "large cargo terminals on one level, adjacent to shipping berths, [that] increase efficiency of freight handling, speed up ship turnaround, and permit prompt loading and discharge of trucks. *The resulting savings more than compensate for the added costs of space*" (1955, own emphasis, p.5). At the Hoboken piers, operations became 25% more efficient following the reconstruction of piers into the wider format (New York Port Authority, 1955). Similarly, contemporaries realized the advantages of single-storey warehouses over multi-storey warehouses for faster access to stored cargo and started developing large "upland areas" – that is, areas away from the terminal to make transshipment more efficient (New York Port Authority, 1955, p.7).

Following the logic above, containerized terminals need more space as it is the easy accessibility of the containers that allows for efficient on- and off-loading. The containers are lined up next to where the ships dock, and space is also needed to rapidly off-load cargo. There are additional dedicated 'upland areas' near the facility that allow for the containers to be temporarily stored

(New York Port Authority, 1958, p.5) and new space needed to be made for large 'railyards' where containers could await transshipment onto rail carriages (Riffenburgh, 2012, pp. xi-xii).[1]

The increased space requirements of containerized facilities were evident from the earliest days of the new technology. Before containerization, there were some smaller innovations in handling breakbulk cargo such as palletization (whereby goods are placed on a pallet and handled as a unit) and pre-slinging (whereby goods are grouped together using slings and the unit is handled together).[2] These new processes also allowed cargo to be handled as a unit, saving some transshipment time, though importantly, *not* in a standardized way (given the different-sized cargo involved).

However, these pre-containerization changes were minor compared to the effect of containerization. As early as 1958 (two years after the first containerized shipments had sailed from New York), the New York Port Authority put in place plans to develop the Elizabeth facility for containerized cargo handling; "Extensive supporting upland area is one of the most important features of the development, since these large open spaces are indispensable in the handling of general cargo in the age of container ships" (1958, p. 5). The Port of San Francisco (the fifth largest port in the U.S. in 1950 according to our data) was lamenting the inadequacy of the city's finger piers to accommodate new types of cargo handling; "The Port [should] commence the phasing out of finger piers. [The piers are] commercially obsolete for the new generation of ships and the new types of cargo handling technology" (Port of San Francisco, 1971, p. 27).

B Empirical appendix

This section discusses additional details and results complementing our analysis in Section 4.

B.1 Operationalizing the main variables of interest

The outcome variable of interest, $\ln(Ship_{it})$, is the log of shipping flows observed in city i at time t. We need to take a stand on the treatment of zeros in the shipping data. In the baseline measure, we annualize the weekly counts of ships from the raw data by multiplying the one-week sample of shipping flows we observe by 52. This is primarily so that our results are consistent with the quantitative estimation of the model (Section 6). Finally, we replace the zeros in the data with ones and take the natural logarithm of this adjusted annualized count. Below (Section B.3), we also show that the results are robust to different ways of dealing with zeros.

Our measure of naturally endowed depth also contains zeros, as there are ports with no cells deeper than 30 feet in the 3-5 km buffer around the port. For this reason, in practice, we use

[1] Of course, warehouses and transit sheds were replaced to a large extent as containerization was rolled out. However, the space requirements of the two are not the same, as warehouses and transit sheds tended to be multi-storey.

[2] UNCTAD (1971) gives a more detailed overview of these trends.

$\ln(1 + \sum_i \mathbb{1}(depth_i \geq 30ft))$, where i denotes a cell.

B.2 Does dredging confound our depth measure?

We test the extent to which our measure of depth captures naturally endowed depth. For 100 random ports in our sample, we obtained access to nautical maps from *marinetraffic.com* (Appendix D.12 contains a description of these data). These clearly demarcate the dredged channels that ships use to navigate to the port. We then construct a binary variable, *'Dredging'*, that takes the value of 1 if a port has a dredged channel in the 3-5 km buffer ring. Table E.6 shows the association between this measure and the depth measure. The unconditional association (column 1) is *negative* and statistically significant. That is, ports that we measure to be shallow are more likely to have a dredged channel. This is what we would expect to find if our measure captured naturally endowed depth. Adding continent or coastline fixed effects (columns 2 and 3, respectively) reduces the size of the negative coefficient and we lose statistical significance in column (3), but the estimated coefficients remain negative.

B.3 Further robustness checks

Figure F.3 shows how the coefficient of interest for each of our stylized facts changes as we drop continents one at a time. Overall, the coefficients are stable and no single region appears to be driving the results.

Table E.7 contains further robustness checks for each of the stylized facts. First, we test robustness to different data construction choices. In particular, we examine different ways of treating zero shipping values, different ways of defining the depth measure for the handful of ports that are located far inland from the coastline and restricting the sample to the subset of cities that had already attained 100,000 inhabitants by 1950 to examine sample selection bias. Once again, the results are robust to these checks.

B.4 Does land reclamation affect the Saiz measure of land scarcity?

Our land scarcity measure is constructed using contemporary GIS data, which captures natural geography in combination with investments in reclaiming land from the sea. To investigate the extent to which reclamation may introduce systematic measurement error, we use data from Martín-Antón, Negro, López-Gutiérrez, and Esteban (2016) on coastal land reclamation conducted for any potential purpose (Appendix D.8 contains a discussion of the data). Table E.8 shows that there is somewhat more land reclamation in cities we measure to be land-scarce. This is what we would expect if the land scarcity measure was mostly capturing natural geography. The reason for this seems to be that while land reclamation is fairly common (76 out of 553 ports report *some* land reclamation), it is typically small relative to the area over which the land scarcity measure is constructed; the median size of reclaimed area in the sample for the non-zero observations is 13 square kilometers, which pales in comparison to the 7850 square kilometers covered in the land scarcity measure. One may also expect that land reclamation is easier in shallower ports. However, the estimated relationship between the depth measure and the binary indicator of land reclamation is small and never statistically significant.

C Theory appendix

C.1 Equilibrium of the model

We define the equilibrium of the model as follows.

Definition. *Given structural parameters α, γ, η, σ, ρ, θ, λ, the number of cities S and the subset of port cities $P \subseteq \{1, ..., S\}$, country populations N_c, city amenities $\bar{a} : \{1, ..., S\} \to \mathbb{R}$, productivities $A : \{1, ..., S\} \to \mathbb{R}$, exogenous transshipment costs $\nu : P \to \mathbb{R}$, inland and sea shipping costs as a function of distance $\phi_\varsigma, \phi_\tau : \mathbb{R} \to \mathbb{R}$ and endogenous transshipment costs as a function of port share $\psi : (0, 1) \to \mathbb{R}$, an* ***equilibrium*** *of the model is a set of city populations $N : S \to \mathbb{R}$, nominal wages $w : S \to \mathbb{R}$, land rents $R : S \to \mathbb{R}$, employment levels $n : S \to \mathbb{R}$, port shares $F : S \to [0, 1)$, port-level shipping flows $Shipping : P \to \mathbb{R}$, the prices of transshipment services $O : P \to \mathbb{R}$, the prices of goods $p : S^2 \to \mathbb{R}$ and the quantities of goods $q : S^2 \to \mathbb{R}$ such that*

1. *workers choose their consumption of goods and city of residence within their country to maximize their utility (4), taking prices and wages as given;*

2. *landlords in each city r choose their consumption of goods and land use to maximize their utility*
$$u_L(r) = \left[\sum_{s=1}^{S} q_L(s, r)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{C.1}$$
taking prices, land rents and shipping flows as given;[3]

3. *competition among landlords drives the price of transshipment services down to marginal cost, (6), and landlords' profits from transshipment down to zero;*[4]

4. *firms in each city r choose their production, employment and land use to maximize their profits,*
$$\max_{n(r), 1-F(r)} p(r, r) \tilde{A}(r) n(r)^\gamma (1 - F(r))^{1-\gamma} - w(r) n(r) - R(r)(1 - F(r)) \tag{C.2}$$

[3] We assume that landlords do not enjoy city amenities and do not have idiosyncratic tastes for cities. As landlords are immobile, this assumption does not have any consequence on their optimal choices and is therefore without loss of generality.

[4] We relax this assumption in the monopolistic competition version of the model, presented in Appendix C.7.

taking prices, land rents and wages as given, where $p(r,r)$ is the factory gate price of the good produced by the firm, and choose the shipping route to each destination to maximize their profits;

5. *competition among firms drives their profits down to zero;*

6. *there is no possibility of arbitrage, implying that the price of good r at s equals the expected iceberg cost over the factory gate price,*

$$p(r,s) = p(r,r)\,\mathbf{E}\left[T(r,s)\right]; \tag{C.3}$$

7. *the market for labor clears in each city r, implying $n(r) = N(r)$;*

8. *national labor markets clear, implying $\sum_{r\in c} N(r) = N_c$ in each country c;*

9. *the market for land clears in each city;*

10. *the market for transshipment services clears in each port city;*

11. *the market for each good clears worldwide.*

Note that this equilibrium definition implies that we do not give landlords the right to choose the amount of transshipment they conduct. In other words, landlords cannot refuse the provision of transshipment services to anyone at the market price. This assumption is needed for computational tractability, as it allows us to abstract from a corner solution in which the supply of transshipment services is zero. In line with this logic, we can relax the assumption and allow landlords to choose any *positive* amount of transshipment, but not zero transshipment. Generalizing the model this way does not change the equilibrium as landlords' profits are linear in the amount of transshipment and zero in equilibrium, hence landlords are indifferent between transshipping any two amounts as long as they are both positive.[5]

C.2 Equilibrium land use, wages, city populations and shipping flows

This section uses the equilibrium conditions of Appendix C.1 to characterize cities' equilibrium land use, wages, populations and shipping flows. To obtain these, we proceed as follows. Appendix C.2.1 solves for workers' optimal location choices. Appendix C.2.2 solves the landlords' problem for the optimal allocation of land between production and transshipment. Appendix C.2.3 solves the firms' problem, while Appendix C.2.4 uses equilibrium prices, the price index and market

[5] In the monopolistic competition version of the model (Appendix C.7), we do not need to make this assumption. In that model, landlords have market power and therefore choose both the price and the quantity of transshipment in a way that maximizes their profits.

clearing to obtain the equations characterizing cities' equilibrium wages and population. Finally, Appendix C.2.5 derives the value of shipments flowing through any port in equilibrium.

C.2.1 Workers' optimal location choices

The utility function of workers, (4), implies that the indirect utility of a worker living in city r equals

$$u_j(r) = \frac{w(r)}{P(r)} a(r) b_j(r)$$

where $w(r)$ is the nominal wage and $P(r)$ is the CES price index of consumption goods in the city.

We assume that $b_j(r)$ is distributed Fréchet with scale parameter one and shape parameter $1/\eta$:

$$Pr(b_j(r) \le b) = e^{-b^{-1/\eta}}$$

from which we obtain that the worker's indirect utility is also distributed Fréchet with scale parameter $\left[\frac{w(r)}{P(r)} a(r)\right]^{1/\eta}$:

$$Pr(u_j(r) \le u) = e^{-\left[\frac{w(r)}{P(r)} a(r)\right]^{1/\eta} u^{-1/\eta}}$$

and hence, by the properties of the Fréchet distribution, the probability with which a worker chooses to live in city r is given by

$$Pr(u_j(r) \ge u_j(s)\ \forall s \ne r) = \frac{\left[\frac{w(r)}{P(r)} a(r)\right]^{1/\eta}}{\sum_{s \in c} \left[\frac{w(s)}{P(s)} a(s)\right]^{1/\eta}}.$$

In equilibrium, the fraction of workers choosing to live in city r coincides with this probability, implying

$$\frac{N(r)}{\sum_{s \in c} N(s)} = \frac{\left[\frac{w(r)}{P(r)} a(r)\right]^{1/\eta}}{\sum_{s \in c} \left[\frac{w(s)}{P(s)} a(s)\right]^{1/\eta}}. \tag{C.4}$$

C.2.2 Landlords' optimal land use

Landlords earn income from providing transshipment services and from renting out land to firms that produce the city-specific good. Their utility function, (C.1), implies that the indirect utility of a landlord in city r equals her nominal income divided by the price index,

$$u_L(r) = \frac{\left[O(r) - (\nu(r) + \psi(F(r)))\, Shipping(r)^{\lambda}\right] Shipping(r) + R(r)(1 - F(r))}{P(r)}$$

where $O(r)$ is the price of transshipment services in city r (taken as given by the landlord), $\nu(r)$ is the exogenous part of transshipment costs, $F(r)$ is the share of land allocated to the port, $Shipping(r)$ is the value of shipments flowing through the port, excluding the price of transshipment services (hence, total demand for transshipment services, again taken as given by the landlord), $R(r)$ is the land rent prevailing in the city, and $1-F(r)$ is the share of land rented out to firms. That is, the first term in the numerator corresponds to the landlord's net nominal income from providing transshipment services, while the second term corresponds to her nominal income from renting out land to firms.

