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Inter-city Trade

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Inter-city Trade*

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Abstract

We propose and apply a new theory-consistent algorithm, which uses disaggregated inter-city trade data to identify a pyramidic city system with central places and associated hinterlands. Because central places possess more industries than the cities in their hinterlands, and because industries, which are exclusive to central places, are more likely to export to the small, peripheral cities in the central place's hinterland, we find that aggregate exports from central places to their hinterlands are two to five times larger than predicted by gravity forces. Using a simple decomposition approach, we show that this upward bias results from aggregation along the extensive industry margin, which is why the bias is much smaller and only marginally significant if estimation is conducted in a theory-consistent way at the disaggregated industry level.

JEL-Classification: F14, F12, R12

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

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1 Introduction

During the last decades the use of the structural gravity equation as a workhorse model of the empirical trade literature has expanded far beyond its intellectual origins in the international trade literature – as evident from a large number of studies, which have adopted the gravity framework to analyse the pattern of intra-national trade.[1]

Most international trade models, that provide micro-foundations for the structural gravity equation, (implicitly) assume that all industries are present in all locations.[2] Focussing on trade between cities in Japan, we argue that the location of industries is endogenous, and that it roughly follows Christaller's (1933) *hierarchy principle* for industries, according to which all industries, that are present in a city of a given size, are expected to be also present in all cities of equal or larger size (cf. Mori, Nishikimi, and Smith, 2008; Mori and Smith, 2011; Hsu, 2012; Schiff, 2015).

Gravity estimations based on aggregate inter-city trade ignore Christaller's (1933) hierarchy principle for industries and lump together industry-level trade flows, which according to Fujita, Krugman, and Mori's (1999a)[3] central place model should be treated as separate observations (obeying the law of gravity at the industry level conditional on industry existence).[4] Because central places possess more industries than the cities in their hinterland, and because industries, which are exclusive to central places, are more likely to export to the small, peripheral cities in the central place's hinterland, we find that aggregate exports from central places to their hinterlands are two to five times larger than predicted by the (structural) gravity model for aggregate inter-city trade. To quantify the importance of aggregation bias in explaining this systematic deviation from the law of gravity, we compare our result to the outcome of a theory-consistent industry-level gravity estimation.[5] Interestingly, we find that the upward

[1]See Wolf (2000); Hillberry and Hummels (2003); Millimet and Osang (2007); Yilmazkuday (2012); Coughlin and Novy (2013, 2016); Felbermayr and Gröschl (2014) as well as Allen and Arkolakis (2014) for studies from the U.S., Combes, Lafourcade, and Mayer (2005) and Briant, Combes, and Lafourcade (2010) for studies from France, and Nitsch and Wolf (2013) as well as Lameli, Nitsch, Südekum, and Wolf (2015) for studies from Germany.

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

[3]A reprint of Fujita et al.'s (1999a) original article can be found in Fujita, Krugman, and Venables (1999b).

[4]Head and Mayer (2014, pp.139-40) show that the structural gravity equation relies on two critical conditions. See Tabuchi and Thisse (2011) and Hsu (2012) for two alternative central place models, that do not fulfil these conditions.

[5]Several studies have used intra-national trade data to identify systematic deviations from the structural gravity equation as the workhorse model of the empirical trade literature (cf. Anderson and van Wincoop, 2004; Anderson, 2011; Head and Mayer, 2013, 2014). Unlike previous studies, which have either focused on defunct historical borders (cf. Nitsch and Wolf, 2013; Felbermayr and Gröschl, 2014) or on the boundaries of generic administrative units at different levels of spatial disaggregation (cf. Wolf, 2000; Hillberry and Hummels, 2003,

bias in the exports from central places to their respective hinterlands is much smaller and only marginally significant in theory-consistent gravity estimations that are conducted at the much more disaggregated industry level.[6]

Another striking discrepancy between inter-city gravity estimations at different levels of aggregation concerns the correct interpretation of the distance elasticity, which in aggregate gravity estimations usually is twice as large as in gravity estimations, that are conducted at the much more disaggregated industry level. Industries systematically differ with respect to the rate at which the probability that a certain city exports the industry's products to its partner city declines in the bilateral distance. As a consequence, we find that there are two margins along which the aggregate volume of inter-city trade declines: at the *intensive* margin the value of industry-level trade flows declines as the trading distance expands, while at the same time there is a reduction in the number of exporting industries at the *extensive* margin. Distance elasticities from aggregate gravity estimations therefore systematically overstate the intensive margin adjustment, which in most international trade models (cf. Head and Mayer, 2014) explains why the (aggregate) trade volume is inversely related to bilateral distance.

Further support for the role of aggregation bias in explaining the above results comes from a simple decomposition analysis (cf. Hillberry and Hummels, 2008), that exploits the full potential of our micro-level shipment data. Decomposing the upward bias in central places' exports in its various in- and extensive margins, reveals that 42.1% to 65.7% of the overall effect can be explained through more trade at the extensive industry margin, while only 2.1% to 10.8% of the upward bias stem from observing more shipments within industries. Also, we find that a substantial share (26.2% to 30.4%) of the trade-reducing distance effect originates from a reduction in the number of exporting industries at the extensive industry margin.

In his previous research on intra-national trade in Japan Wrona (2018) shows that inter-prefectural trade between East- and West-Japan is 23.1% to 51.3% lower than trade within both country parts, and that the lack of east-west trade can be linked to the bipolar structure of trade-creating social and business networks. As a further robustness check and in order to make sure that the upward bias in the exports from large central places (in particular *Tokyo*, *Osaka*, and *Nagoya*) to their respective hinterlands does not follow from a multipolar network

2008; Combes et al., 2005; Yilmazkuday, 2012; Coughlin and Novy, 2016), we show that there is a systematic upward bias in the exports of large centrally located cities to smaller cities in their periphery, which can be rationalised within a multipolar city-system with a hierarchical industry structure as derived by Fujita et al. (1999a).

[6]In contrast to the previous literature, which – in the absence of highly disaggregated industry-level data – has compared intra-national gravity estimations at different levels of spatial aggregation (cf. Hillberry and Hummels, 2008; Briant et al., 2010; Coughlin and Novy, 2016), we are pointing to a form of aggregation bias, that results from lumping together industries with vastly different location patterns, that according to Fujita et al.'s (1999a) central place model should be treated as separate observations.

structure, we therefore show that neither of these additional controls correlates in a meaningful way with our findings.

By developing a simple, theory-consistent algorithm, which not only allows us to rank cities in terms of their *centrality*, but also to associate central places with their respective hinterlands, we make an important methodological contribution, which complements existing research (cf. Tomer and Kane, 2014), that uses atheoretical concentration and centrality measures to characterise the highly concentrated nature of intra-national goods trade.[7] We thereby exploit a unique feature of our data: Instead of associating hinterlands with their central places based on raw distance (cf. Christaller, 1933) or on central places' aggregate exports (cf. Hsu, Mori, and Smith, 2014b), our assignment method is based on a comparison between the industry-specific trade pattern, that we observe from our highly disaggregated industry-level trade data, and the uniform industry-level trade pattern, that would arise in a hypothetical benchmark scenario of a featureless economy, that does not obey Christaller's (1933) hierarchy principle for industries.[8]

We interpret the very fact, that we are able to identify a clear and consistent division into central places and associated hinterland cities as supportive evidence in favour of Fujita et al.'s (1999a) central place theory.[9] Most central place models (cf. Fujita et al., 1999a; Tabuchi and Thisse, 2011; Hsu, 2012) generally share three types of predictions, regarding *i.)* the size and location of cities, *ii.)* the presence of industries across cities, and *iii.)* the pattern of industry-level trade between these cities.[10] To the best of our knowledge, we are the first, who use highly disaggregated industry-level shipment data to verify the predictions regarding the inter-city trade pattern, thereby complementing earlier research, which has exclusively focused on the pattern of industry location (cf. Schiff, 2015) and on the link between city size distribution and industry location (cf. Mori et al., 2008; Mori and Smith, 2011; Hsu, 2012).

Using the most recent wave of our data, we identify eight major central places, which are

[7] Tomer and Kane (2014) extend and modify the Freight Analysis Framework (FAF), Version 3.2 (principally constructed from the 2007 U.S. Commodity Flow Survey (CFS)) to study shipments between U.S. metropolitan areas. While trade concentration is measured by the GINI coefficient, a network approach, that uses information on the total number of connections weighted by their trade value, is used to measure a metropolitan area's centrality.

[8] Neary (2003) uses the term "featureless economy" to describe an economy without heterogeneity across industries in the context of a General Oligopolistic Equilibrium (GOLE) model with Ricardian technology difference across industries.

[9] A simple randomisation test shows that the emerging subregions, consisting of a central place and its associated hinterland, are significantly more compact than the counterfactual subregions, that result under a random assignment of the hinterland cities.

[10] Eaton and Lipsey (1976, 1982), Quinzii and Thisse (1990), Fujita et al. (1999a), Fujita et al. (1999b), Tabuchi and Thisse (2011), as well as Hsu (2012), and Hsu, Holmes, and Morgan (2014a) 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 (2017) for recent reviews of the theoretical central place literature. A unifying feature of all central place models is the multiplicity of spatial equilibria, which implies the possibility of a drastic reconfiguration of the city/industry system in case of a sufficiently large shock. In our empirical analysis we therefore focus on Japan, whose city *and* industry structure has proven too be extremely resilient against large negative shocks in the past (cf. Davis and Weinstein, 2002, 2008).

endogenously ranked in a pyramidic city system with three nested layers. Unsurprisingly, we find that the three largest cities in our sample (*Tokyo*, *Osaka*, and *Nagoya*) also belong to the most highly ranked central places. Although only responsible for 20% of all observed trade flows, our eight central places account for 75% of the inter-city trade volume in 2015, with the other 25% of the total trade volume being distributed over the remaining 80% of all trade flows. Unarguably, it is important to understand how these cities trade, and whether their pattern of trade systematically deviates from the otherwise extremely well performing (structural) gravity equation (cf. Head and Mayer, 2014).

We also contribute to a literature that studies the distortions that arise in gravity estimations from aggregation across heterogeneous industries and/or products (cf. Hillberry, 2002; Anderson and van Wincoop, 2004; Anderson and Neary, 2005). Due to the unavailability of highly disaggregated industry-level trade data at the national level, most studies (with the notable exception of Hillberry (2002)) have focused on disaggregated international trade data. Most notably, Hummels and Klenow (2005) showed that the extensive goods margin accounts for around 60 % of the greater exports of larger economies, and that none of the standard international trade models, that they reviewed in their study was able to explain all of their stylised facts.

French (2017) uses an extension of Eaton and Kortum's (2002) Ricardian trade model to argue that gravity estimation based on sector-level trade data is generally misspecified in the presence of product-level comparative advantage, recommending instead the use of highly disaggregated product-level trade data. Even though we share the general recommendation to use more disaggregated trade data, there is an important difference in the underlying narratives. In French's (2017) extension of the Eaton-Kortum model there is an aggregation bias because all products across all sectors in all countries are produced at different product-specific technology levels. In the absence of Ricardian technology differences at the product-level the aggregation bias disappears. In the context of Fujita et al.'s (1999a) central place theory, aggregate gravity estimation is biased exactly because not all industries are ubiquitously distributed in space. Christaller's (1933) hierarchy principle for industries thereby is the consequence of endogenous market entry and continues to hold, even when there are no Ricardian technology differences at the sub-national level.

The remainder of this paper is structured as follows: In Section 2 we discuss the main features of Fujita et al.'s (1999a) central place model, which subsequently is used to derive our key predictions regarding the pattern of inter-city trade, including the emergence of estimation bias in aggregate gravity estimation. In Section 3 we introduce and discuss central features of our data. The following Section 4 contains two of our main results: At first, we develop a new theory-consistent algorithm to identify central places and their respective hinterlands, which subsequently are used to quantify the upward bias in the exports from central places to their respective hinterlands. Section 5 then provides additional evidence, which suggests that the upward bias in the exports from central places to their respective hinterlands emerges from aggregation along the extensive industry margin. Section 6 concludes.

2 Theoretical Background

As a theoretical foundation for our analysis of Japan's inter-city trade pattern we build up on the work of Fujita et al. (1999a), who were the first to embed Christaller's (1933) and Lösch's (1940) *Central Place Theory* into a tractable general equilibrium framework with monopolistically competitive firms and endogenous market entrance. Deviating from Fujita et al.'s (1999a) original focus on gradual agglomeration processes in a multipolar city system, we are deliberately choosing this modelling environment for two specific reasons: Unlike in other central place models (cf. Tabuchi and Thisse, 2011; Hsu, 2012) the pattern of industry-level inter-city trade obeys the law of (structural) gravity (cf. Anderson and van Wincoop, 2004; Head and Mayer, 2014) conditional on the industry being present in the respective origin city. At the same time, 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.[11]

We structure the remainder of this Section as follows: In Subsection 2.1 we summarise Fujita et al.'s (1999a) main results regarding the distribution of cities and industries, and demonstrate that the pattern of industry-level inter-city trade obeys the law of gravity (conditional on industry existence). The following two subsections then isolate and verify two key predictions from Fujita et al.'s (1999a) central place model, that are of central importance in shaping the pattern of inter-city trade. In Subsection 2.2 we show that the predicted pattern of industry location follows a clear hierarchy, and that there is strong empirical support in favour of this pattern. In Subsection 2.3, it is shown that the extensive margin of industry-level inter-city trade crucially depends on the position of the respective industry in this hierarchy. In the final Subsection 2.4 we argue that the combination of these two patterns leads to biased results in aggregate gravity estimations, that systematically underestimate the exports of large cities in

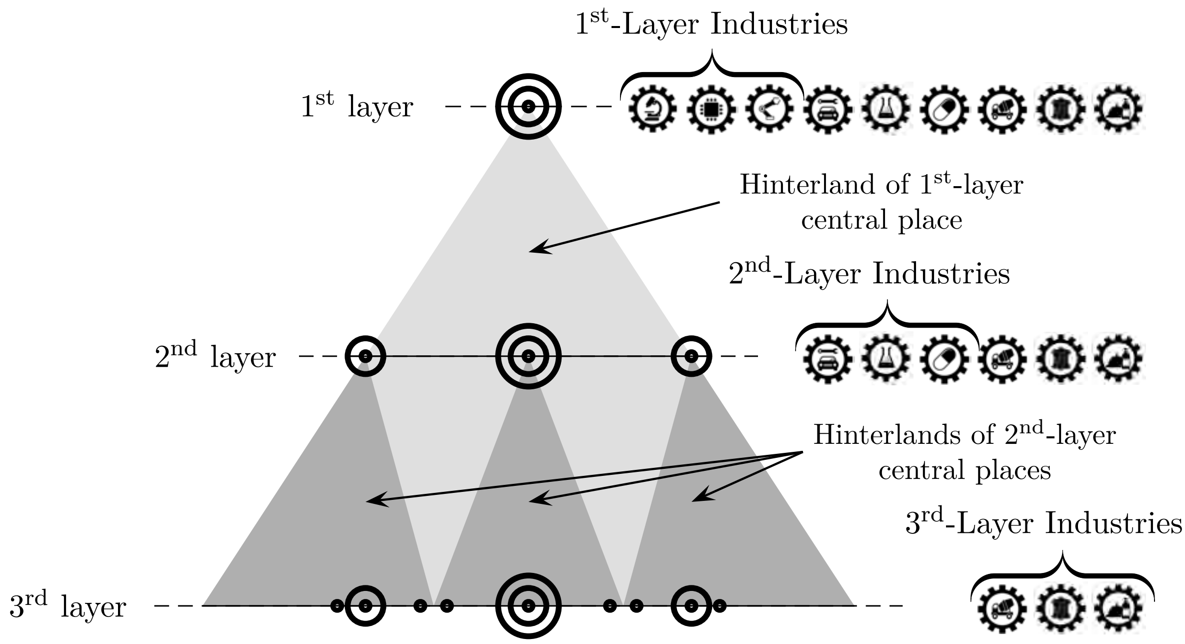
[11]Multi-sector extensions of Eaton and Kortum's (2002) Ricardian trade model and Krugman's (1980) monopolistic competition framework typically assume industries to be ubiquitously distributed (see Costinot and Rodríguez-Clare (2014, pp. 213-216) for a recent summary of the literature). The multi-sector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

a multipolar city system with a hierarchical industry structure.

