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Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

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Tomoya Mori and Jens Wrona[1]

Centrality Bias in Inter-City Trade

Abstract

Large cities (central places) excessively export to smaller cities in their surrounding hinterland. Using Japanese inter-city trade data, we identify a substantial centrality bias: Shipments from central places to their hinterland are 50%-125% larger than predicted by gravity forces. This upward bias stems from aggregating across industries, which are hierarchically distributed across large and small cities, and therefore does not arise in sectoral gravity estimations. When decomposing the centrality bias along the margins of our data, we find that the by far largest part of this aggregation bias can be attributed to the extensive industry margin.

JEL-Code: C43, F10, F12, F14, R12

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

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1 Introduction

This paper documents how the pattern of inter-city trade is shaped through the presence of central places and their associated hinterland cities. In the theory of central places (Christaller, 1933), larger cities (*central places*) are typically surrounded by smaller *hinterland cities*. Mori, Smith, and Hsu (2020a) and Mori, Akamatsu, Takayama, and Osawa (2022) document that this *spatial-grouping property* gives rise to a recursive city system with economic regions that have a fractal structure, and that each consists of a central place and its associated hinterland cities. When distinguishing between these city types in aggregate inter-city gravity estimations, we find that the workhorse model of the empirical trade literature (Head and Mayer, 2014) systematically underestimates the value of total shipments from central places to their associated hinterland cities.

We argue that this unexpected *centrality bias* results from the aggregation of sectoral trade flows. Building on the aggregation theory of Redding and Weinstein (2019), we demonstrate that the summation of sectoral gravity equations results in a log-linear aggregate gravity equation with a structural error term. The magnitude of the typically unobservable structural gravity error depends on two crucial variables: the number of operating industries in the origin city and the extensive industry margin of inter-city trade.

To understand how these variables vary at the city-pair level, we rely on two key insights from the theory of central places. In central place models (Christaller, 1933; Hsu, 2012), industries differ in the size of their *industry-specific market areas*, which we also document in our data. At the same time, the selection of firms/industries into cities obeys the *hierarchy property* of central place theory, according to which industries that are present in a given city should also be present in all cities of equal or larger size (Mori, Nishikimi, and Smith, 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015; Davis and Dingel, 2020; Mori et al., 2022). Differences in the size of industry-specific market areas combined with the hierarchy property imply a spatial grouping of cities. In the resulting multi-polar city system, most industries cluster in a few central places, predominantly serving cities in their respective hinterlands across all those industries, which can not survive in small cities with limited local market size.

To address the systematic heterogeneity in structural gravity errors that follows from such a city system, we propose a parsimonious gravity specification, which includes a set of accordingly defined *central place dummies*. Using a newly constructed data set of highly disaggregated inter-city trade flows from Japan, we find that aggregate shipments from central places to their hinterlands are 50% to 125% larger than predicted by gravity forces alone.

To confirm that the centrality bias in inter-city trade is an artifact of an aggregation process, that does not account for systematic differences in the extensive industry margin of inter-city trade, we proceed in three steps.

In the first step, we repeat our gravity analysis at the sectoral level, where we do not find a sizable and/or statistically significant centrality bias. We interpret this result as suggestive evidence that the centrality bias in inter-city trade originates from the aggregation across industries.

In the second step, we decompose the centrality bias along the various margins of our data (Hillberry and Hummels, 2008). By expressing aggregate trade flows as the sum of their individual shipments, we can decompose the centrality bias in inter-city trade to identify the relative contributions of (*i.*) the extensive industry margin, (*ii.*) the extensive shipment margin, (*iii.*) the intensive price margin and (*iv.*) the intensive quantity margin. As predicted by central place theory, we find that aggregate shipments from central places to their associated hinterlands are larger, not because central places send more shipments per industry or because these shipments are on average larger and sell at higher average prices, but because they ship across a considerably wider range of industries.

In the third step, we follow Redding and Weinstein (2019), who theoretically decompose aggregate shipments into five components, which all depend on the extensive industry margin of inter-city trade. Four of these five components aggregate the sectoral origin- and destination-specific fixed effects, sectoral trade costs, and the variation in sectoral gravity errors (e.g. unobservable sector-level trade costs). The fifth component is a Jensen's inequality correction term, which 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. Differences in the extensive industry margin of inter-city trade should be reflected in each of the five components, which is why we expect that all of them contribute to the centrality bias in inter-city trade. To confirm this prediction, we follow Redding and Weinstein (2019) and regress all five components on our central place dummies and the usual gravity controls. Reassuringly, we find as a result of this decomposition analysis that all five components contribute to centrality bias in inter-city trade.

Our analysis is based on the Japanese Freight Survey, which in a five-year interval from 1995 to 2015, provides detailed information on individual shipments between municipalities in Japan. For the aggregation of shipments to the city-pair level, we use 1km×1km grid cell data on the spatial population distribution in Japan to identify cities as urban agglomerations (Dijkstra and Poelman, 2012; Schmidheiny and Suedekum, 2015; Mori et al., 2020a), which subsequently are matched to the surrounding municipalities. Based on this city classification, we then follow Mori et al. (2020a), and apply a simple algorithm in the spirit of Christaller (1933) to identify central places and their hinterland cities.[1] A key advantage of the Japanese Freight Survey is its detailed industry and commodity classification. By combining this information, we distinguish up to 191 different industries-commodity groups, which allows us to explore the intra-national trade pattern at an unprecedented level of detail.[2]

Data quality is not the only reason why we focus on Japan. 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.[3] Moreover, it 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 (Davis and Weinstein, 2002, 2008). Because the multiplicity of spatial equilibria is a unifying feature of all central place models (Fujita and Krugman, 1995; Tabuchi and Thisse, 2011; Hsu, 2012; Mori et al., 2022), this evidence makes us confident that the validity of our results is not compromised through sudden and drastic shifts in Japan's city/industry system.

To support our empirical analysis, we verify that our newly constructed data set matches the predictions of central place theory. Following Mori et al. (2008), we perform a test, which confirms the hierarchy property of central place theory, according to which all industries, that can be found in a city with a given industry range, should also be present in all cities with a smaller industry range.[4] We also provide stylized evidence for the existence of industry-specific market areas and show that they systematically differ in size (Hsu, 2012). By plotting the extensive industry margin of inter-city trade over various distance intervals, we find that industries which only exist in a limited number of central places are more likely to serve other nearby hinterland cities and have large market areas than ubiquitous industries.

In a series of robustness checks, we verify that our main results not only hold for the baseline year 2015 but also for the years 2010, 2005, 2000, and 1995. We also perform placebo regressions for all years, in which we randomize the association of hinterland cities with central places, to demonstrate that the centrality bias in inter-city trade is not a data artifact. Our

[1] 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.

[2] The availability of micro-level data on bilateral trade flows at a high sectoral and geographical resolution distinguishes our work from earlier contributions, which focused on trade between prefectures (Wrona, 2018) or regions (Okubo, 2004).

[3] 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.

[4] Our results are confirmed by hierarchy tests based on auxiliary data from the Economic Census for Business Activity, which covers the universe of Japanese firms.

results continue to hold when we restrict our sample to fewer cities (by adopting Kanemoto and Tokuoka's (2002) city definition) and if we allow for a varying number of central places (Mori et al., 2020a). To prove that the centrality bias in inter-city trade is not a Japan-specific phenomenon, we show that estimates of similar magnitude also can be obtained for the US.

As our preferred specification, we use linear-in-logs OLS. Linear-in-logs OLS not only follows from the aggregation theory of Redding and Weinstein (2019) but also is required to perform Hillberry and Hummels's (2008) linear decomposition analysis. To address the concern that linear-in-logs OLS gravity estimations are biased in the presence of heteroscedasticity (Santos Silva and Tenreyro, 2006), we follow Head and Mayer (2014), and diagnose gravity errors based on a test statistic proposed by Manning and Mullahy (2001). We find that gravity errors in our data are characterized by a Constant Coefficient of Variation. Heteroscedasticity therefore is a minor concern, which suggests that the possible bias from log-linearization in the presence of heteroscedasticity (Santos Silva and Tenreyro, 2006) can be neglected.

As an additional robustness check, we follow Head and Mayer (2014) and compare the gravity estimates from linear-in-logs OLS with those obtained from Gamma and Poisson PML. While the Gamma PML estimates of the centrality bias in inter-city trade resemble those obtained under linear-in-logs OLS, the same can not be said of the Poisson PML. According to Head and Mayer (2014), this pattern arises because Poisson PML (unlike the OLS and Gamma PML) is sensitive to model misspecification.[5]

With this paper, we contribute to the central place literature and to the gravity literature. Christaller's (1933) seminal contribution to the central place theory has spurred a growing theoretical literature on the implications that a multi-polar city system with central places and hinterlands has for the location of cities and industries as well as for the flow of goods between these cities.[6] While there exists a considerable amount of empirical evidence on the distribution of industries across cities (Mori et al., 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015; Davis and Dingel, 2020) and on the distribution of cities in space (Hsu, 2012; Mori et al., 2020a, 2022), 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 (Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012; Mori et al., 2022) into the nested-gravity framework of Redding and Weinstein (2019), we close this important gap in

[5] Although we allow for heterogeneous central place dummies, our parsimonious fixed effect specification may not be complex enough to fully absorb the aggregation bias characterized by Redding and Weinstein (2019).

[6] Eaton and Lipsey (1976, 1982), Quinzii and Thisse (1990), Fujita, Krugman, and Mori (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.

the literature.

We also contribute to the gravity literature on the aggregation of trade flows across sectors or regions (Anderson and van Wincoop, 2004). This literature is characterized by an interesting dichotomy: Intra-national trade data with a high geographical resolution is typically used to study the effects of spatial aggregation (Hillberry and Hummels, 2008; Briant, Combes, and Lafourcade, 2010; Coughlin and Novy, 2013, 2021), whereas international trade statistics, based on detailed product-level customs data, are used to study the effects of aggregating across products and/or sectors (Anderson and Neary, 2005; French, 2017; Redding and Weinstein, 2017, 2019).[7] By studying the effects of sectoral aggregation in a regional context, we show that the hierarchical distribution of industries in combination with systematic differences in the extensive margin of inter-city trade can explain why central places excessively trade with their hinterland. 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. While they conclude that none of the standard international trade models, reviewed in their study, can fully explain all of the stylized facts that they have found, we argue that the centrality bias in inter-city trade is compatible with the key predictions of central place theory.