The landlord decides on the allocation of land, captured by the single variable $F(r)$, to maximize her utility. As she cannot influence the price index $P(r)$, this is equivalent to maximizing her nominal income:

$$\max_{F(r)} \left[O(r) - (\nu(r) + \psi(F(r)))\, Shipping(r)^{\lambda}\right] Shipping(r) + R(r)(1-F(r))$$

The first-order condition to this maximization problem is

$$-\psi'(F(r))\, Shipping(r)^{1+\lambda} - R(r) = 0$$

from which, by rearranging,

$$-\psi'(F(r)) = \frac{R(r)}{Shipping(r)^{1+\lambda}}. \tag{C.5}$$

C.2.3 Firms' problem

Recall that the representative firm operating in city r faces the production function

$$q(r) = \tilde{A}(r)\, n(r)^{\gamma} (1-F(r))^{1-\gamma}$$

and maximizes its profits, (C.2), by choosing its employment and land use. The first-order conditions to the firm's profit-maximization problem imply

$$R(r) = \frac{1-\gamma}{\gamma} \frac{w(r)\, N(r)}{1-F(r)} \tag{C.6}$$

where we have used labor market clearing, which implies $n(r) = N(r)$. Plugging this back into the firm's cost function and production function, we obtain that the firm's marginal cost of production is equal to

$$\gamma^{-\gamma} (1-\gamma)^{-(1-\gamma)} \tilde{A}(r)^{-1} w(r)^{\gamma} R(r)^{1-\gamma}$$

which, by perfect competition among firms, equals the factory gate price in equilibrium:

$$p(r,r) = \gamma^{-1} A(r)^{-1} (1 - F(r))^{-(1-\gamma)} N(r)^{1-\gamma-\alpha} w(r) \tag{C.7}$$

where we have used (C.6) again, together with the fact that $\tilde{A}(r) = A(r) N(r)^{\alpha}$.

Finally, equation (C.6) also implies that total factor payments in city r equal

$$Y(r) = w(r) N(r) + R(r)(1 - F(r)) = w(r) N(r) + \frac{1-\gamma}{\gamma} w(r) N(r) = \frac{1}{\gamma} w(r) N(r). \tag{C.8}$$

C.2.4 Equilibrium wages and populations

From the workers' and landlords' problems, we can derive the constant-elasticity demand for the city-r good in city s as

$$q(r,s) = p(r,s)^{-\sigma} P(s)^{\sigma-1} Y(s)$$

where $p(r,s)$ is the price paid by the consumer, which includes the shipping cost between r and s. Demand in value terms is equal to

$$p(r,s) q(r,s) = p(r,r)^{1-\sigma} P(s)^{\sigma-1} Y(s) \mathbf{E}[T(r,s)]^{1-\sigma}$$

where we have used equation (C.3).

Market clearing for the good produced in city r implies that total factor payments in r equal worldwide demand for the good (in value terms):

$$\frac{1}{\gamma} w(r) N(r) = \sum_{s=1}^{S} p(r,r)^{1-\sigma} P(s)^{\sigma-1} \frac{1}{\gamma} w(s) N(s) \mathbf{E}[T(r,s)]$$

where we have used equation (C.8) to substitute for total factor payments on both sides. Plugging (C.7) into this equation yields

$$\begin{aligned} w(r) N(r) =& \gamma^{\sigma-1} A(r)^{\sigma-1} (1 - F(r))^{(1-\gamma)(\sigma-1)} N(r)^{-(1-\gamma-\alpha)(\sigma-1)} \cdot \\ & w(r)^{1-\sigma} \sum_{s=1}^{S} P(s)^{\sigma-1} w(s) N(s) \mathbf{E}[T(r,s)]^{1-\sigma}. \end{aligned} \tag{C.9}$$

The CES price index in city r takes the form

$$P(r)^{1-\sigma} = \sum_{s=1}^{S} p(s,r)^{1-\sigma} = \sum_{s=1}^{S} p(s,s)^{1-\sigma} \mathbf{E}[T(s,r)]^{1-\sigma}.$$

Plugging factory gate prices (C.7) into this equation yields

$$P(r)^{1-\sigma} = \gamma^{\sigma-1} \sum_{s=1}^{S} A(s)^{\sigma-1} (1-F(s))^{(1-\gamma)(\sigma-1)} w(s)^{1-\sigma} N(s)^{-(1-\gamma-\alpha)(\sigma-1)} \mathbf{E}[T(s,r)]^{1-\sigma}. \tag{C.10}$$

Rearranging equation (C.4) yields the following expression for the price index:

$$P(r) = \tilde{a}(r) w(r) N(r)^{-\eta} \tag{C.11}$$

where $\tilde{a}(r)$ can be obtained by scaling amenities $a(r)$ according to

$$\tilde{a}(r) = \aleph_c a(r) = \left[\frac{\sum_{s\in c} N(s)}{\sum_{s\in c} \left[\frac{w(s)}{P(s)} a(s)\right]^{1/\eta}} \right]^{\eta} a(r).$$

Plugging equation (C.11) into (C.9) yields

$$\begin{aligned} &A(r)^{1-\sigma} (1-F(r))^{-(1-\gamma)(\sigma-1)} w(r)^{\sigma} N(r)^{1+(1-\gamma-\alpha)(\sigma-1)} = \\ &\gamma^{\sigma-1} \sum_{s=1}^{S} \tilde{a}(s)^{\sigma-1} w(s)^{\sigma} N(s)^{1-\eta(\sigma-1)} \mathbf{E}[T(r,s)]^{1-\sigma} \end{aligned} \tag{C.12}$$

while plugging equation (C.11) into (C.10) yields

$$\begin{aligned} &\tilde{a}(r)^{1-\sigma} w(r)^{1-\sigma} N(r)^{\eta(\sigma-1)} = \gamma^{\sigma-1} \cdot \\ &\sum_{s=1}^{S} A(s)^{\sigma-1} (1-F(s))^{(1-\gamma)(\sigma-1)} w(s)^{1-\sigma} N(s)^{-(1-\gamma-\alpha)(\sigma-1)} \mathbf{E}[T(s,r)]^{1-\sigma}. \end{aligned} \tag{C.13}$$

Note that our assumptions on trade costs guarantee symmetry and hence $\mathbf{E}[T(r,s)]^{1-\sigma} = \mathbf{E}[T(s,r)]^{1-\sigma}$. Given this, we can show that equations (C.12) and (C.13) can be simplified further. To see that this is the case, guess that wages take the form

$$w(r) = \tilde{a}(r)^{\iota_1} A(r)^{\iota_2} (1-F(r))^{\iota_3} N(r)^{\iota_4}.$$

That is, they only depend on local amenities, productivity, land available for production, and population. Inspecting equations (C.12) and (C.13), one can verify that this guess is indeed correct if

$$\iota_1 = -\frac{\sigma-1}{2\sigma-1},$$

$$\iota_2 = \iota_3 = (1-\gamma)\frac{\sigma-1}{2\sigma-1}$$

and

$$\iota_4 = \left[\eta - (1-\gamma)(1-\alpha)(\sigma-1) - 1\right] \frac{1}{2\sigma - 1}$$

as (C.12) and (C.13) reduce to the same equation if the guess is correct with these values of ι_1, ι_2, ι_3 and ι_4. Thus, wages in city r are given by

$$w(r) = \tilde{a}(r)^{-\frac{\sigma-1}{2\sigma-1}} A(r)^{\frac{\sigma-1}{2\sigma-1}} (1 - F(r))^{(1-\gamma)\frac{\sigma-1}{2\sigma-1}} N(r)^{[\eta-(1-\gamma-\alpha)(\sigma-1)-1]\frac{1}{2\sigma-1}}.^{6} \tag{C.14}$$

Finally, plugging (C.14) back into either (C.12) or (C.13) gives us an equation that determines the distribution of population across cities:

$$N(r)^{[1+\eta\sigma+(1-\gamma-\alpha)(\sigma-1)]\frac{\sigma-1}{2\sigma-1}} = \gamma^{\sigma-1}\tilde{a}(r)^{\frac{\sigma(\sigma-1)}{2\sigma-1}} A(r)^{\frac{(\sigma-1)^2}{2\sigma-1}} (1 - F(r))^{(1-\gamma)\frac{(\sigma-1)^2}{2\sigma-1}} MA(r) \tag{C.15}$$

where

$$MA(r) = \sum_{s=1}^{S} \frac{\tilde{a}(s)^{\frac{(\sigma-1)^2}{2\sigma-1}} A(s)^{\frac{\sigma(\sigma-1)}{2\sigma-1}} (1 - F(s))^{(1-\gamma)\frac{\sigma(\sigma-1)}{2\sigma-1}} N(s)^{[1-\eta(\sigma-1)-(1-\gamma-\alpha)\sigma]\frac{\sigma-1}{2\sigma-1}}}{\mathbf{E}\left[T(r,s)\right]^{\sigma-1}}$$

is the market access of city r.

C.2.5 Equilibrium shipping flows

This section derives the equilibrium value of shipping flows through any port. To obtain these, we first need to introduce further notation. Let Z be an $S+P$ by $S+P$ matrix, where P denotes both the set and the number of ports in the model.[7] Each of the first S rows and columns of Z corresponds to a city, while each of the last P rows and columns of Z corresponds to a port. Let us call a city or a port a *location*; that is, each row and column in Z corresponds to one location. We assume that an entry $z(i,\ell)$ of Z is zero if locations i and ℓ are not directly connected, or if $i = \ell$. Otherwise, $z(i,\ell)$ is defined as

$$z(i,\ell) = \left[\bar{T}(i,\ell)\left[1 + O(\ell)\right]\right]^{-\theta}$$

where $\bar{T}(i,\ell)$ is the common cost of shipping from i to ℓ directly, and $O(\ell)$ is the price of transshipment services at ℓ. If ℓ is a port belonging to port city r, then this price is given by equation (6). If ℓ is not a port but a (port or non-port) city, then we define $O(\ell) = 0$.[8]

[6] We can freely choose the intercept of this equation as we have not normalized any price yet. We choose it to be equal to one.

[7] Recall that S is the total number of (port or non-port) cities.

[8] For computational reasons, we need to add a small iceberg cost of shipping between each port and its own city. This cost equals 1.03 in both the inversion and the model simulations.

Following Allen and Arkolakis (2019), we can show that the expected cost of shipping from city r to s can be written as

$$\mathbf{E}\left[T\left(r,s\right)\right]=\Gamma\left(\frac{\theta+1}{\theta}\right)x\left(r,s\right)^{-1/\theta}$$

where $x\left(r,s\right)$ is the $\left(r,s\right)$ entry of the matrix

$$X=\left(I-Z\right)^{-1}$$

and I is the $S+P$ by $S+P$ identity matrix.