2.1 Central Place Theory and the Pattern of Inter-city Trade

In the following we will use the numerical example from Fujita et al. (1999a, Fig. 6, p. 237) to illustrate some of the key features of their central place model. Fujita et al. (1999a) con-

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



sider a multipolar agglomeration model with heterogeneous industries, in which a city not only gets larger by growing in scale but also by growing in scope (i.e. by adding new industries). Agglomeration generates two types of cities: On the one hand, we have a limited number of central places – large, centrally located cities of sufficient size to not only attract ubiquitous industries, whose goods are costly to trade and therefore optimally produced in close proximity to customers (e.g. ready mixed concrete), but also some footloose industries, whose goods are highly tradeable and which therefore prefer centrally located cities with a large home market (cf. Krugman, 1980). On the other hand, there are many small cities in the hinterlands of central places, which due to their insufficient size and/or location only attract a limited set of ubiquitous industries. Sorting central places according to the range of their industries (indicated by the number of circles around a city in Figure 1), then results in a hierarchical city system with nested central places and associated sets of hinterland cities as illustrated in Figure 1. The sorting of industries across a total of three layers in Figure 1 thereby distinguishes between 1st-, 2nd-, and 3rd-layer cities, which systematically differ in terms of their industry diversity (see also Subsection 2.2 below).

Although theoretically not explored by Fujita et al. (1999a), it can be shown that the pattern of industry-level inter-city trade obeys the following set of industry-level gravity equations:

$$X_{ij,k} = \frac{E_{j,k} Y_{i,k}}{Y_k} \left(\frac{\tau_{ij,k}}{\Phi_{i,k} \Omega_{j,k}} \right)^{1-\sigma_k} \quad \forall \quad Y_{i,k} > 0, \tag{1}$$

that hold for each exporting cities i, that produces some output $Y_{i,k} > 0$ in industry k (see Appendix A.1 for derivation). A city's average trade costs as ex- or importer thereby are captured by the ex- and importer-specific multilateral resistance terms:

$$\Phi_{i,k}^{1-\sigma_k} = \sum_j \left(\frac{\psi_{ij} \tau_{ij,k}}{\Omega_{j,k}} \right)^{1-\sigma_k} \frac{E_{j,k}}{Y_k} \quad \text{and} \quad \Omega_{j,k}^{1-\sigma_k} = \sum_i \left(\frac{\psi_{ij} \tau_{ij,k}}{\Phi_{i,k}} \right)^{1-\sigma_k} \frac{Y_{i,k}}{Y_k}. \tag{2}$$

The structural gravity equation in Eq. (1) predicts industry k' bilateral trade volume $X_{ij,k}$ from origin city i to destination city j as a simple multiplicative function, which combines the product of origin i's sectoral production $Y_{i,k} > 0$ and destination j's sectoral expenditure $E_{j,k} > 0$ (normalised by sector k's total production Y_k), with a trade cost term, that includes the bilateral iceberg-type transportation cost $\tau_{ij,k} \geq 1$, as well as the in- and outward multilateral resistance terms $\Phi_{i,k}^{1-\sigma_k} > 0$ and $\Omega_{j,k}^{1-\sigma_k} > 0$, which measure exporter i's and importer j's ease of market access.[12] The sensitivity of the bilateral trade volume with respect to trade frictions thereby is governed by the industry-specific elasticity of substitution $\sigma_k > 1$.

In summary, we not only have shown that endogenous agglomeration in Fujita et al.'s (1999a) central place model results in a pyramidic city system with a hierarchical industry structure, but also that the law of gravity for inter-city trade is expected to hold at the industry level (conditional on industry existence). Theory-consistent gravity estimation therefore should be based on industry-level inter-city trade data and not on aggregate inter-city trade data. In the following we will show that lumping together industry-level trade flows, which according to Fujita et al.'s (1999a) central place model should be treated as separate observation, results in a systematic aggregation bias in aggregate inter-city gravity estimation.

2.2 Christaller's Hierarchy Principle for Industries

As a noticeable feature of the pyramidic city system in Figure 1, we find the distribution of industries across cities to follow a strict hierarchical pattern: All 3rd-layer industries can also be found in 2nd-layer cities, and all 2rd-layer industries are also present in the 1st-layer city.

[12] See Anderson and van Wincoop (2003), Head and Mayer (2014), as well as Larch and Yotov (2016) for a detailed discussion of the various interpretations and applications of the multilateral resistance terms.

Following Mori and Smith (2011), we refer to this pattern as Christaller's (1933) hierarchy principle for industries, expecting all industries, which can be found in a city of a given size, to be also present in all cities of larger size.

To check whether our intra-Japanese trade data obeys Christaller's (1933) hierarchy principle for industries, we propose a simple three-step randomisation test: At first we compute the economy's average hierarchy share (defined by Eq. (3) below) as a measure of how hierarchical industries are distributed across cities. In a second step we then randomise the distribution of industries across cities. In the third and last step we finally compare Japan's average hierarchy share with its counterfactual counterparts, that are obtained from a randomised distribution of industries across cities.

For any two cities i and j we can define the hierarchy share H_{ij} as:

$$H_{ij} \equiv \frac{\#\left(\mathbb{K}_i \cap \mathbb{K}_j\right)}{\min\{K_i, K_j\}} \in [0, 1], \tag{3}$$

with $\mathbb{K}_i$ as the set of industries in city i, and $K_i \equiv \#\mathbb{K}_j$ as the corresponding number of industries in this city.[13] The hierarchy share takes a value of $H_{ij} = 0$ if there is zero overlap between the sets of industries in i and j. 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 $H_{ij} = 1$, which means that Christaller's (1933) hierarchy principle for industries holds without restrictions.

Aggregation across all cities i and j requires us to proceed in two steps. We begin by aggregating across all cities i that host more industries than city j (i.e. $K_i > K_j$). City j's average hierarchy share $H_j(\kappa)$ can then be computed as:

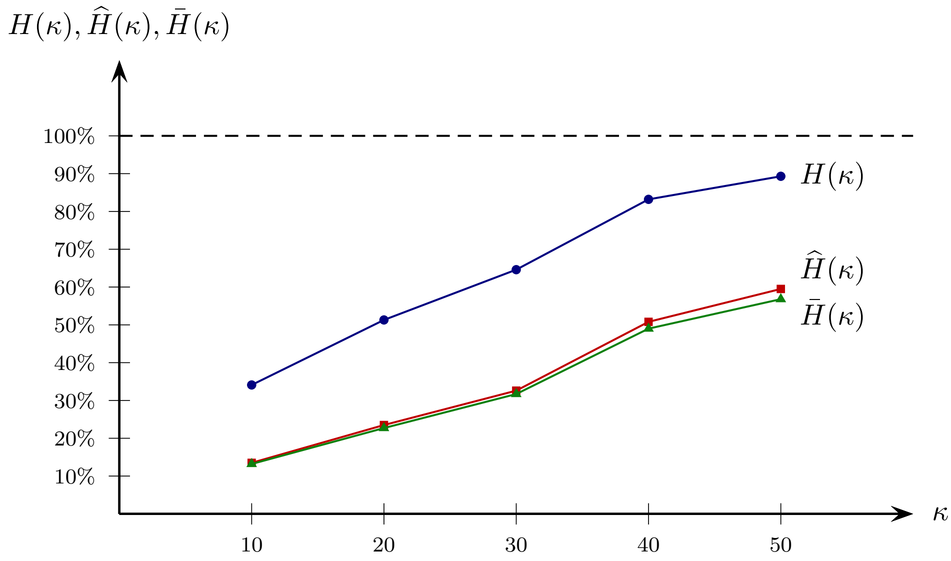
$$H_j(\kappa) = \frac{1}{\#\mathbb{G}_j(\kappa)} \sum_{\mathbb{G}_j(\kappa)} H_{ij} \quad \text{with} \quad \mathbb{G}_j(\kappa) \equiv \{i : K_i > K_j \ \& \ K_i > \kappa\}, \tag{4}$$

in which $\kappa > 0$ is an exogenous threshold, that restricts the set $\mathbb{G}_j(\kappa)$ of cities i, whose number of industries is larger than the maximum of κ and K_j. Given the definition of $H_j(\kappa)$ we can finally compute the economy-wide average hierarchy share $H(\kappa)$ as a simple arithmetic mean $H(\kappa) = \sum_{j=1}^{N} H_j(\kappa)/N$ over all cities j.

As evident from Figure 2, we find Christaller's (1933) hierarchy principle for industries to hold particularly well when conditioning only on cities with a sufficiently large number of industries (i.e. the average hierarchy share $H(\kappa)$ converges to its maximum value of one for increasing threshold levels of κ). However, even in the absence of Christaller's (1933) hierarchy principle for industries we would expect the hierarchy share between cities i and j with a larger

[13]See Section 3 below for a more detailed discussion of how cities and industries are defined.

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



difference, $|K_i - K_j|$, in their industrial diversity to take larger values. A simple randomisation test, that holds the number of industries in each city as observed in reality but shuffles the industry types, therefore delivers a natural benchmark $\widetilde{H}(\kappa)$ for the average hierarchy share. In Figure 2 we plot the mean and maximum values $\bar{H}(\kappa)$ and $\widehat{H}(\kappa)$ of $\widetilde{H}(\kappa)$ that emerge from 1,000 random counterfactuals. Across all threshold levels of κ we find Japan's average hierarchy share $H(\kappa)$ to be significantly larger than the random benchmark, which allows us to reject a random distribution of industries in favour of Christaller's (1933) hierarchy principle for industries.[14]

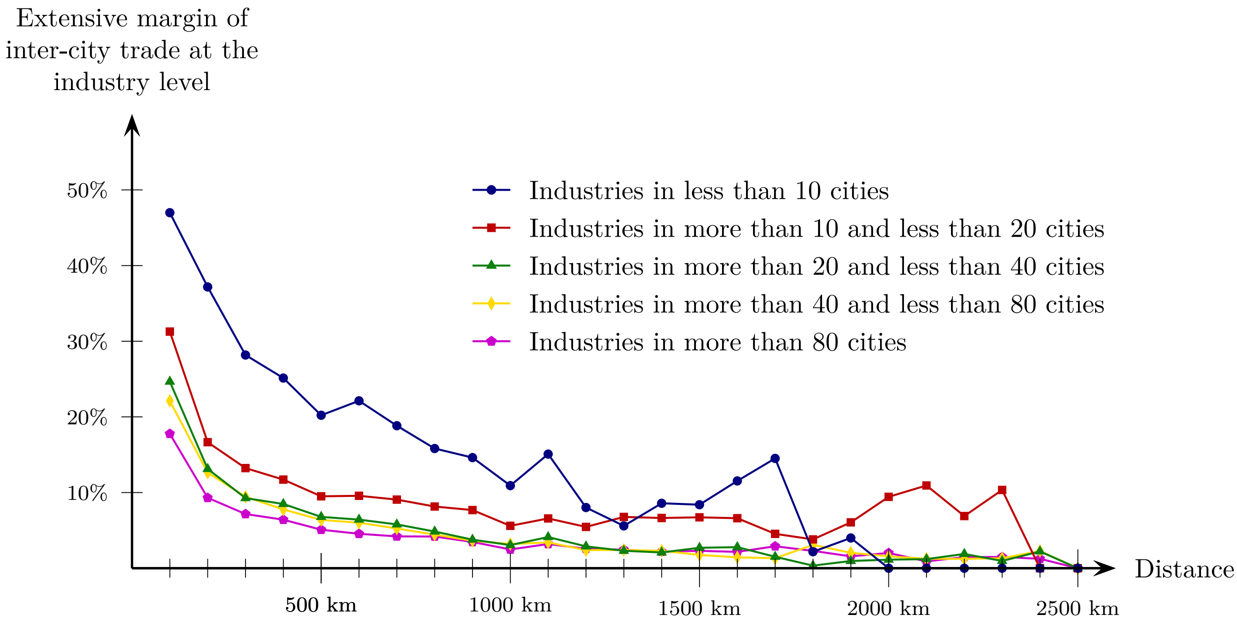
2.3 The Heterogeneous Extensive Margins of Inter-city Trade

Having established Christaller's (1933) hierarchy principle for industries, we now explore the heterogeneity in the industry-specific pattern of inter-city trade that is created by this principle. For the sake of simplicity, we are reducing the complexity of the problem by distinguishing only between footloose and ubiquitous industries as basic industry categories (e.g. 2^{nd}-layer versus 3^{rd}-layer industries in Figure 1). As illustrated by Fujita et al. (1999a, Fig. 10, p. 244), we expect footloose (2^{nd}-layer) industries – which only exist in small number of large but relatively far apart central places – to have high market shares, which due to the absence of any close-by competitors remain rather stable in their hinterland as the distance from the central place increases. In contrast, we expect ubiquitous (3^{rd}-layer) industries to have smaller market shares, which in the presence of competitors quickly decline as the distance, over which the respective

[14] See also Mori et al. (2008), Mori and Smith (2011), Hsu (2012) and Schiff (2015) for further supportive empirical evidence in favour of Christaller's (1933) hierarchy principle for industries.

goods are traded, expands. In the presence of fixed market entry costs, which were not present in Fujita et al.'s (1999a) original model but have become an integral part of the trade literature since then (cf. Melitz, 2003), we would expect this pattern in market shares to be reflected by the extensive margin of industry-level inter-city trade.[15]

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



In Figure 3, we distinguish industries according to their position in the hierarchy from Figure 1 by classifying them according to the number of cities in which they were present in 2015. For each set of industries we then plot the extensive margin of inter-city trade (i.e. the share of all possible destinations, which are actually importing goods produced by this industry) over a total of 25 different distance intervals, that capture the bilateral distance between origin and destination city.[16] In line with our above argumentation we find that footloose industries, which are only present in a limited set of cities, feature a substantially higher probability of exporting (at least over the first 1,000 km), which declines less steeply over increasing distances than the extensive margin of ubiquitous industries.[17]

[15]In Hsu's (2012) central place model each firm only serves to a finite set of cities out of an infinite mass of cities located in an unbounded one-dimensional space.