The remainder of this paper is structured as follows: Sections 2 and 3 introduce our data and the theoretical background. In Section 4, we quantify the centrality bias in inter-city trade, which we subsequently decomposed in Section 5. Section 7 replicates our main result for the US. Section 8 concludes.

2 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).[8] The survey includes only manufacturing establishments with at least four employees. Establishments are classified according to

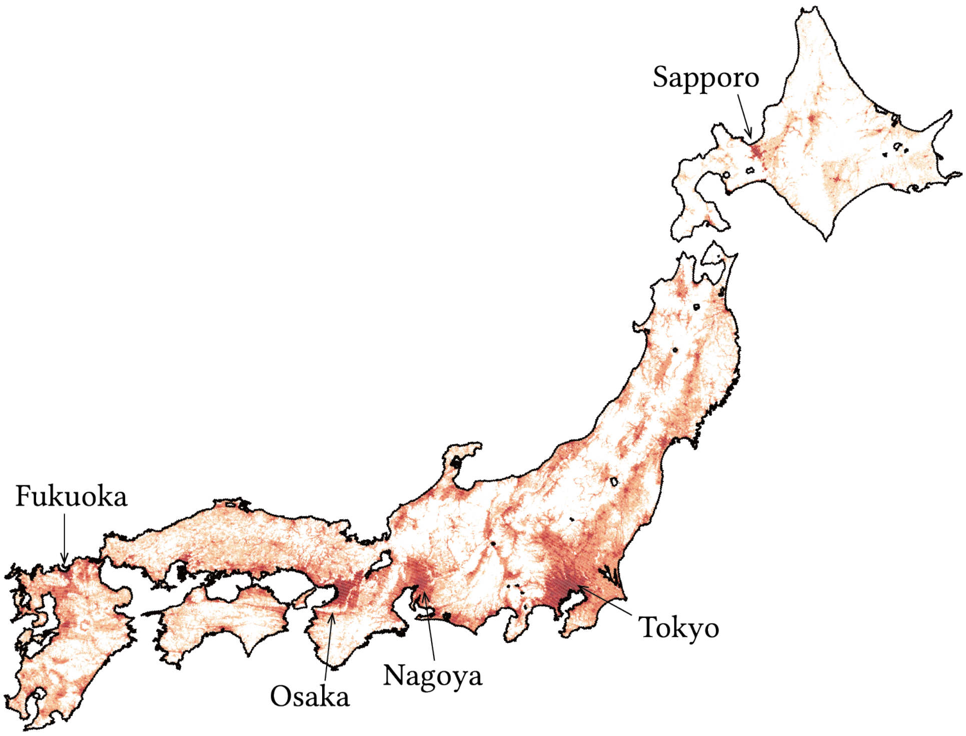
[7] A notable exception is the paper of Hillberry (2002), which uses disaggregated data from the US Commodity Flow Survey to show that endogenous industry location patterns and the presence of zero observations in a commodity-level trade result in upward-biased border effect estimates.

[8] 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 favors 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.

the Japan Standard Industrial Classification (JSIC), which distinguishes between 24 two-digit manufacturing industries (22 two-digit manufacturing industries in 1995 and 2000).[9] 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 (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 (Fig. 1), cities are constructed

Figure 1: *Japanese Population Distribution in 2015*



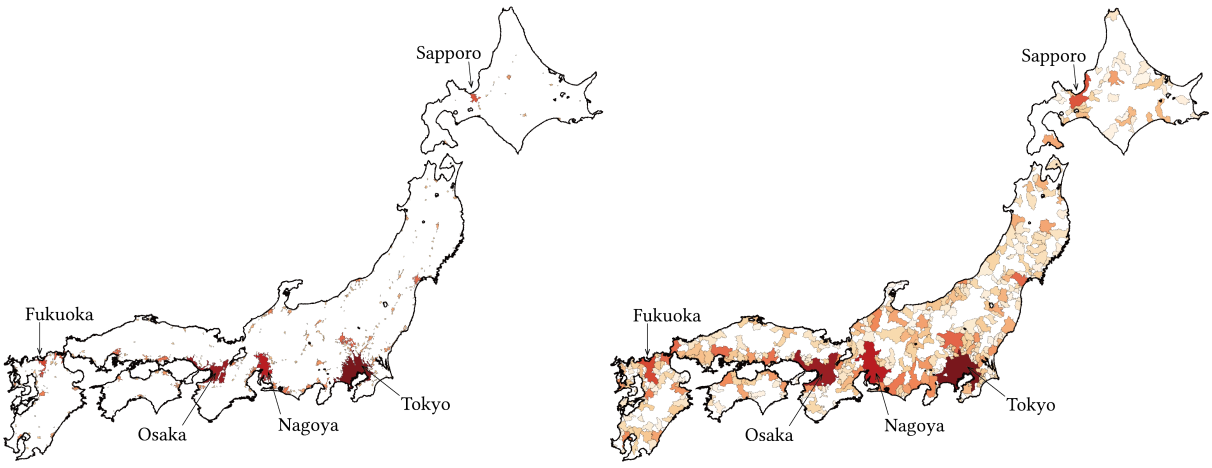
Note: *Fig. 1 is based on the Japanese Population Census, and depicts the spatial distribution of population in Japan in 2015 at the level of a 1km×1km grid cells. Comparable maps for 1995, 2000, 2005, and 2010 are reported in the Online Appendix.*

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 kilometer and a total population of at least 10,000 inhabitants.[10] 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

[9] In 2015, a total of 14,620 or 7.0% of all 208,029 relevant manufacturing establishments were sampled. For the earlier waves, the numbers 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.

[10] Our definition of an urban agglomeration follows Dijkstra and Poelman (2012, 2014), who propose a harmonized definition of urban areas, which is applied by Schmidheiny and Suedekum (2015) to identify European cities.

Figure 2: *Definition of Cities as Basic Unit of Observation*



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

Note: *Fig. 2 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.*

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. Aggregating our municipality-level shipment data to the city level leaves us with 400 cities in 2015, of which 292 cities ship to at least ten other cities in our sample.[11] Fig. 2 illustrates the definition of cities as the basic unit of observation by showing how we narrow down our 450 urban agglomerations (Fig. 2a) to 400 cities (Fig. 2b).

One common drawback shared by most commodity flow surveys (Wolf, 2000; Hillberry and Hummels, 2003, 2008; Combes, Lafourcade, and Mayer, 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 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.[12] 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 way, we also check whether certain product categories (e.g. 7022: "clothes and belongings") are too broadly defined and,

[11] 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.

[12] Some of the recorded shipments clearly are not representative of the establishment's typical sales (e.g. food manufacturer who is shipping a single automobile, probably selling off a former investment good).

therefore, could be split 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.[13]

Our highly disaggregated inter-city trade data is complemented by information on 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×1km cells in these municipalities.[14] 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 (Statistics Bureau, Ministry of Internal Affairs and Communications of Japan, 2015), which can be approximated by $(128/45\pi)\sqrt{a/\pi}$, in which a is the habitable area of the municipality (Combes et al., 2005). Following Head and Mayer (2009), bilateral distance between destination and origin city is then computed as a trade-weighted harmonic mean of the bilateral distances between all the municipalities that belong to the destination and origin city, respectively.[15]

3 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.

[13] 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.

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

[15] 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.

3.1 The Basic Setup

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, also include all intra-city trade flows. (*ii.*) Instead of using an Armington model as a micro-foundation for the aggregation analysis, we focus on a setting with monopolistic competition (Krugman, 1980), that allows us to discuss the role of firm entry for the sectoral and the aggregate trade pattern. (*iii.*) 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 (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 Ω_{os} with $M_{os} \equiv |\Omega_{os}|$ in origin o and sector s to be exogenously given and explicitly allow for the possibility that $\Omega_{os} = \emptyset$ is an empty set because no firm in sector s finds it optimal to locate in o such that $M_{os} = 0$

(Anderson and van Wincoop, 2004). We refer to the set of origin cities from which destination d imports commodities in sector s in strictly 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 that a log-linear gravity equation for aggregate trade

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

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 (see Appendix A.1). 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. For our purpose, it suffices to remember that the terms Γ_{do}, Λ_{do}, T_{do} and U_{do} aggregate up their sector-level equivalents γ_{os}, λ_{ds}, τ_{dos} and u_{dos}, whereas J_{do} is a Jensen's inequality correction term, which 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 into a log-linear aggregate gravity equation.[16] Unlike in Redding and Weinstein (2019), who assume that firms from all sectors $s \in \mathcal{S}$ are present in

[16]Theoretical definitions of the five components Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} are reported in Appendix A.1.

all origins $o \in \mathcal{R}$, we explicitly allow the set Ω_{os} of firms in sector s in origin o to be empty. Because the five aggregates Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} are obtained from the summation across the subset $\mathcal{S}_{do} \subseteq \mathcal{S}_o$ of sectors s across which destination d imports from origin o (with $\mathcal{S}_o$ as the subset of active sectors s in origin o), it follows that systematic differences in cities' industry range (i.e. the set $\mathcal{S}_o$) are shaping the components Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} and therefore the structural error term v_{do}.

We show next that the range of active sectors which ship their goods to other cities differs systematically between central places and the surrounding hinterland cities. Aggregating across 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 origins.