Similarly, we can show that, if a good is shipped from city r to s, the probability that it is shipped through port k is given by

$$\pi\left(k|r,s\right)=\frac{x\left(r,k\right)x\left(k,s\right)}{x\left(r,s\right)} \tag{C.16}$$

and therefore the total value of goods shipped through port k from city r to city s (excluding the price paid for transshipment services at k) equals

$$Shipping\left(k|r,s\right)=\left[1+O\left(k\right)\right]^{-1}p\left(r,s\right)^{1-\sigma}P\left(s\right)^{\sigma-1}\frac{1}{\gamma}w\left(s\right)N\left(s\right)\pi\left(k|r,s\right).$$

Combining this with equations (C.3), (C.7), (C.11) and (C.16) yields

$$Shipping\left(k|r,s\right)=\gamma^{\sigma-2}\left[1+O\left(k\right)\right]^{-1}A\left(r\right)^{\sigma-1}\left(1-F\left(r\right)\right)^{\left(1-\gamma\right)\left(\sigma-1\right)}N\left(r\right)^{-\left(1-\alpha-\gamma\right)\left(\sigma-1\right)}\cdot$$

$$w\left(r\right)^{1-\sigma}\tilde{a}\left(s\right)^{\sigma-1}N\left(s\right)^{1-\eta\left(\sigma-1\right)}w\left(s\right)^{\sigma}\mathbf{E}\left[T\left(r,s\right)\right]^{1-\sigma}\frac{x\left(r,k\right)x\left(k,s\right)}{x\left(r,s\right)}$$

and therefore the total value of shipping through port k is given by

$$Shipping\left(k\right)=\gamma^{\sigma-2}\left[1+O\left(k\right)\right]^{-1}\sum_{r}D_{1}\left(r\right)x\left(r,k\right)\sum_{s}D_{2}\left(s\right)\frac{\mathbf{E}\left[T\left(r,s\right)\right]^{1-\sigma}}{x\left(r,s\right)}x\left(k,s\right) \tag{C.17}$$

where

$$D_{1}\left(r\right)=A\left(r\right)^{\sigma-1}\left(1-F\left(r\right)\right)^{\left(1-\gamma\right)\left(\sigma-1\right)}N\left(r\right)^{-\left(1-\alpha-\gamma\right)\left(\sigma-1\right)}w\left(r\right)^{1-\sigma}$$

and

$$D_{2}\left(s\right)=\tilde{a}\left(s\right)^{\sigma-1}N\left(s\right)^{1-\eta\left(\sigma-1\right)}w\left(s\right)^{\sigma}.$$

C.3 Inverting the model

This section describes how we invert the equilibrium conditions of the model to back out amenities up to a country-level scale, productivities and exogenous transshipment costs as a function of observed population, wages and the value of shipments. As a first step, we use the observed data to back out port shares in the model. To this end, we combine equations (C.5) and (C.6) to obtain port shares as a function of wages $w(r)$, population $N(r)$ and the value of shipments $Shipping(r)$ in each port city r:

$$-\psi'(F(r))(1-F(r)) = \frac{1-\gamma}{\gamma}\frac{w(r)N(r)}{Shipping(r)^{1+\lambda}} \tag{C.18}$$

Given the assumptions we made on ψ', the left-hand side of equation (C.18) is strictly decreasing in $F(r)$. Moreover, the left-hand side takes every real value between zero and infinity as ψ' is continuous, $\lim_{F\to 1}\psi'(F) = 0$ and $\lim_{F\to 0}\psi'(F) = -\infty$. This guarantees that solving equation (C.18) identifies a unique value of $F(r) \in (0,1)$ for every port city.

The second step consists of solving for $\tilde{a}(r)$, $A(r)$ and $\nu(r)$ for the observed $N(r)$, $w(r)$ and $Shipping(r)$, as well as the $F(r)$ recovered in the previous step. This is done using an algorithm that consists of an outer loop and an inner loop. In the inner loop, we obtain the values of $\tilde{a}(r)$ that solve the system of equations

$$\tilde{a}(r)^{1-\sigma} w(r)^{1-\sigma} N(r)^{\eta(\sigma-1)} = \gamma^{\sigma-1}\sum_{s=1}^{S}\tilde{a}(s)^{\sigma-1} w(s)^{\sigma} N(s)^{1-\eta(\sigma-1)}\mathbf{E}[T(r,s)]^{1-\sigma} \tag{C.19}$$

derived from equations (C.12) and (C.13) for a *fixed* set of exogenous transshipment costs $\nu(r)$, and hence for fixed $\mathbf{E}[T(r,s)]$. For any $\mathbf{E}[T(r,s)]$, this system yields a unique solution for $\tilde{a}(r)$. Rearranging equation (C.14), we can then uniquely express productivity $A(r)$ as a function of the recovered $\tilde{a}(r)$:

$$A(r) = \tilde{a}(r)(1-F(r))^{\gamma-1} w(r)^{\frac{2\sigma-1}{\sigma-1}} N(r)^{-[\eta-(1-\gamma-\alpha)(\sigma-1)-1]\frac{1}{\sigma-1}} \tag{C.20}$$

In the outer loop, we search for the set of $\nu(r)$ for which the value of shipments implied by equation (C.17) – hence, by $N(r)$, $w(r)$, $F(r)$ and the recovered $\tilde{a}(r)$ and $A(r)$ – rationalize the shipping flows observed in the data. In practice, we start from a uniform guess of $\nu(r) = \bar{\nu}$, then perform a large number of iterations in which we update $\nu(r)$ gradually to get closer to satisfying equation (C.17). We also update $\mathbf{E}[T(r,s)]$ in every iteration step. Even though we cannot prove that this procedure identifies a unique set of $\nu(r)$, the algorithm has been converging to the same fixed point for various different initial guesses on $\nu(r)$, even when guessing non-uniform distributions of $\nu(r)$ initially.

C.4 Counterfactual simulation

This section describes how we perform counterfactual simulations in the model. First, we need to choose the absolute level of amenities $a(r)$ in each city r, as the inversion only identifies amenities up to a country-level scale, $\tilde{a}(r) = \aleph_c a(r)$. Unfortunately, nothing in the data guides us with this choice. Hence, we make the simplest possible assumption by assuming that average amenities are the same across countries and are equal to one:

$$\frac{1}{C_c} \sum_{r \in c} a(r) = \frac{1}{C_c} \sum_{r \in c} \frac{\tilde{a}(r)}{\aleph_c} = 1$$

where C_c denotes the number of cities in country c. Rearranging yields

$$\aleph_c = \frac{1}{C_c} \sum_{r \in c} \tilde{a}(r)$$

and hence we can obtain the absolute level of amenities in each city r as

$$a(r) = \frac{\tilde{a}(r)}{\aleph_c} = \frac{C_c}{\sum_{s \in c} \tilde{a}(s)} \tilde{a}(r).$$

We also need to remove endogenous, shipping-related disamenities from $a(r)$ and recover fundamental amenities $\bar{a}(r)$. This can be done by rearranging equation (5):

$$\bar{a}(r) = a(r) \left[1 + Shipping(r)\right]^{\rho}$$

where $Shipping(r)$ is the observed value of shipments at r.

Second, we solve for the counterfactual equilibrium of the model using an algorithm that consists of three loops embedded in each other. In the innermost loop, we obtain the distribution of population $N(r)$ that solves equation (C.15) for a *fixed* set of $\aleph_c$, $F(r)$ and $Shipping(r)$ (implying that $\mathbf{E}[T(r,s)]$ are also fixed). For any $\tilde{a}(r)$, $F(r)$ and $Shipping(r)$, equation (C.15) can be shown to have a unique positive solution if

$$\alpha < 1 - \gamma + \eta$$

which holds under the assumptions made in Section 5.1. Moreover, the solution can be obtained by simply iterating on equation (C.15), starting from any initial guess on $N(r)$. The proof of these results follows directly from the proof of equilibrium uniqueness in Allen and Arkolakis (2014).

In the middle loop, we solve for the set of country-specific $\aleph_c$ that guarantee that the sum of city populations equals total country population in each country:

$$\sum_{r \in c} N(r) = N_c$$

where N_c denotes the exogenously given population of country c. We also solve for wages using equation (C.14) and for rents using equation (C.6).

In the outermost loop, we iterate on the distribution of port shares and shipping flows that satisfy both equations (C.5) and (C.17), also updating $\mathbf{E}[T(r,s)]$ in every step. We use the distributions of port share and shipping obtained in the inversion as our initial guesses. Even though we cannot prove that this procedure yields a unique equilibrium, we have been converging to the same distribution of endogenous variables for different initial guesses.

C.5 Benchmark models

This section provides a description of the two benchmark models (Benchmark 1 and Benchmark 2) used to decompose the aggregate effects of containerization. To implement these decompositions, we first take Benchmark 1 and Benchmark 2 to our 1990 data. Next, we conduct the no-containerization counterfactual in each benchmark model. In particular, we conduct the counterfactual such that the world trade to GDP ratio changes to the same extent ($+4.2$ pp) in each benchmark as in our baseline model. Hence, differences in the welfare effects across the models do not stem from trade changing to a different extent.

Here, we introduce each benchmark model in detail and show how they are taken to the data and how they are simulated for counterfactuals.

C.5.1 Benchmark 1: No land use in transshipment

In Benchmark 1, we abstract from endogenous (land-dependent) transshipment costs. Thus, the cost of handling one unit of a good at port p_m is given by

$$\nu(p_m)\, Shipping(p_m)^{\lambda}$$

and, by perfect competition, the price of transshipment services equals this cost:

$$O(p_m) = \nu(p_m)\, Shipping(p_m)^{\lambda} \tag{C.21}$$

As production is the only sector in which land can be productively used in this model, landlords optimally set the fraction of production land to one: $1 - F(r) = 1$. The remaining assumptions are the same as in the baseline model. Naturally, equation (C.5) does not hold in Benchmark 1, since all port shares are equal to zero.

Taking Benchmark 1 to the data. Taking Benchmark 1 to 1990 data follows similar steps as taking our baseline model to the data. We keep the structural parameters and the inland and sea shipping costs unchanged relative to the baseline model. To back out amenities, productivities and exogenous transshipment costs after containerization, we invert Benchmark 1 using 1990 data on population, wages and the value of shipments. This inversion procedure differs from the inversion of the baseline model in that we do not need to solve equation (C.5) for equilibrium port shares. As a result, we can skip the first step of the inversion procedure and immediately start with what we labeled as the second step in Appendix C.3.

In particular, we solve an algorithm that consists of an outer loop and an inner loop. In the inner loop, we obtain the values of city amenities $\tilde{a}(r)$ that solve equation (C.19), which holds in Benchmark 1 as well, for a *fixed* set of $\nu(r)$, hence for fixed $\mathbf{E}[T(r,s)]$. Once we have $\tilde{a}(r)$, we can obtain city productivities $A(r)$ from equation (C.20), which also holds in Benchmark 1, such that we set $1 - F(r) = 1$.

In the outer loop, we search for the set of $\nu(r)$ such that shipments implied by equation (C.17) equal the shipping flows observed in the data. Equation (C.17) also holds in Benchmark 1, except that we need to use $1 - F(r) = 1$ and equation (C.21) instead of equation (6) to calculate transshipment prices. In practice, we start from a uniform guess of $\nu(r) = \bar{\nu}$, then perform a large number of iterations in which we update $\nu(r)$ gradually to get closer to satisfying equation (C.17). We also update $\mathbf{E}[T(r,s)]$ in every iteration step.

Counterfactual simulation of Benchmark 1. When conducting the no-containerization counterfactual in Benchmark 1, we again stay as close as possible to our baseline model. We offset the relationship between $\log \nu(r)$ and port depth, and increase all $\log \nu(r)$ by a constant ν_{CF} such that we have the same increase in international trade to world GDP as in the baseline model (Section 7.1). We also use the same procedure to obtain $\bar{a}(r)$ from $\tilde{a}(r)$ (Appendix C.4). When conducting the targeted port development counterfactual, we decrease exogenous transshipment costs in the 24 targeted ports by 10%, as in the baseline model.

We solve for counterfactual equilibria using an algorithm that consists of three loops embedded in each other. In the innermost loop, we obtain the distribution of population $N(r)$ that solves equation (C.15) for a *fixed* set of $\aleph_c$ and $Shipping(r)$ (implying that $\mathbf{E}[T(r,s)]$ are also fixed). Equation (C.15) is unchanged relative to the baseline model, except that we need to use $1 - F(r) = 1$. We follow the same iterative procedure as in Appendix C.4 to solve equation (C.15).

In the middle loop, we solve for the set of country-specific $\aleph_c$ such that the sum of city populations equals total country population in each country. We also solve for wages using equation (C.14), which is the same as in the baseline model, except that $1 - F(r) = 1$.

In the outermost loop, we iterate on equation (C.17) to obtain equilibrium shipping flows, also updating $\mathbf{E}[T(r,s)]$ in every step. In contrast to the baseline model, we use $1 - F(r) = 1$ and equation (C.21) instead of equation (6) in this process. We use the 1990 shipping flows as our initial guess.

C.5.2 Benchmark 2: Land use in transshipment identical across port cities

In Benchmark 2, we allow for endogenous (land-dependent) transshipment costs. This implies that transshipment prices are given by equation (6), just like in our baseline model. However, we restrict transshipment land use to be identical across port cities. More precisely, we set the 1990 port share of each port city equal to the average 1990 port share in the baseline model. Similarly, we set the no-containerization counterfactual port share equal to the average port share in the no-containerization counterfactual of our baseline model. The remaining assumptions are the same as in the baseline model. Similar to Benchmark 1, equation (C.5) does not hold in this model since port shares are set exogenously through the above procedure, rather than optimally by port city landlords.