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

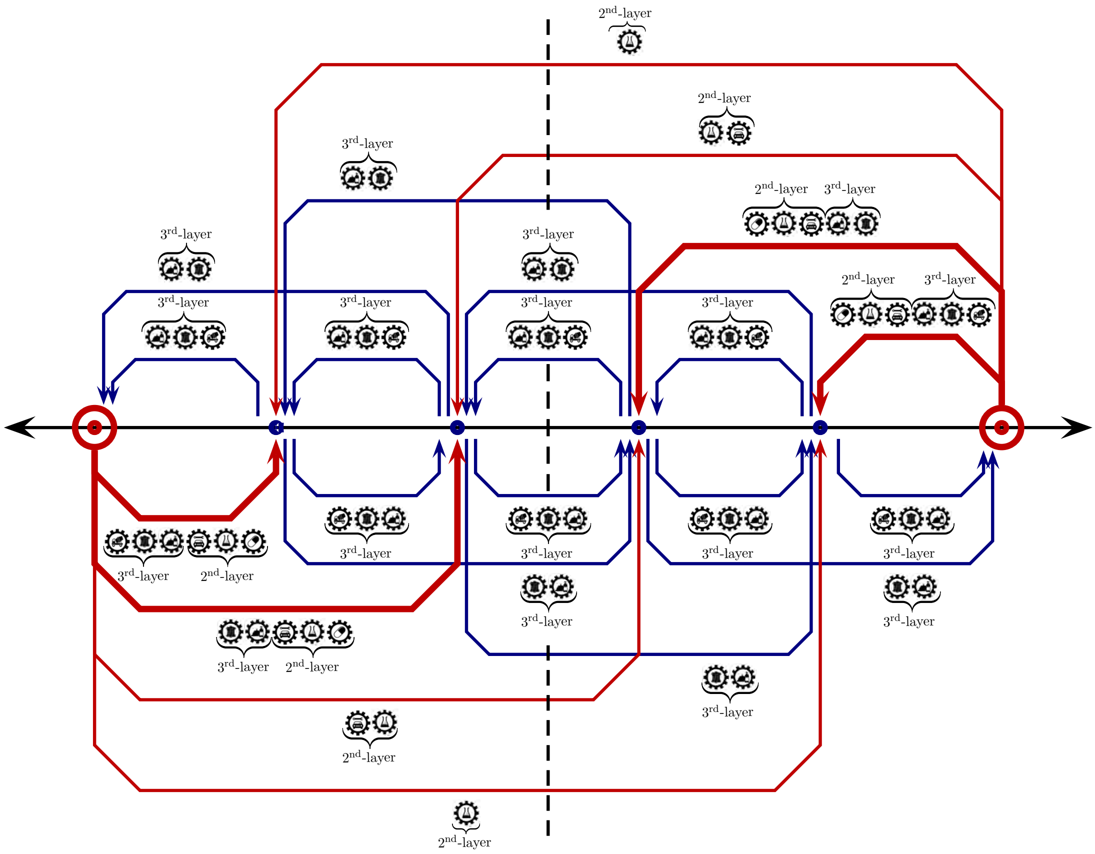
[17]The underlying National Commodity Flow Survey [*Zenkoku Kamotsu Jun Ryudo Chosa*] is introduced in Section 3. There we also explain why we observe a relatively large number of zero trade flows (even over short distances of less than 100 km).

2.4 Central Places, Hinterlands, and Aggregation Bias

The gravity literature (cf. Hillberry, 2002; Hillberry and Hummels, 2008) has identified various reasons why aggregation across (heterogeneous) industries may generally result in an estimation bias (see Anderson and van Wincoop (2004, pp.725-729) as well as Anderson and Neary (2005, pp. 183-185) for a summary of the earlier literature). We contribute to this literature by establishing a new rationale for the emergence of aggregation bias in gravity estimations based on inter-city trade data.

In sum the empirical evidence from the previous Subsections 2.2 and 2.3 implies that central places have more industries and the cities in their hinterland, and that the industries, which are exclusive to the respective central place, are more likely to export to the smaller, peripheral cities, that are located in the central place's hinterland. To understand how these two factors interact in creating an aggregation bias, we develop in Figure 4 a simple, illustrative example, which depicts the pattern of trade between two 2^{nd}-layer central places in red and four hinterland cities in blue (two in each of the central places hinterlands, which are separated by a dashed line in Figure 4). In contrast to the omnipresent 3^{rd}-layer industries, 2^{nd}-layer industries can

Figure 4: *Central Places, Hinterlands, and Aggregation Bias*



only be found in sufficiently large central places. Also these industries differ with respect to the extensive margin: All three 3$^{\text{rd}}$-layer industries export to the next adjacent city. But only two of the 3$^{\text{rd}}$-layer industries export to the one that comes after the next city. No 3$^{\text{rd}}$-layer industry exports beyond this city. The extensive margin for 2$^{\text{nd}}$-layer industries is less sensitive to increasing distances: All three 2$^{\text{nd}}$-layer industries export to the next city and the city that comes after this city. As the distance increases further the number of exporting 2$^{\text{nd}}$-layer industries then drops from three to two, to one, and finally to zero.

Two important insights can be gained from Figure 4: If we compare the aggregate volume of exports from central places to their respective hinterland (bold, red arrows in Figure 4) with the aggregate exports between the average city pair, we notice that these trade flows are made up of a larger number of industry-level trade flows. Instead of treating these industry-level trade flows as separate observations, as suggested by Subsection 2.1, they end up being aggregated into a single inter-city trade flow, that naturally is much larger than what the structural gravity model for aggregate inter-city trade would make us expect. Also, we find that the aggregate trade volume is generally declining along two margins. Within each industry the trade volume decreases at the intensive margin as distance widens, while at the same time the number of exporting industries is declining at the extensive margin. We therefore expect the distance elasticity at the aggregate level to be substantially larger than the distance elasticity, that emerges from a theory-consistent garvity estimation at the industry-level.

3 Data

Our main data source is Japan's National Commodity Flow Survey [*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 National Commodity Flow Survey provides detailed information on establishment-level shipments between all connected municipalities, which are located at Japan's four main islands (*Hokkaido, Honshu, Shikoku and Kyushu*).[18] The survey includes only manufacturing establishments with at least four employees, which are classified according to the Japanese Standard Industrial Classification (JSIC), which distinguishes between 24 two-digit manufacturing industries (22 two-digit manufacturing industries in 1995 and 2000).[19] In addition to the establishments' two-digit industry classification we also have de-

[18]Due to several administrative reforms Japan recently has seen a number of municipality mergers. We focus on 1,807 connected municipalities in 2015, and use the concordance tables from Kirimura's (2018) Municipality Map Maker (MMM) to harmonise the municipality classification across all five survey waves.

[19]In 2015 a total of 14,620 or 7.0% of all 208,029 relevant manufacturing establishments were sampled. For the earlier waves the number of sampled manufacturing establishments are 14,097 or 5.4% out of 263,052 in 2010; 13,684 or 4.7% out of 294,170 in 2005; 15,452 or 4.1% out of 373,108 in 2000; and 18,520 or 4.9% out of 378,167

tailed information on the shipped commodities, which are disaggregated into 9 basic product categories and 85 sub-categories.

In line with the underlying theoretical model (cf. Fujita et al., 1999a) we focus on cities as the basic geographic unit of our analysis. Using highly disaggregated grid data from the Japanese Population Census, cities are constructed based on urban agglomerations (UAs), which are identified as contiguous and disjoint sets of 1km$\times$1km grid cells with at least 1,000 people per square kilometre and a total population of at least 10,000 inhabitants.[20] The 450 UAs, which we identify based on the Japanese Population Census from 2015, are home to 77% of Japan's total population and occupy 12% of the country's contiguous landmass.[21] 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 up our municipality-level shipment data to the city level leaves us with 292 cities in 2015, which export to at least ten other cities in our sample.[22]

One common drawback shared by most commodity flow surveys (cf. Wolf, 2000; Hillberry and Hummels, 2003, 2008; Combes et al., 2005; Nitsch and Wolf, 2013) is the rather coarse classification of commodities based on a limited number of industries, which stands in marked contrast to the availability of high-resolution international trade data. To obtain a sufficiently detailed industry classification, we combine the establishment-level industry classification (22 to 24 two-digit Japanese Standard Industrial Classification (JSIC) industries) with the shipment-specific product codes (67 relevant subcategories).[23] Not all of the $24 \times 67 = 1607$ feasible combinations of industry and product code are relevant for our analysis.[24] In order to exclude outliers, we manually check each industry$\times$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 therefore could be splitted into multiple sub-categories depending on industry classification of the sending establishment (e.g. 403: "textil" versus 412: "leather

in 1995. A more detailed discussion of our primary data, including the definition of industries and products, can be found in an Online Supplement, which is available from the corresponding author's website.

[20]See Dijkstra and Poelman (2012, 2014) for a harmonised definition of functional urban areas, which is applied by Schmidheiny and Suedekum (2015) to identify European cities.

[21]Figure 7 (delegated to the Appendix) uses a heatmap to illustrate the population distribution across Japan's 450 urban agglomerations.

[22]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.

[23]We omit all product categories that are related to the disposal of scrap and waste. A complete list of all industry and product categories can be found in an Online Supplement, which is available from the corresponding author's website.

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

and leather products"). As a result of the data cleaning process we end up with 212 relevant industry-product combinations, which we henceforth will use in our analysis.[25]

Our highly disaggregated inter-city trade data is complemented by information on real-road distances between municipality pairs based on the distance along the road network obtained from OpenStreetMap (as of July, 2017). The bilateral distance between each pair of municipalities thereby is computed as the distance between the centroids of the most populated 1km×1km cells in these municipalities using `osrmtime` (cf. Huber and Rust, 2016), which is the STATA interface of the Open Source Routing Machine. We approximate intra-municipality distance by the average line-distance between a pair of locations on a circle with the area equal to the habitable area of the municipality (cf. 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. Following Head and Mayer (2009), bilateral distance between city i and j is then computed as a trade-weighted harmonic mean of the bilateral distances between all the municipalities that belong to city i and j, respectively.[26]

In addition to the information on bilateral distances the National Commodity Flow Survey also provides detailed information on the total transportation cost per shipment, including both distance-related (i.e. gas, tolls, etc.) and time-related (i.e. salaries, insurance, etc.) expenses. We use this unique information to compute average and industry-specific *ad valorem* transportation costs at the city-pair level (as for example in Hertel, Hummels, Ivanic, and Keeney, 2007).

To assess the representativeness of our data set and as future reference for our later analysis we conduct a standard gravity estimation, regressing the bilateral trade volume (in logs) $\ln X_{ij}$ on the following trade cost function:

$$\begin{aligned} \ln \tau_{ij} = \beta_{\text{TRANS\_COST}} \times \ln(1+\text{FREIGHT}_{ij}) + \beta_{\text{DIST}} \times \ln \text{DIST}_{ij} \\ + \beta_{\text{HOME}} \times \text{HOME}_{ij} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{ij}, \end{aligned} \tag{5}$$

and the complete set of origin- and destination-specific fixed effects. We thereby distinguish between average real-road distance between and within cities DIST_{ij} and the average *ad valorem* transportation costs $1+\text{FREIGHT}_{ij}$, which are defined as one plus the freight rate FREIGHT_{ij} (cf. Hertel et al., 2007). Following Wolf (2000), Hillberry and Hummels (2003, 2008), as well as Millimet and Osang (2007), we account for non-linear distance effects by introducing a

[25]A complete list of all industry-product combinations can be found in an Online Supplement, which is available from the corresponding author's website.

[26]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).

"home bias" dummy $\text{HOME}_{ij} \in \{0, 1\}$, which assumes a value of one for intra-city trade (i.e. $i = j$) and a value of zero otherwise. To account for non-linearities in transportation costs due to Japan's geography as an archipelago (consisting of the four main islands *Hokkaido*, *Honshu*, *Shikoku*, and *Kyushu*), we additionally control for intra-island trade by adding an island dummy $\text{ISLAND}_{ij} \in \{0, 1\}$, which takes a value of one for intra-island trade and a value of zero otherwise. Table 1 summarises the estimation results, which in terms of magnitude and significances are comparable to those found in the empirical trade literature (cf. Head and Mayer, 2014).

Table 1: *A First Exploration of Japan's Inter-city Trade*

Dependent variable: Exports from city i to city j										
Year:	**2015**		**2010**		**2005**		**2000**		**1995**	
Model:	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ln Distance_{ij}	-0.7084^{***}	-0.5971^{***}	-0.6847^{***}	-0.5400^{***}	-0.6294^{***}	-0.4931^{***}	-0.6521^{***}	-0.4968^{***}	-0.6953^{***}	-0.5500^{***}
	(.0232)	(.0209)	(.0229)	(.0211)	(.0223)	(.0204)	(.0228)	(.0211)	(.0194)	(.0178)
ln Transportation cost_{ij}		-6.2627^{***}		-9.2228^{***}		-6.5300^{***}		-7.7930^{***}		-7.5985^{***}
		(.2190)		(.3276)		(.2383)		(.3450)		(.2423)
Intra-city trade	0.6498^{***}	0.7119^{***}	1.0031^{***}	1.1426^{***}	0.6473^{***}	0.8652^{***}	0.5137^{***}	0.7579^{***}	0.5391^{***}	0.7961^{***}
	(.1808)	(.1663)	(.1644)	(.1575)	(.1805)	(.1680)	(.1841)	(.1713)	(.1583)	(.1473)
Intra-island trade	0.0333	0.0144	0.0973	0.0138	-0.0506	0.0046	0.1888^{***}	0.1853^{***}	0.0134	-0.0292
	(.0717)	(.0642)	(.0668)	(.0608)	(.0702)	(.0631)	(.0660)	(.0606)	(.0554)	(.0491)
Fixed effects:										
Exporter (i):	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Importer (j):	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:										
Number of observations:	15,261	15,261	16,184	16,184	18,098	18,098	17,146	17,146	22,183	22,183
R-squared	0.437	0.541	0.418	0.540	0.442	0.552	0.443	0.551	0.440	0.558

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

The trade literature has articulated three major concerns, that arise from the use of the structural gravity equation as the workhorse model for the analysis of intra-national shipments. In the following we will explain in detail how each of these concerns is addressed.

