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Centrality Bias in Inter-city Trade[1]

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Abstract

Large cities with central location excessively export to smaller cities in close proximity. Using Japanese inter-city trade data, we identify a substantial centrality bias: Exports from central places to their hinterland are 40%-100% larger than predicted by gravity forces. This upward bias stems from aggregating industries, which are hierarchically distributed across large and small cities. Decomposing the centrality bias along the margins of our data, we identify the extensive industry margin as the main driver behind this aggregation bias. Relying on a theory-consistent decomposition of the aggregate gravity equation, we also sort out the underlying theoretical channels that are responsible for the manifestation of the centrality bias.

Keywords: Inter-city trade, central place theory, gravity equation, aggregation bias

JEL classification: C43, F10, F12, F14, R12

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1 Introduction

In this paper, we use highly disaggregated intra-national trade data from Japan to demonstrate that large and centrally located cities (*central places*) excessively export to smaller cities in their nearby economic hinterland. Building on Redding and Weinstein's (2019) nested gravity framework, we argue that this *centrality bias* in inter-city trade is an artifact of aggregating across sectors whose spatial distribution obeys Christaller's (1933) hierarchy principle for industries. According to Christaller's (1933) *hierarchy principle* for industries we expect all industries, that are present in a city of a given size, to be also present in all cities of equal or larger size (cf. Mori, Nishikimi, and Smith, 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015; Davis and Dingel, 2020). The hierarchical distribution of industries across cities and the specific grouping of cities in space that both follow from this principle are the cornerstones of *central place theory* as first developed by Christaller (1933) and Lösch (1940). In such a system of cities, industries that are specific to a few central places are more likely to serve smaller cities with a limited industry diversity in the central place's hinterland. As a consequence, we find that central places export to their hinterland across a wider and on average more export-oriented set of industries, which is why in 2015 central places in Japan exported 40% to 100% more to their hinterland than predicted by the aggregate gravity equation.

During the recent decade, the use of the structural gravity equation as a workhorse model of the empirical trade literature (cf. Anderson, 2011; Head and Mayer, 2014) has expanded far beyond its intellectual origins in the international trade literature (cf. Anderson, 1979; Anderson and van Wincoop, 2003).[1] A key decision for researchers estimating gravity equations based on intra-national trade data is the level of aggregation.[2] Redding and Weinstein (2019) show how a log-linear aggregate gravity equation with a structural error term can be consistently derived from aggregating sectoral gravity equations. Aggregate gravity estimations, that do not account for this typically unobservable structural error term, suffer from aggregation bias and should be regarded at best as log-linear approximations of the true underlying trade relationship at the sectoral level. Taking into account a key prediction of *central place theory* (cf. Fujita, Krugman, and Mori, 1999a; Tabuchi and Thisse, 2011; Hsu, 2012), we explore in this paper how the structural error term in the aggregate gravity equation derived by Redding and Weinstein

[1] Many studies have adopted the gravity framework to analyze the pattern of intra-national trade. See Wolf (2000); Hillberry and Hummels (2003); Millimet and Osang (2007); Coughlin and Novy (2013, 2016); Felbermayr and Gröschl (2014) as well as Allen and Arkolakis (2014) for studies from the US; Combes, Lafourcade, and Mayer (2005) and Briant, Combes, and Lafourcade (2010) for studies from France; Nitsch and Wolf (2013) as well as Lameli, Nitsch, Südekum, and Wolf (2015) for studies from Germany; and Okubo (2004) as well as Wrona (2018) for studies on Japan.

[2] See for example Hillberry (2002), Hillberry and Hummels (2008), Briant et al. (2010) and Coughlin and Novy (2013, 2016).

(2019) is shaped by the hierarchical distribution of industries in space.[3]

Following Mori, Smith, and Hsu (2020a), we apply a simple algorithm in the spirit of Christaller (1933) to identify central places and their associated hinterland cities. The identification of central places and their hinterland cities in a hierarchical city system is based on the recursive spatial grouping of cities as a key-prediction of central place theory (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012).[4] Using 1km×1km grid cell data on population density in Japan, we identify cities as functional urban areas (cf. Dijkstra and Poelman, 2012; Schmidheiny and Suedekum, 2015) approximated by the surrounding municipalities, which are the smallest regional units for which micro-level shipment data is available. Highly disaggregated shipment-level data from five waves of the Japanese Commodity Flow Survey (1995-2015), is then used to explore the pattern of inter-city trade in Japan at an unprecedented level of detail, which distinguishes between up to 191 different industries.

To explore how the hierarchical sorting of industries into central places and hinterland cities affects the pattern of inter-city trade, we separately compute the residual diagnostics of aggregate gravity estimations based on the classification of trading partners as central places and/or hinterland cities. Exports from central places to their hinterland cities are associated with larger average residuals than those to the hinterland cities of other central places, which suggests that aggregate gravity estimations systematically underestimate the trade volume for these city pairs. To capture this centrality bias more systematically, we include a set of *central place dummies* in these aggregate gravity estimations, which take a value of one whenever an origin city exports as a central place to one of its hinterland cities and a value of zero otherwise. Across all five waves of Japan's Commodity Flow Survey we find a large and significant centrality bias, which translates into a percentage trade increase that ranges from 30% to 167%.[5]

In search for an explanation that rationalizes the systematic upward bias in aggregate exports from central places to their hinterland cities, we replicate our analysis at the much more disaggregated industry level. Suppose the centrality bias results from the aggregation of in-

[3]International trade models, that provide micro-foundations for the structural gravity equation, typically assume that all industries are present in all locations. Head and Mayer (2014) review various single-sector models that provide micro-foundations for the structural gravity equation. Multi-sector extensions of Eaton and Kortum's (2002) Ricardian trade model and Krugman's (1980) monopolistic competition framework, as for example reviewed by Costinot and Rodríguez-Clare (2014, pp. 213-216), typically assume industries to be active in all locations. Although the multi-sector version of the Armington trade model (cf. Anderson and van Wincoop, 2004, p. 708) in principle is flexible enough to capture any kind of industry location pattern, there is no endogenous mechanism, which tells us what kind of industry configuration we should expect.

[4]Tomer and Kane (2014) extend and modify the Freight Analysis Framework (FAF) (principally constructed from the 2007 US Commodity Flow Survey) to measure a metropolitan area's centrality based on an atheoretical network approach, that uses information on the total number of connections weighted by their trade value.

[5]To rule out that the centrality bias is a statistical artifact, we scrutinize our main result by randomizing the association of hinterland cities with central places. Reassuringly, we find that the point estimates for our central place dummy in several ten thousand placebo regressions are almost always in the vicinity of zero and typically statistically insignificant at commonly applied levels of significance.

dustries that are hierarchically distributed across large and small cities. Then, sectoral gravity estimates should exhibit no systematic upward bias in central places' exports to their associated hinterland cities. Reassuringly, we fail to identify a sizable and/or statistically significant centrality bias in sectoral gravity estimations.[6] City-pair-specific residual diagnostics, which are based on the classification of trading partners as central places and/or hinterland cities confirm this result: Average residuals for exports from central places to their hinterland cities are much smaller than their counterparts from aggregate gravity estimations and typically close to zero.

Given that the centrality bias in inter-city trade is an artifact of sectoral aggregation, we proceed by decomposing the bias along the margins of our data (cf. Hillberry and Hummels, 2008) and along the margins predicted by Redding and Weinstein's (2019) aggregation theory.

Hillberry and Hummels's (2008) data-driven decomposition approach exploits the high resolution of our shipment-level intra-national trade data. By decomposing aggregate trade flows into a sum of shipments, it is possible to quantify the relative contributions of various extensive and intensive margins in our data. Thereby it turns out that the extensive industry margin is responsible for the by far largest contribution to the centrality bias: In accordance with Christaller's (1933) hierarchy principle for industries, we find that central places export relatively more to their hinterland not because they send more shipments per industry or because their shipments are more valuable, but because they export across a considerably wider range of industries.

Complementary evidence comes from Redding and Weinstein's (2019) theory-based decomposition approach, according to which total bilateral trade can be deconstructed into five multiplicatively separable components. Four of them capture the sectoral variation in origin and destination fixed effects as well as in observable and unobservable trade costs. The remaining one is a Jensen-inequality correction term arising from the fact that the log of aggregate trade is defined as the log of the sum of sectoral trade flows and not as the sum of log sectoral trade flows. Our results suggest that all the five components systematically correlate with the centrality bias in inter-city trade. To understand where these correlations come from, we examine the average residuals obtained from aggregate gravity estimations, which regress each of these five components on the standard set of gravity variables (excluding our central place dummies). Average residuals are thereby computed separately for different origin-destination relationships based on the classification of cities as central places or hinterland cities. The identified pattern of city-pair-specific average residuals not only explains the observed correlations between the

[6] For our results, it thereby does not matter whether the sectoral analysis is based on the Ordinary Least Squares (OLS) estimator or the Poisson Pseudo Maximum Likelihood (PPML) estimator (cf. Santos Silva and Tenreyro, 2006; Correia, Guimarães, and Zylkin, 2020), which accounts for heteroscedasticity and zero trade flows that are correlated with bilateral trade costs.

five aggregate gravity components and the centrality bias in inter-city trade but also is compatible with Christaller's (1933) hierarchy principle for industries. Quantitatively the largest contribution to the centrality bias in inter-city trade stems from the sectoral variation in residual trade costs. This is compatible with a systematic selection of low-trade-cost industries into central places, as predicted by Fujita et al. (1999a) and Hsu (2012). The second-largest contribution stems from the Jensen-inequality correction term, which is compatible with a broader industry diversity in central places as predicted by Christaller's (1933) hierarchy principle.

Having identified and explained a sizable upward bias in the aggregate exports of Japanese central places to cities in their hinterland, we conclude our analysis by demonstrating that a similarly sized centrality bias also can be found in the intra-national trade between US cities. Using data from the 2017 US Commodity Flow Survey, we show that by incorporating an accordingly defined set of central place dummies, it is possible to account for the systematic aggregation bias in the exports from central places to their hinterland.

Christaller's (1933) and Lösch's (1940) early contributions to central place theory have spurred a growing theoretical literature on the implications that a pyramidic city system with a hierarchical industry distribution has for the location of cities and industries as well as for the flow of goods between these cities.[7] While there exists a considerable amount of empirical evidence on Christaller's (1933) hierarchy principle for industries (cf. Mori et al., 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015; Davis and Dingel, 2020) and on the spatial distribution of cities (cf. Hsu, 2012; Mori et al., 2020a), little is known about how the predictions of central place theory are reflected in the pattern of inter-city trade. By incorporating key predictions of the latest generation of central place models (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012) into the nested-gravity framework of Redding and Weinstein (2019) this paper aims at closing this important gap in the literature.

We also contribute to the gravity literature on the aggregation of trade flows across sectors or regions (cf. Anderson and van Wincoop, 2004). An interesting dichotomy has emerged in this literature: Intra-national trade data with a high geographical resolution is typically used to study the effects of spatial aggregation (cf. Hillberry and Hummels, 2008; Briant et al., 2010; Coughlin and Novy, 2013, 2016), whereas international trade statistics, based on detailed product-level customs data, are used to study the effects of aggregating across products and/or sectors (cf. Anderson and Neary, 2005; French, 2017; Redding and Weinstein, 2017, 2019).[8]

[7] Eaton and Lipsey (1976, 1982), Quinzii and Thisse (1990), Fujita et al. (1999a), Fujita, Krugman, and Venables (1999b), Tabuchi and Thisse (2011), as well as Hsu (2012), and Hsu, Holmes, and Morgan (2014) have developed different theoretical models to incorporate the basic ideas of Christaller's (1933) and Lösch's (1940) central place theory. See Abdel-Rahman and Anas (2004), Berliant (2008), and Mori (2019) for recent reviews of the theoretical central place literature.

[8] A notable exception is the paper of Hillberry (2002), which uses disaggregated data from the US Commod-

With the sectoral composition of trade flows being specific to both the size and location of origin cities, we emphasize the importance of sectoral heterogeneity across cities as a possible cause of the aggregation bias in inter-city gravity estimations. Our results thereby resemble those of Hummels and Klenow (2005), who show that the extensive goods margin accounts for around 60% of the greater exports of larger countries. They conclude that none of the standard international trade models reviewed in their study can explain all of the stylized facts they found. In contrast, we argue that the centrality bias in inter-city trade is compatible with the predictions of central place theory (cf. Fujita et al., 1999a; Hsu, 2012).

Our focus on Japan has several important reasons. The key advantage is the availability of micro-level data on bilateral trade flows at a high sectoral and geographical resolution, which distinguishes our work from earlier contributions focusing on trade between prefectures (cf. Wrona, 2018) or regions (cf. Okubo, 2004). As the largest island economy in the world with one of the lowest trade-to-GDP ratios among all OECD countries, Japan offers an ideal setting to study the pattern of inter-city trade in isolation from the country's international trade relationships.[9] It moreover is a well-known fact that Japan's city and industry structure has proven to be extremely resilient against historical shocks such as the bombing of Japanese cities during WWII (cf. Davis and Weinstein, 2002, 2008). Because the multiplicity of spatial equilibria is a unifying feature of all central place models (cf. Fujita and Krugman, 1995; Tabuchi and Thisse, 2011; Hsu, 2012), this evidence makes us confident that our results are not compromised by a sudden and drastic reconfiguration of Japan's city/industry system.

The remainder of this paper is organized as follows. Building upon the theoretical work of Redding and Weinstein (2019), we argue in Section 2 that the structural error term in an aggregate gravity equation, obtained from summing up sectoral gravity equations, is crucially shaped by Christaller's (1933) hierarchy principle for industries. In Section 3, we then introduce our disaggregated intra-national trade data, that in the subsequent Section 4, is used to identify a sizable upward bias in the aggregate exports from central places to their respective hinterland cities. In search for an explanation that rationalizes this bias, we replicate in Section 5 our analysis at the disaggregated sectoral level (cf. Subsection 5.1) before decomposing the centrality bias in its various components (cf. Subsection 5.2). In Section 6 we then apply our methodology to the US, where we identify a centrality bias that is comparable in magnitude to the one found for Japan. Section 7 finally concludes.

ity Flow Survey to show that endogenous industry location patterns and the presence of zero observations in commodity-level trade result in upward-biased border effect estimates.

[9] Due to its remote location and a business model which favors foreign direct investments over exporting, Japan's ratio of ex- or import to GDP is with 18% in 2015 one of the lowest among all OECD members and significantly below the OECD average of 29% for ex- and 28% for imports. See also Lawrence (1987, 1991) and Saxonhouse (1993) for earlier discussions on Japan's exceptionally low export/import-to-GDP ratio.

2 Theoretical Background

Following Redding and Weinstein (2019), we demonstrate that aggregate trade flows which are obtained from the summation of sectoral gravity equations can be characterized through a log-linear gravity equation with a structural error term. Since it is not possible to control for the structural error term without observing the underlying sectoral trade flows, aggregate gravity estimations are typically biased and should be interpreted at best as a log-linear approximation of the true underlying trade relationship.

Redding and Weinstein's (2019) aggregation approach is adopted with three minor adjustments: (*i.*) Whereas intra-national trade flows typically cannot be observed in international trade data, our highly disaggregated intra-national trade data allows us to observe trade within and between cities. When aggregating from the sectoral to the aggregate level we therefore include all intra-city trade flows. (*ii.*) Instead of using an Armington (1969) model as a micro-foundation for the aggregation analysis, we focus on a setting with monopolistic competition (cf. Krugman, 1980), that allows us to discuss the role of firm entry for the sectoral and the aggregate trade pattern. (*iii.*) Finally, we allow the supply of a given sector in a certain location to be zero when no firm in this sector has chosen to locate there (cf. Anderson and van Wincoop, 2004).

Let us consider a country that consists of a set of cities $\mathcal{R}$ indexed by $d, o \in \mathcal{R}$ with $R \equiv |\mathcal{R}|$ as the number of cities, d as a mnemonic for destination, and o as a mnemonic for origin. Preferences of the representative consumer in each destination are defined over consumption indexes Q_{ds} for a set $\mathcal{S}$ of sectors indexed by $s \in \mathcal{S}$ with $S \equiv |\mathcal{S}|$ as the number of sectors and s as a mnemonic for sector. The utility function is assumed to take the following constant elasticity of substitution (CES) form

$$U_d = \left[\sum_{s \in \mathcal{S}} (\Phi_{ds} Q_{ds})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

in which $\sigma > 1$ is the elasticity of substitution between sectors, and $\Phi_{ds} > 0$ is the taste of the representative consumer in destination d for goods produced by sector s.

The consumption index Q_{ds} for destination d in sector s is defined over the consumption $q_{dos}(\omega_{os})$ of different varieties $\omega_{os} \in \Omega_{os}$ in the variety set $\Omega_{os} \subseteq \mathbb{R}^+$ produced by sector s in origin o. We assume that

$$Q_{ds} = \left(\sum_{o \in \mathcal{R}_{ds}} \left\{ \int_{\omega_{os} \in \Omega_{os}} [\phi_{dos} q_{dos}(\omega_{os})]^{\frac{\sigma_s - 1}{\sigma_s}} d\omega_{os} \right\} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{2}$$

also takes the CES form with $\sigma_s > 1$ as the sector-specific elasticity of substitution between varieties from different producers. Tastes of the representative consumer in destination d for goods produced by origin o in sector s are captured by the multiplicatively separable term $\phi_{dos} \equiv \varphi_{ds}\varphi_{os}\varphi_{dos} \geq 0$. We assume the mass of firms/varieties $M_{os} \equiv |\Omega_{os}|$ in origin o and sector s to be exogenously given and explicitly allow for the possibility that $\Omega_{os} = \varnothing$ is an empty set because no firm in sector s finds it optimal to locate in o such that $M_{os} = 0$ (cf. Anderson and van Wincoop, 2004). We refer to the set of origin cities from which destination d imports commodities in sector s in positive amounts as $\mathcal{R}_{ds} \subseteq \mathcal{R}$.

Assuming monopolistic competition at (symmetric) location-specific marginal costs c_{os} and sector-specific iceberg-type trade costs τ_{dos} allows us to solve for the sectoral gravity equation

$$\ln x_{dos} = \gamma_{os} + \lambda_{ds} - (\sigma_s - 1)\ln \tau_{dos} + u_{dos} \quad \text{if} \quad M_{os} > 0, \tag{3}$$

with γ_{os} as an origin-specific fixed effect in sector s, λ_{ds} as a destination-specific fixed effect in sector s, and u_{dos} as a stochastic error. The origin fixed effect $\gamma_{os} = \ln M_{os} + (1-\sigma_s)\{\ln[\sigma_s/(\sigma_s - 1)] + \ln c_{os} - \ln \varphi_{os}\}$ controls for the number of firms M_{os}, the unit production costs c_{os}, and the common origin-sector component of tastes across all destinations φ_{os}. The destination fixed effect $\lambda_{ds} = \ln X_{ds} + (\sigma_s - 1)(\ln P_{ds} + \ln \varphi_{ds})$ controls for destination d's expenditure X_{ds} and price index P_{ds} in sector s as well as for the common destination-sector component of tastes across all origins φ_{ds}. The stochastic error term u_{dos} captures the idiosyncratic component of tastes φ_{dos} that is specific to an individual origin-destination-sector observation. Importantly, the sectoral gravity equation in Eq. (3) only holds if there is a positive supply by sector s in origin o, i.e. $M_{os} > 0$.