Taking Benchmark 2 to the data. We keep the structural parameters and the inland and sea shipping costs unchanged relative to the baseline model. To back out amenities, productivities and exogenous transshipment costs after containerization, we invert Benchmark 2 using 1990 data on population, wages and the value of shipments. Just like in Benchmark 1, we do not need to solve equation (C.5) for equilibrium port shares. As a result, we can skip the first step of the inversion procedure and immediately start from the second step. This second step, in turn, is conducted exactly as in the baseline model (see Appendix C.3 for details), except that we use the average 1990 port share in the baseline model as $F(r)$ in each port city.

Counterfactual simulation of Benchmark 2. In the no-containerization counterfactual simulation of Benchmark 2, we offset the relationship between $\log \nu(r)$ and port depth, and increase all $\log \nu(r)$ by a constant ν_{CF} such that we have the same increase in international trade to world GDP as in the baseline model (Section 7.1). We also use the same procedure to obtain $\bar{a}(r)$ from $\tilde{a}(r)$ (Appendix C.4).

Finally, we solve for the counterfactual equilibrium using an algorithm that consists of three loops embedded in each other. In the innermost loop, we obtain the distribution of population $N(r)$ that solves equation (C.15) for a *fixed* set of $\aleph_c$, $F(r)$ and $Shipping(r)$ (implying that $\mathbf{E}[T(r,s)]$ are also fixed). We use the average port share in the counterfactual of the baseline model as $F(r)$ in each port city. We follow the same iterative procedure as in Appendix C.4 to solve equation (C.15).

In the middle loop, we solve for the set of country-specific $\aleph_c$ such that the sum of city populations equals total country population in each country. We also solve for wages using equation (C.14), which is the same as in the baseline model. We again use the same $F(r)$ in each port city.

In the outermost loop, we iterate on equation (C.17) to obtain equilibrium shipping flows, also updating $\mathbf{E}[T(r,s)]$ in every step. We again use the same $F(r)$ in each port city. We use the 1990 shipping flows as our initial guess.

C.6 A model with labor used in transshipment

This section presents a generalization of our baseline model in which the provision of transshipment services may require not only land, but also potentially labor. We show that, as long as the share of labor relative to land in transshipment is sufficiently low, this more general framework delivers predictions on port development and city populations that are similar to the predictions of our baseline model. On the other hand, if the share of labor in transshipment is high, the model's predictions are in contrast with the empirical findings of Section 4, as we describe below.

We now present the setup of the model with transshipment labor. Assume that the cost of transshipping one unit of a good in port city r equals

$$\left(\nu\left(r\right)+\psi\left(n^{P}\left(r\right)^{\gamma_{P}}F\left(r\right)^{1-\gamma_{P}}\right)\right)Shipping\left(r\right)^{\lambda}$$

where $0\leq\gamma_{P}\leq1$. That is, γ_{P} is labor's share and $1-\gamma_{P}$ is land's share in transshipment services. Our baseline model is a special case in which $\gamma_{P}=0$. The remaining model assumptions are the same as in the baseline model.

We now show how our model predictions – more precisely, Proposition 1 – change in this more general framework. First, note that the first-order conditions to the landlord's problem with respect to $n^{P}\left(r\right)$ and $F\left(r\right)$ together imply

$$n^{P}\left(r\right)=\frac{\gamma_{P}}{1-\gamma_{P}}\frac{R\left(r\right)}{w\left(r\right)}F\left(r\right). \tag{C.22}$$

On the production side, the first-order conditions to the firm's problem imply

$$n\left(r\right)=\frac{\gamma}{1-\gamma}\frac{R\left(r\right)}{w\left(r\right)}\left(1-F\left(r\right)\right). \tag{C.23}$$

Adding equations (C.22) and (C.23) yields total demand for labor in the city,

$$N\left(r\right)=\frac{\gamma}{1-\gamma}\frac{R\left(r\right)}{w\left(r\right)}\left(1-\tilde{\gamma}F\left(r\right)\right) \tag{C.24}$$

where $\tilde{\gamma}=\frac{\gamma/(1-\gamma)-\gamma_{P}/(1-\gamma_{P})}{\gamma/(1-\gamma)}$. Land rents can be obtained from equation (C.24) as

$$R\left(r\right)=\frac{1-\gamma}{\gamma}\frac{w\left(r\right)N\left(r\right)}{1-\tilde{\gamma}F\left(r\right)}$$

whereas total income in city r is given by

$$\frac{1}{\gamma}w(r)\,n(r)=\frac{1}{\gamma}\frac{1-F(r)}{1-\tilde{\gamma}F(r)}w(r)\,N(r)\,.$$

Using these results in the derivation of the equilibrium conditions, we obtain that the population of city r is the solution to the following equation:

$$\begin{aligned}N(r)^{[1+\eta\sigma+(1-\gamma-\alpha)(\sigma-1)]\frac{\sigma-1}{2\sigma-1}} =& \gamma^{\sigma-1}\tilde{a}(r)^{\frac{\sigma(\sigma-1)}{2\sigma-1}}A(r)^{\frac{(\sigma-1)^2}{2\sigma-1}}\left(1-\tilde{\gamma}F(r)\right)^{[1+(1-\gamma)(\sigma-1)]\frac{\sigma-1}{2\sigma-1}}\,.\\ &(1-F(r))^{-\frac{\sigma-1}{2\sigma-1}}MA(r)\end{aligned} \tag{C.25}$$

where

$$\begin{aligned}MA(r)=&\sum_{s=1}^{S}\tilde{a}(s)^{\frac{(\sigma-1)^2}{2\sigma-1}}A(s)^{\frac{\sigma(\sigma-1)}{2\sigma-1}}(1-F(s))^{\frac{\sigma-1}{2\sigma-1}}\left(1-\tilde{\gamma}F(s)\right)^{[(1-\gamma)\sigma-1]\frac{\sigma-1}{2\sigma-1}}\,.\\ &N(s)^{[1-\eta(\sigma-1)-(1-\gamma-\alpha)\sigma]\frac{\sigma-1}{2\sigma-1}}\,\mathbf{E}\left[T(r,s)\right]^{1-\sigma}\,.\end{aligned}$$

Equation (C.25) allows us to state the following proposition, which is the counterpart of Proposition 1 in Section 5.2.

Proposition 2. *If $\gamma_P<1$, then an increase in the share of land allocated to the port in city in r, $F(r)$, decreases shipping costs $\mathbf{E}[T(r,s)]$, thus increasing $MA(r)$. Everything else fixed, an increase in $MA(r)$ increases the population of the city (market access effect). Holding $MA(r)$ fixed, if $\gamma_P\geq\gamma$, an increase in $F(r)$ draws additional people into the city (employment effect). If $0<\gamma_P<\gamma$, an increase in $F(r)$ may trigger either a positive employment effect or migration out of the city (land use effect), depending on the values of structural parameters γ, γ_P and σ. If and only if $\gamma_P=0$ (our baseline model), the model implies a negative land use effect irrespectively of the values of structural parameters. Finally, an increase in $F(r)$ increases shipping flows, thus lowering amenities $\tilde{a}(r)$ and, therefore, city population (disamenity effect).*

Proof. The results follow directly from equation (C.25). □

According to Proposition 2, an expansion of port activity has different implications on city population depending on labor's share in transshipment. Besides the standard market access and disamenity effects, port development affects city population in two ways. First, it draws people into the transshipment sector as long as labor's share in the sector is different from zero. Second, it decreases the amount of land available for the production of the city-specific good, which induces workers in this sector to leave the city. If labor's share in the transshipment sector is sufficiently high, the first effect always dominates the second one (employment effect). This implies that the population of the city should increase even more than what is implied by the standard market access effect. Such a positive effect on population, however, is not consistent with what we find in the data (Section 4.3), unless the disamenity effect is so extremely strong that it can offset the combined effects of market access and port employment.

To sum up, the model presented in this section sheds light on two facts. First, if the share of labor in transshipment is too high, the model with transshipment labor has different implications than our baseline framework. These implications, however, are in contrast with the empirical findings of Section 4.3. Second, if the share of labor in transshipment is sufficiently low, the model with transshipment labor is more complex in its structure but delivers predictions that are similar to the predictions of our baseline framework.

C.7 A model with monopolistic competition in transshipment

This section presents a version of our baseline model in which landlords providing transshipment services engage in monopolistic competition. This implies that, unlike in our baseline model, port activity involves positive profits. We also show how we take the model with monopolistic competition to the data and how we simulate the same no-containerization counterfactual in it for one of the robustness exercises in Appendix C.8.

We first present the setup of the monopolistic competition model. As in our baseline model, we assume that each city is inhabited by a continuum of landlords. Without loss of generality, we normalize the mass of these landlords to one in each city, and index an individual landlord by $m \in [0, 1]$.

Unlike in our baseline model, we assume that transshipment services are differentiated products. Firms shipping through port city r may use the services of any number of landlords m residing in the city. Firms aggregate transshipment services in a CES function with elasticity of substitution $\zeta \in (1, \infty)$ across the services performed for them by the individual landlords. As $\zeta < \infty$, these services are imperfect substitutes. Hence, each firm uses the transshipment service of each landlord in equilibrium.[9]

Landlords are aware that they are the sole provider of their differentiated transshipment service but cannot influence city-wide prices and quantities. Thus, they engage in monopolistic competition, choosing their land allocation, transshipment price and transshipment quantity to maximize their net nominal income. In other words, landlord m in port city r solves the problem

$$\max_{F_m(r), O_m(r), Shipping_m(r)} \left[O_m(r) - (\nu(r) + \psi(F_m(r))) \, Shipping(r)^{\lambda} \right] Shipping_m(r) + R(r)(1 - F_m(r))$$

[9] To fix ideas, one may think that one port city landlord provides the cranes, another the storage, and so on. As a result, firms use the services of all landlords, not only one.

where $O_m(r)$ is the price of transshipment services that landlord m charges, $\nu(r)$ is the exogenous part of transshipment costs, $F_m(r)$ is the share of land that the landlord allocates to transshipment, $Shipping(r)$ is the total value of shipments flowing through the port excluding the price of transshipment services, $R(r)$ is the land rent prevailing in the city, and $1 - F_m(r)$ is the share of land rented out to firms.

As the price elasticity of demand for each landlord's transshipment service is constant at $-\zeta$, each landlord charges a constant markup over her marginal cost in equilibrium:

$$O_m(r) = \frac{\zeta}{\zeta - 1}\left(\nu(r) + \psi(F_m(r))\right) Shipping(r)^{\lambda}$$

As landlords in a given port city are symmetric, we can drop their index and simply write

$$O(r) = \frac{\zeta}{\zeta - 1}\left(\nu(r) + \psi(F(r))\right) Shipping(r)^{\lambda} \tag{C.26}$$

from which we get that landlords earn profits on transshipment equal to

$$\Pi(r) = \frac{1}{\zeta - 1}\left(\nu(r) + \psi(F(r))\right) Shipping(r)^{1+\lambda}. \tag{C.27}$$

For simplicity, we assume that landlords spend these profits outside our set of cities S. This implies that we do not need to take profits into account when calculating demand for goods in the city, or city GDP. This assumption helps us keep the model computationally tractable.

The first-order condition to the landlord's maximization problem with respect to $F_m(r)$ implies

$$-\psi'(F(r))\, Shipping(r)^{1+\lambda} - R(r) = 0$$

from which, by rearranging,

$$-\psi'(F(r)) = \frac{R(r)}{Shipping(r)^{1+\lambda}}.$$

Note that this equation is identical to equation (C.5) of our baseline model. More generally, as the remaining model assumptions in the monopolistic competition model are the same as those in the baseline model, the only equation that differs between the two frameworks is equation (C.26), which replaces equation (6) in the baseline model. The remaining equilibrium conditions are all identical.

In Section C.8, we conduct a robustness check in which we take the model with monopolistic competition to the data to measure the aggregate and local effects of containerization. Inverting and simulating the monopolistic competition model follows the same steps as described in Appendix C.3 and Appendix C.4, with one exception: we use equation (C.26) instead of equation (6) whenever we calculate transshipment prices.

To do so, we need to choose the value of the markup parameter ζ. Note that, by equation (C.27), transshipment profits are decreasing in ζ. Data on profits of ports are hard to find, especially during our period of interest, but we were able to obtain profit and revenue data for a number of ports from annual reports of port authorities between 1950 and 1990.[10] In this sample, profits as a percentage of revenue are on average 28%, with no clear trends over time. Choosing $\zeta = 3$, our model predicts an average profit margin of 27% and a median profit margin of 33% across ports. Hence, we use $\zeta = 3$ in the inversion and the counterfactual simulation.[11]

C.8 Aggregate and local effects of containerization: robustness

In Table E.9, we examine the sensitivity of the model-implied aggregate effects of containerization to different values of the containerization shock and some alternative modeling choices. We focus on the sensitivity of our three headline findings: the aggregate welfare gains from containerization; the aggregate resource costs; and the aggregate specialization gains. Row (1) of Table E.9 repeats these results in our baseline model calibration, while rows (2) to (12) report them for each of our eleven robustness exercises.