The first concern relates to the fact that the same products may enter the shipment data through multiple records.[27] However, several factors mitigate the double counting problem in the Japanese context: Shipments in the National Commodity Flow Survey are defined at the transaction level, which means that the un- and reloading of (inter-modal) shipments at warehouses, ports, and railway freight terminals does not inflate the total number of shipments/transactions. Also it is rather unlikely that the presence of middleman and intermediaries causes a significant double counting problem, as the data collection for the National Commodity Flow Survey takes place over a relatively short time span of just three days. Despite these safeguards we account in our analysis for a potential over-representation of short-distance shipments by following the standard procedure of including a binary indicator variable that controls

[27] Using the U.S. commodity flow survey Hillberry and Hummels (2003) demonstrate that hub and spoke distribution patterns translate into relatively short distances for shipments that originate from wholesalers rather than from manufacturers.

for the home bias in intra-city trade.[28]

The second concern addresses the role of international trade in shaping the intra-national trade pattern. Since Japan is an archipelago, the by far largest part of its international trade is channelled through its well developed system of international ports. Due to the non-random location of harbours in large cities, we would expect that those cities' internal trade with nearby non-harbour cities is systematically upward biased due to their role as international gateways. Again there are several mitigating factors that moderate the impact that Japan's external trade has on the intra-national pattern of inter-city trade. Indeed, it turns out that Japan is the prime example of a large developed country, whose internal trade pattern can be studied without being too much concerned about the in- and outflow of its external trade. Generally, Japan's external trade is dwarfed by the size of its domestic economy. Due to its remote location and a business model which favours 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.[29] Also the internal distribution of international shipments is highly localised. Analysing the 2013 wave of Japan's International Container Trade Survey [*Zenkoku Yushutsunyu Kontena Kamotsu Ryudo Chosa*] and the 2014 wave of Japan's Commodity Flow Survey for Bulky Goods [Buruku Kamotsu Ryudo Chosa], Wrona (2018) finds that an overwhelming share of 80.2% of all containerised exports and a even larger share of 93.4% of all bulky exports (89.2% of all containerised imports and 98.6% of all bulky imports) are shipped out (shipped in) through a port, that is located within the region of origin (destination).[30] Finally, it is important to note that the National Commodity Flow Survey does not include any shipments which originate from one of Japan's harbours. We therefore can rule out the internal distribution of goods, that were imported from abroad, as a potential reason for disproportionately large internal exports from central places to their respective hinterlands.

Finally, there is a third concern regarding the role of zeros trade flows in intra-national trade data, that is constructed from commodity flow surveys (cf. Hillberry and Hummels, 2008). Since all international trade flows have to be reported to customs authorities, the presence of zero trade flows in the international trade literature typically is rationalised through prohibitively high trade costs. As a consequence, it has become best practice to estimate the structural gravity model in its multiplicative form (using Santos Silva and Tenreyro's (2006) Poisson

[28] Adding additional controls at higher levels of aggregation to control for a potential upward bias in intra-prefectural and intra-regional trade does not cause substantial changes in the results from Table 1.

[29] See also Lawrence (1987, 1991) and Saxonhouse (1993) for earlier contributions discussing Japan's low export/import to GDP ratio.

[30] Japan can be divided into nine administrative regions, which are *Hokkaido*, *Tohoku*, *Kanto*, *Chubu*, *Kansai*, *Chugoku*, *Shikoku*, *Kyushu* and *Okinawa*.

Pseudo-maximum Likelihood (PPML) estimator) to include observations with zero trade flows, which ensures that the analysed trade flows are not systematically selected on non-prohibitive trade costs. In addition to prohibitively high trade costs, which we expect to be much less an issue for intra-national trade within a geographically confined island economy with one of world's most highly developed transportation sectors, there are two other important reasons why we expect to find a considerable amount of zeros in our highly disaggregated industry-level trade data.[31] As already discussed in Subsection 2.2, we would not expect all industries to be present in all locations, which is why bilateral industry-level trade flows are expected be zero, whenever the respective industry is not present in the city of origin. More importantly, however, our trade data is based on a stratified random sample of manufacturing firms, whose shipments were recorded over the relatively short time span of just three days. As a consequence, there is a large amount of zeros, that emerge simply because a shipment between a specific combination of origin and destination city by chance did not occur within this rather short sampling period. As we would dramatically overestimate the trade reducing effect of distance by including these zero trade flows, we follow Hillberry and Hummels (2008) and restrict our analysis to observations with positive trade flows.

4 Aggregation Bias in Inter-city Trade

How does the aggregation bias, that results from Christaller's (1933) hierarchy principle for industries, affect the pattern of inter-city trade? To answer this question we proceed in two steps: In Subsection 4.1 we develop a new theory-consistent algorithm to identify central places and their associated hinterlands in Japan's pyramidic city system, whose successful application provides first indirect evidence in favour of the previously derived aggregation bias. In the following Subsection 4.2 we then use the information on central places and their associated hinterlands to quantify the upward bias in the exports from central places to their associated hinterlands.

4.1 In Search for Central Places and their Hinterlands

In order to uncover the pyramidic city system from Figure 1 as theoretically predicted by Fujita et al. (1999a), we develop a simple algorithm in the spirit of Christaller (1933), who was the first to compare the actual distribution of city characteristics with a hypothetical benchmark

[31] According to the the World Bank's Logistics Performance Index (LPI) Japan occupied the 5th rank of 160 countries, that were compared in 2018. In the 2nd pillar of the World Economic Forum's Global Competitiveness Index (GCI), which measures the quality of infrastructure, Japan also occupied the 5th rank of 140 countries, that were compared in 2015/16.

scenario, that did not feature a hierarchical city system.[32] To learn about Japan's hierarchical city system we therefore compare the actual volume of industry-level inter-city trade to the hypothetical volume of industry-level inter-city trade in a featureless economy without sectoral heterogeneity, in which the volume of industry-level inter-city trade is directly proportional to the volume of aggregate trade as predicted by the structural gravity model (cf. Head and Mayer, 2014).

In order to identify central places based on their trading patterns we conduct the following simple thought experiment: How would the pattern of industry-level inter-city trade look like in the absence of a hierarchical city system (i.e. without inter-sectoral heterogeneity)? In a featureless economy without inter-sectoral heterogeneity (except for differences in sectoral expenditure shares β_s) the sectoral gravity equation from Eq. (1) simplifies into :

$$\widetilde{X}_{ij,k} = \beta_k \widetilde{X}_{ij} \quad \text{with} \quad \widetilde{X}_{ij} = \frac{\widetilde{E}_j \widetilde{Y}_i}{\widetilde{Y}_M} \left(\frac{\tau_{ij}}{\widetilde{\Phi}_i \widetilde{\Omega}_j} \right)^{1-\sigma}, \tag{6}$$

in which $\widetilde{\Phi}_i > 0$ and $\widetilde{\Omega}_j > 0$ are analogously defined to $\Phi_{i,k}$ and $\Omega_{j,k}$ from Eq. (2).[33] Intuitively, the hypothetical industry-level trade flows $\widetilde{X}_{ij,k}$ are symmetric across industries and proportional to the volume of aggregate manufacturing trade $\widetilde{X}_{ij}$. According to Christaller's (1933) hierarchy principle for industries, we expect the exports of highly localised industries, which only settle in sufficiently large and centrally located cities, to exceed the respective trade flows, that we would observe in a featureless economy without inter-sectoral heterogeneity, in which all industries are ubiquitously distributed across all cities, i.e. $X_{ij,k} > \widetilde{X}_{ij,k}$. For any destination city j it is then possible to compute a pair-specific measure of import dependence $D_{ij} \in [0, 1]$, which equals the share of sectors k for which the sectoral imports $X_{ij,k}$ from origin city i exceed the hypothetical trade volume $\widetilde{X}_{ij,k}$, that would have resulted in a featureless economy.[34] If a city is a central place, it is expected to be the dominant origin city in terms of import dependence D_{ij} for as many as possible destination cities j. We therefore aggregate

[32] In order to rank cities from Southern Germany in terms of their centrality Christaller (1933, pp. 142) computed the surplus in the number of telephones per capita in a given city (e.g. Munich: 50,290 telephones/747,200 residents ≈ 6.7%) relative to the average number of telephones per capita in the surrounding region (3.0%) or in the overall sample (2.5%).

[33] A tilde is used to indicate counterfactual variable values in the hypothetical scenario without inter-sectoral heterogeneity.

[34] Rather than to relate the number $N_{ij} \geq 0$ of industries with $X_{ij,k} > \widetilde{X}_{ij,k}$ to the total number of sectors, we define bilateral import dependence as $D_{ij} \equiv N_{ij}/M_{ij}$, where M_{ij} is the size of set $\mathbb{K}_{ij} = \mathbb{K}_i^E \cup \mathbb{K}_j^I$, which is the union of the set of all export industries $k \in \mathbb{K}_i^E$ in origin city i (across all destination cities $j \neq i$) and the set of all import industries $k \in \mathbb{K}_j^I$ in destination city j (across all origin cities $i \neq j$). Thereby, the set $\mathbb{K}_i^E$ of origin city i's export industries is defined as the power set over the sets of export industries $\mathbb{K}_{ij}^E$ for each destination city $j \neq i$. Analogously, the set $\mathbb{K}_j^I$ of destination city j's import industries is defined as the power set over the sets of import industries $\mathbb{K}_{ji}^I$ for each origin $i \neq j$.

across all destinations $j \neq i$ to obtain our centrality measure:

$$C_i = \sum_{j \neq i} I_j \cdot D_{ij} \geq 0 \quad \text{with} \quad I_j = \begin{cases} 1 & \text{if } D_{ij} > D_{\hat{\imath}j} \ \forall \ \hat{\imath} \neq i \\ 0 & \text{otherwise} \end{cases}, \tag{7}$$

in which $I_j \in \{0, 1\}$ is an indicator variable, taking the value one if destination city j's import dependence of D_{ij} vis-à-vis origin city i is higher than for any other origin city $\hat{\imath} \neq i$. In order to approximate the trade flows in a counterfactual featureless economy $\widetilde{X}_{ij,k}$ we exploit the fact that industry-level trade is proportional to aggregate manufacturing trade $\widetilde{X}_{ij,k} = \beta_k \widetilde{X}_{ij}$. We thus can replace $\beta_k \widetilde{X}_{ij}$ by $\hat{\beta}_k \widehat{X}_{ij}$, which is the product of sector k's average expenditure share $\hat{\beta}_k$ in our sample and the predicted level of aggregate manufacturing trade $\widehat{X}_{ij}$ based on the regression results from Table 1.

In Table 12 (delegated to the Appendix) we present the 50 top-ranked cities in terms of centrality for the year 2015 (see Table 13 to 16 for the years 1995 to 2010). In a featureless economy (without inter-sectoral heterogeneity) we would expect the centrality ranking of cities to be inconclusive and in particular uncorrelated with city size. Reassuringly we find the top ranks of our centrality ranking occupied by Japan's three largest cities *Tokyo*, *Osaka*, and *Nagoya*. Despite the fact that for the top 10 cities the centrality ranking largely is consistent with a ranking in terms of city size, there is no one-to-one mapping between centrality and population size, which can be easily illustrated by comparing two cities from the northeast of Japan: *Sapporo*, which is remotely located on Japan's most northern island *Hokkaido*, is ranked 6$^{\text{th}}$ in terms of centrality and 5$^{\text{th}}$ in terms of population size. *Sendai*, which is located half the way from *Sapporo* to *Tokyo*, follows closely in terms of the 8$^{\text{th}}$ city size rank but is only ranked 27$^{\text{th}}$ in terms of centrality. Unlike *Sapporo*, which is sufficiently isolated to be uncontested in terms of its centrality, *Sendai* stands in the shadow of the much larger *Tokyo*, which explains the much lower centrality rank.[35]

Equipped with the theory-consistent ranking of cities in terms of their centrality, we now proceed by linking all (potential) central places to the set of cities in their respective economic hinterland. Working through the complete list of Japan's cities in decreasing order of centrality, each city j is associated with a higher ranked central place i such that the level of import dependence D_{ij} vis-à-vis the central place is maximised (in comparison to all other central places). We call a city j that is linked to central place i in this way a direct hinterland city of central place i, and acknowledge that each city, which is not ranked as the most central city

[35] A similar pattern has already been documented by Christaller (1933, p. 165), who rationalised the centrality ranking of cities in Southern Germany through their relative position with respect to *Munich* as the most central city in his sample.

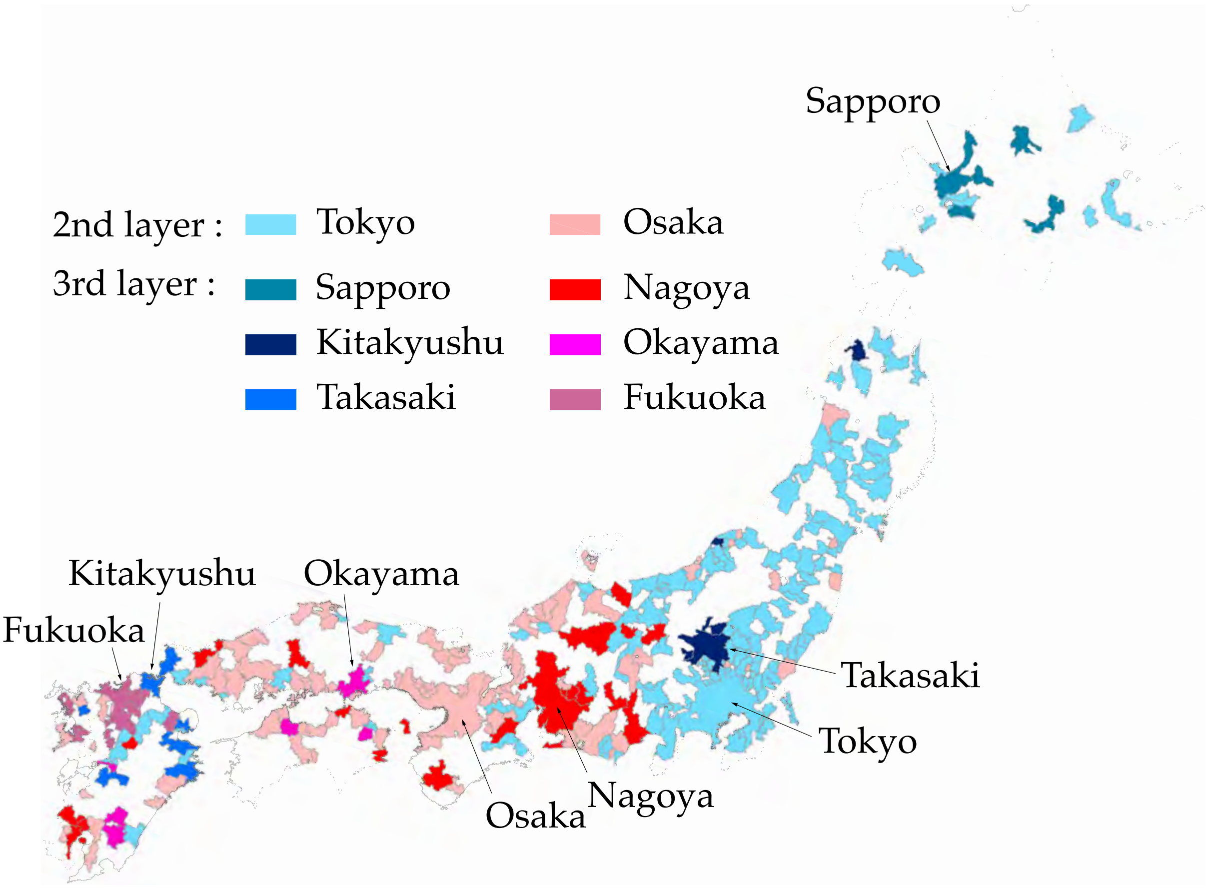
(i.e. Tokyo), can be both a central place on its own and a direct hinterland city of another more centrally ranked city. To obtain the complete set of cities that belong to the economic hinterland of a specific central place we exploit this recursive structure and aggregate up not only all direct hinterland cities but also all direct hinterland cities of these direct hinterland cities (and so forth and so on...).[36] For any arbitrary subset of central places it is then possible to come up with a partition of Japan into economic subregions consisting of a central place and its associated hinterland.