Following Redding and Weinstein (2019), we demonstrate (in Appendix 8.1) that a log-linear gravity equation for aggregate trade

$$\ln X_{do} = \gamma_o + \lambda_o - \theta \ln \tau_{do} + v_{do} \tag{4}$$

can be derived by summing up the sectoral gravity equations from Eq. (3) across all sectors $s \in \mathcal{S}_{do} \subseteq \mathcal{S}$ in which destination d imports from origin o. In the aggregate gravity equation from Eq. (4) an origin-specific fixed effect γ_o and a destination-specific fixed effect λ_d control for all origin-specific and all destination-specific variations, and aggregate bilateral trade cost τ_{do} enters with a constant elasticity θ. The typically unobservable structural error term

$$v_{do} = (\Gamma_{do} - \gamma_o) + (\Lambda_{do} - \lambda_d) - (T_{do} - \theta \ln \tau_{do}) + J_{do} + U_{do} \tag{5}$$

is the reason why aggregate gravity estimations are generally biased. Introducing $\mathcal{S}_{do} \subseteq \mathcal{S}_o$ with $S_{do} = |\mathcal{S}_{do}|$ as the subset of sectors s across which destination d imports from origin o and $\mathcal{R}_d \subseteq \mathcal{R}$ with $R_d = |\mathcal{R}_d|$ as the subset of origins o that export to destination d we can characterise the five components of the structural error term v_{do} as follows:

(*i*) bilateral variation in average sectoral origin fixed effects $\Gamma_{do} \equiv \bar{\gamma}_{do} - \bar{\gamma}_d$ for destination d in which $\bar{\gamma}_{do} \equiv \sum_{s\in\mathcal{S}_{do}} \gamma_{os}/S_{do}$ and $\bar{\gamma}_d \equiv \sum_{o\in\mathcal{R}_d} \bar{\gamma}_{do}/R_d$,

(*ii*) bilateral variation in average sectoral destination fixed effects $\Lambda_{do} \equiv \bar{\lambda}_{do} - \bar{\lambda}_d$ for origin o in which $\bar{\lambda}_{do} \equiv \sum_{s\in\mathcal{S}_{do}} \lambda_{ds}/S_{do}$ and $\bar{\lambda}_d \equiv \sum_{o\in\mathcal{R}_d} \bar{\lambda}_{do}/R_d$,

(*iii*) bilateral variation in the average effect of sectoral trade costs $T_{do} \equiv \bar{t}_{do} - \bar{t}_d$ for the destination-origin pair $d\times o$, in which $\bar{t}_{do} \equiv \sum_{s\in\mathcal{S}_{do}} (\sigma_s - 1) \ln \tau_{dos}/S_{do}$ and $\bar{t}_d \equiv \sum_{o\in\mathcal{R}_d} \bar{t}_{do}/R_d$,

(*iv*) a Jensen's inequality term $J_{do} \equiv \ln X_d + \bar{y}_d - \bar{z}_{do}$, in which $\bar{y}_d = \frac{1}{R_d}\sum_{o\in\mathcal{R}_d} \frac{1}{S_{do}} \sum_{s\in\mathcal{S}_{do}} \ln \mathscr{Y}_{dos}$ with $\mathscr{Y}_{dos} \equiv x_{dos}/\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{do}} x_{djr}$ and $\bar{z}_{do} = \frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln \mathscr{Z}_{dos}$ in which $\mathscr{Z}_{dos} = x_{dos}/\sum_{r\in\mathcal{S}_{do}} x_{djr}$,

(*v*) an error term $U_{do} \equiv \bar{u}_{do} - \bar{u}_d$ in which $\bar{u}_{do} \equiv \sum_{s\in\mathcal{S}_{do}} u_{dos}/S_{do}$ and $\bar{u}_d \equiv \sum_{o\in\mathcal{R}_d} \bar{u}_{do}/R_d$.

From the definition of the structural error term in Eq. (5) it follows that the ability of the aggregate gravity model in Eq. (4) to correctly predict aggregate bilateral trade flows crucially depends on the composition of the set $\mathcal{S}_{do}$ of sectors s across which destination city d imports from origin city o. If different city pairs trade across vastly different set of sectors $\mathcal{S}_{do}$, and if these sectors also differ in terms of their sectoral gravity components γ_{os}, λ_{ds}, τ_{dos}, and u_{dos} underlying Eq. (3), we would expect that an aggregate gravity model, that does not account for the structural error term v_{do}, will mispredict the aggregate trade volume for at least some city pairs.

In addition to the gravity components γ_{os}, λ_{ds}, τ_{dos}, and u_{dos}, which naturally shape the structural error term v_{do}, there also is a Jensen's inequality correction term J_{do}. This term accounts for the fact that the absolute value of sectoral trade x_{dos} and not the log of the sectoral trade flow $\ln x_{dos}$ from Eq. (3) are aggregated up to obtain the log-linear aggregate gravity equation from Eq. (4).

In the following Subsection 2.1 we argue that the composition of the subsets of exporting sectors s in origins o differs systematically between origin cities that are large and centrally located and origin cities that are small and ubiquitously distributed. Aggregating over these vastly different subsets of sectors therefore results in a structural error term v_{do} that systematically differs between central places and hinterland cities as origin cities.

2.1 Central Places, Hinterlands, and Chistaller's Hierarchy Principle

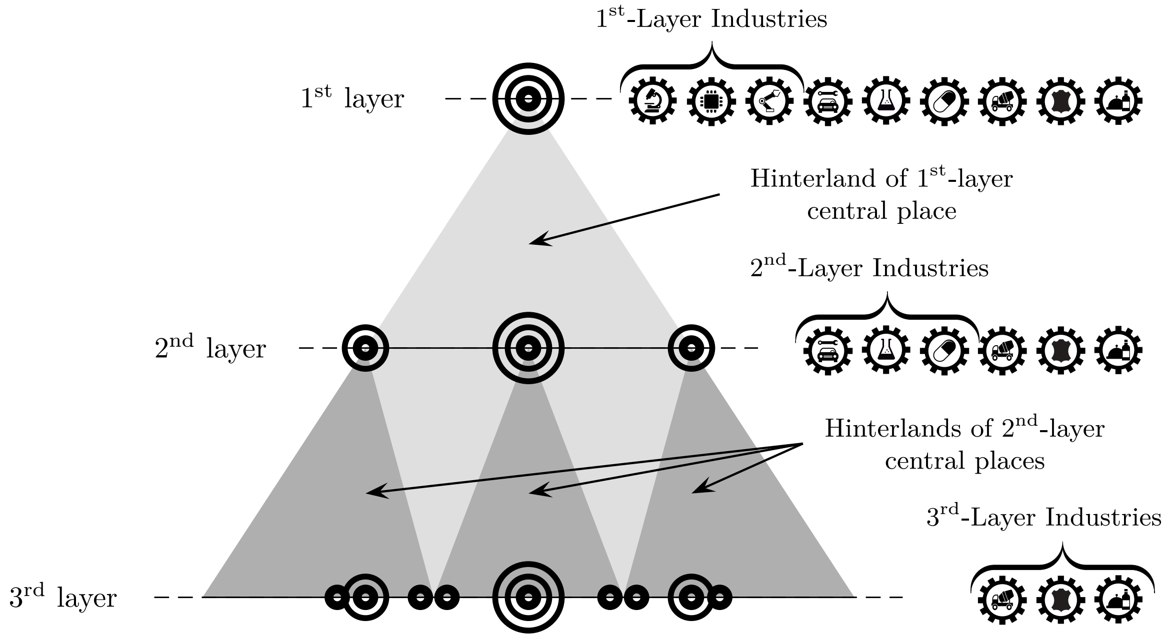
We proceed by showing that the size and composition of the subset $\mathcal{S}_{do}$ of sectors s across which destination d imports from o crucially depends on Christaller's (1933) hierarchy principle for industries, which systematically shapes the distribution of sectors across space. Endogenous market entrance thereby results in a hierarchical industry structure, which stands in marked contrast to the exogenously fixed distribution of industries in most international trade models.[10]

Building up on the early work of Christaller (1933) and Lösch (1940), several more recent contributions (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012) have shown how to embed the key predictions of Christaller's (1933) and Lösch's (1940) central place theory into different general equilibrium frameworks. Whereas in Fujita et al. (1999a); Tabuchi and Thisse (2011) a hierarchical industry structure is derived from inter-sectoral differences in the variable iceberg-type trade costs and the sector-specific elasticities of substitution, a similar sorting of firms from different industries is established by Hsu (2012) under the assumption of heterogeneous market entry fixed costs. To illustrate Christaller's (1933) hierarchy principle for industries we resort in the following paragraph to a simple and therefore illustrative numerical example from Fujita et al. (1999a, Fig. 6, p. 237), which highlights some of the key predictions of central place theory.

Fujita et al. (1999a) consider a multipolar agglomeration model with heterogeneous industries, in which a city not only gets larger by growing in scale but also by growing in scope (i.e. by adding new industries). Agglomeration generates two types of cities: On the one hand, we have a limited number of central places. These are large, centrally located cities of sufficient size to not only attract ubiquitous industries, whose goods are costly to trade and therefore optimally produced in close proximity to customers, but also some footloose industries, whose goods are traded at low costs and which therefore prefer centrally located cities with a large home market (cf. Krugman, 1980). On the other hand, there are many small cities in the hinterlands of central places, which due to their insufficient size and/or location only attract a limited set of ubiquitous industries. In Figure 1, we depict a one dimensional space, in which the location of cities are indicated by circles, and in which the number of industries in a given city is proportional to the number of circles representing this city. Figure 1 also illustrates to what Mori et al. (2020a) refer as the *spatial grouping property* of central place theory: Large

[10]Multi-sector extensions of Eaton and Kortum's (2002) Ricardian trade model and Krugman's (1980) monopolistic competition framework typically assume industries to be ubiquitously distributed (see Costinot and Rodríguez-Clare (2014, pp. 213-216) for a recent summary of the literature). The multi-sector version of the Armington trade model (cf. Anderson and van Wincoop, 2004, p. 708) is flexible enough to replicate arbitrary patterns of industry location but does not provide theoretical guidance with respect to the underlying determinants of the observed industry location pattern.

Figure 1: *Central Places and their Hinterlands in a Hierarchical City System*



Note: *Figure 1 illustrates the spatial distribution of cities in Fujita et al.'s (1999a) central place model. Cities thereby are represented by circles with the number of circles being proportional to the number of industries per city. Sorting cities into layers according to their industry diversity, we can identify central places, which serve nearby hinterland cities at lower layers.*

central places are surrounded by smaller hinterland cities, which means that they have to be geographically more separated than under a random spatial distribution. Building on multi-country evidence regarding the spacing out of central places provided by Mori et al. (2020a), we later rely on this spatial grouping property to identify central places and their associated hinterlands in Japan (see Subsection 4.1 below).

Sorting central places according to the range of their industries (indicated by the number of circles around a city in Figure 1) results in a hierarchical city system with nested central places and associated sets of hinterland cities as illustrated in Figure 1. The sorting of industries across a total of three layers in Figure 1 thereby distinguishes between 1st-, 2nd-, and 3rd-layer cities, which systematically differ in terms of their industry diversity. As a noticeable feature of the pyramidic city system in Figure 1, we find the distribution of industries across cities to follow a strict hierarchical pattern: All 3rd-layer industries can also be found in 2nd-layer cities, and all 2rd-layer industries are also present in the 1st-layer city. Following Mori and Smith (2011), we refer to this pattern as Christaller's (1933) hierarchy principle for industries, expecting all industries, which can be found in a city of a given size, to be also present in all cities of larger size.

Several authors (cf. Mori et al., 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015) have accumulated supportive empirical evidence in favour of Christaller's (1933) hierarchy principle for industries. We contribute to this strand of the literature by highlighting the importance of Christaller's (1933) hierarchy principle for our specific application. More specifically, we propose a simple three-step randomisation test: At first we compute the economy's average hierarchy share as a measure of how hierarchical industries are distributed across cities. In a second step we then fix the number of industries in each city, randomising the allocation of industries across cities. In the third and last step we compare the average hierarchy share with its counterfactual counterparts, that are obtained from a randomised distribution of industries across cities.

For any two cities d and o we can define the hierarchy share H_{do} as:

$$H_{do} \equiv \frac{|\mathcal{S}_d \cap \mathcal{S}_o|}{\min\{S_d, S_o\}} \in [0, 1], \tag{6}$$

with $\mathcal{S}_d$ as the set of industries in city d and $S_d \equiv |\mathcal{S}_d|$ as the corresponding number of industries in this city. The hierarchy share takes a value of $H_{do} = 0$ if there is zero overlap between the sets of industries in d and o. If all industries, that are present in the smaller city, can also be found in the larger city the hierarchy share takes its maximum value of $H_{do} = 1$, which means that Christaller's (1933) hierarchy principle for industries holds without restrictions.

Aggregation across all cities d and o requires us to proceed in two steps. We first aggregate across all cities d that host more industries than city o (i.e. $S_d > S_o$). City o's average hierarchy share H_o can then be computed as:

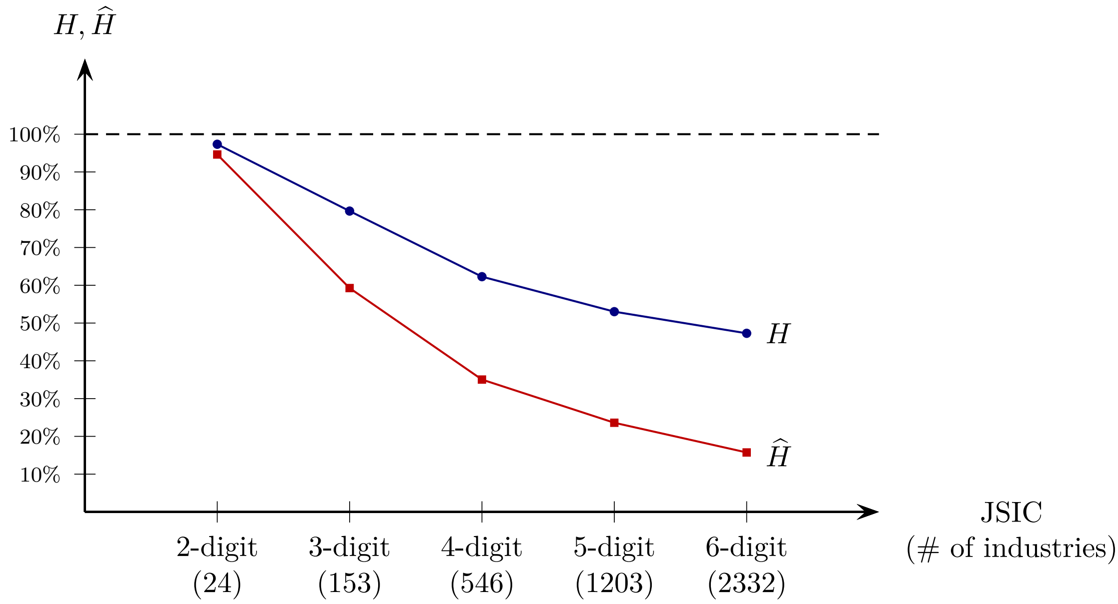
$$H_o = \frac{1}{G_o} \sum_{d \in \mathcal{G}_o} H_{do} \quad \text{with} \quad \mathcal{G}_o \equiv \{d : S_d > S_o\}, \tag{7}$$

with $G_o \equiv |\mathcal{G}_o|$. Given the definition of H_o we can finally compute the economy-wide average hierarchy share H as a simple arithmetic mean $H = \sum_o H_o/(R-1)$ over all cities o, excluding the city with the largest number of industries.

We begin by analysing the location of industries that we can infer from our highly disaggregated intra-national trade data for Japan (see Section 3 below for a detailed description). Computing the average hierarchy shares H_o of cities o under the assumption that partner cities d with a larger set of industries (i.e. $S_d > S_o$) possess a certain minimum number of industries $\underline{S} \in \{10, 20, 30, 40, 50\}$, we find that observed average hierarchy shares always exceed their counterfactual counterparts, and that in a one-sided statistical test their equality can be always rejected at conventional levels of statistical significance. Instead of reporting the complete results (relegated to the Online Appendix), we focus here on an exemplary specification, assuming that all partner cities have at least 30 industries. For 2015 the average hierarchy share based on a total of 188 observed industries can then be computed as $H = 0.6266$, taking a considerably larger value than the maximum of the $1,000$ hierarchy shares obtained under randomisation $\widehat{H} = 0.2981$.

To scrutinise this first results we rely on auxiliary data from the Economic Census for Business Activity (cf. Statistical Bureau, Ministry of International Affairs and Communications; Ministry of Economy, Trade and Industry of Japan, 2016), which is used to reproduce our simple three-step randomisation test at different levels of disaggregation in the Japan Standard Industry Classification (JSIC). Unlike our intra-national trade data, which is obtained from surveying a representative sub-sample of Japanese firms over the course of three days, the 2016 Economic Census for Business Activity provides detailed information on the location and industry classification of all $3,856,457$ establishments that existed in Japan at the 1st of June 2016. With the universe of Japanese firms being covered we can be sure that our hierarchy measure H is not downward biased because missing information on industry location (particularly in small cities) obscures the true extent to which industries are hierarchically distributed in Japan.

Figure 2: *Testing for Christaller's (1933) Hierarchy Principle for Industries*



Note: *Figure 2 is based on the Economic Census for Business Activity (cf. Statistical Bureau, Ministry of International Affairs and Communications; Ministry of Economy, Trade and Industry of Japan, 2016), which covers all manufacturing establishments in Japan in 2016. The figure plots the observed versus the counterfactual average hierarchy shares for different levels of disaggregation in the Japan Standard Industry Classification (JSIC) with the number of different industries in parenthesis.*

In Figure 2 we plot the average hierarchy share H together with the maximum counterfactual hierarchy share $\widehat{H}$ selected from 1,000 randomised samples at different levels of disaggregation in the Japan Standard Industry Classification (JSIC). At the 2-digit level the JSIC only distinguishes between 24 aggregate industries. Unsurprisingly, these 24 aggregate industries can be found almost everywhere, resulting in observed and counterfactual hierarchy shares close to one. At lower levels of disaggregation we find that the observed average hierarchy shares are always much larger than the counterfactual hierarchy shares that are obtained from randomising the identity of industries across locations with a fixed number of industries.