3.2 Central Places, Hinterlands, and Chistaller's Hierarchy Property

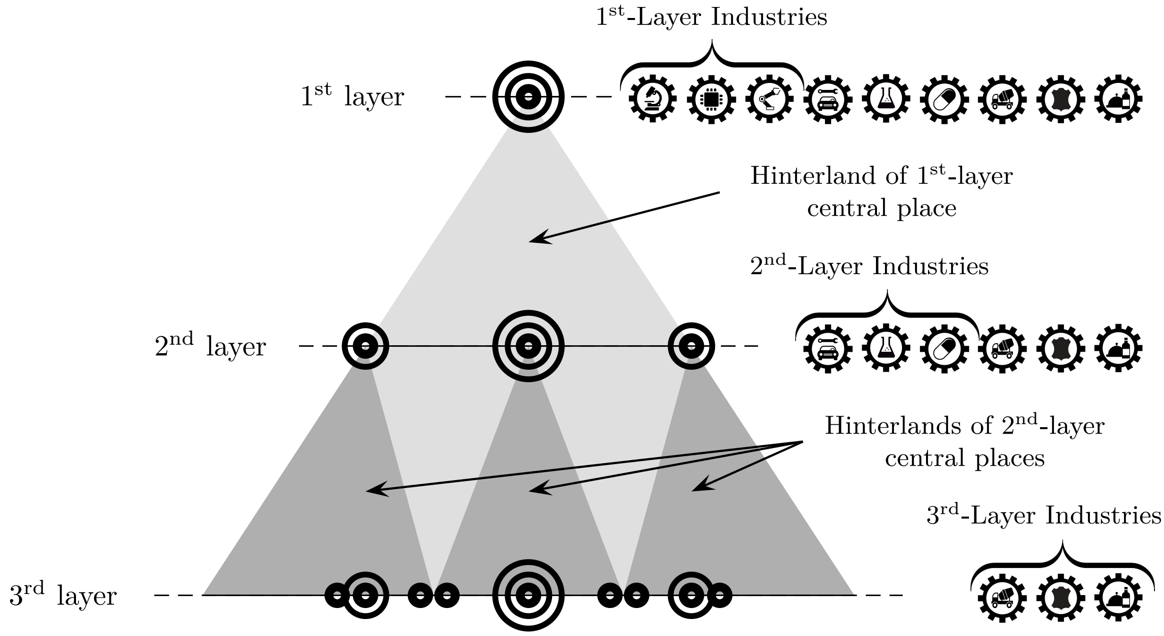
We show that the subset $\mathcal{S}_{do}$ of sectors s which exist in origin o and ship their goods to destination d is determined by the *hierarchy property* of central place theory (Hsu, 2012; Mori et al., 2022). Within the class of central place models, endogenous market entrance results in a hierarchical industry structure, which stands in marked contrast to the exogenously fixed distribution of industries in most international trade models.[17]

Building upon the early work of Christaller (1933), several more recent contributions have shown how to embed the key predictions of 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 is established by Hsu (2012) under the assumption of heterogeneous market entry fixed costs. To illustrate hierarchy property of centralplace theory, we resort in the following to a simple and therefore illustrative numerical example from Fujita et al. (1999a, Fig. 6, p. 237), which highlights the key predictions of central place theory.

Fujita et al. (1999a) consider a multi-polar 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 cities of sufficient size to not only attract ubiquitous industries, whose goods are costly to trade and therefore optimally produced in close

[17] 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 (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 3: *Central Places and their Hinterlands in a Hierarchical City System*



Note: *Fig. 3 illustrates the spatial distribution of cities in Fujita et al.'s (1999a) central place model. Cities 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.*

proximity to customers, but also some footloose industries, whose goods are traded at low costs and which therefore are best produced in centrally located cities with a large home market (Krugman, 1980). On the other hand, there are many small cities in the hinterland of central places, which due to their insufficient size only attract a limited set of ubiquitous industries. In Fig. 3, we depict a one-dimensional space, in which city locations 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. The figure also illustrates that according to the spatial grouping property (Mori et al., 2020a, 2022) larger central places are surrounded by smaller hinterland cities. We later rely on this spatial grouping property to identify central places and their hinterlands in Japan (see Section 4.1 below).

Sorting central places according to the range of their industries (indicated by the number of circles around a city in Fig. 3) results in a hierarchical city system, with nested central places and associated sets of hinterland cities as illustrated in Fig. 3. The sorting of industries across a total of three layers in Fig. 3 thereby distinguishes between 1st-, 2nd-, and 3rd-layer central places, which systematically differ in terms of their industry diversity. As a noticeable feature of the pyramidic city system in Fig. 3, 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 2^{rd}-layer industries are also present in the 1^{st}-layer city. Following Hsu (2012); Mori et al. (2022), we refer to this regularity as the hierarchy property of central place theory, expecting all industries, which can be found in a city with a given industry range, to be also present in all cities with a smaller industry range.

Several authors (Mori et al., 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015; Mori et al., 2022) have accumulated supportive empirical evidence in favor of the hierarchy property. We contribute to this strand of the literature by highlighting the importance of hierarchy property for our specific application. More specifically, we propose a simple three-step randomization test: At first, we compute the economy's average hierarchy share defined below as a measure of how hierarchical industries are distributed across cities. In the second step, we then fix the number of industries in each city, randomizing 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 randomized 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 overlaps 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 the hierarchy property holds perfectly.

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 analyzing the distribution of industries that we can infer from our highly disaggregated intra-national trade data for Japan. 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. Table 1 summarizes the results from the 2015-wave of the Freight Census.[18]

Table 1: *Hierarchy Test*

Year	$\underline{S}$	# of Industries	H	# of Samples	p-Value	$\widehat{H}$	H_{99}	H_{95}	H_{90}	$\bar{H}$
2015	10	188	0.3587	1,000	0.0000	0.1320	0.1314	0.1309	0.1306	0.1297
2015	20	188	0.4720	1,000	0.0000	0.1896	0.1883	0.1877	0.1872	0.1856
2015	30	188	0.6266	1,000	0.0000	0.2981	0.2964	0.2946	0.2938	0.2909
2015	40	188	0.7410	1,000	0.0000	0.3987	0.3963	0.3935	0.3925	0.3880
2015	50	188	0.8377	1,000	0.0000	0.4930	0.4902	0.4876	0.4860	0.4802

Notes: H denotes the observed average hierarchy share, $\widehat{H}$ denotes the maximum counterfactual average hierarchy share, H_{99} denotes the 99$^{\text{th}}$ percentile of the counterfactual average hierarchy shares, H_{95} denotes the 95$^{\text{th}}$ percentile of the counterfactual average hierarchy shares, H_{90} denotes the 90$^{\text{th}}$ percentile of the counterfactual average hierarchy shares, $\bar{H}$ denotes the arithmetic mean of the counterfactual average hierarchy shares.

To scrutinize this first result, we also rely on auxiliary data from the Economic Census for Business Activity (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 randomization test at different levels of disaggregation in the 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 1$^{\text{st}}$ of June 2016. With the universe of Japanese firms being covered, we can be sure that our hierarchy measure H is not biased because missing information on industry location (particularly in small cities) obscures the true extent to which industries are hierarchically distributed in Japan. In the Online Appendix, we plot the average hierarchy share H together with the maximum counterfactual hierarchy share $\widehat{H}$ selected from 1,000 randomized 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 aggregation, we find that the observed average hierarchy shares are always larger than the counterfactual hierarchy shares that are obtained from randomizing the identity of industries across locations with a fixed number of industries.

Summing up the results of our hierarchy test, we find that the distribution of industries across cities of varying sizes follows a strong hierarchical pattern that is compatible with hierarchy property of central place theory.

[18]Similar results are obtained for the years 1995, 2000, 2005, and 2010. We report these additional results in the Online Appendix.

3.3 The Heterogeneous Extensive Margins of Sectoral Inter-city Trade

Having confirmed the hierarchy property of central place theory, we now explore the sector-specific patterns of inter-city trade that follow from this property. 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 Fig. 4, we plot for each set of industries the (average) extensive margin of inter-city trade (i.e. the average share of all destination cities consuming goods produced by these industry) over a total of 20 different distance intervals, that capture the bilateral distance between origin and destination city.[19]

Fig. 4 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 sectoral trade is declining in the distance to the destination city. For ubiquitous industries, the extensive margin sharply declines in distance over the first 200-300 kilometers, then flattens 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 more resilient against increasing shipment distances. Summarizing our findings from Fig. 4, we conclude that footloose industries tend to serve a wider market area than the ubiquitous ones.

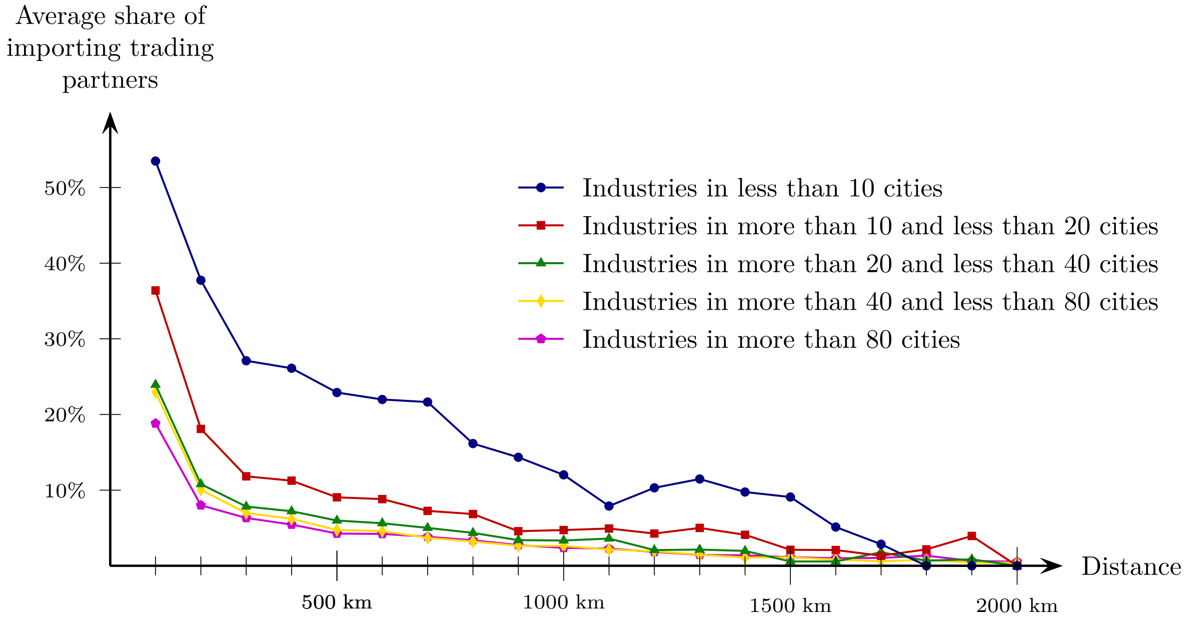
It is worth noting that the differences in market areas between footloose and ubiquitous industries in Fig. 4 exactly match the predictions of the central place model by Hsu (2012). In this model the combination of perfectly inelastic demand across an one-dimensional space and Bertrand competition among 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 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.[20]

Taking stock, we can conclude that the hierarchy property of central place theory not only

[19]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 (Hillberry and Hummels, 2008).