In order to narrow the number of relevant partitions down to a limited number of layers as illustrated in Figure 1, and in order to ensure the comparability of the different economic subregions at these layers, we exploit the recursive linkages between central places and their direct and indirect hinterland cities, that we have derived above. Thereby each central place can be nested into a pyramidic layer structure, with *Tokyo* as Japan's most central city naturally occupying the pyramid's top layer. In order to map the central places together with their recursively identified direct and indirect hinterland cities into the pyramidic layer structure from Figure 1 we proceed in two steps: At first, we acknowledge that no city can be nested in the same layer as the central place to which this city has been allocated as a direct or indirect hinterland city. To give an example: the city of *Fukuoka*, which is a direct hinterland city of *Osaka*, which itself is a direct hinterland city of *Tokyo*, can be at most a 3$^{\text{rd}}$-layer central place but not a central place at the 1$^{\text{st}}$ or 2$^{\text{nd}}$ layer. What complicates the assignment of central places to layers, is that *Osaka* also reappears as a central place in all layers below the 2$^{\text{nd}}$ layer. It therefore is *a priori* not clear whether *Fukuoka* is a 3$^{\text{rd}}$-layer city below *Osaka* as a 2$^{\text{nd}}$-layer city or a 4$^{\text{th}}$-layer city below *Osaka* as a 3$^{\text{rd}}$-layer city. In order to determine a city's final layer assignment we therefore return to our centrality measure C_i, and assert that no central place may be ranked in a layer below a central place with a lower centrality index. In the context of the above example no city with a lower centrality index than the one of *Fukuoka* can be found at the 2$^{\text{nd}}$ layer, confirming *Fukuoka*'s assignment as a 3$^{\text{rd}}$-layer central place.

In Figure 5 we illustrate the hierarchical structure of central places, that we have derived from the 2015 wave of the National Commodity Flow Survey (see Figure 8 from the Appendix for the years 1995-2010). To avoid clutter, we impose the additional constraint that each central place must be associated with at least five distinct hinterland cities. We distinguish economic subregions at the 2$^{\text{nd}}$ layer by plotting the sets of hinterland cities that are directly or indirectly associated with *Tokyo* and *Osaka* in the two baseline colours blue and red, respectively. As there

[36] Trivially, the recursive aggregation process of adding up the direct hinterland cities of the direct hinterland cities comes to a halt if all sets of direct hinterland cities associated with the previous sets of direct hinterland cities are empty.

Figure 5: *Central Places and Hinterland Cities at the 2nd and 3rd Layer in 2015*



are eight different central places with associated hinterlands at the 3rd layer, we use different shades of blue and red in order to illustrate the hinterlands of 3rd-layer central places, depending on the respective 2nd-layer central place being either *Tokyo* or *Osaka*.

Despite a single outlier for 2015 (e.g. *Kitakyushu*), we find the economic subregions (i.e. central places + hinterland) in Figure 5 to be rather compact in their shape, with the vast majority of Japan's northeastern cities in the hinterland of *Tokyo* as a 2nd-layer central place and the vast majority of Japan's southwestern cities in the hinterland of *Osaka* as a 2nd-layer central place. We interpret the compactness of these subregions (which are identified from Japan's disaggregated inter-city trade data) as indirect evidence for the importance of central places in shaping the intra-Japanese trade pattern. The clear east-west pattern that emerges from Figure 5 thereby is well in line with the finding of Wrona (2018), who shows that there is more inter-prefectural trade within the East and West of Japan than between both country parts.[37]

In Table 2 we report all 2nd- and 3rd-layer central places from 1995 to 2015 with the number

[37] Wrona (2018) also shows that the east-west bias in inter-prefectural trade becomes somewhat smaller – although not insignificant – if the analysis is conducted at the more disaggregated level of 68 two-digit product groups, which is compatible with a (partial) explanation in terms of aggregation bias.

of associated hinterland cities in parenthesis. In line with our theoretical predictions from

Table 2: *Central Places in Japan*

Central Places in Japan from 1995 to 2015										
Year:	**2015**									
	1	*Tokyo* (292)								
Layer:	**2**	*Tokyo* (162)					*Osaka* (130)			
	3	*Tokyo* (146)	*Kitakyushu* (6)	*Sapporo* (5)	*Takasaki* (5)		*Osaka* (91)	*Nagoya* (22)	*Fukuoka* (11)	*Okayama* (6)
Year:	**2010**									
	1	*Tokyo* (291)								
Layer:	**2**	*Tokyo* (170)					*Osaka* (121)			
	3	*Tokyo* (147)	*Nagoya* (13)	*Sendai* (10)			*Osaka* (99)	*Fukuoka* (14)	*Kitakyushu* (6)	
Year:	**2005**									
	1	*Tokyo* (307)								
Layer:	**2**	*Tokyo* (146)			*Nagoya* (32)		*Osaka* (129)			
	3	*Tokyo* (141)	*Sendai* (5)		*Nagoya* (32)		*Osaka* (118)	*Fukuoka* (6)	*Kitakyushu* (5)	
Year:	**2000**									
	1	*Tokyo* (310)								
Layer:	**2**	*Tokyo* (167)		*Nagoya* (20)		*Osaka* (123)				
	3	*Tokyo* (167)		*Nagoya* (20)		*Osaka* (99)	*Okayama* (9)	*Fukuoka* (9)	*Kitakyushu* (6)	
Year:	**1995**									
	1	*Tokyo* (347)								
Layer:	**2**	*Tokyo* (164)			*Osaka* (183)					
	3	*Tokyo* (156)	*Niigata* (8)		*Osaka* (130)	*Nagoya* (34)	*Sapporo* (7)	*Kitakyushu* (7)	*Fukuoka* (5)	

Notes: Number of associated hinterland cities in parenthesis.

Section 2 and as evident from Figure 2, we find Japan's hierarchical city system to be rather stable over time. *Tokyo* and *Osaka*, which always appear as central places at the 2^{nd} layer, are joined by *Nagoya* in 2000 and 2005, which otherwise appears as a 3^{rd}-layer central place in the hinterland of either *Tokyo* or *Osaka*.[38]

To test in a more systematic way for the compactness of the identified subregions (i.e. central place + hinterland) in Figure 5 and Table 2 we conduct a simple randomisation test: Holding the number of subregions and the number of cities within subregions at a given layer and for a specific year fixed, we randomise the assignment of cities into subregions. A comparison of the average distances $D_l = \sum_i \sum_j D_{ij}/N_l$ between all cities i and j, which belong to the same subregion at the l^{th}-layer (with N_l as the total number of these city pairs), reveals that the identified subregions in Figure 5 and Table 2 are much more compact than those obtained from 1,000 independent draws under a random assignment. In particular, we find that the average distance $\bar{D}_l$ in Figure 9 (delegated to the Appendix) is consistently larger than the average and minimum distances $\bar{D}_l$ and $\check{D}_l$, which we obtain under a randomised assignment.

[38]Overall we observe only two outliers. *Kitakyushu* appears in the hinterland of *Tokyo* as 2^{nd}-layer central place in 2015, although typically associated with *Osaka* as a central place at the 2^{nd} or 3^{rd} layer. Similarly, we find *Sapporo* to be a hinterland city of *Osaka* as 2^{nd}-layer central place in 1995, although usually associated with *Tokyo* as a central place at the 2^{nd} or 3^{rd} layer.

4.2 Exploring the Pattern of Inter-city Trade in Japan

Having identified a hierarchical structure of central places and associated hinterlands with three different layers, we are now equipped to explore the pattern of inter-city trade between these different entities (i.e. central places versus hinterlands) and to quantify the aggregation bias predicted in Subsection 2.4. In total 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).

Table 3: *Descriptive Analysis – Inter-City Trade*

Descriptive Analysis	**Inter-City Trade**										
Year:		**2015**									
Measure:		**% of Trade Flows**					**% of Trade Volume**				
Direction:		**Importer:**					**Importer:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1st Layer:											
Exporter:	**CP:**	0.0001	–	0.0186	–	0.0187	0.0588	–	0.0658	–	0.1247
	HC:	0.0187	–	0.9626	–	0.9813	0.1350	–	0.7403	–	0.8753
	All:	0.0188	–	0.9812	–	1.0000	0.1939	–	0.8061	–	1.0000
2nd Layer:											
Exporter:	**CP:**	0.0001	0.0001	0.0189	0.0182	0.0373	0.1023	0.0200	0.0754	0.0389	0.2360
	HC:	0.0187	0.0180	0.5219	0.4041	0.9627	0.1270	0.0773	0.4031	0.1560	0.7634
	All:	0.0188	0.0181	0.5408	0.4223	1.0000	0.2293	0.0973	0.4785	0.1949	1.0000
3rd Layer:											
Exporter:	**CP:**	0.0005	0.0037	0.0185	0.0768	0.0995	0.2260	0.1110	0.0548	0.1037	0.4955
	HC:	0.0180	0.0883	0.3914	0.4028	0.9005	0.1080	0.1500	0.1407	0.1058	0.5045
	All:	0.0185	0.0920	0.4099	0.4796	1.0000	0.3340	0.2610	0.1955	0.2095	1.0000

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

In Table 3 we use the 2015 wave of our data to report two different summary measures, which are computed separately for the previously derived classifications of central places and hinterlands at the 1st, 2nd, and 3rd layer.[39] To understand how the pattern of inter-city trade is shaped by Japan's pyramidic city system with central places and associated hinterlands we compute the frequency (i.e. the fraction of non-zero trade flows between city pairs) as well as the trade shares (i.e. the share of the traded value) for all possible trading relationships between central places and associated as well as unassociated hinterland cities.

[39] The results for the earlier waves from 1995 to 2010 closely resemble the findings in Table 3. We therefore have delegated these additional results to an Online Supplement, which is available from the corresponding author's website.

Table 3 confirms the overall importance of central places for the pattern of inter-city trade. *Tokyo* as the 1st-layer central place accounts alone for roughly 12.5% of all exports and 19.4% of all imports. At the 2nd layer *Tokyo* and *Osaka* together are responsible for 23.6% of all exports and 22.9% of all imports. Although exports to hinterland and non-hinterland city occur at the same frequency (1.9% versus 1.8%), we find that the total volume of exports to hinterland cities is twice as large as the total export volume to non-hinterland cities (7.5% versus 3.9%). The same picture also emerges at the 3rd layer: In total the eight central places at the third layer, although only responsible for 10% of all observed exports, account for 50% of the export volume in 2015. At the same time, the other 50% of the export volume are made up of the remaining 90% of the observed export flows. Although exporting to non-hinterland cities is four times as common as exporting to hinterland cities (7.7% versus 1.9%) we find that the total exports to non-hinterland cities are only twice as large as the total exports to hinterland cities (10.4% versus 5.5%).

Taking stock, we not only have documented the quantitatively important role of central places for understanding the pattern of inter-city trade, but also that trade is more intense with cities in the hinterlands of central places. Of course we would expect that central places trade more with nearby cities in their hinterland than with far away cities in the hinterlands of other central places. Using the structural gravity model as the workhorse model of the empirical trade literature, we demonstrate in the following that central places continue to have disproportionately large exports vis-à-vis the cities in their hinterlands even when the trade-reducing effect of distance is explicitly taken into account.

How large is the estimation bias, that results from not taking into account Japan's pyramidic city system with a hierarchical industry structure (as uncovered in Subsection 4.1)? To answer this question we employ in a first step the standard model of a structural gravity equation (cf. Head and Mayer, 2014), which fits the observed volume of aggregate bilateral trade in 2015 to 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 to the complete set of ex- and importer-specific fixed effects without explicitly taking into account Japan's hierarchical city system.[40] If the pattern of inter-city trade is fully explained by the usual gravity variables, we would not expect to find systematic patterns when clustering the gravity residuals according to Japan's hierarchical city system.

In order to asses the overall fit of the structural gravity equation as workhorse model of

[40]To ensure comparability across different levels of aggregation in the subsequent analysis we adopt a parsimonious trade cost specification, omitting the *ad valorem* transportation costs $1 + \text{FREIGHT}_{ij}$ from Eq. (5), which is only incompletely observed at the more disaggregated industry level. Reassuringly, our results remain qualitatively and quantitatively unchanged when also controlling for average and industry-specific *ad valorem* transportation costs.

the empirical trade literature in a systematic way, we report in Table 4 the residual diagnostics for the ex- and imports of central places (CP) and their associated hinterland cities (HC). We thereby distinguish between the same eight mutually exclusive trading relationships as in Table 3. For each category we then conduct a simple sign test, computing the share of trade flows for which the structural gravity model underestimates the actual trade volume (indicated through a positive residual $X_{ij} - \widehat{X}_{ij} > 0$). To quantify the resulting up- or downward bias that results from over- or underestimation, we complement our simple sign test by also computing the mean residual $X_{ij} - \widehat{X}_{ij}$ for each category.