Summing up the results of our simple hierarchy test, we find that the distribution of industries across cities of varying size follows a strongly hierarchical pattern that is compatible with Christaller's (1933) hierarchy principle for industries.

2.2 The Heterogeneous Extensive Margins of Sectoral Inter-city Trade

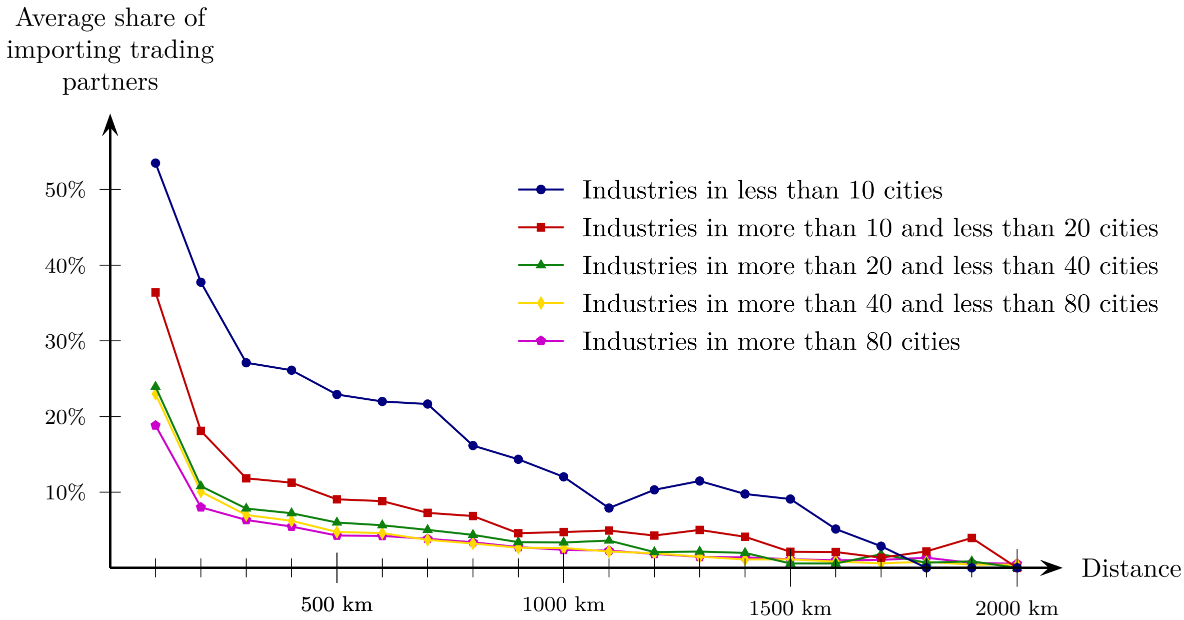
Having established Christaller's (1933) hierarchy principle for industries, we are now exploring the sector-specific patterns of inter-city trade that follow from this principle. For this purpose we sort industries into 5 different bins according to the number of cities in which they can be found in 2015. Specifically, we distinguish industries which are present in less than 10 cities, in 10 or more but less than 20 cities, in 20 or more but less than 40 cities, in 40 or more but less than 80 cities, or in 80 or more cities. In Figure 3 we plot for each set of industries the (average) extensive margin of inter-city trade (i.e. the average share of all destination cities importing goods produced by these industry) over a total of 20 different distance intervals, that capture the bilateral distance between origin and destination city.[11]

Figure 3 shows a clear ranking of industries, according to which industries that are located in a limited number of cities are more likely to serve other markets than industries that can be found across a wide range of cities. We moreover find that the extensive margin of trade is declining in the distance to the destination city. For ubiquitous industries the extensive margin of trade strongly declines in distance over the first 200-300 kilometers then flattening out at a low level in the vicinity of zero. On the contrary, we find that the extensive margin of trade for footloose industries appears to be much more resilient against increasing shipment distances. Summarizing our findings from Figure 3, we can conclude that footloose industries tend to serve a wider market area than their ubiquitously distributed counterparts.

It is worth noting that the differences in market areas between footloose and ubiquitous industries in Figure 3 exactly match the predictions of the central place model by Hsu (2012). In this model the combination of perfectly inelastic demand across an one-dimensional space and Bertrand competition among a set of firms that differ in terms of their scale economies (i.e. production fixed costs) gives rise to a hierarchical sorting of industries into cities. Industries with

[11] To be classified as a potential destination for the goods produced by a specific origin city there must be at least some demand for those goods in these cities (cf. Hillberry and Hummels, 2008).

Figure 3: *Heterogeneity in the Extensive Margins of Inter-city Trade at the Industry Level*



Note: *Figure 3 is based on Japan's Freight Census, and plots the average share of importing trading partners in different industries against the distance between origin and destination city.*

high fixed costs require a larger (exclusive) market area to break even and therefore optimally locate further apart than industries with lower fixed costs. As a consequence, we find that industries which cluster in a small number of central places serve more cities over larger distances than industries which can be found across a wider range of cities.

The existence of well-defined finite market areas is what distinguishes the central place model of Hsu (2012) from Fujita et al.'s (1999a) central place model, in which each industry irrespective of its location always serves all possible destination cities, and in which sectoral trade flows only vary along the intensive margin (cf. Fujita et al., 1999a, Fig. 10, p. 244). The variation along the intensive margin would of course also be reflected along the extensive margin, if the iso-elastic demand model by Fujita et al. (1999a) is extended to allow for exporting fixed costs.

Taking stock, we can conclude that Christaller's (1933) hierarchy principle for industries not only shapes the set of exporting industries across origin cities but also the extensive margin of sectoral inter-city trade. Combining the theoretical insights from Redding and Weinstein's (2019) aggregation exercises with the predictions of central place theory (cf. Fujita et al., 1999a; Hsu, 2012) therefore leads us to the conclusion that aggregate gravity estimations between cities are prone to aggregation bias, and that the direction and magnitude of this aggregation bias crucially depends on the central-place-to-hinterland relationship between origin and destination cities.

3 Data

Our main data source is Japan's Freight Census [*zenkoku kamotsu jun ryudo chosa*], which is compiled by the Ministry of Land, Infrastructure, Tourism and Transport (MLIT). The commodity flow data comes in five waves, which have been collected in a five-year interval from 1995 to 2015. The Freight Census provides detailed information on establishment-level shipments between municipalities in Japan, among which we focus on those located on the four main islands (*Hokkaido*, *Honshu*, *Shikoku* and *Kyushu*).[12] The survey includes only manufacturing establishments with at least four employees. Establishments are classified according to the Japan Standard Industrial Classification (JSIC), which distinguishes between 24 two-digit manufacturing industries (22 two-digit manufacturing industries in 1995 and 2000).[13] In addition to the establishments' two-digit industry classification we also have detailed information on the shipped commodities, which are disaggregated into 9 basic product categories and 85 sub-categories.

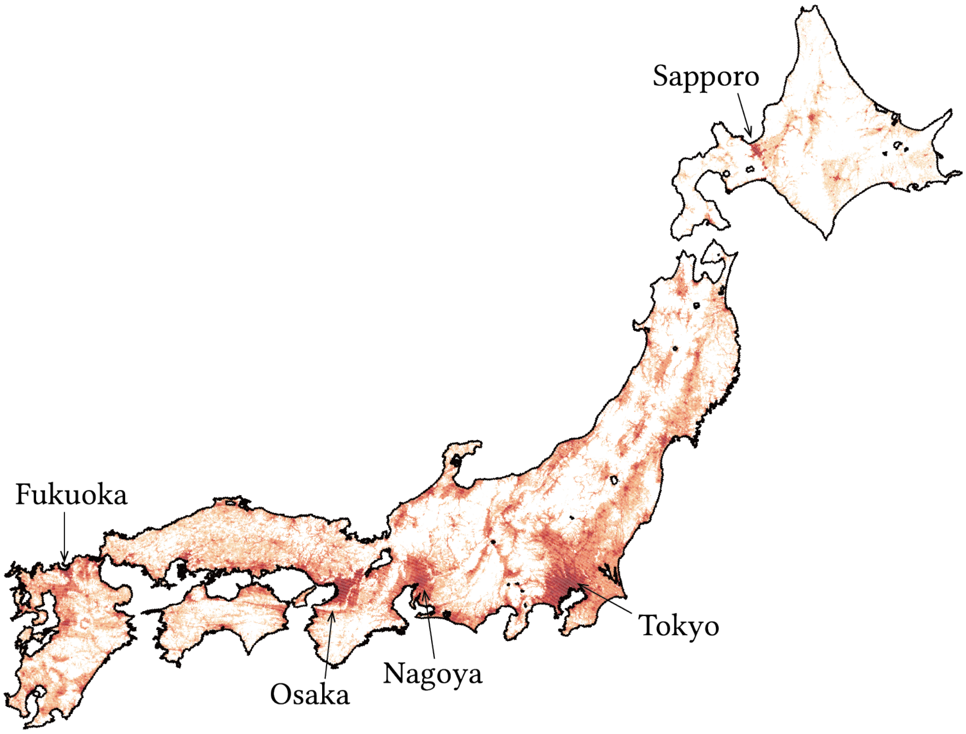
In line with the underlying central place theory (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012) we focus on cities as the basic geographic unit of our analysis. Using highly disaggregated grid data from the Japanese Population Census (cf. Figure 4), cities are constructed based on urban agglomerations (UAs), which are identified as contiguous and disjoint sets of 1km×1km grid cells with at least 1,000 people per square kilometre and a total population of at least 10,000 inhabitants.[14] The 450 UAs, which we identify based on the Japanese Population Census from 2015, are home to 77% of Japan's total population and occupy 12% of the country's contiguous landmass. To aggregate individual shipments from the municipality to the city level, we assign municipalities that overlap with one or multiple UAs to the UA with the largest population share, calling the set of associated municipalities henceforth a city.

[12] Since our focus is on Japan's internal trade, we drop all shipments designated for exporting. Due to its remote location and a business model which favours foreign direct investments over exporting, Japan's export to GDP ratio is with 18% in 2015 one of the lowest among all OECD members and significantly below the OECD average of 29%. See also Lawrence (1987, 1991) and Saxonhouse (1993) for earlier contributions discussing Japan's low export to GDP ratio.

[13] In 2015 a total of 14,620 or 7.0% of all 208,029 relevant manufacturing establishments were sampled. For the earlier waves the number of sampled manufacturing establishments are 14,097 or 5.4% out of 263,052 in 2010; 13,684 or 4.7% out of 294,170 in 2005; 15,452 or 4.1% out of 373,108 in 2000; and 18,520 or 4.9% out of 378,167 in 1995. A more detailed discussion of our primary data, including the definition of industries and products, is relegated to the Online Appendix.

[14] Our definition of an urban agglomeration (UA) follows Dijkstra and Poelman (2012, 2014), who propose a harmonised definition of functional urban areas, which is applied by Schmidheiny and Suedekum (2015) to identify European cities. To identify Japanese cities we prefer to use urban agglomerations (UAs) instead of Urban Employment Areas (UEAs), which have been constructed by Kanemoto and Tokuoka (2002) to resemble US metropolitan areas (MAs), and which are often used in the Japanese context. In the Online Appendix we show that Kanemoto and Tokuoka's (2002) definition of UEAs systematically overstates (understates) the size of cities in the middle (at the lower end) of the city size distribution. Because the hierarchical distribution of industries across cities is highly correlated with city size it is important to ensure that the size of cities is correctly measured and that the total number of cities is not systematically underestimated because many small cities are merged into a smaller number of larger medium-sized cities.

Figure 4: *Japanese Population Distribution for 2015*



Note: *Figure 4 is based on the Japanese Population Census, and depicts the spatial distribution of the Japanese population in 2015 at the level of a 1km×1km grid cells. Comparable maps for 1995, 2000, 2005, and 2010 are reported in the Online Appendix.*

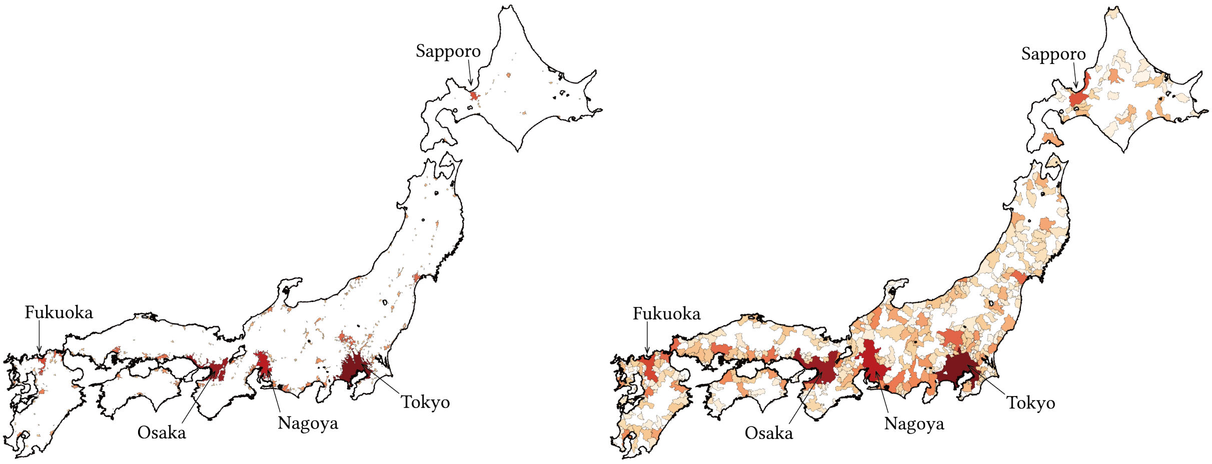
Aggregating up our municipality-level shipment data to the city level leaves us with 400 cities in 2015 of which 292 cities export to at least ten other cities in our sample.[15] Figure 5 illustrates the definition of cities as basic unit of observation by showing how we narrow down our 450 urban agglomerations (Subfigure 5a) to 400 cities (Subfigure 5b).

One common drawback shared by most commodity flow surveys (cf. Wolf, 2000; Hillberry and Hummels, 2003, 2008; Combes et al., 2005; Nitsch and Wolf, 2013) is the rather coarse classification of commodities based on a limited number of industries, which stands in marked contrast to the availability of high-resolution international trade data. To obtain a sufficiently detailed industry classification, we combine the establishment-level industry classification (22 to 24 two-digit Japan Standard Industrial Classification (JSIC) industries) with the shipment-specific product codes (67 relevant subcategories). Not all of the $24 \times 67 = 1608$ feasible combinations of industry and product code are relevant for our analysis.[16] In order to exclude outliers, we manually check each industry×product combination to see whether the recorded shipments make sense to be recognized as an output of the sending establishment. In the same

[15]For the earlier waves of the survey we end up with a total of 291 cities in 2010; 307 cities in 2005; 310 cities in 2000 and 347 cities in 1995.

[16]Some of the recorded shipments clearly are not representative for the establishments typical sales (e.g. a food manufacture who is shipping a single automobile, probably selling off a former investment good).

Figure 5: *Definition of Cities as Basic Unit of Observation*



(a) *450 Urban Agglomerations* **(b)** *400 Cities*

Note: *Figure 5 is based on the Japanese Population Census, and depicts 450 urban agglomerations (left panel), which are approximated by surrounding municipalities (right panel), resulting in a total of 400 cities. Comparable maps for 1995, 2000, 2005, and 2010 are reported in the Online Appendix.*

way we also check whether certain product categories (e.g. 7022: "clothes and belongings") are too broadly defined, and therefore could be splitted into multiple sub-categories depending on industry classification of the sending establishment (e.g. 403: "textile" versus 412: "leather and leather products"). As a result of the data cleaning process we end up with 212 relevant industry-product combinations for 2015. Since not all of these industry-product combinations were traded in the three day period during which the Freight Census was conducted, we end up with a total of 188 observed industry-product combinations for 2015.[17]

Our highly disaggregated inter-city trade data is complemented by information on real-road distances between municipality pairs based on the distance along the road network obtained from OpenStreetMap (as of July, 2017). The bilateral distance between each pair of municipalities thereby is computed as the distance between the centroids of the most populated 1km$\times$1km cells in these municipalities.[18] We approximate intra-municipality distance by the average line-distance between a pair of locations on a circle with the area equal to the habitable area of the municipality (cf. MIAC of Japan, 2015), which can be approximated by $(128/45\pi)\sqrt{a/\pi}$, in which a is the habitable area of the municipality (cf. Combes et al., 2005). Following Head and Mayer (2009), bilateral distance between city d and o is then computed as a trade-weighted

[17]In the Online Appendix we report the complete lists of all plausible industry-product combinations for 2010-2015, 2005, and 1995-2000. There we also report the lists of industry-product combinations that we actually observe across our samples. Of the 212 plausible industry-product combinations that we identify for 2010-2015 we observe 188 in 2015 and 186 in 2010. Of the 193 plausible industry-product combinations that we identify for 2005 we observe 191 in 2005. Of the 176 plausible industry-product combinations that we identify for 1995-2000 we observe 169 in 2000 and 167 in 1995.

[18]See also Mori, Smith, and Hsu (2020b) for the details of how to compute the road-distances using OpenStreetMap.

harmonic mean of the bilateral distances between all the municipalities that belong to city d and o, respectively.[19]

4 Aggregation Bias in Inter-city Trade

How does the aggregation bias, that results from Christaller's (1933) hierarchy principle for industries, affect the pattern of inter-city trade? To answer this question we proceed in two steps: In Subsection 4.1 we apply a simple theory-consistent algorithm in the spirit of Christaller (1933), which has recently been proposed by Mori et al. (2020a) to identify central places and their associated hinterlands. In the following Subsection 4.2 we then use this information to quantify the upward bias in the exports from central places to their associated hinterland cities.