In the exercises of rows (2) and (3), we use higher and lower values of our transshipment cost parameter β, respectively. As we argued in Section 6.1, the endogenous port development mechanism plays a stronger role in the model under higher values of β. In line with this, we find higher aggregate resource costs and higher specialization gains when β is high, while the opposite holds when β is low. At the same time, the aggregate welfare gains from containerization stay very similar across these different specifications.

In row (4), we do not offset the relationship between exogenous transshipment costs and port depth in the counterfactual. We find aggregate welfare gains, resource costs and specialization gains that are fairly close but larger than our baseline estimates.

In rows (5) and (6), we choose ν_{CF} to target different (30% and 20%, respectively) changes in the sum of exogenous and endogenous transshipment costs. Unsurprisingly, a larger change in total transshipment costs is associated with higher aggregate gains, resource costs and specialization gains. The opposite is true if we assume that total transshipment costs changed less.

To study how the assumption of perfect competition in transshipment influences our results, we develop a model in which the provision of transshipment services is subject to monopolistic competition in Appendix C.7. The key difference relative to our baseline setup is that transship-

[10]We describe these data in Section D.13.

[11]We compute the profit margin of port r in the model as $\frac{\Pi(r)-R(r)F(r)}{O(r)Shipping(r)}$. These margins vary across ports and are in fact negative for a few of them. As these ports operate in the data, we do not let them shut down in the model and assume they are subsidized from the outside economy.

ment activity involves positive profits in this monopolistic competition model. Row (7) reports the aggregate effects of containerization in the monopolistic competition model. While the results obviously change to some extent, they remain very close to our baseline model.

Rows (8) and (9) add a uniform 10% and 20% change in the elasticity of inland shipping costs to distance, respectively. This amounts to making inland shipping costs higher in the counterfactual, mimicking a decline in inland shipping costs brought about by containerization besides the change in transshipment costs. Obviously, adding an inland shipping cost reduction increases the estimated aggregate gains. However, the resource costs and specialization gains from containerization remain very similar to our baseline model. The reason for this is that the overland cost reduction has two opposing effects of roughly similar magnitude. On the one hand, overland transport cost reductions make these routes more attractive relative to sea routes, leading to less endogenous port development. However, they also increase the overall volume of shipping, which increases port development.[12] Put differently, we find no evidence of missing interaction effects between the aspect of containerization we are interested in, and the overland transport cost reductions, which we do not account for in the main analysis of this paper.

Rows (10) to (12) study the robustness of our results to alternative versions of port city disamenities. In row (10), we assume that disamenities are present in 1990, but not in the pre-containerization equilibrium. In other words, we assume that it was containerization that brought about the disamenities associated with port activities. Unsurprisingly, loading all the negative disamenity effects on containerization substantially lowers the overall welfare gains from the new technology. At the same time, it leaves the estimated land use costs and specialization gains almost unchanged.

In row (11), disamenities are present both before and after containerization but the value of parameter ρ that disciplines their strength is twice as large as in the baseline calibration. By contrast, in row (12), we shut down disamenities completely, setting $\rho = 0$. Overall, we conclude that the estimated aggregate effects of containerization are fairly stable across these different model specifications.

C.9 Elasticity of port city disamenities with respect to shipping

Welfare in Los Angeles, according to our model, is

$$u(LA) = GDP(LA) * \bar{a}(LA) * [1 + Shipping(LA)]^{-\rho}$$

Marquez and Vallianatos (2012) estimate the economic cost of pollution emitted by the ports of Los Angeles and Long Beach to be $30 billion annually (including economic cost associated with

[12]The canceling out of these two forces is also reflected in the fact that mean port size changes are very similar with and without overland cost changes; in both cases, the increase is about 3 percentage points.

deaths as well as medical care for illnesses and missed school and work days). This is equivalent to 5% of the GDP of Los Angeles (averaged across 2002 and 2010, from *Canback*, see Appendix section D.4). Therefore,

$$1 - \frac{pollutioncost(LA)}{GDP(LA)} = (1 + Shipping(LA))^{-\rho}$$

Rearranging and plugging in the shipping for LA ports, which amounted to 7,959 vessels in 2005 for the ports of Los Angeles and Long Beach according to our own data, yields $\rho = 0.005$.

D Data

In this section, we provide additional details about data construction and sources for the variables used in the analysis.

D.1 Lloyd's List shipping data

We clean the shipping data by manually matching them to the 1953 and 2017 editions of the *World Port Index (WPI)*, which is a widely used reference list of worldwide ports. The initial Lloyd's List sample of 'ports' included ports on navigable rivers such as Budapest, Hungary. We therefore chose to discipline the sample of ports using WPI. We use a historic and current edition of the WPI to ensure we capture both ports that may no longer exist, and ones that only appear later in the period. A different approach would have been to choose a distance threshold from the coast and drop any port located further from the coast than the threshold. This definition, however, is very sensitive to the precision of the coastline shapefile used to calculate distance form the coast, which is why we did not choose this method. Despite filtering the Lloyd's List sample through the WPI, our final sample still contains a handful of ports that are very far inland. In the empirical analysis, we show that our results are robust to different ways of treating these 'inland ports.' Our base sample consists of Lloyd's List ports that match to at least one of the WPI editions.

D.2 Underwater elevation levels

We use data on underwater elevation levels from the *General Bathymetric Chart of the Oceans (GEBCO)*. We use the 2014 version of these data. Most observations in the dataset are from ship-track soundings with interpolation between soundings guided by satellite-derived gravity data. The data are continuously updated with sources from local bathymetry offices and coastal navigation charts. More details on dataset construction can be found at http://www.gebco.net.

D.3 Saiz land scarcity measure

The following sources are used to calculate the Saiz measure for our sample of cities. The coastline shapefile needed to distinguish between land and sea cells is from GSHHG (https://www.soest.hawaii.edu/pwessel/gshhg/). Inland bodies of water and wetlands are from the World Wildlife

Fund's *Global Lakes and Wetlands Database*.[13] Finally, data on land elevations used to calculate the slope of each cell is from GEBCO's land data, described above.

D.4 Predicted city-level GDP per capita

Here we provide a more detailed discussion of how we estimate city level GDP per capita for our full sample of cities (port and non-port cities). First, we merge the *Canback* data with our city list, and construct GDP per capita from the level of GDP and the population data provided by *Canback*. GDP are reported at purchasing power parity (in 2005 USD). We have estimates from this source for 898 cities in our sample.

We estimate city-level GDP for the full sample by extrapolating the estimated relationship between GDP per capita and nighlight luminosity. We begin by estimating the linear fit of GDP per capita on nightlight luminosity, building on a growing body of evidence suggesting that income can be reasonably approximated using nightlight luminosity data (Donaldson and Storeygard, 2016).

We construct the 'luminosity' of each city in the following way. We take the 1992 30 arc-second grid layer from NOAA's *National Geophysical Data Center* (source: https://ngdc.noaa.gov/products/) as the baseline input, as this is the closest year to 1990 – the year for which we have city income from *Canback*. We define a cell in this raster to be 'lit up' if its luminosity level is above 25. This threshold defines meaningful levels of economic activity in the cell - as proxied by nightlights.[14] We then construct a polygon from contiguous cells with luminosity above 25 for each city in our sample. We observe luminosity for 2,294 cities in our dataset.[15] With these data in hand, we then define a city i's luminosity, $luminosity_i$, to be the sum of all cells' luminosity levels within the polygon. Note that in this summation, we drop any cells identified as 'gas flares' in the source data, as these do not contain meaningful information on economic activity.

For the remaining 342 cities (13%), we either fail to identify an area polygon assigned to the city (340 cities) or a gas flare completely covers the polygon of the city (2 cities). We observe both GDP per capita and luminosity for a subset of 810 cities. For this subset, we estimate the relationship between GDP per capita and luminosity. More precisely, we estimate

$$\ln(GDP/capita)_i = \beta * \ln(luminosity_i) + FE_c + \epsilon_i \tag{D.28}$$

where $GDP/capita_i$ is city-level GDP per capita as compiled in the *Canback Global Income Distribution Database (CGIDD)* for the year 1990 which covers 898 cities, and $luminosity_i$ measures the sum of luminosity in the cells in the polygon that defines the area of the city.

[13]Link: https://www.worldwildlife.org/pages/global-lakes-and-wetlands-database.

[14]We experimented with different cutoffs and this was the one for which the R^2 in the regression of income on luminosity was highest.

[15]We have cities with 'missing' luminosity data if we fail to detect *any* cells with luminosity levels above 25 in the vicinity of the city's geocode.

Note that most of the papers in this literature estimate the level of GDP within a country, where the level of development is not as widely dispersed as across cities worldwide. To account for these differences and the way in which they affect luminosity, we include country fixed effects FE_c in our estimation. However, in order to identify country fixed effects, we need to drop 21 cities that are the only cities with GDP per capita data in their respective country, leaving a sample of 789 cities for the estimation.

The results of this regression are given in column (1) of Table E.11. We then predict GDP per capita for all cities for which we observe luminosity that are also in the set of countries used in this regression. This allows us to predict GDP per capita for a total of 2,289 cities. For the remaining 341 cities, we use the following approximation. For 89 cities, we observe GDP per capita directly, which we use. For 240 cities, we only observe population in 1990, so we use this to predict GDP per capita based on the estimated relationship between GDP per capita and population in 1990 for all cities in our sample for which we observe both measures. This estimated relationship is given in column (2) of Table E.11. Finally, for 18 cities, we only observe population in 1980, so we use the latter to predict GDP per capita for all cities in our sample for which we observe both variables, resulting in the estimated relationship in column (3) of Table E.11.

This procedure yields a city-level estimate for GDP per capita for all 2,636 cities in our dataset.

D.5 Port shares for 1990

Here, we provide details on the construction of port share data and the sources used. First, it is important to note that historical data on the area occupied by the port are very difficult to find. For example, data on port area are only sporadically and inconsistently reported in *Lloyd's Ports of the World*, and they are usually not found in ports' annual reports. These are in fact the two sources from which we take the measure for the ports where port area is observed. We also experimented with using satellite images from the 1980s, but the resolution is too low to detect port areas.

We observe data on port area in 1990 for seven cities. These are: Aarhus (Denmark), Helsinki (Finland), Copenhagen (Denmark), Hamburg (Germany), Los Angeles (USA), New Orleans (USA) and Seattle (USA).[16] Data for the European ports and for the port of Los Angeles are from *Lloyd's Ports of the World* (1990). We complemented these with data for other U.S. ports where planning maps and annual reports gave information on the land area of the port. In all these cases, we verified or cleaned the data to ensure that a consistent definition of port area was used. In particular, these measures only include the total land (and not sea) area occupied by the port. Data for the remaining U.S. ports are from Port Authority of Seattle (1989) and Port of New Orleans (1984). These documents were shared by the port authorities based on requests we made. For Long Beach, we take port area in 1971 from the port's annual report (Port of Long Beach, 1971) and add addi-

[16]The port area for Los Angeles includes the area occupied by the ports of Los Angeles and Long Beach.

tional land acquired from a detailed history of port projects (Riffenburgh, 2012). To construct the port shares, we use the area of *land* occupied by the city as reported in Wikipedia.

D.6 Area per throughput calculation for the Port of Seattle

We obtained 'Property Books' that allow us to calculate the area of the Port of Seattle from the *Port of Seattle Public Records Office*. These volumes contain engineering maps for each parcel of land under the ownership of the port. Each map includes an estimate of the land area. For both years 1961 and 1973, we used only land parcels directly related to port activities. In particular, we excluded the airport and the marina terminal. Data on annual total throughput (in short tons, including both domestic and international sea-borne trade) and the share of containerized cargo were collected from *Annual Reports* that are archived at the *Puget Sound Regional Archives*. To smooth out fluctuations in year-to-year capacity utilization, we took the five-year moving-average of throughput.

Table E.12 reports the numbers. While the expansion of traffic during this period was impressive (throughput doubled), the area occupied by the port expanded even more rapidly (increasing almost fourfold), such that area per throughout increased by 90% during this period. The *Annual Reports* paint a consistent picture. In the early 1960s, the port acquired vast parcels of land in the Lower Duwamish Industrial Development District. Throughout the latter half of the decade, the port continued to acquire more land in this area and to simultaneously develop the acquired tracts. These were completed in the late 1960s, early 1970s. We illustrate this in Figure F.7 which shows the set of acquired land parcels and an example of a completed container facility.