Table 4: *In Search for Systematic Deviations from Structural Gravity*

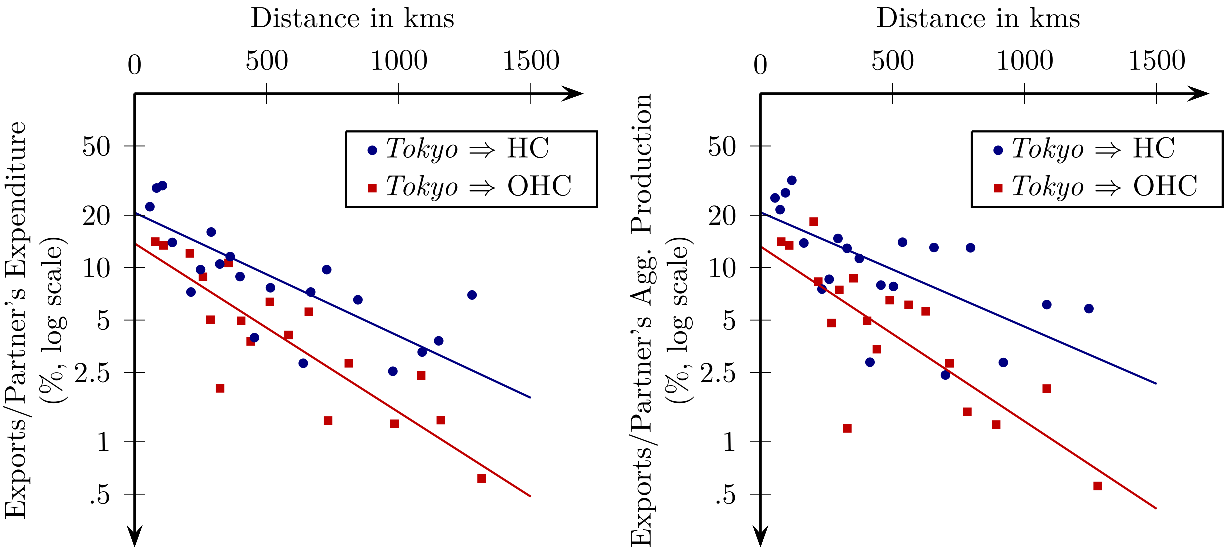
Residual Diagnostics											
Year:		**2015**									
Measure:		**Share of $X_{ij} > \widehat{X}_{ij}$**					**Mean of $X_{ij} - \widehat{X}_{ij}$**				
Direction:		**Importer:**					**Importer:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1^{st} Layer:											
Exporter:	**CP:**	1.0000	–	0.5845	–	0.5860	0.2247	–	−0.0008	–	0.0000
	HC:	0.5594	–	0.5138	–	0.5148	−0.0008	–	0.0000	–	0.0000
	All:	0.5610	–	0.5148	–	0.5161	0.0000	–	0.0000	–	0.0000
2^{nd} Layer:											
Exporter:	**CP:**	1.0000	1.0000	0.6505	0.5054	0.5824	0.4750	1.4110	0.2966	−0.3230	0.0000
	HC:	0.5930	0.5236	0.5144	0.5082	0.5135	0.2421	−0.2646	0.0027	0.0041	0.0000
	All:	0.5621	0.5236	0.5143	0.5082	0.5161	0.0000	−0.2646	0.0000	0.0041	0.0000
3^{rd} Layer:											
Exporter:	**CP:**	0.8750	0.8393	0.6773	0.5256	0.5672	1.3268	1.0069	0.4677	−0.1697	0.0000
	HC:	0.5818	0.5205	0.5112	0.5054	0.5104	0.2265	−0.2624	0.0013	0.0124	0.0000
	All:	0.5400	0.5156	0.5131	0.5039	0.5161	0.0000	−0.0958	0.0000	0.0104	0.0000

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

According to Table 4 we systematically underestimate the bilateral trade volume between central places and their associated hinterlands by relying on the structural gravity equation as the workhorse model of intra-national trade. At each layer the share of underestimated trade flows $X_{ij} > \widehat{X}_{ij}$ between central places and their hinterland cities exceeds the respective share in the overall sample, with the deviation being larger for central places' exports (rather than imports). Accordingly, we find that central places' average residual trade is positive, when trading with their associated hinterlands but negative when trading with the hinterland cities associated to another central place at the same layer.[41]

[41] In accordance with Fujita et al.'s (1999a) central place model we also underestimate the volume of trade among and within central places (see Columns (1) and (2) as well as Columns (6) and (7) in Table 4). We interpret these findings with great caution, because (*i.*) computations are based on a rather limited number of observations, and (*ii.*) there is an overlap between higher-layer hinterland cities and lower-layer central places.

Figure 6: *Tokyo's Exports to its own and other Hinterland Cities*



(a) *Tokyo's Exports at the 2^{nd} Layer* **(b)** *Tokyo's Exports at the 3^{rd} Layer*

In Figure 6 we use a binned scatter plot (cf. Stepner, 2013) to highlight the upward bias in the (residual) exports from central places to their respective hinterlands by focussing on *Tokyo* as 2^{nd}- and 3^{rd}-layer central place. The plot thereby captures the "spirit of gravity" (cf. Head and Mayer, 2014, p. 134) by simultaneously taking into account size and distance effects.[42] Conditional on the partner city's size and the distance to *Tokyo* we find that *Tokyo* as a 2^{nd}- and 3^{rd}-layer central place exports larger volumes to its respective 2^{nd}- and 3^{rd}-layer hinterland cities than to cities, that belong to the hinterlands of other central places at the same layer.

To quantify the estimation bias, that results from not taking into account Japans hierarchical city system from Subsection 4.1, in a more comprehensive way we embed the pyramidic city structure with multi-layer central places and associated hinterlands from Figure 2 into an otherwise standard gravity estimation. To this end, we extend our trade cost function to include not only the geographic controls: DIST_{ij}, HOME_{ij}, and ISLAND_{ij} (summarised by the trade cost vector τ_{ij}) but also the following set of indicator variables:

$$\ln t_{ij} = \sum_{l=2}^{3} \beta_{\text{EXP\_}l} \times \text{EXP\_CP\_HC\_}l\text{LY}_{ij} + \sum_{l=2}^{3} \beta_{\text{IMP\_}l} \times \text{IMP\_CP\_HC\_}l\text{LY}_{ij} \;\; \forall \;\; l \in \{2, 3\}, \quad (8)$$

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 directional indicator variables $\text{EXP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ and $\text{IMP\_CP\_HC\_}l\text{LY}_{ij} \in$

[42] We focus on *Tokyo* as a 2^{nd}- and 3^{rd}-layer central place because as a 1^{st}-layer central place all other cities belong to *Tokyo*'s hinterland.

$\{0,1\}$, taking a value of one whenever a *unique* central place from the l^{th}-layer exports (imports) to (from) its respective hinterland, and a value of zero otherwise. Since central places from higher layers keep reappearing at lower layers, we include each central place only at its highest layer. The city of *Osaka*, which is always identified as a 2^{nd}-layer central place, but therefore also reappears as a central place on lower layers, hence is treated as a 2^{nd}-layer and not as a 3^{rd}-layer central place.

By definition there exists only a single 1^{st}-layer central place (viz. *Tokyo*), whose hinterland is formed by the sum of all other cities in Japan. Due to prefect multicollinearity of the indicator variables $\text{EXP\_CP\_HC\_1LY}_{ij}$ and $\text{IMP\_CP\_HC\_1LY}_{ij}$ with the the respective exporter- and importer-specific fixed effects, it is impossible to independently identify parameters $\beta_{\text{EXP\_1}}$ and $\beta_{\text{IMP\_1}}$ at the 1^{st} layer. We hence focus only on lower layers (i.e. $l \geq 2$) with multiple central places, and consider each central place only on its highest possible layer. Although estimation of the 2^{nd}-layer parameters $\beta_{\text{EXP\_2}}$ and $\beta_{\text{IMP\_2}}$ is feasible, identification is based on a limited number of 2^{nd}-layer central places.[43] To understand how the pattern of inter-city trade is shaped by Japan's hierarchical city/industry system, we therefore primarily focus on the ex- and imports of 3^{rd}-layer central places to and from their respective hinterlands.

Table 5 summarises the results for all waves of the commodity flow survey from 1995 to 2015. As baseline specification ordinary least squares (OLS) is used to estimate a log-linearised (aggregate) gravity equation, imposing the complete set of origin- and destination-specific fixed effects. In our preferred specification we focus on the 3^{rd}-layer, which features a larger number of distinct central places. Throughout all waves of our data we find a large and statistically significant upward bias in the exports from 3^{rd}-layer central places to their respective hinterlands. Aggregate exports from 3^{rd}-layer central places to their respective hinterlands thereby exceed the export volume between comparable city pairs (conditional on gravity forces) by a factor of two to five. Interestingly, there is no evidence that 3^{rd}-layer central places disproportionately import from their hinterlands. 2^{nd}-layer results for 2015, 2010, and 1995 capture *Osaka*'s increased ex- and imports to and from its hinterland. Reassuringly, the upward bias in central places' imports is much smaller for the years 2005 and 2000, when identification is based on multiple central places (i.e. *Osaka* and *Nagoya*).[44]

Having quantified the upward bias in exports from central places to their respective hinterlands as predicted in Section 2.4, we now want to further validate our findings by scrutinizing

[43] In addition to *Osaka*, which is always identified as a 2^{nd}-layer central place, *Nagoya* is ranked at the 2^{nd} layer in 2000 and 2005

[44] Note that the upward bias in *Osaka*'s imports as a 2^{nd}-layer central place can be partly explained by the fact that *Osaka* also imports from various 3^{rd}-layer central places in its own hinterland. Excluding these cities from the definition of $\text{IMP\_CP\_HC\_2LY}_{ij}$ somewhat lowers the import bias.

Table 5: *Central Places, Hinterlands, and the Pattern of Inter-city Trade*

Dependent variable: Exports from city i to city j					
Year:	**2015**	**2010**	**2005**	**2000**	**1995**
Model:	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
2nd Layer:					
Exports CP $\rightarrow$ HC	0.6712***	0.5553**	0.3865**	0.4020*	0.2420
	(.2365)	(.2170)	(.1684)	(.2071)	(.1832)
Imports CP $\leftarrow$ HC	0.7977***	0.6873***	0.1799	0.3529*	0.5032**
	(.2387)	(.2157)	(.1870)	(.1827)	(.2168)
3rd Layer:					
Exports CP $\rightarrow$ HC	1.0092***	1.5756***	1.8439***	1.2634***	1.0215***
	(.2818)	(.2367)	(.5043)	(.3570)	(.2283)
Imports CP $\leftarrow$ HC	0.1072	−0.2481	−0.2058	0.3566	0.1478
	(.3092)	(.3375)	(.5898)	(.3506)	(.2758)
Controls:					
ln Distance$_{ij}$	−0.6974***	−0.6764***	−0.6250***	−0.6468***	−0.6893***
	(.0233)	(.0230)	(.0224)	(.0229)	(.0195)
Intra-city trade	0.6563***	1.0081***	0.6317***	0.5036***	0.5368***
	(.1802)	(.1637)	(.1801)	(.1831)	(.1581)
Intra-island trade	0.0332	0.0964	−0.0575	0.1832***	0.0167
	(.0719)	(.0672)	(.0704)	(.0663)	(.0556)
Fixed effects:					
Exporter (i):	✓	✓	✓	✓	✓
Importer (j):	✓	✓	✓	✓	✓
Summary statistics:					
Number of observations:	15,261	16,184	18,098	17,146	22,183
R^2	0.438	0.419	0.442	0.443	0.441

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

the conditions under which we can expect to find such a systematic deviation from structural gravity. We therefore conduct a series of placebo regressions, in which we randomise the assignment of hinterland cities (holding the central places fixed). Throughout we thereby maintain the basic hierarchical structure from Table 2, fixing the number of layers, the number of central places on each layer, as well as the number of hinterland cities in the respective hinterland of each central place. We then randomly construct 10.000 hypothetical divisions into central places and associated hinterland cities, from which we can derive counterfactual central place dummies akin to $\text{EXP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ and $\text{IMP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ from Eq. (8). We implement these counterfactual central place dummies in an 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. Clearly, if the associated hinterland cities are randomly picked, we would not expect to find a systematic deviation from the structural gravity model. Table 6 compares the outcomes of the placebo regression to the baseline results from Table 5.

Table 6: *Placebo Regressions with Randomised Assignment of Hinterlands*

Randomised Hinterlands:								
Year	**Benchmark:**		**Number of Samples**	**Mean of** $\beta^{\text{random}}_{\text{EXP\_3}}$	**Significant Estimates at:**			**Share of** $\beta^{\text{random}}_{\text{EXP\_3}} > \beta_{\text{EXP\_3}}$
	$\beta_{\text{EXP\_3}}$	**S. E.**			$p < 0.01$	$p < 0.05$	$p < 0.10$	
2015	1.0092***	(.2818)	10,000	.0055	.0118	.0388	.0659	.0053
2010	1.5756***	(.2367)	10,000	-.0053	.0143	.0410	.0658	.0000
2005	1.8439***	(.5043)	10,000	.0027	.0416	.0819	.1151	.0116
2000	1.2634***	(.3570)	10,000	.0004	.0199	.0508	.0765	.0193
1995	1.0215***	(.2283)	10,000	.0019	.0105	.0371	.0631	.0000

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

Focussing again on the exports of 3rd-layer central places to their respective hinterlands, we find no systematic upward bias if the assignment of hinterland cities is randomised. The vast majority of the estimated coefficients $\beta^{\text{random}}_{\text{EXP\_3}}$ are in the vicinity of zero and typically statistically insignificant at the commonly applied significance levels of $\alpha = 1\%$, $\alpha = 5\%$, and $\alpha = 10\%$. At a significance level of $\alpha = 1\%$ only 1.1% to 4.2% of all placebo regressions yield a positive and significant point estimate if the assignment of hinterland cities (central places) is randomised. The fraction of placebo regressions that deliver coefficients $\beta^{\text{random}}_{\text{EXP\_3}}$, which exceed the baseline coefficients $\beta_{\text{EXP\_3}}$ from Table 5 ranges from 0.0% to 1.9%.

Summing up the results of this section, we have shown that exports of large and centrally located cities to smaller cities in their nearby hinterland are systematically underestimated by a structural gravity estimation, that does not take into account Christaller's (1933) hierarchy principle for industries. The upward bias in aggregate exports of 3rd-layer central places to their hinterland cities is statistically significant and quantitatively important, suggesting that exports are two to five times larger than predicted by gravity forces. In a series of placebo regressions, in which the assignment or hinterlands is randomised and not systematically derived as in Section 4.1, it is almost impossible to find comparable effects of similar magnitude.

5 Disaggregation and Decomposition

Having quantified the upward bias in aggregate exports from central places to their respective hinterlands based on Japan's pyramidic city system, we are now providing further evidence that the unexpectedly high aggregate exports of central places are an artefact of the underlying aggregation process (as explained in Subsection 2.4).

To rationalise the findings from Subsection 4.2 in terms of aggregation bias we follow Anderson and van Wincoop (2004, p. 729), whose "obvious recommendation is to disaggregate." Table 7 therefore replicates the residual diagnostics from Table 4 based on a theory-consistent structural gravity estimation, which is conducted at the much more disaggregated industry-level. To ensure comparability we employ the same trade cost specification as in Table 4, and include the complete set of origin- and destination-specific fixed effects. We stick to the basic structure of Table 4, and distinguish between up to eight mutually exclusive combinations of two origin categories (central place (CP) versus hinterland city (HC)) and four destination categories (central place (CP), other central place (OCP), hinterland city (HC) and other hinterland city (OHC)).