4.1 In Search for Central Places and their Hinterlands

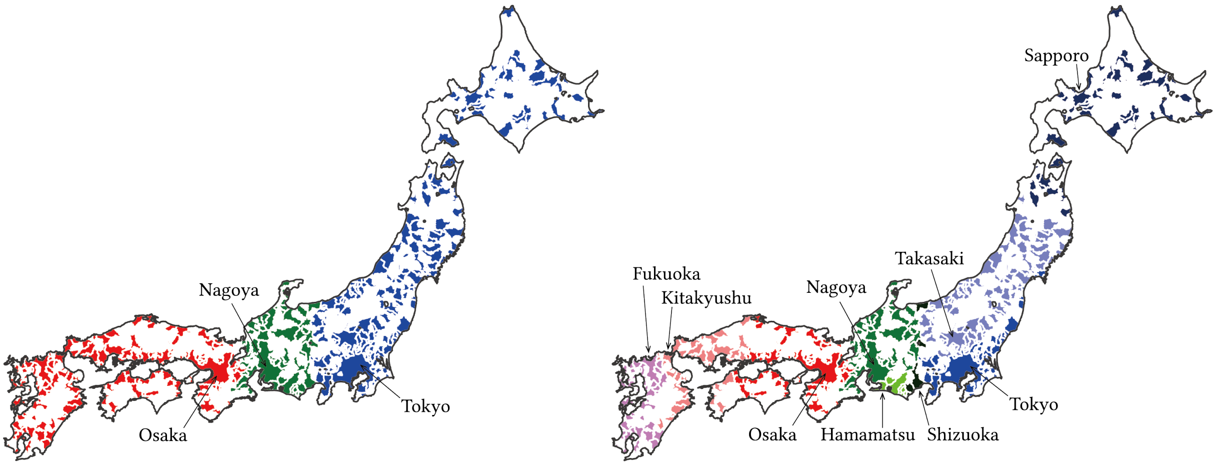
In order to partition the set of cities in our sample into central places with associated hinterlands (cf. Figure 1) we follow Mori et al. (2020a), who propose a simple and transparent classification algorithm, which consistently captures the recursive spatial grouping of cities as a key-prediction of central place theory (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012). It is required that each cell of a partition consists of the largest city (the central place) in that cell and a set of smaller hinterland cities surrounding it. A spatial hierarchical structure emerges because each cell can be further partitioned in a lower layer, in which each cell again has a spatial grouping property.

Specifically, we are assuming a hierarchical city system with possibly many layers. For a given number of cells (central places plus surrounding hinterland cities) at a certain layer there exists a unique Voronoi K-partition (based on real-road distance) for each cell, that partitions this cells into $K > 1$ sub-cells for a specified number of K lower-layer central places, which are the largest K cities in this cell.[20] By specifying the number of lower-layer central places per cell K (in our case $K = 3$) together with a stopping rule, it is possible to construct the structure of the hierarchical city system recursively. With the set of all cities in a country forming a unique cell at the 1^{st} layer the largest city (i.e. *Tokyo*) is always chosen as 1^{st}-layer central place. The 2^{nd} layer is a unique Voronoi K-partition with respect to the K largest cities in the country. At the l^{th} layer ($l = 2, \ldots, L$), the Voronoi K-partition of each cell with respect to the largest

[19] See Rauch (2016) for a geometric analogy between gravity in physics and gravity in trade, which suggest that distances between regions in empirical gravity estimations should be measured as weighted harmonic means over pairwise distances of local economic activity (see Head and Mayer (2009) for a detailed review of the literature).

[20] While there exists a multitude of possibilities to construct a hierarchical city system, we follow Christaller (1933), who originally assumed that the number K of lower-layer central places in each cell of a partition is the same across all layers.

Figure 6: *2^{nd}- and 3^{rd}-layer Central Places and their Hinterlands*



(a) *2^{nd}-layer Voronoi Partition* **(b)** *3^{rd}-layer Voronoi Partition*

Note: *Figure 6 depicts 2^{nd}- and 3^{rd}-layer Voronoi K-partitions for central places and associated hinterlands in Japan for 2015. Similar partitions are obtained for earlier waves (1995, 2000, 2005, and 2010) of the Freight Census. We report these additional results in the Online Appendix.*

K cities in the cell generates K cells at the $(l+1)^{\text{th}}$ layer. Each cell is partitioned as long as it contains at least K cities. Thus, the process eventually stops at the L^{th} layer if no cell contains more than K cities.

Several aspects render Mori et al.'s (2020a) partition scheme particularly useful for our application: Being defined in the spirit of Christaller (1933), the above classification algorithm only requires a modest input of data, and in particular does not rely on the inter-city trade data that we seek to analyze below (see Section 4). The ranking of cities in terms of population size thereby can be justified through the high correlation between population size and industrial diversity predicted throughout a wide class of central place models (cf. Christaller, 1933; Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012).[21]

Figure 6 depicts 2^{nd}- and 3^{nd}-layer Voronoi partitions, fixing the number of sub-cells on lower layers to $K = 3$.[22] At the 2^{nd} layer in Subfigure 6a we distinguish partition cells (i.e. a central place plus its hinterland) through different colors and explicitly label the respective central place of each cell. 3^{rd}-layer cells in the hinterland of 2^{nd}-layer central places (cf. Subfigure 6b) are colored in different shades of the color associated with their 2^{nd}-layer central places from Subfigure 6a.

Having identified a hierarchical city system with central places and associated hinterlands,

[21] In 2016, the Spearman's rank correlation between the population size and the number of industries located in Japanese cities is 1.0 when all the 3-digit secondary and tertiary industries are included and 0.7320 if only manufacturing industries are included (cf. Statistical Bureau, Ministry of International Affairs and Communications; Ministry of Economy, Trade and Industry of Japan, 2016).

[22] 2^{nd}- and 3^{nd}-layer Voronoi partitions for the years 1995-2010 are reported in the Online Appendix.

we are focusing in the following on the top five layers when exploring the pattern of inter-city trade between these city types. In each layer we can thereby distinguish between up to eight mutually exclusive trading relationships, which emerge from the combination of the two possible origin categories: central place (CP) versus hinterland city (HC) with up to four possible destination categories: central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC).

Table 1: *Descriptive Analysis – Inter-City Trade*

Descriptive Analysis – Inter-City Trade											
Year:		**2015**									
Measure:		**% of Trade Flows**					**% of Trade Volume**				
Direction:		**Destination:**					**Destination:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1^{st} **Layer:**											
Origin:	**CP:**	0.0000	–	0.0159	–	0.0159	0.0788	–	0.0614	–	0.1402
	HC:	0.0145	–	0.9696	–	0.9841	0.1219	–	0.7379	–	0.8598
	All:	0.0145	–	0.9855	–	1.0000	0.2007	–	0.7993	–	1.0000
2^{nd} **Layer:**											
Origin:	**CP:**	0.0001	0.0002	0.0160	0.0303	0.0467	0.2294	0.0652	0.0668	0.1016	0.4630
	HC:	0.0148	0.0260	0.4864	0.4261	0.9533	0.1129	0.0988	0.2479	0.0774	0.5370
	All:	0.0149	0.0262	0.5024	0.4564	1.0000	0.3423	0.1640	0.3147	0.1790	1.0000
3^{rd} **Layer:**											
Origin:	**CP:**	0.0004	0.0029	0.0149	0.0839	0.1021	0.2494	0.1111	0.0452	0.1373	0.5430
	HC:	0.0136	0.0753	0.2405	0.5685	0.8979	0.0654	0.1560	0.1270	0.1087	0.4570
	All:	0.0140	0.0782	0.2554	0.6524	1.0000	0.3148	0.2671	0.1722	0.2460	1.0000
4^{th} **Layer:**											
Origin:	**CP:**	0.0010	0.0219	0.0136	0.1627	0.1992	0.2693	0.1884	0.0259	0.1473	0.6310
	HC:	0.0128	0.1589	0.1206	0.5083	0.8008	0.0361	0.1743	0.0731	0.0855	0.3690
	All:	0.0138	0.1808	0.1342	0.6710	1.0000	0.3054	0.3627	0.0990	0.2328	1.0000
5^{th} **Layer:**											
Origin:	**CP:**	0.0023	0.0842	0.0118	0.2343	0.3327	0.2831	0.2634	0.0132	0.1649	0.7247
	HC:	0.0104	0.2314	0.0530	0.3726	0.6673	0.0127	0.1737	0.0407	0.0483	0.2753
	All:	0.0127	0.3138	0.0648	0.6069	1.0000	0.2958	0.4371	0.0539	0.2132	1.0000

Notes: Abbreviations are defined as follows: central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC).

In Table 1 we use the 2015 wave of our inter-city trade data to report two different summary measures, which are computed separately for the previously derived classifications of central places and hinterlands at the 1^{st}, 2^{nd}, 3^{rd}, 4^{th}, and 5^{th} layer.[23] To understand how the pattern of inter-city trade is shaped by Japan's pyramidic city system with central places and associated hinterlands we compute the frequency (i.e. the fraction of non-zero trade flows between city

[23]The results for the earlier waves from 1995 to 2010 closely resemble the findings in Table 1. We therefore have relegated these additional results to the Online Appendix.

pairs) as well as the trade shares (i.e. the share of bilateral in total trade) for all possible trading relationships between central places and associated as well as unassociated hinterland cities.

Unsurprisingly, Table 1 confirms the overall importance of central places for the pattern of inter-city trade. *Tokyo* as the 1$^{\text{st}}$-layer central place accounts alone for roughly 14.0% of all exports and 20.1% of all imports. At the 2$^{\text{nd}}$ layer *Tokyo*, *Osaka*, and *Nagoya* together are responsible for 46.3% of all exports and 34.2% of all imports. Although 2$^{\text{nd}}$-layer central places exports to non-hinterland cities at twice the rate as they exports to their own hinterland cities (3.0% versus 1.6%), we find that the total volume of exports to non-hinterland cities is less than twice as large as the total export volume to hinterland cities (10.2% versus 6.7%). The same picture consistently emerges throughout lower layers: At the 3$^{\text{rd}}$ layer a total of the $3^2 = 9$ central places, although only responsible for 10.2% of the export incidence, account for 54.3% of the export volume in 2015. At the same time, the other 45.7% of the export volume are made up of the remaining 89.8% of the observed export flows. Although exporting to non-hinterland cities is more than five times as common as exporting to hinterland cities (8.4% versus 1.5%) we find that the total exports to non-hinterland cities are only three times as large as the total exports to hinterland cities (13.7% versus 4.5%). At the 5$^{\text{th}}$ layer we find that $3^4 = 81$ central places account for one third of the export incidence but for almost three quarter of all trade flows. And, although non-hinterland cities are about twenty times more likely to be an export destination than hinterland cities, we find that the volume of exports to non-hinterland cities exceeds the export volume to hinterland cities only by a factor of 12.5.

Taking stock, we not only have documented that central places are the largest exporters, but also that they are disproportionately exporting to cities in their own hinterlands. Of course, it is no surprise that central places export more to nearby cities in their own hinterlands than to far away cities in the hinterlands of other central places. Using the gravity equation for aggregate trade as the workhorse model of the empirical trade literature, we demonstrate in the following that central places continue to have disproportionately large exports vis-à-vis the cities in their hinterlands even when the trade-reducing effect of distance is explicitly taken into account.

4.2 Centrality Bias in Aggregate Inter-city Gravity Estimation

To see whether the hierarchical city system with central places and associated hinterlands from Subsection 4.1 is associated with a systematic bias in aggregate gravity estimations, we start out from a standard gravity model, regressing the bilateral trade volume (in logs) $\ln X_{do}$ on the trade cost function

$$\ln \tau_{do} = \beta_{\text{DIST}} \times \ln \text{DIST}_{do} + \beta_{\text{HOME}} \times \text{HOME}_{do} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{do}, \tag{8}$$

and the complete set of origin- and destination-specific fixed effects. Following standard practice we control for average real-road distance between and within cities DIST_{do} to proxy for geography as a barrier to trade and a "home bias" dummy $\text{HOME}_{do} \in \{0,1\}$, which assumes a value of one for intra-city trade (i.e. $d = o$) and a value of zero otherwise, to an account for non-linear distance effect (cf. Wolf, 2000; Hillberry and Hummels, 2003, 2008; Millimet and Osang, 2007). To account for non-linearities in transportation costs due to Japan's geography as an archipelago (consisting of the four main islands *Hokkaido*, *Honshu*, *Shikoku*, and *Kyushu*), we additionally control for intra-island trade by adding an island dummy $\text{ISLAND}_{do} \in \{0,1\}$, which takes a value of one for intra-island trade and a value of zero otherwise. The first column of Table 3 summarizes the estimation results, which in terms of magnitude and significance are comparable to those found in the empirical trade literature (cf. Head and Mayer, 2014).

How large is the estimation bias, that results from not taking into account the structure of Japan's pyramidic city system captured by the structural error term v_{do} from Eq. (5)? To answer this question we compute in the first step the residual diagnostics for the aggregate gravity estimation from the first column of Table 3. If the pattern of inter-city trade is fully explained by the usual trade cost vector from Eq. (8), we would not expect to find systematic patterns when clustering the gravity residuals according to Japan's hierarchical city system.

In order to asses the overall fit of the aggregate gravity equation as workhorse model of the empirical trade literature in a systematic way, we report in Table 2 the residual diagnostics for the ex- and imports of central places (CP) and their associated hinterland cities (HC). We thereby distinguish between the same eight mutually exclusive trading relationships as in Table 1. For each category we then conduct a simple sign test, computing the share of trade flows for which the structural gravity model underestimates the actual trade volume (indicated through a positive residual $X_{do} - \widehat{X}_{do} > 0$). To quantify the resulting up- or downward bias that results from over- or underestimation, we complement our simple sign test by also computing the mean residual $X_{do} - \widehat{X}_{do}$ for each category. According to Table 2 we systematically underestimate the bilateral trade volume between central places and their associated hinterlands by relying on the aggregate gravity equation. At each layer the share of underestimated trade flows $X_{do} > \widehat{X}_{do}$ between central places and their hinterland cities exceeds the respective share in the overall sample. Accordingly, we find that central places' average residual trade is positive, when trading with their associated hinterlands but negative when trading with the hinterland

Table 2: *In Search for Systematic Deviations from Structural Gravity*

Residual Diagnostics											
Year:		**2015**									
Measure:		**Share of** $X_{do} > \widehat{X}_{do}$					**Mean of** $X_{do} - \widehat{X}_{do}$				
Direction:		**Destination:**					**Destination:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1st Layer:											
Origin:	**CP:**	0.0000	–	0.5938	–	0.5922	−0.6082	–	0.0016	–	0.0000
	HC:	0.5442	–	0.5138	–	0.5143	0.0017	–	0.0000	–	0.0000
	All:	0.5426	–	0.5151	–	0.5161	0.0000	–	0.0000	–	0.0000
2nd Layer:											
Origin:	**CP:**	0.3333	1.0000	0.6263	0.5504	0.5782	0.2371	1.7610	0.2310	−0.1375	0.0000
	HC:	0.5882	0.5302	0.5178	0.5026	0.5124	0.1285	−0.0903	−0.0003	0.0015	0.0000
	All:	0.5532	0.5302	0.5139	0.5026	0.5155	0.0000	−0.0903	0.0000	0.0015	0.0000
3rd Layer:											
Origin:	**CP:**	0.7778	0.9577	0.6778	0.5052	0.5443	1.2481	2.0498	0.4595	−0.1586	0.0000
	HC:	0.5593	0.5063	0.5192	0.5089	0.5122	0.1278	−0.1089	−0.0099	0.0156	0.0000
	All:	0.5296	0.5063	0.5141	0.5089	0.5155	0.0000	−0.1089	0.0000	0.0156	0.0000
4th Layer:											
Origin:	**CP:**	0.8400	0.7335	0.6900	0.4976	0.5384	1.2959	0.9613	0.5781	−0.1856	0.0000
	HC:	0.5370	0.4884	0.5161	0.5143	0.5098	0.0834	−0.1474	0.0109	0.0414	0.0000
	All:	0.5210	0.4884	0.5142	0.5143	0.5155	0.0000	−0.1474	0.0000	0.0414	0.0000
5th Layer:											
Origin:	**CP:**	0.8571	0.6091	0.6608	0.4877	0.5272	1.4628	0.3749	0.5334	−0.1761	0.0000
	HC:	0.5913	0.4823	0.5016	0.5256	0.5097	0.3091	−0.1651	−0.0735	0.1043	0.0000
	All:	0.5210	0.4823	0.5129	0.5256	0.5155	0.0000	−0.1651	0.0000	0.1043	0.0000

Notes: Abbreviations are defined as follows: central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC). Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Feight Census. We report these additional results in the Online Appendix.

cities that belong to another central place at the same layer.[24]

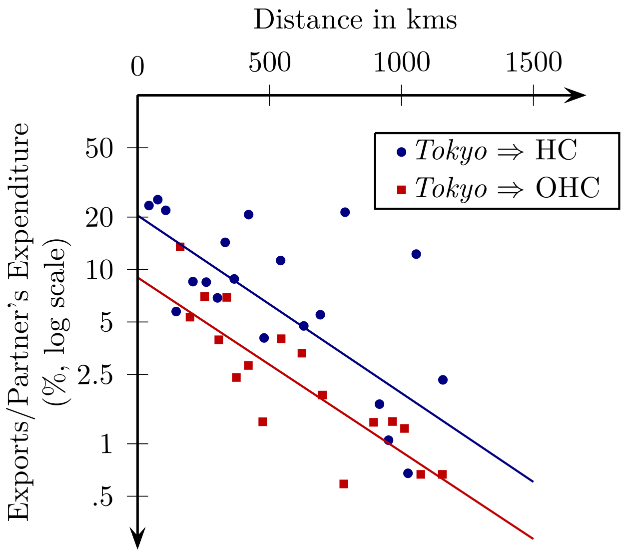
To highlight the upward bias in (residual) exports from central places to their respective hinterlands we focus in Figure 7 on *Tokyo* as one of three 2nd-layer central places. The binned scatter plot (cf. Stepner, 2013) in Figure 7 thereby captures the "spirit of gravity" (cf. Head and Mayer, 2014, p. 134) by simultaneously taking into account size and distance effects.[25] Conditional on the partner city's size and the distance to *Tokyo* we find that *Tokyo* as a 2nd-layer central place exports larger volumes to its respective hinterland cities (blue dots) than to cities, that belong to the hinterlands of other central places at the same layer (red dots).

To quantify the estimation bias that results from not taking into account Japan' s hierar-

[24] In accordance with central place theory we also underestimate the volume of trade among and within central places (see Columns (1) and (2) as well as Columns (6) and (7) in Table 2). We interpret these findings with great caution, because computations are based on a rather limited number of observations, and there is an overlap between higher-layer hinterland cities and lower-layer central places.

[25] We focus on *Tokyo* as a central place at the 2nd layer because at the 1st-layer all other cities belong to *Tokyo*'s hinterland. All 2nd-layer central place (i.e. *Tokyo*, *Osaka*, and *Nagoya*) have been excluded as possible destination cities in Figure 7.