D.7 Google Earth port area and containerization, modern data

We compiled data on the area of all ports for a random subset of port cities in our dataset (236 cities, which is 43% of the full sample), resulting in 252 individual ports. For each port, we hand-coded polygons that contain port activities based on satellite imagines from *Google Earth*. We used the name tags of buildings as well as visual markers (e.g., stacked containers, ships). We aimed to be conservative in that we only included areas that could clearly be identified as containing port-related activities. As such, we did not include warehouses (as they cannot be unambiguously identified) or highways or railways. A port can have multiple polygons, e.g., in the case of terminals that are not directly connected. *Google Earth* reports the area (in km^2) of each polygon, which we aggregate to the level of Geopolis port cities. The average area of a port in our data is 3.6 km^2 (median: 2 km^2), with a minimum of 0.03 km^2 and a maximum of 30 km^2 (Los Angeles, including the Port of Long Beach). The latter occupies 43 km^2 according to Wikipedia (https://en.wikipedia.org/wiki/Port_of_Long_Beach and https://en.wikipedia.org/wiki/Port_of_Los_Angeles), so while our measure most likely underestimates the true size of ports, the measure is arguably in the correct range.

Data on total (in tons) and containerized (in TEUs; twenty-foot equivalent units) volume of cargo handled by each port is taken from the 2009 edition of *Le Journal de la Marine Marchande (JMM)*. We use the average of the reported numbers for 2008 and 2009 in order to maximize the number of observations, as some ports only report data for one of the two years. In order to generate the share of container traffic in total merchandise traffic, we use the average weight per TEU of 12 tons as recommended by the *European Sustainable Shipping Forum*.[17]

We match the dataset on the area of ports and cargo volume based on the names, countries and geocodes of the ports, resulting in 123 observations.

D.8 Land reclamation

Data on land reclaimed from the sea are taken from Martín-Antón et al. (2016). The authors compare historical maps to current Google Earth images to examine whether land reclamation has taken place in a city. We matched these data to our sample of port cities. The authors report three measures; i) any land reclamation, ii) coastal land reclamation, iii) coastal and island land reclamation. This contains land reclaimed for any purpose, not just for port activities. In our analysis, we use their coastal land reclamation measure, though the results are essentially the same regardless of the measure used.

The authors systematically examined the coastlines of the world, paying particular attention to South East Asia, the Persian Gulf, Europe and the U.S., where land reclamation has been more extensive. Any systematic measurement error introduced in this way will be accounted for in our specifications that control for continent and coastline fixed effects. Reassuringly, the coefficients of interest do not change substantially with the inclusion of these, suggesting that these issues – if present – are not quantitatively large.

D.9 Country GDP per capita

Data on country-level GDP per capita are from the *Penn World Tables*. We take real GDP at constant 2011 prices (USD) and divide by country population reported from the same source. In theory, the data exist for 1950 (our first sample year), but in practice there are many missing observations. For this reason, in robustness checks, we always use the data for 1960. This is observed for many, though not all, countries.

D.10 Identifying city centroids for within port-city moves

In Section 4, we discussed evidence that showed that ports had moved further towards the outskirts of the city during our sample period. To conduct this exercise, we use data on ports' geocodes from two editions of the *World Port Index*: 1953 and 2017. We also need to identify the geocode of each city's centroid. To this end, we use daylight satellite data to identify a city's contiguous

[17]Downloaded on March 11, 2021, from https://ec.europa.eu/clima/sites/clima/files/docs/0108/20170517_guidance_cargo_en.pdf.

built-up area and find the city centroid within this polygon. We closely follow the methodology in Baragwanath, Goldblatt, Hanson, and Khandelwal (2019). In particular, we use an extremely high resolution dataset of daylight satellite data, the *Global Human Settlement Built-Up Grid* available at 38 m resolution (source: https://ghsl.jrc.ec.europa.eu/ghs_bu.php). Using this raster and the geocodes of our cities, we construct a polygon for each city consisting of contiguous built-up cells around the geocode. We take the centroid of this polygon to be the centroid of the city.

D.11 Ship size data

The evolution of ship sizes, illustrated in Figure F.8, is based on data purchased from the *Miramar Ship Index* (Haworth, 2020), accessible at http://www.miramarshipindex.nz. The *Miramar Ship Index* is a comprehensive list of all newly built ships and their main characteristics going back to the 19th century. We calculate the average tonnage of all newly built ships in the years 1960, 1990, and 2010, distinguishing between container-ships and non-container ships.

D.12 Nautical maps for dredging dummy variable

We obtained access to nautical maps of ports around the world from *marinetraffic.com*, see https://www.marinetraffic.com/en/online-services/single-services/nautical-charts. These detailed nautical charts have been constructed based on information from hydrographic organizations of different countries. They provide pilotage information including depth of water at high spatial disaggregation. Dredged channels are demarcated on these maps by a 'safety contour' that distinguishes the channel from the surrounding shallow waters (defined as less than 5 meters). We constructed a binary variable, *'Dredging'*, that takes the value 1 if a dredged channel is visible on the nautical chart in the 3-5 km buffer ring around the port.

D.13 Annual reports for ports

We were able to acquire annual reports for a number of port authorities in the United States during our sample period, 1950 to 1990, and for a handful of ports worldwide. Some ports have made historical annual reports available online, while for others, we have obtained the reports by contacting the port authorities. We use these reports i) for historical evidence (Section 2), ii) in the case of the Port of Seattle, to measure changes in land per unit of throughput during the period in which they containerized (Section 4.2), and iii) to calculate profit rates (Section C.7).

As accounting and reporting standards changed across ports and over time, we only kept ports that reported consistent information on profits over time (defined as revenue minus operating expenses and depreciation). These ports are: Houston, Los Angeles, Long Beach, New York/New Jersey, New Orleans, Seattle and Townsville (Australia). We tried to collect at least one observation per port for each decade between 1950 and 1990, and ended up with on average three decadal observations per port. The average profit margin across all observations in our sample is 28%, with no clear time trend. Data sources are as follows;

Houston. Port of Houston Authority of Harris County, Texas: 'Comprehensive Annual Financial Report' (various years). Thank you to Dollores Villareal at the Port of Houston for responding to our request and digitizing the data for us.

Los Angeles. Port of Los Angeles Board of Harbor Commissioners: 'Annual Report' (various years). Thank you to Kurt Arendt at the Port of Los Angeles for responding to our request and sharing data.

Long Beach. The Port of Long Beach California: 'Harbor Highlights' (various years). Accessible at https://www.polb.com/port-info/history#historical-publications.

New York/New Jersey. The Port Authority of New York and New Jersey: 'Annual Report' (various years). These can be accessed online at https://corpinfo.panynj.gov/pages/annual-reports/.

New Orleans. Board of Commissioners of the Port of New Orleans: 'Annual Report Fiscal' (various years). Thank you to Mandi Venderame at the Port of New Orleans for responding to our request and sharing data.

San Francisco. The Port of San Francisco: 'Annual Report', other reports and planning maps from various years. Thank you to Randolph Quezada at the Port of San Francisco for numerous helpful conversations and for sharing scans.

Seattle. The Port of Seattle: 'Annual Report' (various years) and planning maps. Thank you to Midori Okazaki, archivist at Puget Sound Regional Archives, for scanning the files during the COVID-19 lockdown while the archives were closed to the public.

Townsville (Australia). Townsville Harbor Board: 'Report' (various years). Thank you to the Port Authority for responding to our data request.

E Tables

Table E.1: Summary statistics

	Observations	Mean	Standard Deviation
Shipment (annualized)	2,765	2,913	7,051
Population (in ’000s): *All Cities*	12,698	386	1,086
Population (in ’000s): *Port Cities*	2,735	724	1,886
Depth	553	2.19	1.49
Saiz land scarcity measure	553	0.44	0.19

Notes: Shipment reports the annualized flow of shipments across all port city – year pairs (in levels). Population refers to the level of the population of each city-year pair in thousands. Depth and the Saiz land scarcity measure are time invariant measures and are defined in the main text.

Table E.2: Relationship between containerization and port area

	Ln(Port area, km2)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Container traffic, TEUs)	0.288***	0.127***	0.133***	0.151***	0.153***	0.144***
	(0.049)	(0.045)	(0.044)	(0.047)	(0.046)	(0.053)
Ln(Total merchandise traffic, tons)		0.375***	0.283*	0.311***	0.247	0.356***
		(0.080)	(0.166)	(0.080)	(0.161)	(0.118)
Ln(Non-bulk traffic, tons)			0.014		0.008	
			(0.099)		(0.096)	
Ln(Country GDP/capita)				0.311***	0.292**	
				(0.108)	(0.134)	
Observations	123	123	73	122	73	123
R-squared	0.287	0.395	0.327	0.431	0.352	0.672
Country FEs	×	×	×	×	×	✓

Notes: Non-bulk traffic is all traffic net of liquid and solid bulk. Container traffic and total merchandise traffic are averaged across 2008 and 2009 in order to maximize the sample size. Country level GDP per capita and non-bulk traffic are for 2009. Data sources: *Google Earth* and *Le Journal de la Marine Marchande*. See Appendix D.7 for details on the construction of the data. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.3: Shipping increased more in less land-scarce cities (Stylized fact 2)

	ln(Ship)			
Independent variables	(1)	(2)	(3)	(4)
Depth × post 1970	0.464***	0.566***	0.437***	0.497***
	(0.138)	(0.152)	(0.142)	(0.166)
Depth × Saiz land scarcity × post 1970	-0.408*	-0.707**	-0.431	-0.586*
	*-0.122**	*-0.211***		
	(0.220)	(0.323)	(0.308)	(0.331)
Saiz land scarcity × post 1970		0.975	-0.052	1.176
		(0.804)	(0.811)	(0.749)
Observations	2765	2765	2765	2360
R-squared	0.128	0.129	0.250	0.143
Number of cities	553	553	553	472
Year FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Population 1950 × Year	✓	✓	✓	✓
Coastline × Year FE	×	×	✓	×
GDP pc (country) × Year	×	×	×	✓

Notes: 'Depth' indicates the port suitability measure. 'Saiz land scarcity' is the Saiz land scarcity measure defined in Saiz (2010). Each measure is interacted with an indicator for decades including and after 1970. Standardized coefficients in italics underneath the baseline coefficients. Standard errors clustered at the city level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.4: The local causal effect of shipping on population – full panel specification

	Panel Regression				
	ln(Pop)	ln(Ship)	ln(Pop)	ln(Ship)	ln(Pop)
Independent variables	(1)	(2)	(3)	(4)	(5)
ln(Ship)	0.015				
	0.035				
	(0.049)				
Depth × post 1970		0.268***	0.004		
		*0.143****	*0.005*		
		(0.058)	(0.013)		
Depth × 1960				-0.042	-0.003
				(0.064)	(0.008)
Depth × 1970				0.246***	0.007
				(0.069)	(0.013)
Depth × 1980				0.213***	-0.002
				(0.079)	(0.017)
Depth × 1990				0.280***	0.002
				(0.086)	(0.020)
Observations	2734	2734	2734	2734	2734
Number of cities	552	552	552	552	552
Year FE	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓
Population 1950 × Year	✓	✓	✓	✓	✓
Population 1950	×	×	×	×	×
Specification	2SLS	FS	RF	dyn FS	dyn RF
KP F-stat	21.13				

Notes: 'Depth' indicates the port suitability measure. It is interacted with decade dummies or indicator variables for decades including and after 1970, as indicated. Standardized coefficients in italics underneath the baseline coefficients. Notation for specification as follows: 'FS' refers to the first stage, 'RF' to the reduced form, 'dyn FS' to the fully flexible first stage and 'dyn RF' to the fully flexible reduced form. Standard errors clustered at the city level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.5: The local causal effect of shipping on population – robustness

	ln(Population)			
Independent variables	(1)	(2)	(3)	(4)
ln(Ship)	0.015	-0.071	0.018	-0.015
	(0.049)	(0.060)	(0.051)	(0.051)
Observations	2734	2734	2734	2338
R-squared	0.717	0.759	0.717	0.756
Number of cities	552	552	552	471
Year FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Population 1950 × Year	✓	✓	✓	✓
Coastline × Year FE	×	✓	×	×
Saiz × Year	×	×	✓	×
GDP pc (country) × Year	×	×	×	✓
Specification	2SLS	2SLS	2SLS	2SLS
KP F-stat	21.13	13.71	16.26	19.48