[20]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 (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 fixed trade costs.

Figure 4: *Heterogeneity in the Extensive Margins of Inter-city Trade at the Industry Level*



Note: *Fig. 4 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.*

determines the set $\mathcal{S}_o$ of active sectors s shipping from origin city o but also the extensive margin of sectoral inter-city trade, which determines the subset $\mathcal{S}_{do} \subseteq \mathcal{S}_o$ of sectors s from origin o that actually serve destination d. Using the insights from central place theory (Fujita et al., 1999a; Hsu, 2012), to qualify the predictions of Redding and Weinstein's (2019) aggregation exercises, we conclude 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.

4 Centrality Bias in Inter-city Trade

How does the aggregation bias that follows from the hierarchy property of central place theory affect the pattern of inter-city trade? To answer this question, we proceed in two steps. In Section 4.1, we follow Mori et al. (2020a) by applying a simple theory-consistent algorithm in the spirit of Christaller (1933) to identify central places and their associated hinterlands. Based on the obtained classification of cities as central places or hinterlands, we then quantify in Section 4.2 the upward bias in the shipments from central places to their hinterland cities.

4.1 In Search for Central Places and their Hinterlands

To partition the set of cities $\mathcal{R}$ in our sample into central places with associated hinterlands (cf. Fig. 3), we follow Mori et al. (2020a) and consider a *K-partition*, a hierarchical Voronoi partition of $\mathcal{R}$ for a given integer $K \geq 2$. We take the K largest cities, or *central places*, and assign all other cities to the closest ones among them, yielding K disjoint subsets, or (partition) cells, of $\mathcal{R}$. Recursively generating a new partition for each cell concerning the K largest cities in the cell (as long as the cell has at least K cities), we obtain a unique hierarchical partition of $\mathcal{R}$. Each city j's *hinterland* is defined by the highest-layer, hence the largest, cell of the hierarchical partition that j serves as the central place.[21]

With the set of all cities in a country forming a unique cell in the 1st-layer partition, the largest city, Tokyo, is always the unique 1st-layer central place. Fig. 5 depicts 2nd- and 3nd-layer of the 3-partition.[22] In the 2nd layer in Fig. 5a, we distinguish partition cells by different colors and explicitly label the respective central place of each cell. The 3rd-layer cells in the hinterland of the 2nd-layer central places (cf. Fig. 5b) are colored in different shades of the color associated with their 2nd-layer central places in Fig. 5a. The hinterland of the second largest city, Osaka, is the set of cities in the red cell in the 2nd-layer of Fig. 5a, and that of Fukuoka (the second largest city in the Osaka's hinterland) is the lighter-red cell of Fig. 5b.

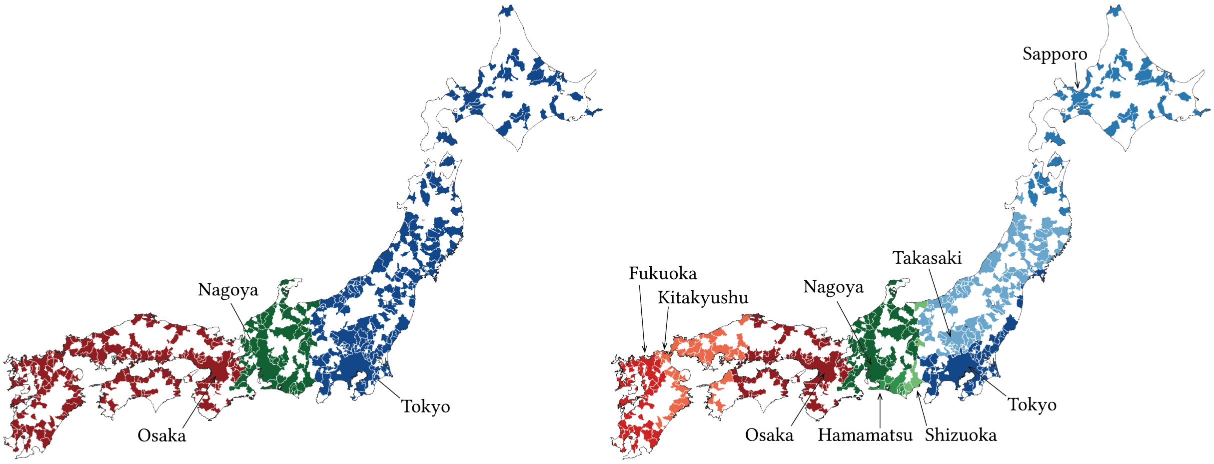
Several aspects render Mori et al.'s (2020a) partition scheme particularly useful for our application. As defined in the spirit of Christaller (1933), the above classification algorithm only requires a modest input of data and, in particular, does not rely on the inter-city trade data that we seek to analyze below (see Section 4.2).

Having identified a hierarchical city system with central places and associated hinterlands, we focus on the top five layers to explore the pattern of inter-city trade. In each layer, we can 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). Delegating detailed descriptive statistics for all five waves (1995 to 2015) of the Freight Census on the relative importance of these trading relationships to the Online Appendix, we highlight in Table 2 the importance of central places for Japan's internal trade. Tokyo, as the only central place at the 1st layer,

[21] 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.

[22] The 2nd- and 3nd-layer of the 3-partition for the years 1995, 2000, 2005 and 2010 are reported in the Online Appendix. There we also report the 2nd- and 3nd-layer of the 2-partition for the years 1995, 2000, 2005, 2010 and 2015, which we are using later to confirm our results for the 3-partition.

Figure 5: *2^{nd}- and 3^{rd}-layer Central Places and their Hinterlands*



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

Note: *Fig. 5 depicts 2^{nd}- and 3^{rd}-layer 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 (see Online Appendix).*

accounts for 14% of Japan's internal trade as an origin and for 20% of Japan's internal trade as a destination. A total of 5% (4%) of all observed trading pairs have the 2^{nd}-layer central places Tokyo, Osaka or Nagoya as an origin (destination). Together these three central places account for 46% (51%) of total trade as origins (destinations). At the 3^{rd} layer, $3^2 = 9$ central places account for 10% (9%) of all trading pairs and 54% (58%) of the total trade value as origins (destinations).

Table 2: *Descriptive Statistics – Shipments from/to Central Places*

Shipments from/to Central Places					
Central Place:	$\mathbf{1^{st}}$ Layer	$\mathbf{2^{nd}}$ Layer	$\mathbf{3^{rd}}$ Layer	$\mathbf{4^{th}}$ Layer	$\mathbf{5^{th}}$ Layer
Origin:					
Trading pairs:	1.59 %	4.67 %	10.21 %	19.92 %	33.27 %
Trade value:	14.02 %	46.30 %	54.30 %	63.10 %	72.47 %
Destination:					
Trading pairs:	1.45 %	4.11 %	9.22 %	19.46 %	32.65 %
Trade value:	20.07 %	50.63 %	58.19 %	66.81 %	73.29 %

Notes: Table 2 reports for 2015 the share of all trading pairs and the share of the total trade value with central places at the 1^{st}, 2^{nd}, 3^{rd}, 4^{th} and 5^{th} layer as origin/destination .

4.2 Centrality Bias in Aggregate Inter-city Gravity Estimation

To see whether the hierarchical city system with central places and their hinterlands from Section 4.1 is associated with a systematic bias in aggregate gravity estimations, we start from a parsimonious specification and regresses 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. We control for average road distance between and within cities DIST_{do} to proxy for geography as a barrier to trade and include a "home bias" dummy $\text{HOME}_{do} \in \{0, 1\}$ (Wolf, 2000; Hillberry and Hummels, 2003, 2008; Millimet and Osang, 2007) and an "island" dummy $\text{ISLAND}_{do} \in \{0, 1\}$ (Wrona, 2018) to a account for non-linear distance effects.[23]

We report the estimation results in Column 1 of Table 4, which establishes a benchmark, that in terms of magnitude and significance is comparable to what has previously been found in the empirical trade literature (Head and Mayer, 2014). Having established this benchmark, we proceed with the residual diagnostics and explore whether Japan's pyramidic city system is reflected in the structural error term v_{do} from Eq. (5). If the pattern of inter-city trade can be fully explained by the trade cost vector from Eq. (8), we would not expect to find a systematic pattern when clustering the gravity residuals along the lines of Japan's hierarchical city system.

We report the residual diagnostics for the shipments between central places (CP) and their hinterland cities (HC) in Table 3, and distinguish between the same eight mutually exclusive trading relationships as in Section 4.1. 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 by a positive residual $\ln X_{do} - \ln \widehat{X}_{do} > 0$). 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 $\ln X_{do} - \ln \widehat{X}_{do}$ for each category. According to Table 3, we systematically underestimate the aggregate trade volume between central places and their hinterlands under our benchmark specification. At each layer, the share of underestimated trade flows (for which $\ln X_{do} > \ln \widehat{X}_{do}$) 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 hinterlands but negative when trading with the hinterland cities that belong to another central place at the same layer.[24]

[23]By including the "home bias" dummy, which takes a value of one for intra-city trade and a value of zero otherwise, we account – among other things – for excessive short-distance trade, which is associated with the local distribution of products. Following a similar logic, we include the "island" dummy, which takes a value of one for intra-island trade and a value of zero otherwise, to account for the fact that Japan is an archipelago (consisting of the four main islands Hokkaido, Honshu, Shikoku and Kyushu).

[24]In accordance with central place theory, we also underestimate the volume of trade among and within central

Table 3: *Residual Diagnostics at the Aggregate Level*

Residual Diagnostics											
Year:		**2015**									
Measure:		**Share of** $\ln X_{do} > \ln \widehat{X}_{do}$					**Mean of** $\ln X_{do} - \ln \widehat{X}_{do}$				
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)**
1^{st} **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
2^{nd} **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
3^{rd} **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
4^{th} **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
5^{th} **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.