Table 7: *Residual Diagnostics at the Industry Level*

Residual Diagnostics at the Industry Level											
Year:		**2015**									
Measure:		**Share of $X_{ij,k} > \widehat{X}_{ij,k}$**					**Mean of $X_{ij,k} - \widehat{X}_{ij,k}$**				
Direction:		**Importer:**					**Importer:**				
Partner City:		**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**	**CP:**	**OCP:**	**HC:**	**OHC:**	**All:**
Column:		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
1st Layer:											
Exporter:	**CP:**	0.5151	–	0.5135	–	0.5136	−0.1493	–	0.0046	–	0.0000
	HC:	0.5268	–	0.5065	–	0.5075	0.0094	–	−0.0005	–	0.0000
	All:	0.5260	–	0.5075	–	0.5082	0.0000	–	0.0000	–	0.0000
2nd Layer:											
Exporter:	**CP:**	0.5160	0.5797	0.5224	0.4812	0.5086	−0.1312	0.4955	0.0612	−0.1187	0.0000
	HC:	0.5417	0.5071	0.5103	0.4997	0.5081	0.0350	−0.0818	0.0090	−0.0079	0.0000
	All:	0.5284	0.5071	0.5060	0.4997	0.5082	0.0000	−0.0818	0.0000	−0.0079	0.0000
3rd Layer:											
Exporter:	**CP:**	0.5316	0.5724	0.5288	0.4916	0.5144	0.0996	0.3466	0.0538	−0.1171	0.0000
	HC:	0.5370	0.4947	0.5145	0.5006	0.5052	0.0187	−0.1551	0.0369	0.0195	0.0000
	All:	0.5141	0.4860	0.5066	0.4980	0.5082	0.0000	−0.1213	0.0000	0.0113	0.0000

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

All indicators suggest that the industry-level gravity estimation from Table 7 outperforms the aggregate gravity estimation from Table 4 in matching the pattern of intra-Japanese inter-city trade. While there is a 15 percentage point difference in the shares of underestimated trade flows (characterised by $X_{ij} > \widehat{X}_{ij}$) for central places' exports to associated versus unassociated hinterland cities in Table 4 (Column (3) versus Column (4)), we find that in Table 7 the difference in these shares (characterised by $X_{ij,k} > \widehat{X}_{ij,k}$) has declined to just 4 percentage points (Column (3) versus Column (4) in Table 7). A similar picture emerges from the comparison of the mean residuals: Mean residuals of central places' trade in Table 4 are 0.2966 (0.4677) for exports to 2nd-layer (3rd-layer) associated hinterlands and −0.3230 (−0.1697) for exports to 2nd-layer (3rd-layer) unassociated hinterlands (Column (8) versus Column (9) in Table 4). In Table 7 the mean residuals of central places' trade shrink to 0.0612 (0.0538) for exports to 2^{nd}-layer (3^{rd}-layer) associated hinterlands and −0.1187 (−0.1171) for exports to 2^{nd}-layer (3^{rd}-layer) unassociated hinterlands (Column (8) versus Column (9) in Table 7).

To quantify the importance of aggregation bias in explaining the upward bias in the exports from central places to their respective hinterlands we replicate the analysis from Table 5 in Table 8, and run an industry-level gravity estimation on Japan's hierarchical city system, captured by the set of fixed effects $\text{EXP\_CP\_HC\_}l\text{LY}_{ij} \in \{0,1\}$ and $\text{IMP\_CP\_HC\_}l\text{LY}_{ij} \in \{0,1\}$ for all $l = 2,3$. In addition to the familiar trade cost vector $\ln \tau_{ij} = \beta_{\text{DIST}} \times \ln \text{DIST}_{ij} + \beta_{\text{HOME}} \times \text{HOME}_{ij} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{ij}$ we also include the complete set of origin- and destination-specific fixed effects.

Table 8: *Central Places, Hinterlands, and the Pattern of Industry-level Inter-city Trade*

Dependent variable: Industry-level exports from city i to city j					
Year:	**2015**	**2010**	**2005**	**2000**	**1995**
Model:	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
2^{nd} Layer:					
Exports CP → HC	0.1501	0.0613	0.0202	0.0913	0.1504^{*}
	(.1075)	(.0998)	(.0827)	(.0835)	(.0850)
Imports CP ← HC	0.1977	0.0813	−0.1601	0.0682	0.1627
	(.1533)	(.1420)	(.1187)	(.1302)	(.1247)
3^{rd} Layer:					
Exports CP → HC	0.3549^{**}	0.2791^{*}	0.4088	0.3477^{**}	0.2682^{**}
	(0.1421)	(0.1512)	(0.3872)	(0.1735)	(0.1045)
Imports CP ← HC	0.0356	−0.0464	−0.3287	−0.4172	−0.0758
	(.1948)	(.2008)	(.3795)	(.2864)	(.1424)
Controls:					
ln Distance_{ij}	-0.3942^{***}	-0.3868^{***}	-0.3518^{***}	-0.3722^{***}	-0.3808^{***}
	(.01731)	(.0170)	(.0171)	(.0172)	(.0142)
Intra-city trade	0.6135^{***}	0.6428^{***}	0.4852^{***}	0.5039^{***}	0.7099^{***}
	(.1021)	(.0905)	(.1063)	(.1147)	(.0988)
Intra-island trade	−0.0743	0.0039	−0.0461	0.0587	−0.0607
	(.0565)	(.0537)	(.0537)	(.0514)	(.0423)
Fixed effects:					
Exporter (i):	✓	✓	✓	✓	✓
Importer (j):	✓	✓	✓	✓	✓
Summary statistics:					
Number of observations:	32,356	35,335	39,262	37,878	54,252
R^2	0.237	0.210	0.231	0.224	0.230

Notes: Robust standard errors are clustered at the city-pair level; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Estimates of the upward bias in central places' exports in Table 8 are much smaller than in Table 5 and at best marginally significant (at the 5% or 10% significance level) if not statistically indistinguishable from zero. Instead of a large upward bias of 200% to 500% for the exports of 3rd-layer central places in Table 5 we find a moderate upward bias of just 30% to 50%. The considerable reduction in the upward bias of exports from central places to their respective hinterlands confirms the theoretical predictions, that we have derived from Fujita et al.'s (1999a) central place model in Section 2.4: Central places are not only exporting across more industries but also are more likely to supply a specific city with the goods of these industries if the city is located in the respective central place's hinterland. By treating industry-level trade flows as separate observations we avoid a systematic estimation bias, that otherwise would result from asymmetrically aggregating up bilateral trade flows across a large number of industries in central places and an on average much smaller number of industries located in the other cities.

It is worth noting that the differences between Table 5 and Table 8 only result from treating industry-level trade flows as separate observations and not from using a less parsimonious specification of the trade cost function. To account for heterogeneity across industries, as assumed in Fujita et al.'s (1999a) central place model, we account in Table 17 (delegated to the Appendix) not only for origin×industry-specific and destination×industry-specific fixed effect but also for industry-specific *ad valorem* transportation costs (by allowing the effect of *ad valorem* transportation costs to differ across industries). Reassuringly, we find that the point estimates for the upward bias of 2nd- and 3rd-layer central places' exports from Table 17 are similar in terms of magnitude and significance to those from Table 8.

In line with our prediction from Subsection 2.4 we also find that the distance elasticities, which ranges from -0.3722 to -0.3942 in Table 8, are much smaller than in Table 5, where the respective point estimates fall into a range from -0.6250 to -0.6974. As in Hillberry and Hummels (2008, pp. 539-40) this difference in distance elasticities can be attributed to the underlying aggregation process – with the major difference, that Hillberry and Hummels (2008) focused on aggregation across different spatial units (3 digit versus 5 digit zip codes) and not at aggregation across different industries.[45] Because the probability of observing a shipment at the industry level is declining in distance (cf. Figure 3), the aggregate volume of inter-city trade is declining at the intensive margin within each industry and at the extensive margin as the number of exporting industries gets smaller over longer distances. As we aggregate across industries, variation at the extensive margin (presence or absence of industry-level shipments) sums up

[45] In line with Hillberry and Hummels's (2008) argumentation, that the home bias in intra-national trade is an artefact of spatial aggregation, we find that the statistically significant upward bias in intra-city trade is only marginally affected by aggregation across different industries.

to a continuous variable (total value of bilateral trade). The response of the aggregate trade volume to increasing distances therefore is substantially larger than at the more disaggregated industry-level.

To further strengthen our argumentation, we are now exploiting the full potential of our micro-level trade data in using Hillberry and Hummels's (2008) decomposition approach to identify the extensive industry margin as the main driver behind the previously identified aggregation bias. We decompose the aggregate value of trade $X_{ij} = \sum_{s=1}^{S_{ij}} P_{ij,s}C_{ij,s}$ from origin city i to destination city j into the number of unique shipments S_{ij} (the extensive margin) and the average value per shipment $\bar{R}_{ij} \equiv \sum_{s=1}^{S_{ij}} P_{ij,s}C_{ij,s}/S_{ij}$ (the intensive margin):

$$X_{ij} = S_{ij}\bar{R}_{ij}, \tag{9}$$

referring to a unique shipment by subscript s.[46] Decomposing the number of unique shipments S_{ij} further into the number of distinct industries K_{ij} across which a certain city exports its goods and the average number of shipments per industry $\bar{S}_{ij} \equiv S_{ij}/K_{ij}$ then results in:

$$S_{ij} = K_{ij}\bar{S}_{ij}. \tag{10}$$

In a final step the average value per shipment $\bar{R}_{ij}$ is decomposed into average price $\bar{P}_{ij}$ and average quantity $\bar{C}_{ij}$ per shipment:

$$\bar{R}_{ij} = \frac{\sum_{s=1}^{S_{ij}} P_{ij,s}C_{ij,s}}{S_{ij}} = \frac{\sum_{s=1}^{S_{ij}} P_{ij,s}C_{ij,s}}{\sum_{s=1}^{S_{ij}} C_{ij,s}} \frac{\sum_{s=1}^{S_{ij}} C_{ij,s}}{S_{ij}} = \bar{P}_{ij}\bar{C}_{ij}. \tag{11}$$

Substituting S_{ij} and $\bar{R}_{ij}$ from Eqs. (10) and (11) back into X_{ij} from Eq. (9) allows us to deconstruct the aggregate volume of bilateral trade:

$$X_{ij} = K_{ij}\bar{S}_{ij}\bar{P}_{ij}\bar{C}_{ij} \tag{12}$$

between origin city i and destination city j into its four components: K_{ij}, $\bar{S}_{ij}$, $\bar{P}_{ij}$ and $\bar{C}_{ij}$. Log-linearising the Eqs. (9) and (12) then yields the first-level decomposition:

$$\ln X_{ij} = \ln S_{ij} + \ln \bar{R}_{ij}, \tag{13}$$

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

and the second-level decomposition:

$$\ln X_{ij} = \ln K_{ij} + \ln \bar{S}_{ij} + \ln \bar{P}_{ij} + \ln \bar{C}_{ij}. \tag{14}$$

While a decomposition analysis of bilateral inter-city is interesting in its own right (yielding similar results as in Hillberry and Hummels (2008)), we are particularly interested in understanding what is responsible for the upward bias in exports from central places to their respective hinterlands. We therefore follow Hillberry and Hummels (2008) by treating each element in the Eqs. (13) and (14) as a dependent variable, which then is separately regressed on the trade cost vector $\ln \tau_{ij} = \beta_{\text{DIST}} \times \ln \text{DIST}_{ij} + \beta_{\text{HOME}} \times \text{HOME}_{ij} + \beta_{\text{ISLAND}} \times \text{ISLAND}_{ij}$, the hierarchy vector $\ln t_{ij}$ from Eq. (8), and the complete set of origin- and destination-specific fixed effects.[47]

Making use of the OLS estimator's linearity, we separately regress $\ln X_{ij}$ and all its log-linearised components on the same set of explanatory variables to obtain coefficients with the useful additive property: $\beta_\ell^X = \beta_\ell^S + \beta_\ell^R$ with $\beta_\ell^S = \beta_\ell^K + \beta_\ell^{\bar{S}}$ and $\beta_\ell^R = \beta_\ell^{\bar{P}} + \beta_\ell^{\bar{C}}$. While superscripts are used to distinguish the dependent variables: X_{ij}, S_{ij}, and R_{ij} as well as K_{ij}, $\bar{S}_{ij}$, $\bar{P}_{ij}$ and $\bar{C}_{ij}$, we use subscripts to identify the explanatory variable (typically the 3rd-layer central place export dummy $\text{EXP\_CP\_HC\_3LY}_{ij} \in \{0, 1\}$ and log distance $\ln \text{DIST}_{ij}$). Based on the decomposition from Eq. (14) we then can quantify each component's contribution to the upward bias in the exports from central places to their hinterlands (conditional on gravity forces).

Table 9 reports the decomposition results for the upward bias in exports of 3rd-layer central places to their respective hinterlands across all waves in a five-year interval from 1995 to 2015.[48] In the first Column of Table 9 we replicate the baseline results from Table 5. By decomposing the strong upward bias in the exports from 3rd-layer central places to their respective hinterlands into its various components from Eq. (14) we can learn more about what causes the systematic deviation from the structural gravity model for aggregate inter-city trade. Suppose the upward bias in 3rd-layer central places' exports is caused by an omitted variable, whose trade-creating effect proportionately scales up the volume of bilateral trade (such as the regionally concentrated

[47]Because two-way fixed effects were computational infeasible, Hillberry and Hummels (2008) eliminated all variation in output and prices, that is specific to the origin city, and all variation in expenditures and prices, that is specific to the destination city, through double demeaning each of their variables (i.e. by dividing them through the variable's respective mean value across all origin cities and through the variable's respective mean value across all destination cities). To make our results comparable to those of Hillberry and Hummels (2008), we also replicate their analysis by double demeaning all outcome variables instead of imposing the complete set of origin- and destination-specific fixed effects. Reassuringly we find that the results obtained under double demanding in Table 18 (delegated to the Appendix) are qualitatively the same as in Table 9. The underlying regressions tables of the complete decomposition analysis are delegated to an Online Supplement, which is available from the corresponding author's website.

[48]The complete decomposition analysis is delegated to an Online Supplement, which is available from the corresponding author's website.

Table 9: *Decomposing the Upward Bias in Exports from Central Places to their Hinterlands*

Explanatory Variable:	**Exports 3rd Layer Central Place → Hinterland**									
Dependent Variable:	$\ln X_{ij}$	$\ln S_{ij}$	$\ln K_{ij}$	$\ln \bar{S}_{ij}$	$\ln \bar{R}_{ij}$	$\ln \bar{P}_{ij}$	$\ln \bar{C}_{ij}$	N	$\frac{\beta^K_{\text{EXP\_3}}}{\beta^X_{\text{EXP\_3}}}$	$\frac{\beta^{\bar{S}}_{\text{EXP\_3}}}{\beta^X_{\text{EXP\_3}}}$
Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Year:										
2015	1.0092***	0.7607***	0.6626***	0.0981***	0.2485	−0.3301**	0.5785**	15,261	65.66%	9.72%
	(.2818)	(.0913)	(.0778)	(.0325)	(.2414)	(.1376)	(.2683)			
	[.44]	[.65]	[.63]	[.30]	[.37]	[.41]	[.42]			
2010	1.5756***	0.9981***	0.8542***	0.1438***	0.5776***	−0.5842***	1.1617***	16,184	54.21%	9.13%
	(.2367)	(.0789)	(.0595)	(.0407)	(.2025)	(.1484)	(.2203)			
	[.42]	[.65]	[.64]	[.29]	[.33]	[.45]	[.41]			
2005	1.8439***	0.8155***	0.7769***	0.0386	1.0284**	−0.3652	1.3936***	18,098	42.13%	2.09%
	(.5043)	(.1242)	(.1050)	(.0318)	(.4166)	(.3040)	(.3793)			
	[.44]	[.65]	[.63]	[.33]	[.36]	[.47]	[.41]			
2000	1.2634***	0.8991***	0.8302***	0.0689*	0.3644	−0.8965***	1.2609***	17,146	65.71%	5.45%
	(.3570)	(.1201)	(.1035)	(.0369)	(.2760)	(.2412)	(.2543)			
	[.44]	[.66]	[.65]	[.32]	[.36]	[.44]	[.43]			
1995	1.0215***	0.7303***	0.6205***	0.1098**	0.2912	−0.7083***	0.9995***	22,138	60.74%	10.75%
	(.2283)	(.1106)	(.0795)	(.0452)	(.1796)	(.1380)	(.1930)			
	[.44]	[.67]	[.66]	[.36]	[.34]	[.45]	[.42]			
Fixed effects:										
Exporter (i):	✓	✓	✓	✓	✓	✓	✓			
Importer (j):	✓	✓	✓	✓	✓	✓	✓			

Notes: R^2 of the underlying regression reported in squared brackets. Robust standard errors in parenthesis; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

business networks in Combes et al. (2005), Requena and Llano (2010), and Wrona (2018)). The disproportionately high exports from 3rd-layer central places to their respective hinterlands then are caused by an increase in the average number of shipments per industry rather than by an increase in the number of exporting industries. Interestingly, we find that the average number of unique shipments per industry $\bar{S}_{ij}$ merely contributes at all to the overall effect (relative contributions $\beta^{\bar{S}}_{\text{EXP\_3}}/\beta^X_{\text{EXP\_3}}$ range between 2.1% and 10.8%). In sharp contrast and in line with our argumentation from Subsection 2.4 we find that the disproportionately large exports from 3rd-layer central places to their respective hinterlands are mainly explained through a larger number of exporting industries – with the extensive (industry) margin's contribution $\beta^K_{\text{EXP\_3}}/\beta^X_{\text{EXP\_3}}$ accounting for 42.1% to 65.7% of the overall effect.[49] Accordingly, we also find that the R^2 in the extensive industry margin regressions (with outcome variable $\ln K_{ij}$) are much larger than those of the other components of $\ln X_{ij}$.