Figure 7: *Tokyo's Exports to its own and other Hinterland Cities at the 2^{nd} Layer*



Note: *Figure 7 plots Tokyo's aggregate exports normalized by the partner city's total expenditure (in logs) over the bilateral distance between Tokyo and its partner cities. To avoid clutter we have used a binned scatter plot with 20 bins, which are based on a total of 382 observations. Similar figures can be compiled based on the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional figures in the Online Appendix.*

chical city system from Subsection 4.1 in a more comprehensive way we embed the pyramidic city structure with multi-layer central places and associated hinterlands from Figure 6 into an otherwise standard gravity estimation. To this end, we extend our trade cost function to include not only the geographic controls: DIST_{do}, HOME_{do}, and ISLAND_{do} (summarized by the trade cost vector τ_{ij}) but also the following set of indicator variables:

$$\ln \tilde{\tau}_{do} = \sum_{l=2}^{5} \beta_{\text{EXP}\_l} \times \text{EXP\_CP\_HC\_}l\text{LY}_{do} \tag{9}$$

which closely mimics the hierarchical structure of Japan's poly-centric city system. To capture the direct trading relationship between a central place and its economic hinterland, we introduce the indicator variable $\text{EXP\_CP\_HC\_}l\text{LY}_{do} \in \{0, 1\}$, which takes a value of one whenever a central place at the l^{th}-layer exports as origin city o to an associated hinterland city as destination d and a value of zero otherwise. Since central places from higher layers keep reappearing at lower layers, we include the indicator variable $\text{EXP\_CP\_HC\_}l\text{LY}_{do} \in \{0, 1\}$ separately at different layers (see Columns (2) to (5) of Table 3) and jointly with the indicator variables from other layers (see Columns (6) to (8) of Table 3).

By definition there exists only a single 1^{st}-layer central place (viz. *Tokyo*), whose hinterland is formed by the sum of all other cities in Japan. Due to prefect multicollinearity of the indicator variables EXP_CP_HC_1LY$_{do}$ with the the respective exporter-specific fixed effect for *Tokyo*, it is impossible to independently identify the parameter $\beta_{\text{EXP\_1}}$ at the 1$^{\text{st}}$ layer. We hence focus in our analysis only on lower layers (i.e. $l \geq 2$) with multiple central places.

Table 3 summarizes the ordinary least squares (OLS) results from estimating a log-linearized (aggregate) gravity equation with the complete set of origin- and destination-specific fixed effects as predicted by Redding and Weinstein (2019). Throughout all specifications, we find a large

Table 3: *Central Places, Hinterlands, and the Centrality Bias in Inter-city Trade*

Dependent variable: Exports from origin city o to destination city d								
Year:	**2015**							
Model:	**OLS-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP → HC fixed effects:								
Exports CP → HC (2$^{\text{nd}}$ layer)		0.3960***				0.1664	0.1715	0.1851
		(.1449)				(.1570)	(.1569)	(.1570)
Exports CP → HC (3$^{\text{rd}}$ layer)			0.5972***			0.5394***	0.3089**	0.3344**
			(.1310)			(.1419)	(.1549)	(.1551)
Exports CP → HC (4$^{\text{th}}$ layer)				0.6990***			0.5418***	0.3628**
				(.1321)			(.1460)	(.1601)
Exports CP → HC (5$^{\text{th}}$ layer)					0.6224***			0.4196***
					(.1393)			(.1537)
Controls:								
ln Distance$_{do}$	−0.8277***	−0.8215***	−0.8156***	−0.8076***	−0.8093***	−0.8142***	−0.8032***	−0.7952***
	(.0187)	(.0188)	(.0188)	(.0190)	(.0191)	(.0189)	(.0191)	(.0193)
Intra-city trade	0.7284***	0.7509***	0.7790***	0.8098***	0.8055***	0.7835***	0.8274***	0.8615***
	(.1411)	(.1413)	(.1414)	(.1418)	(.1421)	(.1415)	(.1420)	(.1425)
Intra-island trade	0.1303**	0.1390***	0.1230**	0.1322***	0.1328***	0.1273**	0.1318***	0.1329***
	(.0507)	(.0508)	(.0507)	(.0507)	(.0507)	(.0509)	(.0509)	(.0509)
Fixed effects:								
Origin (o):	✓	✓	✓	✓	✓	✓	✓	✓
Destination (d):	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:								
Number of observations:	24,203	24,203	24,203	24,203	24,203	24,203	24,203	24,203
R^2:	0.4226	0.4228	0.4231	0.4233	0.4231	0.4231	0.4235	0.4237

Notes: Fractal partition into central places and hinterlands allows for up to 3 central places in hinterlands of central places at next higher layers. Robust standard errors; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

and statistically significant upward bias in the exports from central places to their associated hinterlands at different layers. Across the Specifications (2) to (4) in Table 3 the central place dummy thereby is associated with a substantial percentage increase in the bilateral trade volume of 40% to 100%. When multiple central place dummies are simultaneously included at different layers (Specifications (6) to (8) in Table 3), the trade-creating effect of the 2$^{\text{nd}}$-layer central place dummy becomes statistically insignificant and somewhat smaller. We attribute this result to the multicoliniearity among the central place fixed effects from Eq. (9), which follows by construction from the fractal structure of the hierarchical city system in Figure 6. Reassuringly, we find that coefficients for exports from central places at the 3$^{\text{rd}}$ to 5$^{\text{th}}$ layer in the Specifications (6) to (8) of Table 3 do not lose their statistical significance. The results for the waves 1995, 2000, 2005 and 2010 show exactly the same pattern as in Table 3: Across all waves and at all layers we find a substantial and highly significant upward bias in the exports from central places to their hinterlands, which translates in a percentage trade increase that falls into a ranges between 30% and 167%. We report these additional findings in the Online Appendix.

Having quantified the upward bias in exports from central places to their respective hinterlands, we are now scrutinizing the conditions under which we can expect to find a systematic upward bias in the exports from central places to their hinterlands. We conduct two series of placebo regressions: Under randomization scheme (a) from Table 4 we maintain the basic hierarchical structure from Figure 6. Given the identified central places at each layer, we fix the cell size (number of hinterland cities in each cell) and randomize the identity of hinterland cities that are associated with a certain central place. Randomization scheme (b) from Table 4 follows Mori et al. (2020a), who obtain subcells at lower layers not as Voronoi K-partitions but from a random partition holding the number of cells ($K = 3$) and the cell size fixed. Since the largest $K = 3$ city in each cell are chosen as lower-layer central places their identity may deviate from our baseline specification at all layers $l > 2$. Under both randomization schemes we construct 10,000 counterfactual partitions up to the 5^{th} layer.

From each hypothetical partition into central places and associated hinterland cities we can then derive counterfactual central place dummies akin to $\text{EXP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ from Eq. (9). We implement these counterfactual central place dummies in otherwise standard OLS gravity estimations, taking into account the trade cost vector $\ln \tau_{ij} = \beta_{\text{DIST}} \times \ln \text{DIST}_{ij} + \beta_{\text{HOME}} \times \text{HOME}_{ij} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{ij}$, and imposing the full set of origin- and destination-specific fixed effects.

When the association of hinterland cities with central places is randomized, we would not expect to find the systematic upward bias from Table 3. Table 4 compares the outcomes of the placebo regression to the baseline results from Table 3. Focusing on the specifications (2) to (5) from Table 3, we find no systematic upward bias if the assignment of hinterland cities to central places is randomized. The vast majority of the estimated coefficients $\beta^{\text{random}}_{\text{EXP\_}CP}$ are in the vicinity of zero and typically statistically insignificant at the commonly applied significance levels of $\alpha = 1\%$, $\alpha = 5\%$, and $\alpha = 10\%$. At a significance level of $\alpha = 1\%$ only 0.3% to 2.75% of all placebo regressions yield a positive and significant point estimate if randomization scheme (a) is applied. At the same level of significance only 0.3% to 1.3% of the estimate coefficients are not statistically indistinguishable from zero if randomization scheme (b) is applied. The fraction of placebo regressions that deliver coefficients $\beta^{\text{random}}_{\text{EXP\_CP}}$, which exceed the baseline coefficients

Table 4: *Placebo Regressions with Randomized Assignment of Hinterlands*

Randomized Hinterlands:								
Year:				**2015**				
Layer	**Benchmark:**		**Number of Samples**	**Mean of** $\beta^{\text{random}}_{\text{EXP\_CP}}$	**Significant Estimates at:**			**Share of** $\beta^{\text{random}}_{\text{EXP\_CP}} > \beta_{\text{EXP\_CP}}$
	$\beta_{\text{EXP\_CP}}$	**S. E.**			$p < 0.01$	$p < 0.05$	$p < 0.10$	
Randomization scheme (a):								
2	0.3960***	(.1449)	10,000	.0357	.0030	.0257	.0612	.0006
3	0.5972***	(.1310)	10,000	.0833	.0186	.0712	.1330	.0000
4	0.6990***	(.1321)	10,000	.0562	.0125	.0535	.1060	.0000
5	0.6224***	(.1393)	10,000	-.1451	.0275	.1058	.1769	.0000
Randomization scheme (b):								
2	0.3960***	(.1449)	10,000	-.0121	.0030	.0210	.0560	.0000
3	0.5972***	(.1310)	10,000	-.0315	.0070	.0540	.0950	.0000
4	0.6990***	(.1321)	10,000	-.0467	.0130	.0540	.1080	.0000
5	0.6224***	(.1393)	10,000	-.0518	.0120	.0570	.1000	.0000

Notes: Robust standard errors; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

$\beta_{\text{EXP\_CP}}$ from Table 3 is almost always zero.[26]

Summing up our main results from this section, we have shown that exports of large and centrally located cities (central places) to smaller cities in their nearby hinterland are systematically underestimated by an aggregate gravity estimation, that does not take into account Christaller's (1933) hierarchy principle for industries. The upward bias in aggregate exports of central places to their respective hinterland cities is statistically significant and quantitatively important, suggesting that exports are 40% to 100% larger than predicted by gravity forces alone. In a series of placebo regressions, in which the assignment of hinterland cities to central places is randomized, it is almost impossible to find comparable effects of similar magnitude.

5 Disaggregation and Decomposition

Having quantified the upward bias in aggregate exports from central places to their respective hinterlands based on Japan's pyramidic city system, we are now providing further evidence that the unexpectedly high aggregate exports of central places are an artifact of the underlying aggregation process (as explained in Section 2). We thereby proceed in two steps: In Subsection 5.1 we disaggregate our inter-city trade data to demonstrate that the centrality bias from Section 4 can not be detected in sectoral gravity estimations. In Subsection 5.2 we then apply two alternative decomposition approaches to learn more about the channels that are responsible for the emergence for the centrality bias from Section 4.

[26] Under randomization scheme (a) 6 out of 10,000 placebo regressions at the 2$^{\text{nd}}$ layer deliver point estimates satisfying the condition $\beta^{\text{random}}_{\text{EXP\_CP}} > \beta_{\text{EXP\_CP}}$.

5.1 Disaggregation

To explain the centrality bias from Section 4 as an artifact of an aggregation process that does not account for the hierarchical distribution of sectors across cities we follow Anderson and van Wincoop (2004, p. 729), whose "obvious recommendation is to disaggregate." Table 5 therefore repeats the residual diagnostics from Table 2 based on the results of a sector-level gravity estimation (cf. Column (1) of Table 6). To ensure comparability we use the same trade cost vector as in Table 3 (controlling for the complete set of origin×sector- and destination×sector-specific fixed effects) when estimating our baseline results in Table 6. The results of the corresponding residual diagnostics are then reported in the exact same way as in Table 2, where we distinguish between up to eight different origin/destination relationships.

Table 5: *Residual Diagnostics at the Sectoral Level*

Residual Diagnostics at the Sectoral Level											
Year:		**2015**									
Measure:		**Share of $x_{dos} > \widehat{x}_{dos}$**					**Mean of $x_{dos} - \widehat{x}_{dos}$**				
Direction:		**Destination:**					**Destination:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1st Layer:											
Origin:	**CP:**	0.6154	–	0.5629	–	0.5642	0.1888	–	−0.0048	–	0.0000
	HC:	0.5467	–	0.5500	–	0.5498	−0.0111	–	0.0005	–	0.0000
	All:	0.5506	–	0.5513	–	0.5512	0.0000	–	0.0000	–	0.0000
2nd Layer:											
Origin:	**CP:**	0.6422	0.7295	0.5746	0.5379	0.5635	0.4155	0.9443	0.0114	−0.1033	0.0000
	HC:	0.5259	0.4938	0.5625	0.5386	0.5474	−0.1013	−0.1226	0.0104	0.0242	0.0000
	All:	0.5328	0.4938	0.5534	0.5386	0.5512	0.0000	−0.1226	0.0000	0.0242	0.0000
3rd Layer:											
Origin:	**CP:**	0.6290	0.6342	0.5800	0.5344	0.5575	0.3548	0.4960	0.0196	−0.1078	0.0000
	HC:	0.5204	0.4873	0.5737	0.5548	0.5482	−0.0599	−0.1689	0.0130	0.0534	0.0000
	All:	0.5276	0.4873	0.5564	0.5548	0.5512	0.0000	−0.1689	0.0000	0.0534	0.0000
4th Layer:											
Origin:	**CP:**	0.6207	0.5741	0.5756	0.5357	0.5520	0.3152	0.1999	−0.0135	−0.0964	0.0000
	HC:	0.5206	0.4877	0.5818	0.5781	0.5506	−0.0370	−0.1459	−0.0161	0.0999	0.0000
	All:	0.5256	0.4877	0.5623	0.5781	0.5512	0.0000	−0.1459	0.0000	0.0999	0.0000
5th Layer:											
Origin:	**CP:**	0.6241	0.5488	0.5716	0.5488	0.5526	0.2817	0.0631	−0.0575	−0.0635	0.0000
	HC:	0.5322	0.5039	0.5801	0.5883	0.5496	−0.0160	−0.0933	−0.0828	0.1186	0.0000
	All:	0.5317	0.5039	0.5663	0.5883	0.5512	0.0000	−0.0933	0.0000	0.1186	0.0000

Notes: Abbreviations are defined as follows: central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC). Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

All indicators suggest that the sector-level gravity estimation outperforms the aggregate gravity estimation in matching the pattern of Japan's inter-city trade. While there is a 7.59 to 19.24 percentage point difference in the shares of underestimated trade flows (characterized by $X_{do} > \widehat{X}_{do}$) for central places' exports to associated versus unassociated hinterland cities in Table 2 (Column (3) versus Column (4)), we find that in Table 5 the difference in these shares (characterized by $x_{dos} > \hat{x}_{dos}$) has declined to a range of 2.88 to 4.56 percentage points (Column (3) versus Column (4) in Table 5). A similar picture emerges from the comparison of the mean residuals: Mean residuals of central places' trade in Table 2 are in a range from 0.2310 to 0.5781 for exports to associated hinterland cities at different layers and in a range from −0.1375 to −0.1856 for exports to unassociated hinterland cities at different layers (Column (8) versus Column (9) in Table 2). In Table 5 the mean residuals of central places' trade fall into a much smaller range from 0.0114 to 0.0575 for exports to associated hinterland cities at different layers and a range from −0.0635 to −0.1078 for exports to unassociated hinterland cities at different layers (Column (8) versus Column (9) in Table 5).

Building up on the results from Table 5, which suggest that the previously identified centrality bias is indeed an artifact of an aggregation process that does not account for the hierarchical distribution of sectors across cities, we proceed by re-estimating the gravity model, that lead to the results in Table 3. We thereby include the same trade cost vector from Eq. (8) together with the central place dummies from Eq. (9), controlling for all origin×sector- and destination×sector-specific variation though an accordingly specified set of fixed effects.

Table 6: *Central Places, Hinterlands, and the Pattern of Sectoral Inter-city Trade*

Dependent variable: Sector-level exports from origin city o to destination city d								
Year:	**2015**							
Model:	**OLS-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP → exporter fixed effects:								
Exports CP → HC (2$^{\text{nd}}$ layer)		0.0286				0.0155	0.0117	0.0086
		(.0664)				(.0755)	(.0758)	(.0759)
Exports CP → HC (3$^{\text{rd}}$ layer)			0.0367			0.0287	0.0570	0.0521
			(.0633)			(.0718)	(.0812)	(.0815)
Exports CP → HC (4$^{\text{th}}$ layer)				−0.0246			−0.0627	−0.0322
				(.0729)			(.0832)	(.0942)
Exports CP → HC (5$^{\text{th}}$ layer)					−0.1015			−0.0933
					(.0867)			(.1016)
Controls:								
ln Distance$_{do}$	−0.4341***	−0.4314***	−0.4308***	−0.4360***	−0.4385***	−0.4300***	−0.4327***	−0.4351***
	(.0164)	(.0166)	(.0168)	(.0168)	(.0168)	(.0168)	(.0170)	(.0172)
Intra-city trade	0.4427***	0.4530***	0.4557***	0.4353***	0.4245***	0.4585***	0.4484***	0.4380***
	(.1086)	(.1085)	(.1093)	(.1105)	(.1109)	(.1090)	(.1104)	(.1113)
Intra-island trade	0.0500	0.0535	0.0516	0.0489	0.0487	0.0531	0.0510	0.0506
	(.0445)	(.0440)	(.0445)	(.0444)	(.0445)	(.0439)	(.0439)	(.0439)
Fixed effects:								
Origin (o) × sector (s):	✓	✓	✓	✓	✓	✓	✓	✓
Destination (d) × sector (s):	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:								
Number of observations:	55,785	55,785	55,785	55,785	55,785	55,785	55,785	55,785
R^2:	0.5802	0.5802	0.5802	0.5802	0.5802	0.5802	0.5802	0.5802

Notes: Fractal partition into central places and hinterlands allows for up to 3 central places in hinterlands of central places at next higher layers. Robust standard errors clustered at the city-pair level; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

According to Table 6, which summarizes the estimation results, no centrality bias can be detected in inter-city gravity estimations that are conducted at the sectoral and not at the aggregate level. Throughout the Columns (2) to (6) from Table 6 we find that the coefficients of the dummy variables, capturing exports from central places to their respective hinterlands, are by magnitudes smaller than the ones of their counterparts in Table 3. At conventional levels of significance none of the considered dummy variables is statistically distinguishable from zero. Exactly the same result is found when jointly including the central place dummies from various layers (see Columns (6) to (8) of Table 6).

Interestingly, we find that the distance elasticities in Table 6 (which range from -0.4300 to -0.4385), are much smaller in absolute magnitude than their counterparts in Table 3 (which range from -0.7952 to -0.8277).[27] To rationalize the observed difference in estimated distance elasticities, we borrow from Hillberry and Hummels (2008, pp. 539-40), who attribute a similar result to the underlying aggregation process.[28] Because the probability of observing a shipment at the sector level is declining in distance (cf. Figure 3), the aggregate volume of inter-city trade is declining at the intensive margin within each sector and at the extensive margin as the number of exporting sectors gets smaller over longer distances. As we aggregate across sectors, variation at the extensive margin (presence or absence of sector-level shipments) sums up to a continuous variable (total value of bilateral trade). The response of the aggregate trade volume in Table 3 to increasing distances therefore is substantially larger than at the more disaggregated sector-level in Table 6.