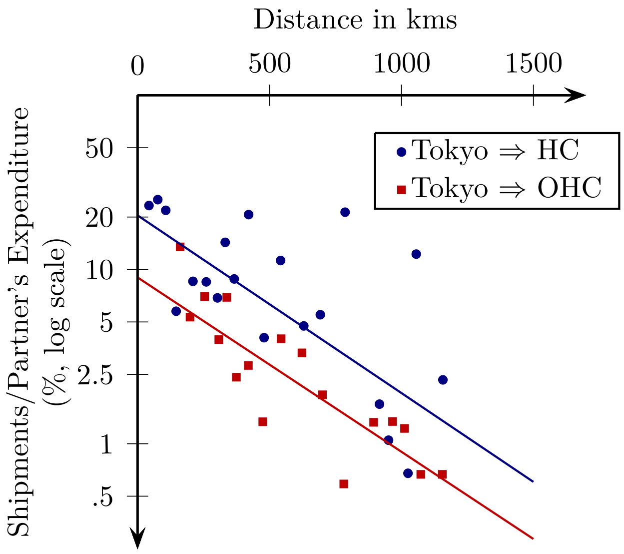
To highlight the upward bias in (residual) shipments from central places to their respective hinterlands based on an illustrative example, we focus on Tokyo as one of three 2^{nd}-layer central places in Fig. 6. The binned scatter plot (Stepner, 2013) in Fig. 6 thereby captures the "*spirit of gravity*" (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 2^{nd}-layer central place ships larger volumes to its interland cities (blue dots) than to cities that belong to the hinterlands of other central places in the same layer (red dots).

To systematically quantify the estimation bias that results from not taking into account Japan's hierarchical city system from Section 4.1, we amend an otherwise standard gravity

places (see Columns (1) and (2) as well as Columns (6) and (7) in Table 3). 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 in the 2^{nd} layer because all other cities belong to Tokyo's hinterland in the 1^{st}-layer . All 2^{nd}-layer central place (i.e. Tokyo, Osaka, and Nagoya) have been excluded as possible destination cities in Fig. 6.

Figure 6: *Tokyo's Shipments to its own and other Hinterland Cities at the 2^{nd} Layer*



Note: *Fig. 6 plots Tokyo's aggregate shipments 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 1995, 2000, 2005, and 2010 waves of the Freight Census. We report these additional figures in the Online Appendix.*

estimation to account for the pyramidic city structure with central places and their hinterlands in multiple layers from Fig. 5. 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

$$\ln \tilde{\tau}_{do} = \sum_{l=2}^{5} \beta_l \times \text{SHP\_CP\_HC\_}l\text{LY}_{do}, \tag{9}$$

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 "central place" dummy $\text{SHP\_CP\_HC\_}l\text{LY}_{do} \in \{0, 1\}$. We specify this indicator variable to take a value of one (instead of zero) for all shipments that originate from a central place, which is present in the l^{th} layer but does not exist in higher layers, and which are bound for a hinterland city associated with this central place.[26] By definition, we only have a single 1^{st}-layer central place (i.e., Tokyo), whose hinterland is formed by all other cities in Japan. Due to prefect multicollinearity of the indicator variables $\text{SHP\_CP\_HC\_1LY}_{do}$ with the respective origin-specific fixed effect for Tokyo, we cannot independently identify the parameter $\beta_{\text{EXP\_1}}$

[26]We do not include central places in multiple layers to minimize multicollinearity problems that otherwise can arise when simultaneously including multiple "central place" dummies to control for different layers.

at the 1st layer, which is why we focus only on lower layers (i.e. $l \geq 2$) with more than one central place. We thereby account for up to 5 layers and include the "central place" dummies for different layers separately (see Columns (2) to (5) of Table 4) and jointly (see Columns (6) to (8) of Table 4). Because Redding and Weinstein's (2019) aggregation approach delivers an additively separable log-linear aggregate gravity equation, we can use ordinary least squares (OLS) to consistently estimate Eq. (4), in which we substitute $\ln \tau_{do}$ from Eqs. (8) to account for bilateral trade costs and $\ln \tilde{\tau}_{do}$ from Eq. (9) to approximate the unobservable structural error term v_{do}.

Table 4: *Central Places, Hinterlands, and the Centrality Bias in Inter-city Trade*

Dependent variable: Shipments from origin city o to destination city d								
Year:	**2015**							
Model:	**OLS-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP fixed effects:								
Shipments CP → HC (2nd layer)		0.3960^{***}				0.4007^{***}	0.4133^{***}	0.4231^{***}
		(.1449)				(.1449)	(.1449)	(.1449)
Shipments CP → HC (3rd layer)			0.5726^{***}			0.5777^{***}	0.5956^{***}	0.6108^{***}
			(.1804)			(.1803)	(.1803)	(.1804)
Shipments CP → HC (4th layer)				0.7676^{***}			0.7924^{***}	0.8114^{***}
				(.1861)			(.1862)	(.1862)
Shipments CP → HC (5th layer)					0.5859^{***}			0.6394^{***}
					(.1952)			(.1952)
Controls:								
$\ln \text{Distance}_{do}$	-0.8277^{***}	-0.8215^{***}	-0.8226^{***}	-0.8155^{***}	-0.8194^{***}	-0.8163^{***}	-0.8033^{***}	-0.7937^{***}
	(.0187)	(.0188)	(.0187)	(.0189)	(.0189)	(.0189)	(.0191)	(.0193)
Intra-city trade	0.7284^{***}	0.7509^{***}	0.7530^{***}	0.7779^{***}	0.7646^{***}	0.7760^{***}	0.8285^{***}	0.8704^{***}
	(.1411)	(.1413)	(.1413)	(.1415)	(.1416)	(.1415)	(.1420)	(.1425)
Intra-island trade	0.1303^{**}	0.1390^{***}	0.1189^{**}	0.1362^{***}	0.1315^{***}	0.1276^{**}	0.1336^{***}	0.1350^{***}
	(.0507)	(.0508)	(.0508)	(.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	0.4228	0.4230	0.4228	0.4230	0.4235	0.4237

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.

Throughout all specifications of Table 4, we find a large and statistically significant upward bias in the shipments from central places to their associated hinterlands in different layers, which is associated with an increase in the bilateral trade volume of 50% to 125%.[27]

4.3 Placebo Regressions

Having quantified the upward bias in shipments from central places to their respective hinterlands, we now scrutinize the conditions under which we can expect to find a systematic upward

[27] In the Online Appendix, we also compute the centrality biases for the 1995, 2000, 2005 and 2010 waves of the Freight Census. In line with our baseline result, we mostly find large and statistically significant upward biases, which are associated with increases in the bilateral trade volume that fall into the range from 30% to 380%. There, we also show that similar results are obtained for the more conservative 2-partition case, in which we end up with $1 + \sum_{l=2}^{5}(2^{l-1} - 2^{l-2}) = 16$ central places instead of $1 + \sum_{l=2}^{5}(3^{l-1} - 3^{l-2}) = 81$ central places.

bias in the shipments from central places to their hinterlands. We conduct two series of placebo regressions: Under randomization scheme (a) from Table 5, we maintain the basic hierarchical structure from Fig. 5. 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 5 follows Mori et al. (2020a), who obtain subcells at lower layers not as Voronoi K-partitions but from random partitioning holding the cell size constant. Since the largest $K = 3$ cities in each cell are chosen as lower-layer (counterfactual) central places in this scheme, 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$^{\text{th}}$ layer. From each hypothetical partition into central places and associated hinterland cities, we can then derive counterfactual central place dummies akin to $\text{SHP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ 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 4. Table 5 compares the outcomes of the placebo regression to the baseline results from Table 4. Focusing on the specifications

Table 5: *Placebo Regressions*

Randomized Hinterlands:						
Year:			**2015**			
Layer	**Benchmark:** $\hat{\beta}_{\text{SHP\_CP}}$	**S. E.**	**Number of Samples**	**Mean of:** $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}}$	**S. E.**	**Share of** $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}} > \hat{\beta}_{\text{SHP\_CP}}$
Randomization scheme (a):						
2	0.3960***	(.1449)	10,000	.0357	(.1339)	.0006
3	0.5726***	(.1804)	10,000	.2684	(.2116)	.0522
4	0.7676***	(.1861)	10,000	.2669	(.2613)	.0187
5	0.5859***	(.1952)	10,000	-.1411	(.3396)	.0178
Randomization scheme (b):						
2	0.3960***	(.1449)	10,000	-.0121	(.1343)	.0000
3	0.5726***	(.1804)	10,000	.0048	(.2129)	.0000
4	0.7676***	(.1861)	10,000	.0050	(.2584)	.0020
5	0.5859***	(.1952)	10,000	-.0860	(.2952)	.0100

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.

(2) to (5) from Table 4, we find that the estimates for the centrality bias in inter-city trade

from the placebo regressions, are on average much smaller than our baseline results. Under randomization scheme (a) the coefficients $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}}$ from the placebo regressions are on average half as large as their counterparts $\hat{\beta}_{\text{SHP\_CP}}$ from the baseline regressions. Under randomization scheme (b) the mean value of $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}}$ is close to zero. The fraction of placebo regressions that deliver coefficients $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}}$, which are larger then the baseline coefficients $\hat{\beta}_{\text{SHP\_CP}}$ from Table 4, ranges from 0.1% to 5.2% under randomization scheme (a) and does not exceed 1% under randomization scheme (b). Reassuringly, we find that in our preferred specification (b), which randomizes not only the hinterland cities but also the central places, the hypothesis $\hat{\beta}^{\text{random}}_{\text{SHP\_CP}} > \hat{\beta}_{\text{SHP\_CP}}$ can always be rejected at 1% level of significance.

5 Disaggregation and Decomposition

Having quantified the upward bias in aggregate shipments from central places to their respective hinterlands based on Japan's pyramidic city system, we now provide further evidence that the unexpectedly high aggregate shipments of central places are an artifact of the underlying aggregation process (as explained in Section 3). We proceed in two steps. In Section 5.1, we repeat our analysis from Section 4 at the more disaggregted sector level to prove that the centrality bias is an aggregation bias. In Section 5.2, we then apply two alternative decomposition approaches to learn more about the origins of the centrality bias from Section 4.