Notes: All specifications are 2SLS, using the depth measure as an instrument for shipping (interacted with a dummy for decades including and after 1970). Standard errors clustered at the city level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.6: Relationship between dredging and measured depth

	Dredging		
Independent variables	(1)	(2)	(3)
Depth	-0.058**	-0.042*	-0.028
	(0.025)	(0.024)	(0.028)
Observations	100	100	100
R-squared	0.059	0.138	0.250
FE	none	continent	coastline

Notes: This table tests the extent to which the baseline measure of depth captures naturally endowed depth (as opposed to depth attained by dredging). Dredging is a binary indicator that takes the value of one if nautical maps from *marinetraffic.com* show the presence of a dredged channel. Depth is the baseline measure of port suitability used in the paper. The sample consists of 100 randomly selected ports from the baseline sample. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.7: Robustness to data choices

Panel A: Depth predicts shipping flows (Stylized fact 1)						
	ln(Shipment)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Shipment +1	IHST	Port Cities	Depth=0	100K
Depth × post 1970	0.247***	0.144***	0.164***	0.218***	0.247***	0.285***
	(0.059)	(0.029)	(0.034)	(0.060)	(0.059)	(0.071)
Observations	2765	2765	2765	2640	2765	1565
R-squared	0.126	0.156	0.155	0.133	0.126	0.139
Number of cities	553	553	553	528	553	313
Panel B: Containerization increased shipping more in less land-scarce cities (Stylized fact 2)						
	ln(Shipment)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Shipment +1	IHST	Port Cities	Depth=0	100k
Depth × post 1970	0.566***	0.318***	0.368***	0.583***	0.566***	0.348**
	(0.152)	(0.079)	(0.090)	(0.147)	(0.152)	(0.177)
Depth × Saiz × post 1970	-0.707**	-0.408**	-0.472***	-0.779**	-0.707**	-0.203
	(0.323)	(0.159)	(0.183)	(0.315)	(0.323)	(0.376)
Saiz × post 1970	0.975	0.740**	0.814*	0.950	0.975	0.694
	(0.804)	(0.376)	(0.436)	(0.802)	(0.804)	(0.963)
Observations	2765	2765	2765	2640	2765	1565
R-squared	0.129	0.161	0.159	0.137	0.129	0.139
Number of cities	553	553	553	528	553	313
Panel C: The local causal effect of shipping on population (Stylized fact 3)						
	ln(Population)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Shipment +1	IHST	Port Cities	Depth=0	100K
ln(Shipment)	0.015	0.027	0.024	0.025	0.015	0.045
	(0.049)	(0.086)	(0.076)	(0.053)	(0.049)	(0.052)
Observations	2734	2734	2734	2609	2734	1563
R-squared	0.717	0.719	0.719	0.720	0.717	0.606
Number of cities	552	552	552	527	552	313

Notes: 'Baseline' reports the baseline specification for comparability. Columns (2)-(3) examine robustness to different ways of dealing with zero shipping flows. Column (2) uses $\ln(Shipment + 1)$ as dependent variable – that is, we take the raw shipping variable and replace the zeros with ones and then take the natural logarithm. Column (3) uses the inverse hyperbolic sine transformation (IHST) for shipment. Different to the baseline, neither of these transformations annualizes the data. Columns (4)-(5) examine robustness to different ways of dealing with 'inland ports.' Column (4) drops them, reducing the sample size. Column (5) assigns depth equal to zero to these cities. Column (6) uses the subset of cities that already attained 100,000 inhabitants in 1950 to examine the effect of sample selection bias. 'Depth' indicates the port suitability measure interacted with indicators for decades including and after 1970. Standard errors clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.8: Relationship between coastal land reclamation and the Saiz land scarcity measure

	Coastal land reclamation (indicator)					
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Saiz land scarcity measure	0.1296*	0.1356**	0.1146			
	(0.0686)	(0.0678)	(0.0754)			
Depth				0.0008	0.0038	-0.0003
				(0.0093)	(0.0096)	(0.0106)
Observations	553	553	553	553	553	553
R-squared	0.00534	0.08521	0.13287	0.00001	0.07991	0.12925
FE	none	continent	coastline	none	continent	coastline

Notes: Dependent variable is equal to one if coastal land reclamation was reported, and zero otherwise. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.9: The aggregate welfare effects of containerization – sensitivity analysis

Model	Welfare effect (%)	Resource cost (pp)	Specialization gains (pp)
1. Baseline	3.38	-0.28	0.12
2. 20% higher β in inversion	3.35	-0.33	0.13
3. 20% lower β in inversion	3.44	-0.23	0.12
4. No depth-dependent change in $\nu(r)$	3.88	-0.42	0.23
5. Larger ν_{CF}: implies 30% change in total transshipment cost	4.08	-0.35	0.16
6. Larger ν_{CF}: implies 20% change in total transshipment cost	2.67	-0.21	0.09
7. Monopolistic competition	3.50	-0.27	0.14
8. Additional 10% inland cost transport reduction	4.92	-0.28	0.11
9. Additional 20% inland cost transport reduction	6.41	-0.28	0.13
10. Disamenities only in inversion	1.53	-0.30	0.13
11. Disamenities twice as large	3.27	-0.28	0.13
12. No disamenities	3.50	-0.29	0.13

Notes: Welfare effect refers to the gain in welfare due to containerization in our baseline model. Resource cost refers to the difference in welfare gains between Benchmark 1 (with exogenous and free transshipment cost reductions) and Benchmark 2 (with identical land use across port cities). Specialization gains refer to the difference in welfare gains between the baseline and Benchmark 2. *** p<0.01, ** p<0.05, * p<0.1.

Table E.10: Maritime Silk Road Counterfactual – country fixed effects

	Baseline				Benchmark 1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ ln(Ship)	Δ ln(Port cost)	Δ ln(Market access)	Δ ln(Population)	Δ ln(Ship)	Δ ln(Port cost)	Δ ln(Market access)	Δ ln(Population)
Treated port city	1.09616***	-0.13066***	0.01597***	-0.02959***	0.90913***	-0.10536***	0.01281***	0.00860***
	(0.10480)	(0.01257)	(0.00280)	(0.00879)	(0.06376)	0	(0.00234)	(0.00308)
Untreated port city in treated country	-0.92762***	0.00936	0.04693***	0.01060	-0.86417***	0	0.05048***	-0.00628
	(0.03864)	(0.00861)	(0.00596)	(0.01040)	(0.07243)	0	(0.00631)	(0.00820)
Port city in untreated country	0.00364***	-0.00006*	-0.00138***	-0.00154	0.00262***	0	-0.00132***	0.00029***
	(0.00045)	(0.00003)	(0.00031)	(0.00121)	(0.00021)	0	(0.00005)	(0.00007)
Inland city in treated country			0.05334***	0.00054			0.05507***	-0.00375
			(0.00482)	(0.00819)			(0.00516)	(0.00668)
Inland city in untreated country			-0.00191***	0.00009			-0.00154***	0.00006
			(0.00005)	(0.00006)			(0.00005)	(0.00006)
Observations	553	544	2636	2636	553	553	2636	2636
R-squared	0.639	0.378	0.942	0.186	0.923	1.000	0.979	0.210

Notes: The regressors are dummy variables that divide the cities into 5 mutually exclusive groups as indicated, the regression is estimated without the constant. 'Treated port' indicates the 24 treated ports of the Maritime Silk Road counterfactual. 'Treated country' indicates countries that have at least one treated port. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.11: Relationship between GDP per capita and nightlight luminosity

	ln(GDP per capita)		
Independent variables	(1)	(2)	(3)
ln(Luminosity)	0.126***		
	(0.014)		
ln(Population, 1990)		0.107***	
		(0.013)	
ln(Population, 1980)			0.100***
			(0.014)
Observations	789	854	871
R-squared	0.926	0.923	0.921
Country FE	✓	✓	✓

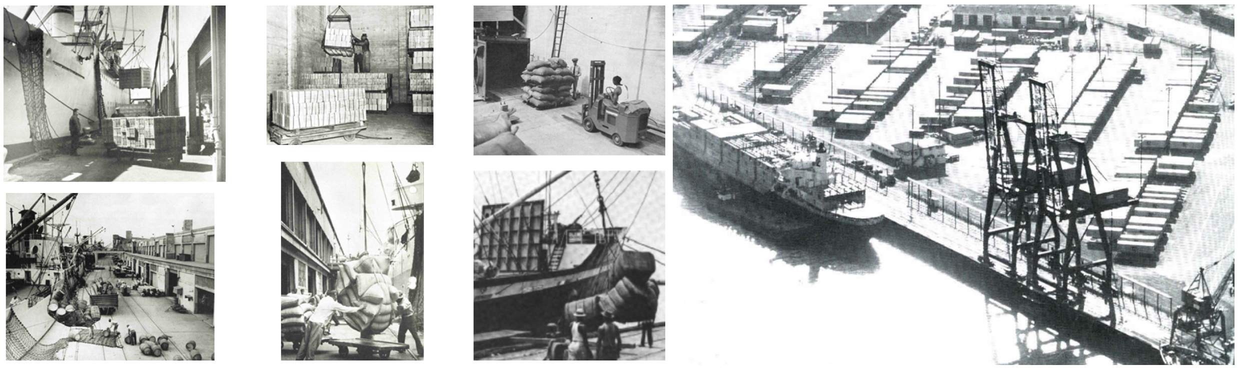
Notes: All regressions include country fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.12: Port of Seattle: area per unit of cargo shipped

Year	Area	Throughput	Area/Throughput
1961	8,651,016	2,022,192	4.28
1973	33,547,908	4,135,795	8.11

Notes: Area reported in square feet, throughput in short tons. Data were not available far enough back in time to allow for the calculation of the five-year moving-average for 1961.

F Figures



Breakbulk shipping, 1950s Container shipping, 1967

Figure F.1: Illustration of changes in port technology

Notes: Sources: Annual reports for the Port of Seattle and the Port of New Orleans (1950, 1951, 1952, 1955).

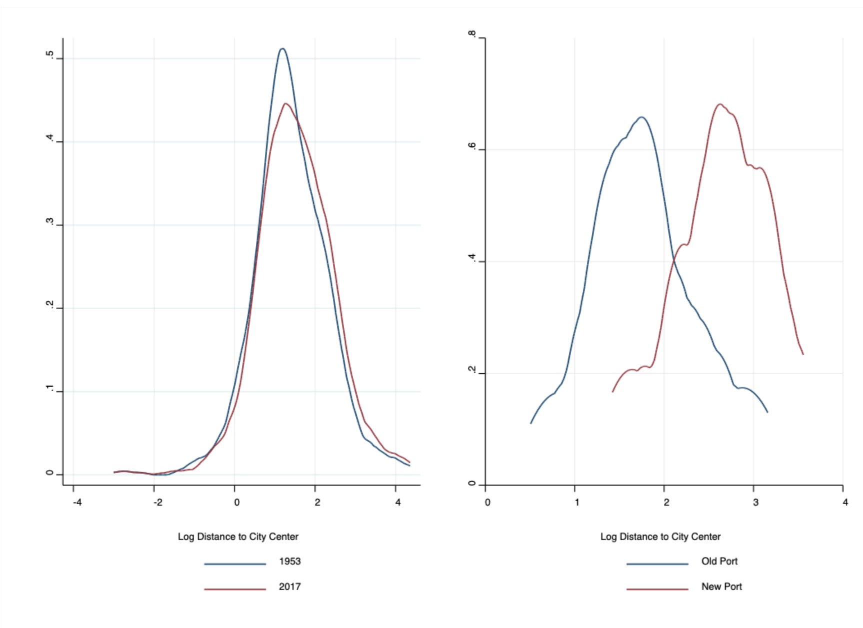


Figure F.2: Location of ports within cities 1953 – 2017

Notes: The figure plots the kernel density of the log distance to the city center for ports in 1953 and 2017. The left panel uses the full sample, the right panel restricts to only those cities where a new port was established after 1953. Data on the geocodes of ports are from the World Port Index. The calculation of city centroids is described in Appendix D.10. Across the full sample, ports moved on average 1 kilometer towards the outskirts (panel A). Where a new port was built, it was on average 9 kilometres further from the centroid of the city than the old port.