Note that the fixed effects estimator from Table 6 yields consistent parameter estimates if all sectoral trade flows between origin cities o and destination cities d are positive (i.e. $x_{dos} > 0$) and if the stochastic error u_{dos} in Eq. (3) is orthogonal to the observed trade costs τ_{dos}. To account for zero trade flows, which could be correlated with bilateral trade costs, and for heteroscedasticity in our sectoral trade data (cf. Santos Silva and Tenreyro, 2006), we replicate the results from Table 6 by using the Poisson Pseudo Maximum Likelihood estimator (PPML) proposed by Correia et al. (2020), which allows us to estimate Eq. (3) in its multiplicative form. We thereby include cities as origins for sectoral trade flows if they export to at least one destination in this sector and as destinations for sectoral trade flows if they import in this sector from at least one origin. Intra- and inter-city distances are computed consistently as population-weighted harmonic means over the bilateral real-road distances between the sets

[27] A similar pattern (with reversed sign) can be observed when comparing the coefficients on the intra-city trade and intra-island trade dummies across Table 3 and 6. Since both of these controls can be thought of as capturing discontinuous distance effects (i.e. the relative ease of trading over short distances), this finding can be directly related to the observed difference in estimated distance elasticities.

[28] Instead of aggregating across sectors Hillberry and Hummels (2008) focused on aggregation across different spatial units (3 digit versus 5 digit zip codes).

of municipalities of which the respective cities are comprised (cf. Head and Mayer, 2009). To account for the systematic differences in the extensive margin of sectoral inter-city trade from Figure 3 we allow the trade-reducing effect of distance to vary across the same five sector categories as in Figure 3, where sectors are differentiated according to the number of origin cities (≤ 10, $11-20$, $21-40$, $41-80$, and > 80) in which they can be found.

We present the results of the PPML estimations in Table 7. Reassuringly, we find that the dummies which have been included to capture the effect of exporting from a central place to its hinterland cities are statistically indistinguishable from zero at conventional levels of significance.

In line with Figure 3, we find that sectoral distance effects in Table 7 are quite heterogeneous and by magnitudes larger than in Table 6. The difference in the (average) size of the distance elasticities thereby can be explained through the inclusion of zeros, which disproportionately are observed across larger shipment distances (see Figure 3). Heterogeneity in the estimated distance elasticities from Table 7 can be explained by the fact that ubiquitous industries, that can be found in many cities, have a rather low average probability of serving nearby destinations. After a short distance (of approx. 200 km) this average probability falls to a remarkably low level of less than 10%. Further increases in the bilateral distance beyond this 200 km threshold then barely affect the already very small average export probability, resulting in comparatively small distance elasticities for ubiquitous industries in Table 7.

In search for an explanation for the upward bias in the exports from central places to their respective hinterland cities in aggregate gravity estimations we have replicated our analysis from Section 4 at the much more disaggregated sectoral level. Unlike in the aggregate gravity estimations from Section 4 no centrality bias can be identified at the sectoral level. We interpret these results as suggestive evidence in favor of aggregation bias. Aggregate exports from central places to their hinterland are systematically underestimated by aggregate gravity estimations that ignore the structural error term which results from summing up sectoral gravity equations.

5.2 Decomposition

To gain a better understanding of how the aggregation of sectoral trade flows results in a specific upward bias in the aggregate exports from central places to their associated hinterland cities we adopt two alternative decomposition approaches: Following Hillberry and Hummels (2008) we first exploit the specific structure of our highly disaggregated transaction-level trade data when decomposing aggregate trade flows along various extensive and intensive margins. Complementing evidence then is obtained in a second step, when applying Redding and Wein-

Table 7: *Central Places, Hinterlands, and the Pattern of Sectoral Inter-city Trade*

Dependent variable: Sector-level exports from origin city o to destination city d								
Year:	**2015**							
Model:	**PPML-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP $\rightarrow$ exporter fixed effects:								
Exports CP $\rightarrow$ HC (2^{nd} layer)		-0.1669				-0.2206	-0.2123	-0.2080
		(.1334)				(.1468)	(.1469)	(.1495)
Exports CP $\rightarrow$ HC (3^{rd} layer)			0.0328			0.1463	0.0554	0.0583
			(.1408)			(.1543)	(.1812)	(.1811)
Exports CP $\rightarrow$ HC (4^{th} layer)				0.2057			0.2254	0.1892
				(.1504)			(.1824)	(.2170)
Exports CP $\rightarrow$ HC (5^{th} layer)					0.2585			0.0991
					(.1983)			(.2493)
Controls:								
ln Distance$_{do}$ (sectors $\leq$ 10 origins)	-1.2137^{***}	-1.2309^{***}	-1.2111^{***}	-1.2023^{***}	-1.2062^{***}	-1.2248^{***}	-1.2186^{***}	-1.2170^{***}
	(.0939)	(.0948)	(.0938)	(.0950)	(.0948)	(.0944)	(.0951)	(.0955)
ln Distance$_{do}$ (sectors 11-20 origins)	-1.0474^{***}	-1.0639^{***}	-1.0448^{***}	-1.0362^{***}	-1.0399^{***}	-1.0575^{***}	-1.0515^{***}	-1.0500^{***}
	(.0523)	(.0552)	(.0532)	(.0547)	(.0539)	(.0549)	(.0561)	(.0568)
ln Distance$_{do}$ (sectors 21-40 origins)	-1.0985^{***}	-1.1144^{***}	-1.0960^{***}	-1.0878^{***}	-1.0910^{***}	-1.1083^{***}	-1.1026^{***}	-1.1010^{***}
	(.0569)	(.0580)	(.0578)	(.0583)	(.0581)	(.0584)	(.0588)	(.0594)
ln Distance$_{do}$ (sectors 41-80 origins)	-0.9341^{***}	-0.9503^{***}	-0.9316^{***}	-0.9231^{***}	-0.9266^{***}	-0.9441^{***}	-0.9382^{***}	-0.9367^{***}
	(.0420)	(.0452)	(.0434)	(.0447)	(.0440)	(.0452)	(.0463)	(.0471)
ln Distance$_{do}$ (sectors > 80 origins)	-0.7409^{***}	-0.7571^{***}	-0.7382^{***}	-0.7297^{***}	-0.7333^{***}	-0.7506^{***}	-0.7447^{***}	-0.7432^{***}
	(.0405)	(.0403)	(.0406)	(.0429)	(.0419)	(.0404)	(.0417)	(.0420)
Intra-city trade	-0.2829^{**}	-0.3524^{**}	-0.2739^{**}	-0.2468^{*}	-0.2621^{**}	-0.3347^{**}	-0.3165^{**}	-0.3124^{**}
	(.1308)	(.1434)	(.1332)	(.1393)	(.1336)	(.1423)	(.1462)	(.1467)
Intra-island trade	-0.2003	-0.2187	-0.1985	-0.1953	-0.2035	-0.2164	-0.2148	-0.2163
	(.1494)	(.1513)	(.1493)	(.1500)	(.1503)	(.1512)	(.1517)	(.1522)
Fixed effects:								
Origin (o) × sector (s):	✓	✓	✓	✓	✓	✓	✓	✓
Destination (d) × sector (s):	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:								
Number of observations:	924,715	924,715	924,715	924,715	924,715	924,715	924,715	924,715

Notes: Fractal partition into central places and hinterlands allows for up to 3 central places in hinterlands of central places at next higher layers. Distance effects are allowed to differ across five sector categories (sectors present in ≤ 10, $11-20$, $21-40$, $41-80$, and > 80 origin cities). Robust standard errors clustered at the city-pair level; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

stein's (2019) structural decomposition approach to decompose aggregate trade flows into the components that shape the structural error term v_{do} derived in Eq. (5).

Following Hillberry and Hummels (2008), we can exploit the full potential of our micro-level inter-city trade data to establish the extensive industry margin as the main driver behind the previously identified centrality bias. We begin by decomposing the aggregate value of trade $X_{do} = \sum_{z=1}^{Z_{do}} P_{doz}Q_{doz}$ from origin city o to destination city d, which is the sum over the product of the shipment-specific price P_{doz} and the shipment-specific quantity Q_{doz}, into the number of unique shipments Z_{do} (the extensive margin) and the average value per shipment $\bar{Y}_{do} \equiv \sum_{z=1}^{Z_{do}} P_{doz}Q_{doz}/Z_{do}$ (the intensive margin)

$$X_{do} = Z_{do}\bar{Y}_{do}, \tag{10}$$

referring to a unique shipment by subscript z.[29] Decomposing the number of unique shipments

[29]As in Hillberry and Hummels (2008) a unique shipment is defined by the triplet: establishment identifier × commodity code × destination municipality. Repeated shipments of the same commodity by the same establishment to the same destination municipality hence are treated as a single shipment, such that there is no difference

Z_{do} further into the number of distinct sectors S_{do} across which a certain city exports its goods and the average number of shipments per sector $\bar{Z}_{do} \equiv Z_{do}/S_{do}$ then results in

$$Z_{do} = S_{do}\bar{Z}_{do}. \tag{11}$$

In a final step the average value per shipment $\bar{Y}_{do}$ is decomposed into average price $\bar{P}_{do}$ and average quantity $\bar{Q}_{do}$ per shipment

$$\bar{Y}_{do} = \frac{\sum_{z=1}^{Z_{do}} P_{doz}Q_{doz}}{Z_{do}} = \frac{\sum_{z=1}^{Z_{do}} P_{doz}Q_{doz}}{\sum_{z=1}^{Z_{do}} Q_{doz}} \frac{\sum_{z=1}^{Z_{do}} Q_{doz}}{Z_{do}} = \bar{P}_{do}\bar{Q}_{do}. \tag{12}$$

Substituting Z_{do} and $\bar{Q}_{do}$ from Eqs. (11) and (12) back into X_{do} from Eq. (10) allows us to deconstruct the aggregate volume of bilateral trade

$$X_{do} = S_{do}\bar{Z}_{do}\bar{P}_{do}\bar{Q}_{do} \tag{13}$$

between origin city o and destination city d into its four components: S_{do}, $\bar{Z}_{do}$, $\bar{P}_{do}$ and $\bar{Q}_{do}$. Log-linearising the Eqs. (10) and (13) then yields the first-level decomposition

$$\ln X_{do} = \ln Z_{do} + \ln \bar{Y}_{do}, \tag{14}$$

and the second-level decomposition

$$\ln X_{do} = \ln S_{do} + \ln \bar{Z}_{do} + \ln \bar{P}_{do} + \ln \bar{Q}_{do}. \tag{15}$$

While a decomposition analysis of bilateral inter-city is interesting in its own right (yielding similar results as in Hillberry and Hummels (2008)), we are particularly interested in understanding what is responsible for the upward bias in exports from central places to their respective hinterland cities. We therefore follow Hillberry and Hummels (2008) by treating each element in Eqs. (14) and (15) as a dependent variable, which then is separately regressed on the trade cost vector $\ln \tau_{do} = \beta_{\text{DIST}} \times \ln \text{DIST}_{do} + \beta_{\text{HOME}} \times \text{HOME}_{do} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{do}$, the hierarchy vector $\ln \tilde{\tau}_{do}$ from Eq. (9), and the complete set of origin×sector- and destination×sector-specific fixed effects.

Making use of the OLS estimator's linearity, we separately regress $\ln X_{do}$ and all its log-linearized components on the same set of explanatory variables to obtain coefficients with the useful additive property: $\beta_v^X = \beta_v^Z + \beta_v^Y$ with $\beta_v^Z = \beta_v^S + \beta_v^{\bar{Z}}$ and $\beta_v^Y = \beta_v^{\bar{P}} + \beta_v^{\bar{Q}}$. While super-

between ten shipments of one million Yen and one shipment of ten million Yen.

scripts are used to distinguish the dependent variables: X_{do}, Z_{do}, and Y_{do} as well as S_{do}, $\bar{Z}_{do}$, $\bar{P}_{do}$ and $\bar{Q}_{do}$, we use the subscript v to distinguish between the explanatory variables (typically the central place dummies $\text{EXP\_CP\_HC\_}l\text{LY}_{do}$ $\forall\ l = 2, \ldots 5$). Based on the decomposition from Eq. (15) we can quantify each component's contribution to the upward bias in the exports from central places to their hinterlands.

Table 8: *Inter-City Trade Decomposition à la Hillberry and Hummels (2008)*

Dependent Variable:	$\ln X_{do}$	$\ln Z_{do}$	$\ln S_{do}$	$\ln \bar{Z}_{do}$	$\ln \bar{Y}_{do}$	$\ln \bar{P}_{do}$	$\ln \bar{Q}_{do}$
Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
CP → HC fixed effects:							
Exports CP → HC (2nd layer)	0.3960***	0.4347***	0.3539***	0.0807***	−0.0387	−0.2375***	0.1989
	(.1449)	(.0318)	(.0290)	(.0089)	(.1338)	(.0900)	(.1557)
	[.4228]	[.6444]	[.6320]	[.2955]	[.3404]	[.4143]	[.4075]
Exports CP → HC (3rd layer)	0.5972***	0.4740***	0.3841***	0.0899***	0.1233	−0.0897	0.2130
	(.1310)	(.0287)	(.0262)	(.0080)	(.1209)	(.0814)	(.1408)
	[.4231]	[.6457]	[.6330]	[.2968]	[.3405]	[.4142]	[.4076]
Exports CP → HC (4th layer)	0.6990***	0.4526***	0.3750***	0.0776***	0.2464**	−0.1087	0.3551**
	(.1321)	(.0289)	(.0264)	(.0081)	(.1220)	(.0821)	(.1420)
	[.4233]	[.6453]	[.6328]	[.2958]	[.3406]	[.4142]	[.4077]
Exports CP → HC (5th layer)	0.6224***	0.3561***	0.3092***	0.0469***	0.2663**	−0.0649	0.3311**
	(.1393)	(.0305)	(.0279)	(.0086)	(.1285)	(.0866)	(.1497)
	[.4231]	[.6436]	[.6316]	[.2940]	[.3406]	[.4141]	[.4076]
Controls:							
$\ln \text{Distance}_{do}$	✓	✓	✓	✓	✓	✓	✓
Intra-city trade	✓	✓	✓	✓	✓	✓	✓
Intra-Island trade	✓	✓	✓	✓	✓	✓	✓
Fixed effects:							
Origin (o):	✓	✓	✓	✓	✓	✓	✓
Destination (d):	✓	✓	✓	✓	✓	✓	✓
Summary statistics:							
Number of observations:	24,203	24,203	24,203	24,203	24,203	24,203	24,203

Notes: Robust standard errors in parentheses; R^2 in squared brackets; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

In the first Column of Table 8 we replicate the baseline results from the Columns (2) to (5) of Table 3. By decomposing the strong upward bias in the exports from central places to their respective hinterlands into its various components from Eq. (15) we can gain a better understanding of the relative importance that these components have for the centrality bias from Table 3. Suppose the upward bias in central places' exports is caused by an omitted variable, whose trade-creating effect proportionately scales up the volume of bilateral trade (such as the regionally concentrated business networks in Combes et al. (2005), Requena and Llano (2010), and Wrona (2018)). The disproportionately high exports from central places to their respective hinterlands would then materialize through an increase in the average number of shipments per sector rather than by an increase in the number of exporting sectors. Interestingly, we find that the average number of unique shipments per sector $\bar{Z}_{do}$ contributes only moderately to the overall effect (relative contributions $\beta^{\bar{Z}}_{\text{EXP\_CP}}/\beta^{X}_{\text{EXP\_CP}}$ range from 7.5% to 20.4%). It rather seems to be the case that the disproportionately large exports from central places to their respective hinterlands are mainly explained through a larger number of exporting sectors – with the extensive industry margin S_{do} being responsible for the by far largest contribution to the overall effect. Accordingly, we also find that the R^2 in the extensive industry margin regressions (with outcome variable $\ln S_{do}$) are much larger than those of the other components of $\ln X_{do}$.[30]

Summing up the results from Table 8, we find that central places export more to their hinterland cities because they serve these cities across a wider range of industries and not because they send more shipments per industry or because these shipments are more valuable. We interpret this result as direct evidence in favor of our theoretical prediction from Section 2: Christaller's (1933) hierarchy principle for industries is responsible for the upward bias in the exports of central places to their hinterlands.

Having identified the extensive industry margin as a main driver behind the centrality bias from Section 4, we are now taking a different perspective by applying Redding and Weinstein's (2019) structural decomposition approach. Substituting the structural error term v_{do} from Eq. (5) into Eq. (4) yields

$$\ln X_{do} = \Gamma_{do} + \Lambda_{do} - T_{do} + J_{do} + U_{do}. \tag{16}$$

The log of aggregate bilateral trade between origin city o and destination city d can be written as an additively separable function of the five structural terms Γ_{do}, Λ_{do}, $-T_{do}$, J_{do}, and U_{do} previously discussed in Section 2.

We proceed by regressing $\ln X_{do}$ and each of its components from Eq. (16) on the familiar set of controls from Eq. (8) and on the separately included 2^{nd}-, 3^{rd}-, 4^{th}- and 5^{th}-layer central place dummies from Eq. (9), imposing the complete set of origin- and destination-specific fixed effects. Due to the linearity of the OLS estimator, the coefficient estimates on all the components of $\ln X_{do}$ from Eq. (16) add up to the coefficient estimate from our baseline regression on $\ln X_{do}$. This property is what allows us to theoretically decompose the effects of the central place dummies $\text{EXP\_CP\_HC\_}l\text{LY}_{do}\ \forall\ l = 2, \dots 5$ on the log of aggregate bilateral trade $\ln X_{do}$.[31]

[30] In the Online Appendix we report all $4 \times 7 = 28$ regressions for 2015 that have been used to compile Table 8. There we also show that the discrepancy between the relatively higher distance elasticity estimates in the aggregate gravity estimations from Table 3 and the relatively lower distance elasticity estimates in the sectoral gravity estimations from Table 6 can be attributed to the trade-reducing effect of distance along the extensive industry margin. Larger bilateral distances are associated with a sizable drop in the number of exporting sectors and a rather small reduction in the average number of shipments per sector. Accounting for the combined effect of these two channels at the extensive margin, we find that distance elasticity at the intensive margin closely resembles the sectoral distance elasticity estimates from Table 6. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census.