5.1 Disaggregation

In order to demonstrate that the centrality bias in inter-city trade from Table 4 is an artifact of an aggregation process that does not account for the hierarchical distribution of sectors across cities, we repeat our analysis from Section 4.2 at the more disaggregated sector level. For residual diagnostics, we regress sectoral shipments on the trade cost vector from Eq. (8) and on the complete set of origin×sector- and destination×sector-specific fixed effects. The residual diagnostics for the sectoral gravity estimations in Table 6 can be directly compared to the residual diagnostics for the aggregate gravity estimations in Table 3. Both of our metrics (i.e. the share of underestimated trade flows and the size of the mean residual) suggest, that the extent to which sectoral gravity estimations underestimate the volume of shipments from central places to their hinterlands is significantly reduced through disaggregation.[28]

Reassuringly, we find this result confirmed, when also including the set of central place

[28] In particular, we find that the percentage point difference between the shares of underestimated shipments from central places to associated versus unassociated hinterland cities drops from a range of 7.59-19.24 percentage points in Table 3 to a range of 2.88-4.56 percentage points in Table 6. The mean residual for shipments from central places to their hinterlands drops from 0.2310-0.5781 in Table 3 to 0.0114-0.0575 in Table 6.

Table 6: *Residual Diagnostics at the Sectoral Level*

Residual Diagnostics at the Sectoral Level											
Year:		**2015**									
Measure:		**Share of** $\ln X_{dos} > \ln \widehat{X}_{dos}$					**Mean of** $\ln X_{dos} - \ln \widehat{X}_{dos}$				
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)**
1^{st} **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
2^{nd} **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
3^{rd} **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
4^{th} **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
5^{th} **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.

dummies from Eq. (9). We report in Table 7 the results of accordingly specified sectoral gravity estimations. Throughout Columns (2) to (8) of Table 7, we find that the coefficients of the central place dummies at different layers are substantially smaller than at the aggregate level (see Table 3) and never statistically distinguishable from zero at the 1% significance level.[29]

As in Hillberry and Hummels (2008, pp. 539-40), we find that distance elasticities which are estimated at a more disaggregated level are relatively smaller than the distance elasticities for aggregate trade flows.[30] Because the probability of observing a shipment at the sector level is

[29]We show in the Online Appendix that our central result from Table 4 and 7 is robust to alternative specifications. Following Kanemoto and Tokuoka (2002), we alternatively identified cities by Urban Employment Areas (UEAs), which are somewhat larger than the UAs that we use in our baseline specification. We also allow the trade-reducing effect of distance to vary across the same five sectoral categories as in Fig. 4, defined according to the number of origin cities ($\leq$ 10, 11-20, 21-40, 41-80, and $>$ 80) in which the respective sector can be found. As an additional result of this exercise, we obtain a ranking of sectors in terms of their distance elasticities. Because the distance elasticity is the product of the sector-specific trade cost elasticity $1 - \sigma_s$ and the unobservable elasticity of trade costs with respect to geographic distance, it is not possible to derive a sectoral ranking of the elasticities of substitutions as for example assumed by Fujita et al. (1999a).

[30]Hillberry and Hummels (2008) focus on spatial rather than on sectoral aggregation and compare gravity estimates obtained at the 3-digit versus the 5-digit zip-code level.

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

Dependent variable: Sector-level shipments from origin city o to destination city d								
Year:	**2015**							
Model:	**OLS-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP $\rightarrow$ fixed effects:								
Shipments CP $\rightarrow$ HC (2nd layer)		0.0295				0.0272	0.0322	0.0335
		(.0667)				(.0668)	(.0667)	(.0667)
Shipments CP $\rightarrow$ HC (3rd layer)			−0.0953			−0.0923	−0.0866	−0.0847
			(.1027)			(.1025)	(.1026)	(.1026)
Shipments CP $\rightarrow$ HC (4th layer)				0.1857			0.1878	0.1903
				(.1274)			(.1272)	(.1273)
Shipments CP $\rightarrow$ HC (5th layer)					0.0782			0.0875
					(.1641)			(.1643)
Controls:								
ln Distance$_{dos}$	-0.4423^{***}	-0.4396^{***}	-0.4442^{***}	-0.4384^{***}	-0.4414^{***}	-0.4416^{***}	-0.4370^{***}	-0.4358^{***}
	(.0162)	(.0166)	(.0163)	(.0164)	(.0163)	(.0167)	(.0168)	(.0169)
Intra-city trade	0.4903^{***}	0.5005^{***}	0.4813^{***}	0.5062^{***}	0.4943^{***}	0.4909^{***}	0.5092^{***}	0.5145^{***}
	(.1088)	(.1079)	(.1099)	(.1094)	(.1094)	(.1089)	(.1096)	(.1103)
Intra-island trade	0.0452	0.0487	0.0476	0.0487	0.0450	0.0508	0.0548	0.0548
	(.0445)	(.0442)	(.0446)	(.0445)	(.0445)	(.0443)	(.0442)	(.0442)
Fixed effects:								
Origin (o) $\times$ sector (s):	✓	✓	✓	✓	✓	✓	✓	✓
Destination (d) $\times$ 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:	0.5805	0.5805	0.5805	0.5805	0.5805	0.5805	0.5806	0.5806

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.

declining in distance (see Fig. 4), 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 shipping 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 aggregate trade in Table 4 to increasing distances therefore is substantially larger than at the more disaggregated sector level in Table 7.

5.2 Decomposition

Following Hillberry and Hummels (2008), we 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. Aggregate trade can be expressed as $X_{do} = \sum_{z=1}^{Z_{do}} P_{doz} Q_{doz}$, where z refers to a shipment, Z_{do} is the number of shipments, and P_{doz} and Q_{doz} are the shipment-specific price and quantity, respectively.[31] We decompose X_{do} into the number of

[31] As in Hillberry and Hummels (2008), a unique shipment is defined by the triplet: establishment identifier $\times$ commodity code $\times$ 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 between ten shipments of one million yen and one shipment of ten million yen.

shipments and the average value per shipment as

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

Decomposing the number of unique shipments Z_{do} further into the number of sectors S_{do} 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 $\bar{Y}_{do}$ 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 trade is interesting in its own right (yielding similar results as in Hillberry and Hummels (2008)), we are particularly interested in understanding the driving forces behind the upward bias in aggregate shipments 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 $\ln \tau_{do}$ from Eq. (8), the hierarchy vector $\ln \tilde{\tau}_{do}$ from Eq. (9), and the complete set of origin- and destination-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 superscripts are used to distinguish the dependent variables: X_{do}, Z_{do}, and $\bar{Y}_{do}$ 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 $\text{SHP\_CP\_HC\_}l\text{LY}_{do}$ $\forall\ l = 2, \dots 5$). Based on the decomposition from Eq. (15), we are now equipped to quantify each component's contribution to the upward bias in the aggregate shipments 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 fixed effects:							
Shipments 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]
Shipments CP → HC (3rd layer)	0.5726***	0.3650***	0.3160***	0.0490***	0.2077	−0.0058	0.2135
	(.1804)	(.0396)	(.0361)	(.0111)	(.1665)	(.1121)	(.1938)
	[.4228]	[.6428]	[.6309]	[.2936]	[.3405]	[.4141]	[.4075]
Shipments CP → HC (4th layer)	0.7676***	0.3804***	0.3234***	0.0570***	0.3871**	−0.0950	0.4821**
	(.1861)	(.0409)	(.0373)	(.0115)	(.1718)	(.1157)	(.2000)
	[.4230]	[.6429]	[.6308]	[.2938]	[.3406]	[.4141]	[.4077]
Shipments CP → HC (5th layer)	0.5859***	0.2243***	0.2004***	0.0239**	0.3616**	−0.0321	0.3937*
	(.1952)	(.0429)	(.0391)	(.0120)	(.1801)	(.1213)	(.2097)
	[.4228]	[.6420]	[.6301]	[.2932]	[.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 Column (1) of Table 8, we replicate the baseline results from Columns (2) to (5) of Table 4. By decomposing the strong upward bias in the shipments from central places to their respective hinterlands into its various components from Eq. (15), we gain a better understanding of the relative importance that these components have for the centrality bias in Table 4. Suppose the upward bias in central places' shipments 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) and Requena and Llano (2010)). The disproportionately high shipments 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 originating 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 $\beta^{\bar{Z}}_{\text{SHP\_CP}}/\beta^{X}_{\text{SHP\_CP}}$ range from 4.1% to 20.4%). It suggests that the disproportionately large shipments from central places to their respective hinterlands are mainly explained by the extensive industry margin S_{do}. 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 $\ln X_{do}$.[32]

Having identified the extensive industry margin as a main driver behind the centrality bias from Section 4, we now provide complementary evidence that aggregation along this extensive industry margin affects aggregate trade flows through the five components Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} derived by Redding and Weinstein (2019). Substituting the structural error term v_{do} from Eq. (5) into Eq. (4) yields

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

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), while imposing the complete set of origin- and destination-specific fixed effects.[33] 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 $\text{SHP\_CP\_HC\_}l\text{LY}_{do}\ \forall\ l = 2, \ldots 5$ on the log of aggregate bilateral trade $\ln X_{do}$. We report the decomposition results for the centrality bias in inter-city trade based on Redding and Weinstein's (2019) aggregation theory in Table 9.[34] As predicted in Section 3, we find that each of the five Γ_{do}, Λ_{do}, $-T_{do}$, J_{do} and U_{do} components contributes to the centrality

[32]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 4 and the relatively lower distance elasticity estimates in the sectoral gravity estimations from Table 7 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 sending 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 resembles the sectoral distance elasticity estimates from Table 7. Similar results are obtained for the 1995, 2000, 2005, and 2010 waves of the Freight Census.

[33]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 4. Reassuringly, we find that the point estimates in Column (1) of Table 9 are not very different from those in Columns (2) to (5) of Table 4.

[34]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 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.