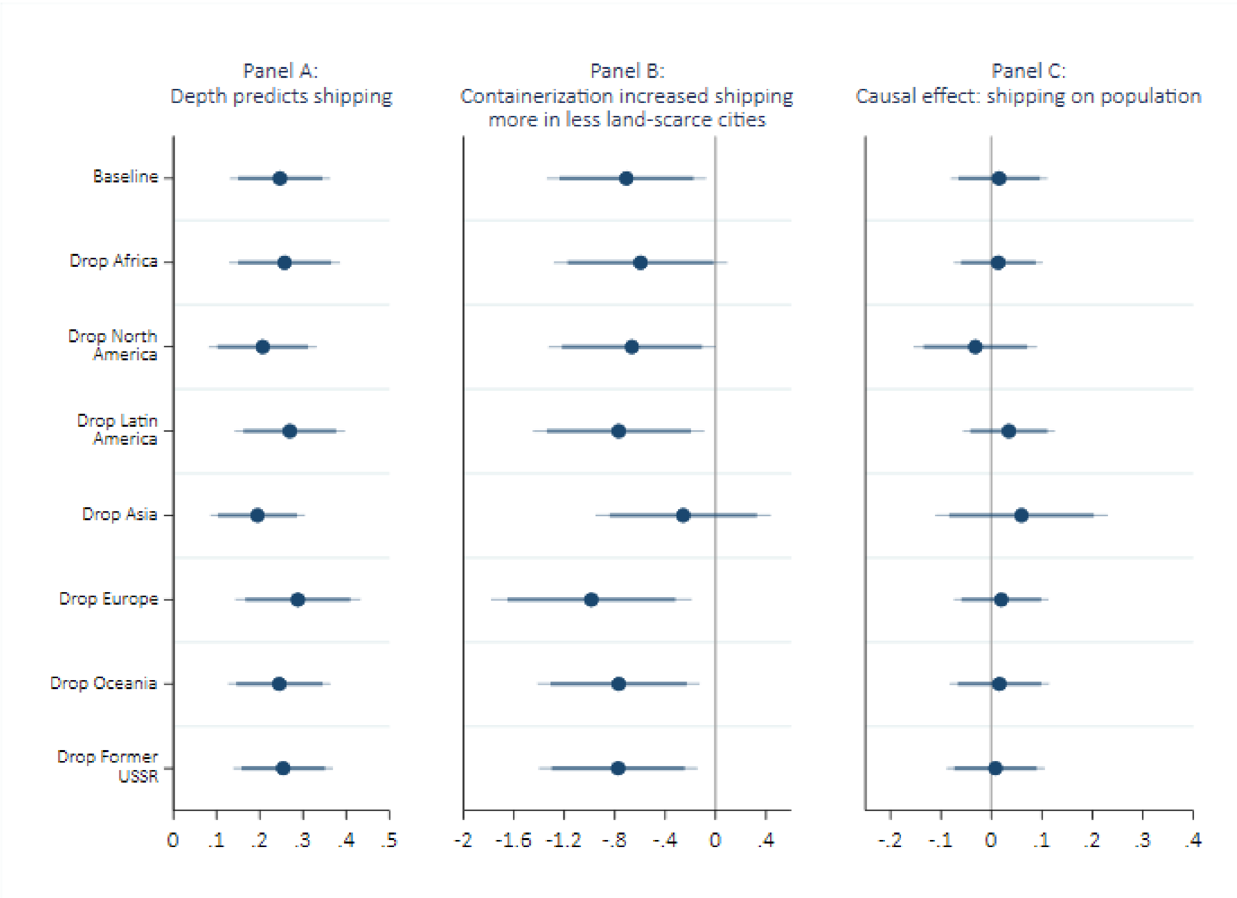


Figure F.3: Dropping continents one at a time

Notes: The plotted coefficients for Panel A are based on the specification in Table 1, column (5). The plotted coefficients for Panel B are based on the specification in Table E.3, column (2). The plotted coefficients for Panel C are based on the specification in Table 2, column (2). 'Baseline' uses the full sample, while the remaining rows drop continents one at a time as labelled.

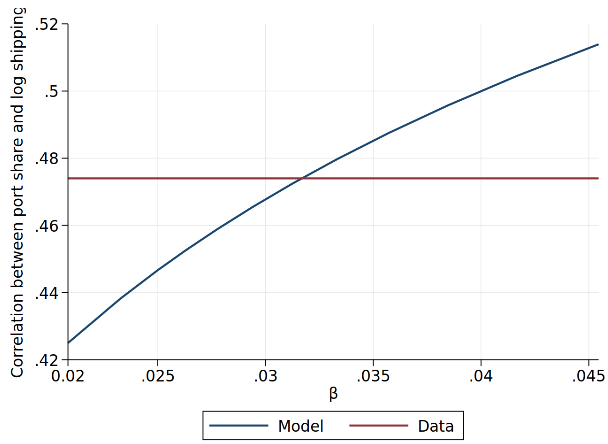


Figure F.4: Correlation between port share and shipping as a function of β

Notes: This figure shows the correlation between the port share and log shipping flows in the model as a function of the transshipment cost parameter β (blue line). It also shows the value of this correlation based on 7 ports in the data (red line).

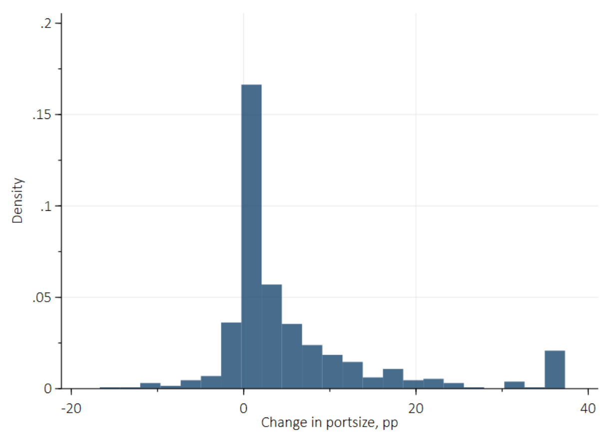


Figure F.5: Histogram of changes in port share between the counterfactual and the 1990 equilibrium, in percentage points

Notes: The figure shows the histogram of the percentage point change in port shares between the model-simulated counterfactual (pre-containerization) and the 1990 equilibrium (after containerization, also model-simulated data).

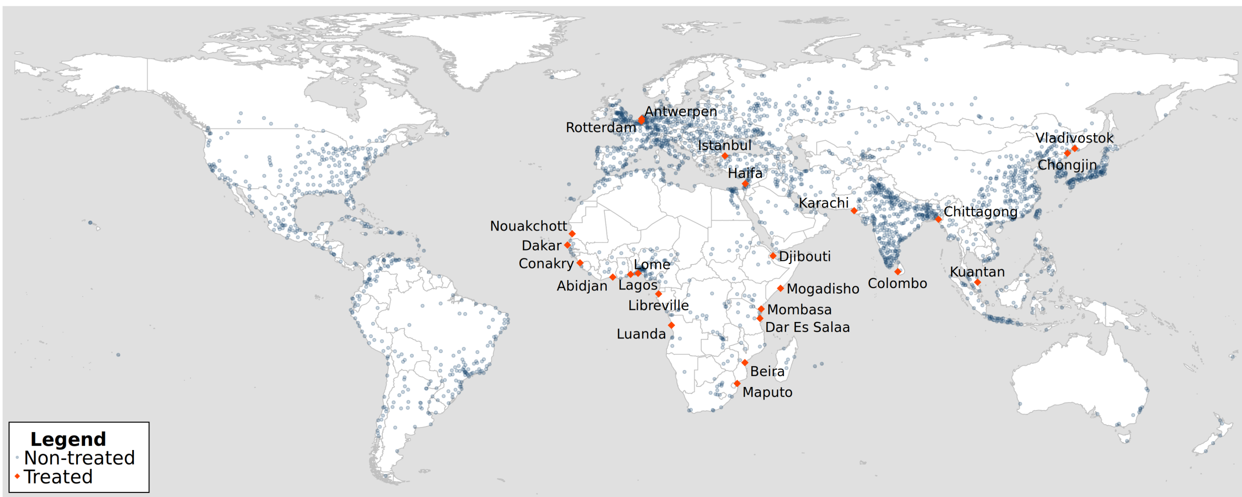
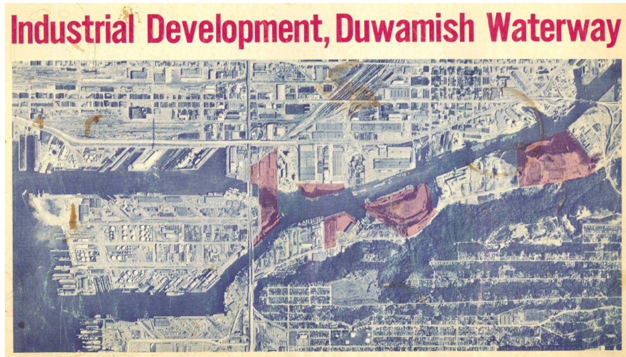
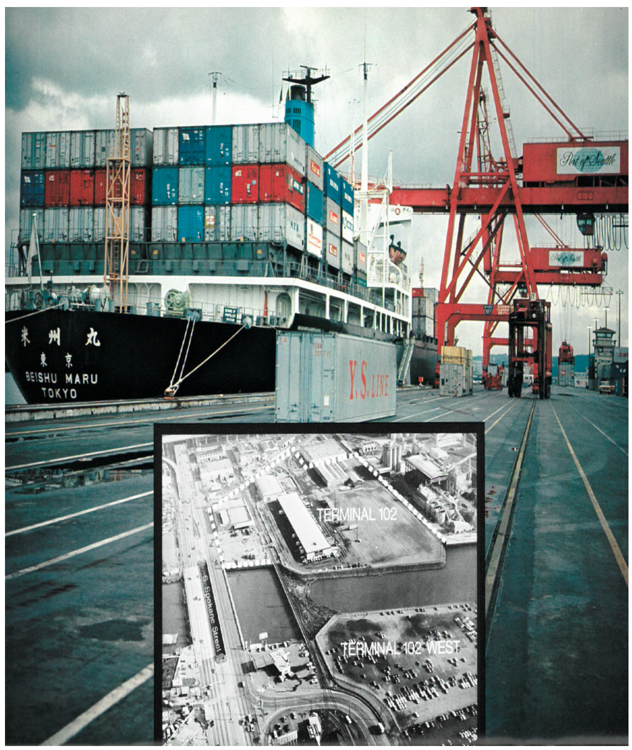


Figure F.6: Maritime Silk Road: targeted ports

Notes: The targeted cities are: Abidjan (Côte d'Ivoire), Antwerpen (Belgium), Beira (Mozambique), Chittagong (Bangladesh), Chongjin (North Korea), Colombo (Sri Lanka), Conakry (Guinea), Dakar (Senegal), Dar Es Salaam (Tanzania), Djibouti (Djibouti), Haifa (Israel), Istanbul (Turkey), Karachi (Pakistan), Kuantan (Malaysia), Lagos (Nigeria), Libreville (Gabon), Lome (Togo), Maputo (Mozambique), Mogadisho (Somalia), Mombasa (Kenya), Nouakchott (Mauritania), Rotterdam (Netherlands) and Vladivostok (Russia). Source: OECD (2018).



Acquired land parcels (red shading), 1963



Completed terminal 102, 1970

Figure F.7: Illustration of port development, Seattle

Notes: The two panels illustrate development of the port through the 1960s. The first panel shows the initial set of land parcels acquired by the port along the Duwamish Waterway in the early 1960s. The second shows a container terminal completed in 1970 within this project. Sources: 'Port of Seattle: Industrial Development, Duwamish Waterway' (1963), 'Annual Report of the Port of Seattle' (1970).

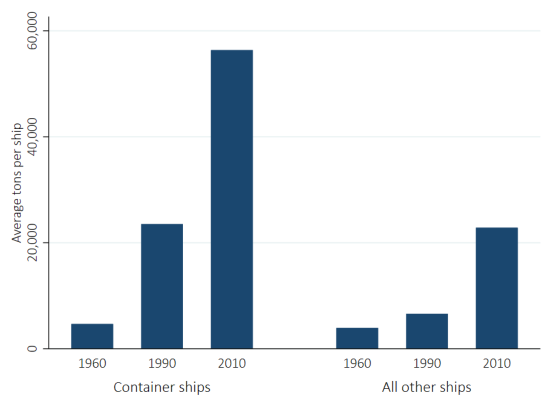


Figure F.8: Development of ship sizes over time, 1960-2010

Notes: The figure illustrates the growth in ship size, as measured in average tons per newly built ship in a given year, for the years 1960, 1990, and 2010, for container-ships and all other ships (i.e., excluding container-ships), respectively. Source: Haworth (2020).

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