[31] In the Online Appendix we report all $4 \times 6 = 24$ regressions for 2015 that have been used to compile Table 9. There we also replicate the results of Redding and Weinstein (2019), who decompose the distance elasticity into its various components from Eq. (16). Unsurprisingly, we find that the by far largest contribution to the

Table 9: *Inter-City Trade Decomposition à la Redding and Weinstein (2019)*

Dependent Variable:	$\ln X_{do}$	Γ_{do}	Λ_{do}	$-T_{do}$	J_{do}	U_{do}
Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CP → HC fixed effects:						
Exports CP → HC (2nd layer)	0.3089**	0.0423*	0.0175	−0.0222	0.1090**	0.1624
	(.1449)	(.0227)	(.0351)	(.0245)	(.0514)	(.0997)
	[.5302]	[.8337]	[.1088]	[.7330]	[.9480]	[.0954]
Exports CP → HC (3rd layer)	0.6614***	0.0523*	0.0696**	0.0727***	0.1909***	0.2759***
	(.1334)	(.0268)	(.0312)	(.0259)	(.0430)	(.0913)
	[.5306]	[.8337]	[.1089]	[.7331]	[.9481]	[.0956]
Exports CP → HC (4th layer)	0.7506***	0.1211***	0.0866**	0.0561**	0.1406***	0.3462***
	(.1237)	(.0302)	(.0350)	(.0282)	(.0389)	(.0907)
	[.5308]	[.8337]	[.1089]	[.7330]	[.9481]	[.0958]
Exports CP → HC (5th layer)	0.6211***	0.1891***	0.0784**	0.0387	0.0789**	0.2360**
	(.1334)	(.0419)	(.0395)	(.0363)	(.0383)	(.1062)
	[.5305]	[.8338]	[.1089]	[.7330]	[.9480]	[.0955]
Controls:						
$\ln \text{Distance}_{do}$	✓	✓	✓	✓	✓	✓
Intra-city trade	✓	✓	✓	✓	✓	✓
Intra-Island trade	✓	✓	✓	✓	✓	✓
Fixed effects:						
Origin (o):	✓	✓	✓	✓	✓	✓
Destination (d):	✓	✓	✓	✓	✓	✓
Summary statistics:						
Number of observations:	18,290	18,290	18,290	18,290	18,290	18,290

Notes: Robust standard errors in parentheses; R^2 in squared brackets; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

Following Redding and Weinstein (2019) we drop in the sectoral gravity estimations, on which the computation of the structural terms Γ_{do}, Λ_{do}, $-T_{do}$, J_{do}, and U_{do} is based, all origin-sector cells with less than 3 destinations and all destination-sector cells with less than 3 origins. Doing so causes the number of observations in Table 9 to be somewhat smaller than in Table 3. Reassuringly, we find that the point estimates in Column (1) of Table 9 are not too different from those in Columns (2) to (5) of Table 3.

To get a better understanding of why $\ln X_{do}$ and each of its components Γ_{do}, Λ_{do}, $-T_{do}$, J_{do} and U_{do} are correlated with the dummy variables $\text{EXP\_CP\_HC\_}l\text{LY}_{do}$ $\forall\ l = 2, \ldots 5$ from Eq. (9), we also report the levels of these components together with their residuals, which are obtained from regressing them on the trade cost vector from Eq. (8) and the complete set of origin- and destination-specific fixed effects. We thereby distinguish between the same eight trade relationships as in the Tables 1, 2, and 5. Descriptive statistics and the residual diagnostics for the gravity components Γ_{do}, Λ_{do}, $-T_{do}$, J_{do} and U_{do} are summarized in Table

distance elasticity comes from the average distance-related trade costs (captured by $-T_{do}$) followed by a much smaller contribution by the Jensen's inequality correction term J_{do}. Similar results are obtained from the 1995, 2000, 2005, and 2010 wave of the Freight Census.

10, which only focuses on the results from the 3rd layer.[32]

Table 10: *Descriptive Analysis and Residual Diagnostics for* Γ_{do}, Λ_{do}, $-T_{do}$, U_{do}, *and* J_{do}

Descriptive Analysis and Residual Diagnostics											
Year:		**2015**									
Layer:		**3rd Layer**									
Measure:		**Mean of Values**					**Mean of Residuals**				
Direction:		**Destination:**					**Destination:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Γ_{do}**:**											
Origin:	**CP:**	1.7238	1.6339	1.8185	1.4460	1.5078	0.0614	0.1389	0.0400	−0.0133	0.0000
	HC:	−1.3508	−1.2595	−1.3948	−1.2497	−1.2887	−0.0056	−0.0050	0.0050	−0.0010	0.0000
	All:	−1.1630	−1.2595	−0.9480	−1.2497	−0.9729	0.0000	−0.0050	0.0000	−0.0010	0.0000
Λ_{do}**:**											
Origin:	**CP:**	−0.1908	0.0109	−0.0382	−0.1009	−0.0884	−0.3431	−0.0162	0.0532	−0.0069	0.0000
	HC:	0.0563	0.0771	−0.0049	0.0117	0.0154	−0.0103	0.0043	−0.0067	0.0022	0.0000
	All:	0.0707	0.0771	−0.0051	0.0117	0.0037	0.0000	0.0043	0.0000	0.0022	0.0000
$-T_{do}$**:**											
Origin:	**CP:**	3.4287	−0.5107	0.6856	−0.6401	−0.4254	−0.0983	0.0832	0.0555	−0.0129	0.0000
	HC:	0.9328	−0.5530	0.8410	−0.5182	−0.1560	0.0465	−0.0113	−0.0043	0.0022	0.0000
	All:	−0.3168	−0.5530	−0.1693	−0.5182	−0.1864	0.0000	−0.0113	0.0000	0.0022	0.0000
U_{do}**:**											
Origin:	**CP:**	0.0458	0.5782	−0.0857	−0.3936	−0.3136	0.9125	1.4878	0.2107	−0.1050	0.0000
	HC:	−0.5959	−0.6736	−0.1587	−0.2384	−0.2717	0.0471	−0.0745	0.0058	0.0089	0.0000
	All:	−0.6171	−0.6736	−0.2319	−0.2384	−0.2764	0.0000	−0.0745	0.0000	0.0089	0.0000
J_{do}**:**											
Origin:	**CP:**	27.5459	26.7781	22.3843	22.0192	22.2598	0.7145	0.8391	0.1457	−0.0651	0.0000
	HC:	25.568	25.2072	21.5749	21.7256	22.1317	−0.0203	−0.0346	0.0001	0.0065	0.0000
	All:	25.3227	25.2072	21.7308	21.7256	22.1461	0.0000	−0.0346	0.0000	0.0065	0.0000

Notes: Abbreviations are defined as follows: central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC). Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional results in the Online Appendix.

All origin×sector-specific fixed effects γ_{os} for the city-pair $d \times o$ are aggregated into $\Gamma_{do} = \bar{\gamma}_{do} - \bar{\gamma}_d$. Thereby $\bar{\gamma}_{do}$ is defined as the average origin×sector-specific fixed effect across all sectors $s \in S_{do}$ that exist in origin o and export to destination d. Summing $\bar{\gamma}_{do}$ across all origins o then yields $\bar{\gamma}_d = \sum_o \bar{\gamma}_{do}$, which is the average origin×sector-specific fixed effect across all sectors $s \in S_{do}$ and all origins $o \in R_d$ from which destination d imports. Intuitively, we expect Γ_{do} to be large if most of the sectors $s \in S_{do}$ across which origin o exports to destination d are large and therefore characterized by sizable origin×sector-specific fixed effects γ_{os}.

Comparing the average values of Γ_{do} for central places and hinterland cities as origin cities in Column (5) of Table 10, we find indeed that central places have on average much larger origin×sector-specific fixed effects γ_{os} than the hinterland cities in our sample. We attribute

[32] Similar results are obtained when focusing on the 2nd, 4th, and 5th layer. We have relegated these additional results to the Online Appendix to economize on space. There we also report the results for 1995, 2000, 2005 and 2010 wave of the Japanese Commodity flow survey.

this result to differences in city size and industry diversity, which is why we find no difference in the averages of the residuals $\Gamma_{do} - \hat{\Gamma}_{do}$ from Column (10) of Table 10, which have been purged from size effects by controlling for the complete set of monadic origin-specific fixed effects. Because monadic origin-specific fixed effects can not fully account for the city-pair variation in the dyadic gravity component Γ_{do}, we find that the average residuals $\Gamma_{do} - \hat{\Gamma}_{do}$ in Table 10 differ across the Columns (6)-(9), when conditioning on different sets of destination cities. The average residual of Γ_{do} for exports from central places is positive if the destination city is an associated hinterland city (cf. Column (8) of Table 10) and negative if the destination city is a hinterland city belonging to another central place (cf. Column (9) of Table 10).

The positive and significant coefficient on our central place dummies $\text{EXP\_CP\_HC\_}l\text{LY}_{do}\ \forall\ l = 2, \ldots, 5$ from Column (2) of Table 9 picks up this variation, which in view of Figure 3 can be rationalised as follows: Central places serve their nearby hinterland cities across a wider range of sectors than the more distant hinterland cities of other central places. Because this difference in industry diversity is systematically correlated with the average size of the origin×sector-specific fixed effects γ_{os} in the different sets of exporting sectors $\mathcal{S}_{do}$, we find that exports from central places to their hinterlands are characterized by larger residuals of Γ_{do}.

There are two potential explanations for why footloose industries have larger origin×sector-specific fixed effects γ_{os}: As theoretically shown by Anderson and van Wincoop (2004, pp. 706-708) the origin×sector-specific fixed effects γ_{os} depend on the value of sectoral output Y_{os} in origin city o and on the outward multilateral resistance term Π_{os} for sector s in origin city o, which captures origin city o's average cost of exporting to all its partner cities.[33] If industries are of the same size as in Hsu (2012) or at least not too different in terms of total expenditure, we would expect that footloose industries, which can only be found in a small number of origin cities, are characterized by a relatively larger value of sectoral output Y_{os} per origin city o than their ubiquitously distributed counterparts.

Note that the term $\Lambda_{do} = \bar{\lambda}_{do} - \bar{\lambda}_{d}$ is analogously defined to Γ_{do}, with the only difference that $\bar{\lambda}_{do}$ now is an average over all destination×sector-specific fixed effects λ_{ds}. To rationalise the positive and significant coefficients on the central place dummies in Column (3) of Table 9 we rely again on our residual diagnostics, which for Λ_{do} are summarised in Table 10. Most notably, we find that imports of hinterland cities from their central place are associated with a positive average residual $\Lambda_{do} - \hat{\Lambda}_{do}$, that is much larger than the average residuals for the imports from other hinterland cities or from central places to which the respective hinterland city does not

[33]Note that the origin×sector-specific fixed effects γ_{os} from Eq. (3) can be rewritten as $\gamma_{os} = \ln Y_{os} + (\sigma_s - 1) \ln \Pi_{os}$ in which Y_{os} is the value of sectoral output and $\Pi_{os}^{1-\sigma_s} = \sum_d (\tau_{dos}/P_{ds})^{1-\sigma_s} X_{ds}/Y_s$ is the outward multilateral resistance term with $Y_s = \sum_o \sum_d x_{dos}$ as the value of total sectoral output.

belong. Aggregate imports from these alternative sources differ in their sectoral composition (i.e. in the share of footloose industries) from the aggregate imports that originate from the hinterland city's central place. These compositional differences follow directly from Christaller's (1933) hierarchy principle for industries, according to which small hinterland cities only host a limited set of ubiquitous industries, and from Figure 3, according to which footloose industries have a substantially lower probability of serving the far away hinterland cities of other central places. Because these differences in industry composition are systematically correlated with the average size of the destination×sector-specific fixed effects λ_{os} in the different sets of importing sectors $\mathcal{S}_{do}$, we find that imports from central places are characterized by larger residuals of Λ_{do}.

Relying again on Anderson and van Wincoop (2004), it can be shown that the destination×sector-specific fixed effects λ_{ds} depend on the expenditure X_{ds} of destination d, on commodities from sector s and on the inward multilateral resistance term P_{ds}.[34] The inward multilateral resistance term thereby captures the average resistance that destination d faces when importing commodities from sector s from all possible suppliers. Intuitively, we would expect that the flow of goods from origin o to destination d is increased by high trade costs from other suppliers to destination d. Except for its own central place the typical hinterland city has only a few other rather costly options (i.e. other central places) to import goods from footloose industries. We therefore expect the inward multilateral resistance terms P_{ds} for footloose industries to be comparably high, which would explain the positive average residuals of Λ_{do} for imports of hinterland cities from their central places in Table 10 and the positive correlation between the Λ_{do} component and our central place dummies EXP_CP_HC_lLY$_{do}$ $\forall\ l = 2, \ldots$ in Column (3) of Table 9.

We proceed by discussing the role of distance-related (inverse) trade costs $-T_{do}$. The term T_{do} thereby is defined as the difference between the average sectoral trade costs $\bar{t}_{do}$ in all sectors across which origin o exports to destination d and the average sectoral trade cost $\bar{t}_d$ of destination d vis-à-vis all origins. Average bilateral trade costs T_{do} therefore are low if all sectors across which destination d imports from origin o are characterized by relatively low sectoral trade costs $(\sigma_s - 1) \ln \tau_{dos}$, whereas the trade costs across all sectors in which destination d imports from origins other than o are relatively high. Because the association of hinterland cities with central places is based on distance, we find that values of $-T_{do}$ in the Columns (1) to (4) of Table 10 mirror the geographical distribution of central places and their hinterlands. In particular lower-

[34] Note that the destination×sector-specific fixed effects λ_{ds} from Eq. (3) can be rewritten as $\lambda_{ds} = \ln X_{ds} + (\sigma_s - 1) \ln P_{ds}$ in which X_{ds} is expenditure in destination d on commodities from sector s and $P_{ds}^{1-\sigma_s} = \sum_o (\tau_{dos}/\Pi_{os})^{1-\sigma_s} Y_{os}/Y_s$ is the inward multilateral resistance term.

layer hinterland cities are located in close proximity to their respective central places, which is reflected by large average values of $-T_{do}$. Most of this variation can be explained by regressing $-T_{do}$ on the trade cost vector from Eq. (8). Residuals from this regression are positive, when conditioning on exports from central places to their respective hinterlands at the 3^{rd}, 4^{th}, and 5^{th} layer, which explains the positive correlations in Column (4) of Table 9. To understand why the trade cost $-T_{do}$ component is not perfectly explained by the trade cost vector from Eq. (8) it is important to remember that $-T_{do}$ also reflects the sectoral composition of aggregate trade flows. Footloose industries account for a relatively larger share in the aggregate exports from central places to their associated hinterland cities and are expected to have lower sectoral trade costs $(\sigma_s - 1) \ln \tau_{dos}$ (cf. Fujita et al., 1999a).

The component U_{do} aggregates the sectoral residuals u_{dos} in a similar fashion as T_{do} aggregates the sectoral trade costs $(\sigma_s - 1) \ln \tau_{dos}$. The sectoral residuals u_{dos} thereby can be interpreted to capture all unobservable sectoral trade costs, that are not included in the trade cost vector from Eq. (8). Comparing the levels of U_{do} in Table 10 for hinterland cities that import from their central place against the levels of U_{do} for hinterland cities that import from other hinterland cities or from another central place, we find a systematic positive difference in levels, which suggests that hinterlands have lower unobservable trade costs when importing from their central place. Reassuringly, we find the exact same pattern in the residuals from regressing U_{do} on the trade cost vector in Eq. (8) and the complete set of origin- and destination-specific fixed effects. Lower unobservable trade costs between central places and their hinterlands thereby can be the result of the systematic selection of footloose industries into central places as predicted by Fujita et al. (1999a) or a consequence of multi-polar trade-creating network structures as documented by Wrona (2018). Irrespective of what exactly is responsible for the lower unobservable trade costs between central places and their hinterlands, we find that U_{do} is responsible for the largest contribution to the upward bias in log aggregate exports $\ln X_{do}$ from central places to their hinterlands.

Finally, it is worth noting that Redding and Weinstein (2019) also identify a Jensen's inequality correction term J_{do}, which accounts for the fact that $\ln X_{do}$ is defined as the log of the sum of sectoral trade flows x_{dos} and not as the sum of log sectoral trade flows $\ln x_{dos}$, which according to Eq. (3) can be characterized through log-linear sectoral gravity equations. To understand why J_{do} is positively correlated with our central place dummies $\text{EXP\_CP\_HC\_}l\text{LY}_{do}\ \forall\ l = 2, \ldots 5$ from Column (5) of Table 9, it is helpful to recall the definition of $J_{do} = \ln X_d + \bar{y}_d - \bar{z}_{do}$ from Eq. (5), in which $\bar{y}_d = \frac{1}{R_d} \sum_{o \in \mathcal{R}_d} \frac{1}{S_{do}} \sum_{s \in \mathcal{S}_{do}} \mathscr{Y}_{dos}$ is the average sectoral import share of destination city d for imports from all origin cities $o \in \mathcal{R}_d$ exporting to this city, and $\bar{z}_{do} = \frac{1}{S_{do}} \sum_{s \in \mathcal{S}_{do}} \mathscr{Z}_{dos}$

is the average sectoral import share of destination city d for imports from origin city o.

For a city pair that consists of a central place as origin city o and an associated hinterland city as destination city d, we would expect the destination city d to import across a wide range of industries from the origin city o. Splitting up aggregate imports from origin city o across a wide range of sectors mechanically results in smaller values of $\mathscr{X}_{dos}$. At the same time, we would expect that in this constellation $\mathscr{Y}_{dos}$ takes rather large values across all footloose industries in which destination city d mainly (if not exclusively) imports from its central place o. In Table 10 we find that the values of J_{do} and its residuals for importing hinterland cities are indeed larger when the origin city is the hinterland city's central place and not another hinterland city or another central place. Our central place dummies $\text{EXP\_CP\_HC\_}l\text{LY}_{do}\ \forall\ l = 2, \ldots, 5$ from Column (5) of Table 9 pick up this variation, which is responsible for a non-negligible contribution to the overall effect of the central place dummies on $\ln X_{do}$.

Summing up the evidence obtained from the decomposition exercises of Hillberry and Hummels (2008), we find overwhelming support for the importance of Christaller's (1933) hierarchy principle for industries as an explanation for why aggregate exports from central places to their hinterlands are systematically upward biased. Complementary evidence is obtained from Redding and Weinstein's (2019) structural decomposition approach, which shows how the systematic selection of (footloose) industries into central places according Christaller's (1933) hierarchy principle for industries is reflected in the shape of various aggregate gravity components, which contribute at varying degrees to the centrality bias in aggregate gravity estimations.