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 fixed effects:						
Shipments 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]
Shipments CP → HC (3rd layer)	0.8878***	0.1384***	0.1020*	0.1341***	0.2118***	0.3015**
	(.2166)	(.0458)	(.0551)	(.0461)	(.0609)	(.1504)
	[.5306]	[.8337]	[.1089]	[.7331]	[.9481]	[.0955]
Shipments CP → HC (4th layer)	0.8755***	0.2038***	0.1053*	0.0042	0.1420***	0.4201***
	(.1819)	(.0459)	(.0543)	(.0434)	(.0484)	(.1432)
	[.5305]	[.8337]	[.1089]	[.7330]	[.9480]	[.0957]
Shipments CP → HC (5th layer)	0.3959*	0.2305***	0.0012	−0.0372	0.0262	0.1752
	(.2068)	(.0736)	(.0614)	(.0580)	(.0508)	(.1753)
	[.5302]	[.8337]	[.1088]	[.7330]	[.9480]	[.0954]
Controls:						
ln 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.

bias in inter-city trade.[35]

In summary, we find that central places ship 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 3 that the hierarchy property of central place theory is responsible for the upward bias in the shipments from central places to their hinterlands.

6 Heteroscedasticity

In our analysis, we follow Redding and Weinstein (2019) and Hillberry and Hummels (2008) in performing log-linearized OLS gravity estimations. Linear-in-logs OLS is our preferred estimator, because the aggregation theory, which we have adopted from Redding and Weinstein (2019), results in a additively separable log-linear gravity equation and because the decompo-

[35] Reassuringly, the effects are most pronounced and in most cases also statistically significant at the 3rd and at the 4th layer, where a sufficiently large number of big enough central places can be identified.

sition approach that we borrow from Hillberry and Hummels's (2008) relies on the linearity of the OLS estimator.

Santos Silva and Tenreyro (2006) show that the expected value of log-linearized gravity errors does not depend on covariates if the conditional variance is proportional to the square of the conditional mean, implying a Constant Coefficient of Variation (CCV). Linear-in-logs OLS is then not only consistent but also the maximum likelihood estimator that should outperform Gamma PML as the efficient Pseudo Maximum Likelihood (PML) estimator and Poisson PML as the most commonly used PML gravity estimator. To address the concern that linear-in-logs OLS gravity estimations are biased in the presence of heteroscedasticity (Santos Silva and Tenreyro, 2006), we follow Santos Silva and Tenreyro (2006) and Head and Mayer (2014), who propose to diagnose gravity errors based on a statistical test (Park, 1966; Manning and Mullahy, 2001).

In a series of Monte Carlo simulations, that compare the performance of the OLS, Gamma and Poisson PML estimators, Head and Mayer (2014) also analyze the performance of Manning and Mullahy's (2001) test under different Data Generating Processes (DGPs). Manning and Mullahy's (2001) test statistic assumes a value of $\lambda = 1$ if the DGP is characterized by a Constant Variance to Mean Ratio (CVMR) and a value of $\lambda = 2$ if the DGP is characterized by a CCV.[36]

Table 10: *Manning and Mullahy's (2001) Test Statistic*

Year:	**2015**	**2010**	**2005**	**2000**	**1995**
$\hat{\lambda}$:	1.9418	1.9569	1.9495	1.9475	1.9128
	(0.0114)	(0.0117)	(0.0106)	(0.0111)	(0.0103)

Notes: Table 10 reports the slope coefficients $\hat{\lambda}$ of the equation in Fn. 36.

When computing Manning and Mullahy's (2001) test statistic for the five waves of the Freight Survey from 1995 to 2015, we obtain estimates of $\hat{\lambda} \approx 2$ (see Table 10).[37] This result implies that heteroscedasticity is a minor concern in our data, and that the possible bias that

[36]Suppose bilateral trade is given by $X_{do} = \exp(\mathbf{z}'_{do}\boldsymbol{\zeta})\eta_{do}$, where all gravity variables are collected by vector $\mathbf{z}_{do}$, coefficients are summarized by vector $\boldsymbol{\zeta}$, and η_{do} is the multiplicative error term. Furthermore, assume that the link between the conditional expectation $\mathrm{E}[X_{do}|\,\mathbf{z}_{do}]$ and the conditional variance $\mathrm{Var}[X_{do}|\,\mathbf{z}_{do}]$ can be modeled through $\mathrm{Var}[X_{do}|\,\mathbf{z}_{do}] = h\,\mathrm{E}[X_{do}|\,\mathbf{z}_{do}]^{\lambda}$. We then obtain a CVMR for $\lambda = 1$ and a CCV for $\lambda = 2$. The test proposed by Manning and Mullahy (2001) hence takes the logs of $\mathrm{Var}[X_{do}|\,\mathbf{z}_{do}] = h\,\mathrm{E}[X_{do}|\,\mathbf{z}_{do}]^{\lambda}$ and replaces $\ln \mathrm{E}[X_{do}|\,\mathbf{z}_{do}]$ and $\ln \mathrm{Var}[X_{do}|\,\mathbf{z}_{do}]$ by their sample counterparts $\ln \widehat{X}_{do} = \exp(\mathbf{z}'_{do}\hat{\boldsymbol{\zeta}})$ and $\ln \hat{\varepsilon}^2_{do} = \ln[X_{do} - \exp(\mathbf{z}'_{do}\hat{\boldsymbol{\zeta}})]^2$ to obtain

$$\ln \hat{\varepsilon}^2_{do} = \text{constant} + \lambda \ln \widehat{X}_{do},$$

which is estimated OLS to obtain $\hat{\lambda}$ (see also Head and Mayer (2014, pp. 173-174) for more details).

[37]Point estimates in Table 10 are estimated at high precision, which is why $\hat{\lambda} = 2$ can always rejected at the 1% significance level. It is noteworthy that Santos Silva and Tenreyro (2006, p. 649) find in their Monte Carlo simulations a mean value of 1.987 that also slightly underestimates the true value of $\lambda = 2$.

results from log-liberalization in the presence of heteroscedasticity can be neglected. For $\lambda = 2$, we also have that Gamma PML is the efficient PML estimator (Poisson PML is efficient for $\lambda = 1$), which explains why we obtain similar standard errors under OLS and Gamma PML, that are much smaller than under Poisson PML.

We complete the discussion of our model selection by referring to Head and Mayer (2014, pp. 176-177), whose handbook chapter concludes that "*rather than selecting the Poisson PML as the single 'workhorse' estimator of gravity equations, it should be used as part of a robustness-exploring ensemble that also includes OLS and Gamma PML*." Following this suggestion, we repeat the analysis from Column 8 of Table 4 also for Gamma and Poisson PML, covering all five waves of the Freight Census from 1995 to 2015.[38] We report and compare the results of these regressions in the Online Appendix. Although the Gamma PML estimates of the centrality bias in inter-city trade are, in most cases, somewhat smaller than the OLS estimates, we find that the results from both regressions are highly correlated and also estimated with similar precision. The same can not be said of the Poisson PML estimates, which appear to be only weakly correlated with the OLS results, and which in most cases are estimated with substantially higher standard errors than their OLS counterparts. According to Head and Mayer (2014), this pattern can arise because Poisson PML (unlike OLS and Gamma PML) is sensitive to model misspecification. Although we allow for heterogeneous central place dummies in the trade cost function from Eq. (9), it seems plausible that this parsimonious specification lacks the necessary complexity to fully absorb the city-pair specific variation in the structural error term v_{do} from Eq. (5).

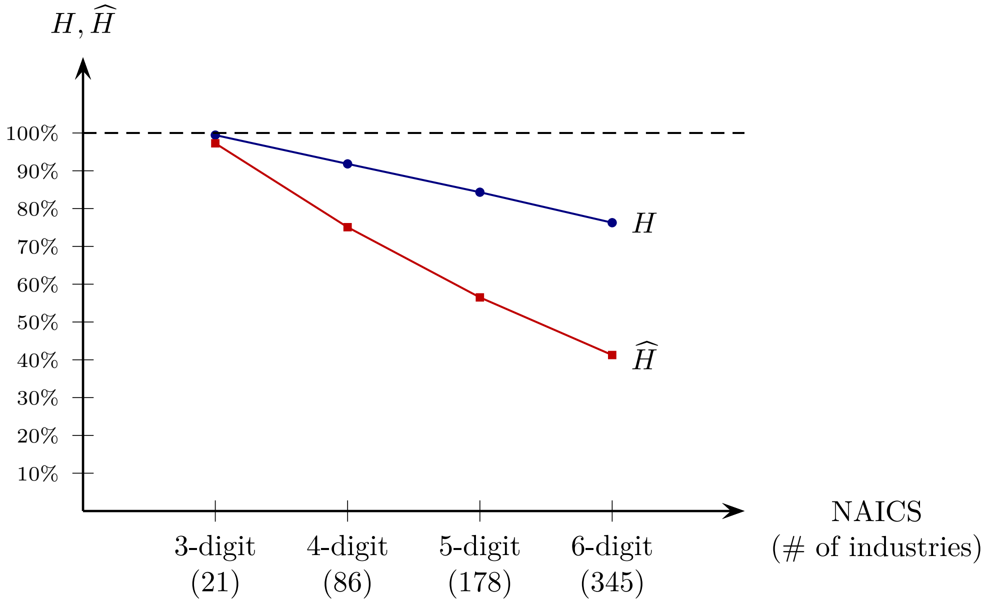
7 Centrality Bias in US Inter-city Trade

To demonstrate that the centrality bias in inter-city trade is not a Japan-specific phenomenon, we replicate our analysis for the US based on the 2017 Commodity Flow Survey (CFS) Public Use File (United States Census Bureau, 2017a).

As potential central places, we focus on 69 CFS Metropolitan Areas (MAs) from the continental US, defined by the 2017 US CFS (the map delegated to the Online Appendix). We begin by showing that the distribution of 3- to 6-digit manufacturing industries in the North American Industry Classification System (NAICS) among the 69 MAs obeys the hierarchy property. To this end, we replicate the hierarchy test from Section 3.2 based on the 2017 County Business Patterns Series (United States Census Bureau, 2017b). Fig. 7 shows that the observed hierar-

[38]We use the `alpaca`-package to conduct Gamma PML estimations with high-dimensional two-way fixed effects (Stammann, 2018).