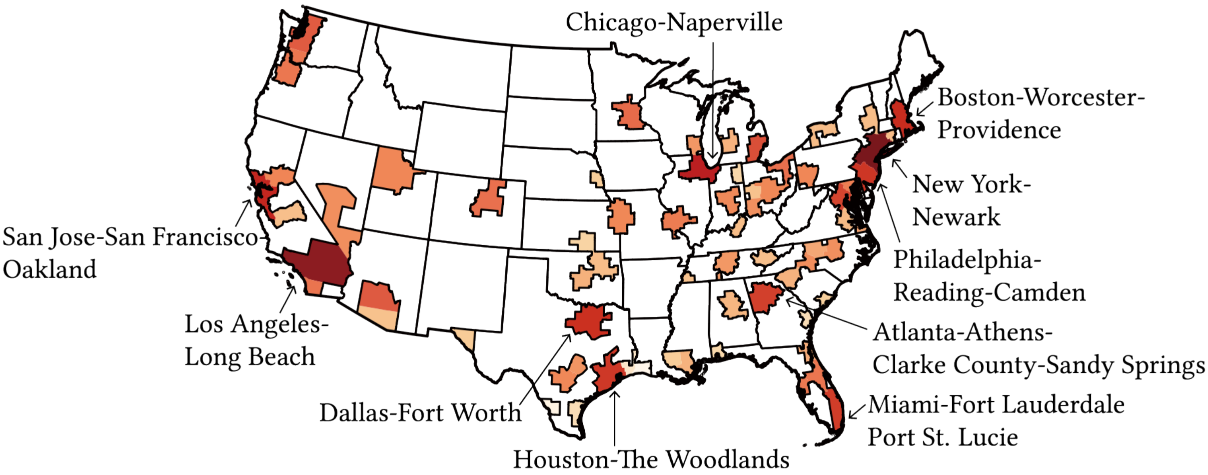
6 Centrality Bias in US Inter-city Trade

Having identified and explained the centrality bias in Japan's inter-city trade, we now demonstrate that comparable results can also be found for the US based on the 2017 Commodity Flow Survey (CFS) Public Use File (cf. United States Census Bureau, 2017a).

As potential central places we focus on 69 CFS Metropolitan Areas (MAs) on the continental US, defined by the 2017 US CFS. In Figure 8, we use darker colors to distinguish these MAs according to their population size, which we depict together with "the remainders" of their respective sates (if applicable).

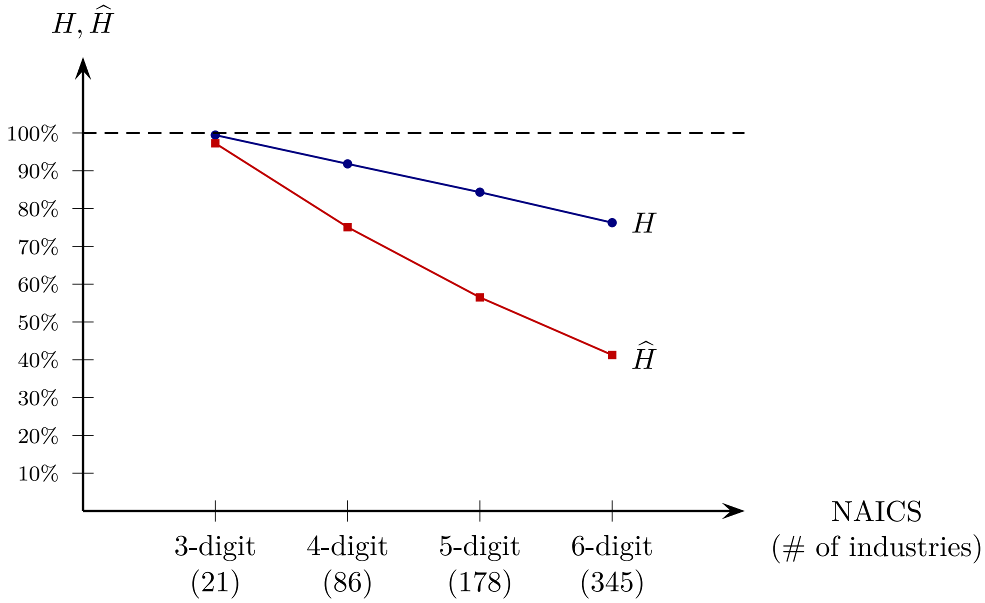
We begin by showing that the distribution of 3-digit to 6-digit manufacturing industries in the North American Industry Classification System (NAICS) among the 69 MAs obeys Christaller's (1933) hierarchy principle. To this end, we replicate the hierarchy test from Section 2.1 based on the 2017 County Business Patterns Series (cf. United States Census Bureau, 2017b). Figure 9 shows that the observed hierarchy share H at low levels of aggregation is

Figure 8: *US Metropolitan Areas in 2017*



Note: *The figure is based on the CFS Metropolitan Areas (MAs) defined by the 2017 US CFS, and depicts 69 continental MAs. Each blank polygon represents the "remainder" of a given state consisting of the state area excluding the area occupied by any MA.*

Figure 9: *Testing for Christaller's (1933) Hierarchy Principle for Manufacturing Industries in the US*

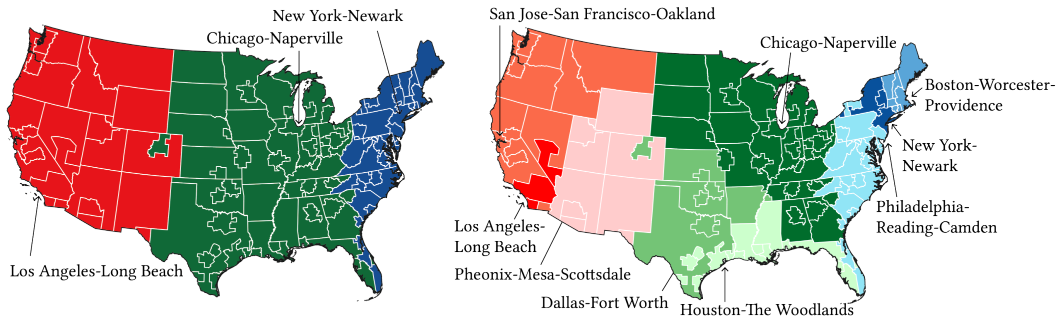


Note: *Figure 9 is based on the County Business Patterns Series (cf. United States Census Bureau, 2017b). The figure plots the observed versus the counterfactual average hierarchy shares for different levels of disaggregation in the North American Industry Classification System (NAICS) with the number of different industries in parenthesis.*

much higher than the maximum hierarchy share $\widehat{H}$ selected from $1,000$ counterfactual samples with a randomized allocation of industries across cities. We interpret this result as suggestive evidence in favor of Christaller's (1933) hierarchy principle for industries, and therefore expect to find a centrality bias in the US CFS.

Treating the 69 MAs as cities, we can apply the algorithm of Mori et al. (2020a), described in Subsection 4.1, to identify 2$^{\text{nd}}$- and 3$^{\text{nd}}$-layer central places together with their associated hinterlands. The ranking of cities in terms of population size thereby is based on county-level population data (cf. United States Census Bureau, 2017c), which we also use to compute bilateral distances between cities as well as between cities and the remainder of states as a population-weighted harmonic means of country-pair-specific real-road distances (cf. Head and Mayer, 2009). Figure 10 depicts 2$^{\text{nd}}$- and 3$^{\text{rd}}$-layer central places (labeled and identified through

Figure 10: *2nd- and 3rd-layer Central Places and their Hinterlands in the US*



(a) *2nd-layer Voronoi Partition* **(b)** *3rd-layer Voronoi Partition*

Note: *Figure 10 depicts 2nd- and 3rd-layer Voronoi 3-partitions for central places and associated hinterlands in the US based on the 2017 Commodity Flow Survey (CFS).*

arrows) together with their economic hinterlands (sharing the same color) based on Voronoi 3-partitions. Each partition cell consists of one of MAs as the central place and its hinterland comprised of smaller MAs and the surrounding "remainders" of states.

Using the identified central places and associated hinterland cities, we construct 2$^{\text{nd}}$-, 3$^{\text{rd}}$, 4$^{\text{th}}$, and 5$^{\text{th}}$-layer central place dummies as in Subsection 4.2 to estimate the centrality bias in the aggregate trade between central places and their associated hinterlands. We thereby focus on aggregate manufacturing trade from the 2017 US CFS, excluding all international exports and all shipments of "Waste and Scrap". Table 11 reports positive and significant estimates of the centrality bias at the 3$^{\text{rd}}$, 4$^{\text{th}}$, and 5$^{\text{th}}$, that are comparable in their magnitude to the results from Japan's CFS reported in Table 3.

In summary our evidence from the US suggests that the upward bias in the exports from central places to their associated hinterlands that we have identified based on Japan's CFS in Subsection 4.2 is not a Japan-specific phenomena. To account for the aggregation bias that results from the summation across city-specific sets of industries, that follow Christaller's (1933) hierarchy principle for industries, we therefore propose to include a set of appropriately defined central place dummies that effectively control for the centrality bias in intra-national trade.

Table 11: *Central Places, Hinterlands, and the Centrality Bias in the US CFS*

Dependent variable: Exports from origin o to destination d								
Year:	2017							
Model:	OLS-FE							
Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CP $\rightarrow$ HC fixed effects:								
Exports CP $\rightarrow$ HC (2nd layer)		-0.0272				-0.1032	-0.1169	-0.1179
		(0.1336)				(0.1376)	(0.1375)	(0.1375)
Exports CP $\rightarrow$ HC (3rd layer)			0.2599^{**}			0.2823^{**}	0.0457	0.0207
			(0.1198)			(0.1235)	(0.1321)	(0.1326)
Exports CP $\rightarrow$ HC (4th layer)				0.6384^{***}			0.6328^{***}	0.4730^{***}
				(0.1172)			(0.1262)	(0.1482)
Exports CP $\rightarrow$ HC (5th layer)					0.5751^{***}			0.3014^{**}
					(0.1197)			(0.1466)
Controls:								
ln Distance$_{do}$	-0.9932^{***}	-0.9936^{***}	-0.9874^{***}	-0.9791^{***}	-0.9835^{***}	-0.9883^{***}	-0.9798^{***}	-0.9788^{***}
	(0.0166)	(0.0167)	(0.0168)	(0.0168)	(0.0167)	(0.0169)	(0.0170)	(0.0170)
Home bias	1.6690^{***}	1.6678^{***}	1.6876^{***}	1.7138^{***}	1.7007^{***}	1.6843^{***}	1.7112^{***}	1.7147^{***}
	(0.1151)	(0.1152)	(0.1154)	(0.1152)	(0.1152)	(0.1155)	(0.1155)	(0.1155)
Fixed effects:								
Origin (o):	✓	✓	✓	✓	✓	✓	✓	✓
Destination (d):	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:								
Number of observations:	13,082	13,082	13,082	13,082	13,082	13,082	13,082	13,082
R^2:	0.7280	0.7280	0.7281	0.7287	0.7285	0.7282	0.7287	0.7288

Notes: Robust standard errors; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Conclusion

In this paper we have shown that aggregate shipments from central places to smaller cities in their economic hinterland are 40% to 100% larger than predicted by the gravity equation for aggregate inter-city trade, and that no such effect can be found in theory-consistent sectoral gravity estimations. We argue that the centrality bias in inter-city trade is an artifact of aggregating across city-specific sets of hierarchically distributed industries, which obey Christaller's (1933) hierarchy principle for industries. According to this principle we expect central places to possess a wider range of industries, including a set of ubiquitous industries which can also be found in smaller cities. Aggregation across industries results in a systematic upward bias because industries that can only be found in central places are more likely to serve cities in the central place's hinterland.

By adopting the theory-consistent aggregation approach of Redding and Weinstein (2019), we have shown that the structural error term that results from the aggregation of sectoral trade flows systematically varies along a specific spatial dimension that follows from the hierarchical distribution of industries into central places and hinterlands. To account for this systematic variation in aggregate gravity residuals, we propose to include a set of straightforwardly defined central place dummies. A theory-consistent decomposition of aggregate trade flows reveals that these central place dummies consistently capture the non-negligible heterogeneity in sector-specific origin and destination fixed effects as well as the substantial heterogeneity in sector-specific observed and unobserved bilateral trade costs that is specific to exports from central places to their hinterlands. Conveniently, these fixed effects also control for the quantitatively important central-place-to-hinterland-specific variation in an Jensen's inequality correction, that accounts for the fact that the log of aggregate trade is defined as the log of the sum of sectoral trade flows and not as the sum of log sectoral trade flows.

To capture the key predictions of central place theory (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012), we have focused in our analysis on trade between cities in Japan and the US, which both feature a hierarchical industry distribution that closely follows Christaller's (1933) hierarchy principle for industries. In accordance with this principle we have found that larger and more centrally located cities disproportionately export at the extensive industry margin to smaller cities in their economic hinterlands. Hummels and Klenow (2005) have shown that larger economies export more in absolute terms than smaller economies, and that the extensive goods margin accounts for 62% of the greater exports of larger economies. To what extent the distribution of industries between countries also follows Christaller's (1933) hierarchy principle for industries, and whether industries that can only be found in larger economies are also more likely to serve smaller countries in close proximity are intriguing questions that we leave for future research.

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8 Appendix

8.1 Aggregation

From the consumption index specified in Eq. (2), the optimal expenditure on variety ω_{os} can be derived as

$$p_{dos}(\omega_{os})q_{dos}(\omega_{os}) = \left[\frac{p_{dos}(\omega_{os})/\phi_{dos}}{P_{ds}}\right]^{1-\sigma_s} X_{ds}, \tag{17}$$

with $p_{dos}(\omega_{os})$ as the price of variety ω_{os} and

$$P_{ds} = \left\{\sum_{o\in\mathcal{R}_{ds}} \int_{\omega_{os}\in\Omega_{os}} \left[\frac{p_{dos}(\omega_{os})}{\phi_{dos}}\right]^{1-\sigma_s} d\omega_{os}\right\}^{\frac{1}{1-\sigma_s}} \tag{18}$$

as the corresponding ideal price index.

For a given number of firms M_{os} in each origin o monopolistic competition results in prices

$$p_{dos} = p_{dos}(\omega_{os}) = \frac{\sigma_s}{\sigma_s - 1}\tau_{dos}c_{os} \tag{19}$$

being chosen as constant sector-specific mark-ups over marginal production costs $c_{os} > 0$ times iceberg-type trade costs $\tau_{dos} \geq 1$.

Substituting the price p_{dos} from Eq. (19) back into Eq. (17) allows us to solve for total expenditure on goods imported from origin o

$$x_{dos} = M_{os}p_{dos}q_{dos} = \left(\frac{\sigma_s}{\sigma_s - 1}\frac{\tau_{dos}c_{os}/\phi_{dos}}{P_{ds}}\right)^{1-\sigma_s} X_{ds}, \tag{20}$$

with

$$P_{ds} = \left[\sum_{o\in\mathcal{R}_{ds}} M_{os}\left(\frac{\sigma_s}{\sigma_s - 1}\frac{\tau_{dos}c_{os}}{\phi_{dos}}\right)^{1-\sigma_s} d\omega_{os}\right]^{\frac{1}{1-\sigma_s}} \tag{21}$$

as the corresponding sectoral price index. We log-linearize the multiplicative sectoral gravity equation in Eq. (20) to obtain Eq. (3).

In order to derive the aggregate gravity equation from Eq. (4) we begin by rewriting destination d's aggregate imports X_{do} from origin o. Thereby we express X_{do} as the sum over x_{dos} across all importing sectors $s \in \mathcal{S}_{do}$, writing x_{dos} as the product of x_{dos}/X_d and X_d, with x_{dos}/X_d being the share of sector s' imports from origin o in destinations d's total expenditure $X_d = \sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}$

$$X_{do} = \sum_{s\in\mathcal{S}_{do}} x_{dos} = \sum_{s\in\mathcal{S}_{do}} \frac{x_{dos}}{X_d}X_d = \left(\frac{\sum_{s\in\mathcal{S}_{do}} x_{dos}}{\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}}\right) X_d. \tag{22}$$

In the presence of zero sectoral trade we thereby sum over all sectors $s \in \mathcal{S}_{do} \in \mathcal{S}$ across which destination d imports from origin o and all origins $o \in \mathcal{R}_d \in \mathcal{R}$ from which destination d imports at least in a single sector.

We proceed by defining $\mathscr{Z}_{dos}$, which is the share of destination d's sectoral imports x_{dos} from origin o in destination d's total imports from origin o

$$\mathscr{Z}_{dos} \equiv \frac{x_{dos}}{\sum_{s\in\mathcal{S}_{do}} x_{dos}} \quad \Rightarrow \quad \sum_{s\in\mathcal{S}_{do}} x_{dos} = X_{do} = \frac{x_{dos}}{\mathscr{Z}_{dos}}. \tag{23}$$

Since for all sectors $s \in \mathcal{S}_{do}$ the ratio $x_{dos}/\mathscr{Z}_{dos}$ must be equal to the sum $X_{do} = \sum_{r\in\mathcal{S}_{do}} x_{dos}$, we can take logs before averaging both sides of the above equation to obtain

$$\ln\left(\sum_{s\in\mathcal{S}_{do}} x_{dos}\right) = \left[\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln\left(\frac{x_{dos}}{\mathscr{Z}_{dos}}\right)\right], \tag{24}$$

in which $S_{do} = |\mathcal{S}_{do}|$ is the number of sectors across which destination d imports from origin o.

Let us now define $\mathscr{Y}_{dos}$, which is the share of destination d's sectoral imports x_{dos} from origin o in destination d's total imports

$$\mathscr{Y}_{dos} \equiv \frac{x_{dos}}{\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}} \quad \Rightarrow \quad \sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr} = X_d = \frac{x_{dos}}{\mathscr{Y}_{dos}}. \tag{25}$$

Since for all sectors $s \in \mathcal{S}_{do}$ and all origins $o \in \mathcal{R}_d$ the ratio $x_{dos}/\mathscr{Y}_{dos}$ must be equal to the sum $X_d = \sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}$, we can take logs before averaging both sides of the above equation to obtain

$$\ln\left(\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}\right) = \left[\frac{1}{R_d}\sum_{o\in\mathcal{R}_d}\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln\left(\frac{x_{dos}}{\mathscr{Y}_{dos}}\right)\right], \tag{26}$$

in which $S_{do} = |\mathcal{S}_{do}|$ is the number of sectors across which destination d imports from origin o and $R_d = |\mathcal{R}_d|$ is the number of origins o that export to destination d.

Finally, we can take logs of Eq. (22) to get $\ln X_{do} = \ln(\sum_{s\in\mathcal{S}_{do}} x_{dos}) - \ln(\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}) + \ln X_d$, in which we can substitute from Eqs. (24) and (26) to derive

$$\ln X_{do} = \left[\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln\left(\frac{x_{dos}}{\mathscr{Z}_{dos}}\right)\right] - \left[\frac{1}{R_d}\sum_{o\in\mathcal{R}_d}\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln\left(\frac{x_{dos}}{\mathscr{Y}_{dos}}\right)\right] + \ln X_d. \tag{27}$$

Substituting the sectoral gravity equation from Eq. (3) into the above expression then allows us to solve for

$$\ln X_{do} = \Gamma_{do} + \Lambda_{do} - T_{do} + J_{do} + U_{do}, \tag{28}$$

which can be rewritten to obtain the aggregate gravity equation in Eq. (4) with the components Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} being defined in the text. This completes the proof. ■