Figure 7: *Testing for Christaller's (1933) Hierarchy Property for Manufacturing Industries in the US*



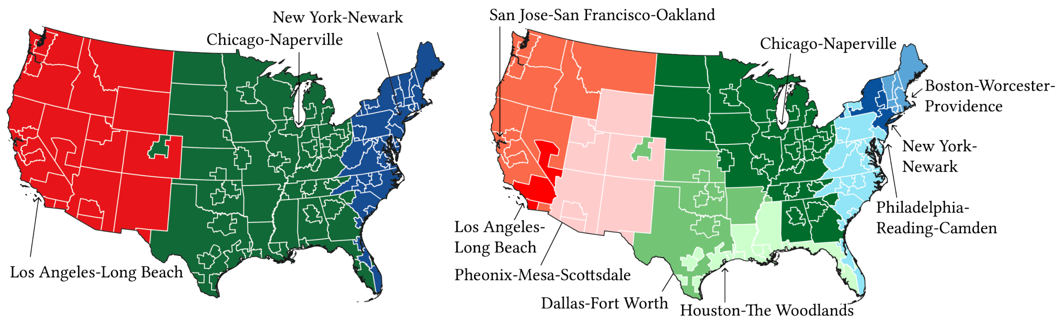
Note: *Fig. 7 is based on the County Business Patterns Series (United States Census Bureau, 2017b). The figure plots the observed versus the counterfactual average hierarchy shares for different levels of disaggregation in the North American Industry Classification System (NAICS) with the number of different industries in parenthesis.*

chy share H at low levels of aggregation is 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 the hierarchy property, 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 Section 4.1, to identify 2^{nd}- to 5^{th}-layer central places together with their associated hinterlands. The ranking of cities in terms of population size is based on county-level population data (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 road distances (Head and Mayer, 2009). Fig. 8 depicts 2^{nd}- and 3^{rd}-layer central places (labeled and identified by arrows) together with their hinterlands (sharing the same color) based on the 3-partition. Each partition cell consists of one of the 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^{nd}-, 3^{rd}, 4^{th}, and 5^{th}-layer central place dummies as in Section 4.2 to estimate the centrality bias in the

Figure 8: *2^{nd}- and 3^{rd}-layer Central Places and their Hinterlands in the US*



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

Note: *Fig. 8 depicts 2^{nd}- and 3^{rd}-layer Voronoi 3-partitions for central places and associated hinterlands in the US based on the 2017 Commodity Flow Survey (CFS).*

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

Dependent variable: Shipments from origin o to destination d								
Year:	**2017**							
Model:	**OLS-FE**							
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CP fixed effects:								
Shipments CP $\rightarrow$ HC (2^{nd} layer)		-0.0272				-0.0216	-0.0127	-0.0052
		(.1336)				(.1336)	(.1334)	(.1334)
Shipments CP $\rightarrow$ HC (3^{rd} layer)			0.3712^{**}			0.3708^{**}	0.4050^{***}	0.4070^{***}
			(.1450)			(.1450)	(.1449)	(.1449)
Shipments CP $\rightarrow$ HC (4^{th} layer)				0.9290^{***}			0.9452^{***}	0.9555^{***}
				(.1536)			(.1537)	(.1537)
Shipments CP $\rightarrow$ HC (5^{th} layer)					0.3988^{**}			0.4354^{**}
					(.1914)			(.1912)
Controls:								
ln Distance$_{do}$	-0.9932^{***}	-0.9936^{***}	-0.9870^{***}	-0.9841^{***}	-0.9923^{***}	-0.9873^{***}	-0.9773^{***}	-0.9761^{***}
	(.0166)	(.0167)	(.0168)	(.0167)	(.0166)	(.0169)	(.0170)	(.0170)
Home bias	1.6690^{***}	1.6678^{***}	1.6886^{***}	1.6987^{***}	1.6730^{***}	1.6875^{***}	1.7199^{***}	1.7250^{***}
	(.1151)	(.1152)	(.1153)	(.1150)	(.1151)	(.1155)	(.1154)	(.1154)
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	0.7282	0.7288	0.7281	0.7282	0.7290	0.7291

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

aggregate trade between central places and their 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^{rd}, 4^{th}, and 5^{th} layer, that are comparable in their magnitude to the results from the Japanese Freight Survey reported in Table 4.

In summary, the evidence from the US suggests that the upward bias in the shipments from central places to their associated hinterlands, that we have identified based on the Japanese Freight Survey in Section 4.2, is not a Japan-specific phenomenon. To account for the aggregation bias that results from the summation across city-specific sets of industries, we therefore propose to include a set of appropriately defined central place dummies that help to control for the centrality bias in intra-national trade.

8 Conclusion

In this paper, we have shown that in aggregate inter-city gravity estimations, the total shipments from central places to smaller cities in their hinterland are 50% to 125% larger than predicted by gravity forces. We argue that the centrality bias in inter-city trade is an artifact of aggregating across city-specific sets of industries, which obey the hierarchy property of central place theory. According to this property, we expect central places to possess a wider range of industries, including a set of ubiquitous industries that are also 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. When decomposing the centrality bias in inter-city trade along the margins of our data, we find supportive evidence for this explanation, which shows that the by far largest part of the centrality bias can be attributed to the extensive industry margin of inter-city trade.

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A Appendix

A.1 Aggregation

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

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

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

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

as the corresponding ideal price index.

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

$$p_{dos} = p_{dos}(\omega_{os}) = \frac{\sigma_s}{\sigma_s - 1}\tau_{dos}c_{os} \tag{A.3}$$

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. (A.3) back into Eq. (A.1) allows us to solve for total expenditure on goods imported from origin o

$$x_{dos} = M_{os} p_{dos} q_{dos} = \left(\frac{\sigma_s}{\sigma_s - 1} \frac{\tau_{dos} c_{os}/\phi_{dos}}{P_{ds}} \right)^{1-\sigma_s} X_{ds}, \tag{A.4}$$

with

$$P_{ds} = \left[\sum_{o \in \mathcal{R}_{ds}} M_{os} \left(\frac{\sigma_s}{\sigma_s - 1} \frac{\tau_{dos} c_{os}}{\phi_{dos}} \right)^{1-\sigma_s} d\omega_{os} \right]^{\frac{1}{1-\sigma_s}} \tag{A.5}$$

as the corresponding sectoral price index. We log-linearize the multiplicative sectoral gravity equation in Eq. (A.4) 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 $X_d = \sum_{j \in \mathcal{R}_d} \sum_{r \in \mathcal{S}_{dj}} x_{djr}$

$$X_{do} = \sum_{s \in \mathcal{S}_{do}} x_{dos} = \sum_{s \in \mathcal{S}_{do}} \frac{x_{dos}}{X_d} X_d = \left(\frac{\sum_{s \in \mathcal{S}_{do}} x_{dos}}{\sum_{j \in \mathcal{R}_d} \sum_{r \in \mathcal{S}_{dj}} x_{djr}} \right) X_d. \tag{A.6}$$

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

$$\mathcal{Z}_{dos} \equiv \frac{x_{dos}}{\sum_{s \in \mathcal{S}_{do}} x_{dos}} \quad \Rightarrow \quad \sum_{s \in \mathcal{S}_{do}} x_{dos} = X_{do} = \frac{x_{dos}}{\mathcal{Z}_{dos}}. \tag{A.7}$$

Since for all sectors $s \in \mathcal{S}_{do}$ the ratio $x_{dos}/\mathcal{Z}_{dos}$ 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

$$\ln \left(\sum_{s \in \mathcal{S}_{do}} x_{dos} \right) = \left[\frac{1}{S_{do}} \sum_{s \in \mathcal{S}_{do}} \ln \left(\frac{x_{dos}}{\mathcal{Z}_{dos}} \right) \right], \tag{A.8}$$

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

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

$$\mathcal{Y}_{dos} \equiv \frac{x_{dos}}{\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}} \quad \Rightarrow \quad \sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr} = X_d = \frac{x_{dos}}{\mathcal{Y}_{dos}}. \tag{A.9}$$

Since for all sectors $s \in \mathcal{S}_{do}$ and all origins $o \in \mathcal{R}_d$ the ratio $x_{dos}/\mathcal{Y}_{dos}$ 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

$$\ln\left(\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{dj}} x_{djr}\right) = \left[\frac{1}{R_d}\sum_{o\in\mathcal{R}_d}\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}}\ln\left(\frac{x_{dos}}{\mathcal{Y}_{dos}}\right)\right], \tag{A.10}$$

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. (A.6) 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. (A.8) and (A.10) to derive

$$\ln X_{do} = \left[\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}}\ln\left(\frac{x_{dos}}{\mathcal{Z}_{dos}}\right)\right] - \left[\frac{1}{R_d}\sum_{o\in\mathcal{R}_d}\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}}\ln\left(\frac{x_{dos}}{\mathcal{Y}_{dos}}\right)\right] + \ln X_d. \tag{A.11}$$

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

$$\ln X_{do} = \Gamma_{do} + \Lambda_{do} - T_{do} + J_{do} + U_{do}, \tag{A.12}$$

which can be rewritten to obtain the aggregate gravity equation in Eq. (4). The components Γ_{do}, Λ_{do}, T_{do}, J_{do} and U_{do} thereby are defined 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 $\bar{y}_d = \frac{1}{R_d}\sum_{o\in\mathcal{R}_d}\frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln \mathcal{Y}_{dos}$ with $\mathcal{Y}_{dos} \equiv x_{dos}/\sum_{j\in\mathcal{R}_d}\sum_{r\in\mathcal{S}_{do}} x_{djr}$ and $\bar{z}_{do} = \frac{1}{S_{do}}\sum_{s\in\mathcal{S}_{do}} \ln \mathcal{Z}_{dos}$ in which $\mathcal{Z}_{dos} = x_{dos}/\sum_{r\in\mathcal{S}_{do}} x_{djr}$,

(*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 $\bar{u}_d \equiv \sum_{o\in\mathcal{R}_d} \bar{u}_{do}/R_d$.

This completes the proof. ■