Following our above argumentation, we can now also look into what causes the discrepancy between aggregate distance elasticities in Table 5 and their smaller industry-level counterparts in Table 8. As argued in Subsection 2.4, we find that a substantial fraction (26.2% to 30.4%) of the trade-reducing effect of distance in Table 10 can be attributed to less trade at the extensive

[49] It is worth to note that exports from 3rd-layer central places to their respective hinterlands are also characterised by disproportionately large average quantities $\bar{C}_{ij}$, which more than compensate for an on average smaller price $\bar{P}_{ij}$. Given that the trade-reducing effect of distance can be decomposed into a positive price effect, that is dominated by a negative quantity effect (see also Hillberry and Hummels, 2008), it is only natural to expect that short-distance trade between central places and their rather close hinterlands is characterised by large quantities and low prices.

industry-margin, which explains why the combined effect at the intensive and extensive margin in Table 5 exceeds the intensive margin effect in Table 8. Reassuringly, we find that the point

Table 10: *Decomposing the Distance Elasticity*

Explanatory Variable:	$\ln$ **Distance**$_{ij}$									
Dependent Variable:	$\ln X_{ij}$	$\ln S_{ij}$	$\ln K_{ij}$	$\ln \bar{S}_{ij}$	$\ln \bar{R}_{ij}$	$\ln \bar{P}_{ij}$	$\ln \bar{C}_{ij}$	N	$\frac{\beta^K_{\text{DIST}}}{\beta^X_{\text{DIST}}}$	$\frac{\beta^{\bar{R}}_{\text{DIST}}}{\beta^X_{\text{DIST}}}$
Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Year:										
2015	-0.6974^{***}	-0.2022^{***}	-0.1830^{***}	-0.0193^{***}	-0.4952^{***}	0.3588^{***}	-0.8539^{***}	15,261	26.24%	71.01%
	(.0233)	(.0050)	(.0046)	(.0014)	(.0215)	(.0152)	(.0250)			
	[.44]	[.65]	[.63]	[.30]	[.37]	[.41]	[.42]			
2010	-0.6764^{***}	-0.2065^{***}	-0.1865^{***}	-0.0200^{***}	-0.4699^{***}	0.3346^{***}	-0.8045^{***}	16,184	27.57%	69.47%
	(.0230)	(.0051)	(.0047)	(.0014)	(.0212)	(.0144)	(.0248)			
	[.42]	[.65]	[.64]	[.29]	[.33]	[.45]	[.41]			
2005	-0.6250^{***}	-0.1931^{***}	-0.1759^{***}	-0.0171^{***}	-0.4320^{***}	0.3277^{***}	-0.7597^{***}	18,098	28.14%	69.12%
	(.0224)	(.0050)	(.0046)	(.0013)	(.0208)	(.0147)	(.0238)			
	[.44]	[.65]	[.63]	[.33]	[.36]	[.47]	[.41]			
2000	-0.6468^{***}	-0.1915^{***}	-0.1707^{***}	-0.0208^{***}	-0.4553^{***}	0.3083^{***}	-0.7636^{***}	17,146	26.39%	70.39%
	(.0229)	(.0051)	(.0045)	(.0016)	(.0213)	(.0146)	(.0246)			
	[.44]	[.66]	[.65]	[.32]	[.36]	[.44]	[.43]			
1995	-0.6893^{***}	-0.2360^{***}	-0.2096^{***}	-0.0264^{***}	-0.4533^{***}	0.3693^{***}	-0.8225^{***}	22,138	30.41%	65.76%
	(.0195)	(.0049)	(.0044)	(.0014)	(.0178)	(.0125)	(.0214)			
	[.44]	[.67]	[.66]	[.36]	[.34]	[.45]	[.42]			
Fixed effects:										
Exporter (i):	✓	✓	✓	✓	✓	✓	✓			
Importer (j):	✓	✓	✓	✓	✓	✓	✓			

Notes: R^2 of the underlying regression reported in squared brackets. Robust standard errors in parenthesis; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

estimates for the intensive margin effect from Column (5) of Table 10 are comparable in size and magnitude to those from Table 8.[50]

Following our above argumentation, there is little room for an explanation of the disproportionately high exports from 3$^{\text{rd}}$-layer central places to their respective hinterlands in terms of omitted variable bias. To scrutinise this finding, we explicitly control in Table 11 for potential alternative explanations. In particular, we follow Wrona (2018), who shows that the multipolar structure of social and business networks leads to less inter-prefectual trade between the East and the West of Japan. To account for the role of social networks (cf. Helliwell, 1997; Head and Ries, 1998; Millimet and Osang, 2007; Wrona, 2018) we use bilateral migration stocks at the municipality level from the 2010 Population Census (provided by the Statistical Bureau of the Ministry of Internal Affairs and Communications), which are aggregated up to city-pair level.[51] Following Combes et al. (2005) and Wrona (2018), we use Japan's 2014 Economic Census [*Keizai Sensasu*] to compute the total number of bilateral headquarter-plant links at the city-pair level. By construction, the resulting business-network variable is symmetric,

[50] As in Hillberry and Hummels's (2008) decomposition analysis at the 3-digit zip code level, we find that at the extensive margin there is less trade across increasing distances because the number of shipments and the number of shipped commodities declines, while at the intensive margin a positive price effect is dominated by negative quantity effect – a finding that is also consistent with the results in Hummels and Skiba (2004).

[51] Following Combes et al. (2005) we acknowledge that ex- and imports may be both affected by the structure of social networks. We therefore use the total stock of lagged migration at the city-pair level to approximate the structure of social networks.

suggesting that headquarter-plant linkages are equally important for ex- and imports at the city-pair level. To account for a potential heterogeneity in the trade-creating effect of social and business networks, that could explain the upward bias in central places' exports from Table 5, we follow Chen (2004) and interact the indicator variables $\text{EXP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ and $\text{IMP\_CP\_HC\_}l\text{LY}_{ij} \in \{0, 1\}$ with our two network variables. In Table 11 we compare the baseline results for 2015 from the Tables 5 and 8 with two specifications that explicitly take into account the potentially heterogeneous effects that can arise from the presence of social and business networks. Reassuringly, we find that all interaction effects are statistically insignificant, which implies that the upward bias in the exports from central places to their hinterlands can not be explained through a systematic heterogeneity in the trade-creating effect of social and business networks.[52] In accordance with this result, we also find that the point estimates for the upward bias in central places' exports from the Tables 5 and 8 basically remain unchanged in Table 11.

In summary, we have shown that the upward bias in the exports from 3^{rd}-layer central places to their respective hinterlands, that we have quantified in Subsection 4.2, does not reappear if the underlying gravity estimation is conducted in a theory-consistent way at the much more disaggregated industry level. We interpret this finding as supportive evidence in favour of an explanation in terms of aggregation bias and present further empirical support based on a mirco-level decomposition of Japan's inter-city trade that is also well in line with this explanation.

6 Conclusion

Inter-city gravity estimations suffer from a systematic aggregation bias: central places export two to five times more to their associated hinterlands than predicted by a structural gravity model, that is based on aggregate inter-city trade data. Central places export more than proportionately to their hinterlands because they possess more industries than the small, peripheral cities in their hinterlands, and because there is a higher probability that an industry, which only exists in a central place, will export to the central place's hinterland. Using a simple decomposition approach, we verify that the by far largest part of the upward bias in central places' exports stems from aggregating trade along the extensive industry margin, which is also why the upward bias is much smaller and only marginally significant if estimation is conducted in a theory-consistent way at the much more disaggregated industry level.

Another important discrepancy between aggregate and industry-level gravity estimations

[52] Interestingly, we find the trade-creating effect of social and business networks to be not only larger but also statistically different from zero, in the theory-consistent industry-level gravity estimations of the Columns (4) to (6) from Table 11.

Table 11: *In Search for Alternative Explanations*

Dependent variable: Exports from city i to city j						
Year:	**2015**					
Model:	**OLS-FE**					
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
2nd Layer:						
Exports CP $\rightarrow$ HC	0.6712***	0.6544***	0.6652***	0.3433**	0.2498	0.2665
	(.2365)	(.2429)	(.2464)	(.1656)	(.1705)	(.1684)
Imports CP $\leftarrow$ HC	0.7977***	0.8105***	0.8025***	0.3169	0.2822	0.2784
	(.2387)	(.2465)	(.2486)	(.2056)	(.2183)	(.2167)
3rd Layer:						
Exports CP $\rightarrow$ HC	1.0092***	0.9604***	0.9522***	0.4155**	0.4443**	0.3283*
	(.2818)	(.3722)	(.3208)	(.1952)	(.2113)	(.1899)
Imports CP $\leftarrow$ HC	0.1072	0.0284	0.0431	0.0433	−0.2616	−0.1279
	(.3092)	(.3960)	(.3369)	(.2324)	(.2213)	(.2049)
Alternative explanatory variables:						
Lagged migration$_{ij}$		0.0001			0.0008***	
		(.0001)			(.0001)	
2nd Layer:						
Lagged migration$_{ij}$ ×exports CP $\rightarrow$ HC		0.0009			0.0100	
		(.0029)			(.0077)	
Lagged migration$_{ij}$ ×imports CP $\leftarrow$ HC		−0.0010			−0.0094	
		(.0029)			(.0076)	
3rd Layer:						
Lagged migration$_{ij}$ ×exports CP		−0.0009			−0.1085	
		(.0140)			(.0876)	
Lagged migration$_{ij}$ ×imports CP $\leftarrow$ HC		0.0014			0.1118	
		(.0140)			(.0875)	
Headquarter-plant linkages$_{ij}$			0.0002			0.0012***
			(.0002)			(.0002)
2nd Layer:						
Headquarter-plant linkages$_{ij}$ ×exports CP $\rightarrow$ HC			0.0003			0.0075
			(.0032)			(.0062)
Headquarter-plant linkages$_{ij}$ ×imports CP $\leftarrow$ HC			−0.0004			−0.0074
			(.0032)			(.0061)
3rd Layer:						
Headquarter-plant linkages$_{ij}$ ×exports CP $\rightarrow$ HC			−0.0002			−0.0341
			(.0154)			(.1055)
Headquarter-plant linkages$_{ij}$ ×imports CP $\leftarrow$ HC			0.0005			0.0357
			(.0154)			(.1055)
Controls:						
ln Distance$_{ij}$	−0.6974***	−0.6981***	−0.6980***	−0.4228***	−0.4383***	−0.4381***
	(.0233)	(.0233)	(.0233)	(.0239)	(.0234)	(.0234)
Intra-city trade	0.6563***	0.6259***	0.6138***	0.6974***	0.2625*	0.2393
	(.1802)	(.1838)	(.1835)	(.2061)	(.1514)	(.1518)
Intra-island trade	0.0332	0.0329	0.0337	−0.0333	−0.0316	−0.0264
	(.0719)	(.0719)	(.0719)	(.0761)	(.0746)	(.0745)
Fixed effects:						
Exporter (i):	✓	✓	✓	✓	✓	✓
Importer (j):	✓	✓	✓	✓	✓	✓
Summary statistics:						
Number of observations:	15,261	15,261	15,261	26,134	26,134	26,134
R^2	0.438	0.438	0.438	0.649	0.651	0.651

Notes: Robust standard errors; Industry-level regressions clustered at the city-pair level; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

concerns the distance elasticity, which at the aggregate level is twice as large as in gravity estimations, that are conducted at the more disaggregate industry level. Aggregating across industry-level trade flows transforms a *de facto* binary variation at the extensive margin (presence or absence of industry-level shipments) into a continuous variable (total value of trade).

For larger bilateral distances the total value of trade then declines at the extensive and at the intensive margin, which is why the trade reducing effect of distance in aggregate gravity estimations is overstated in comparison to a theory-consistent gravity estimation at the industry level.

In accordance with the underlying central place model by Fujita et al. (1999a), we have focused in our analysis on intra-national trade between cities in Japan, which proves to be an ideal testing ground due to its status of an isolated island economy. Although similar patterns with regard to the extensive goods margin have also been found for international trade (cf. Hummels and Klenow, 2005), it remains an open question whether these patterns can be equally well explained by Fujita et al.'s (1999a) central place model, which rests on the central assumption of free labour mobility and does allow for frictions, such as imperfect technology transmission across regions. We leave this question for future research.

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A Theory Appendix

A.1 Derivation of Eq. (1)

We adopt the preference specification from Fujita et al. (1999a):

$$U_j = \beta_A \ln C_{j,A} + \beta_k \sum_{k=1}^{K} \ln C_{j,k} \quad \text{with} \quad \beta_A + \sum_{k=1}^{K} \beta_k = 1, \tag{A.1}$$

and

$$C_{j,k} = \left[\int_{v_k \in \mathbb{V}_k} C_{j,k}(v_k)^{\frac{\sigma_k - 1}{\sigma_k}} dv_k \right]^{\frac{\sigma_k}{\sigma_k - 1}} \quad \text{with} \quad \sigma_k > 1 \ \forall \ k = 1, \ldots, K, \tag{A.2}$$

in which $\beta_A > 0$ denotes the constant expenditure share of a homogeneous agricultural good (indexed by subscript A), which is produced under perfect competition, whereas $\beta_k > 0 \ \forall \ k = 1, \ldots, K$ denote the constant expenditure shares of the $K > 1$ horizontally differentiated manufacturing goods (indexed by subscript $k = 1, \ldots, K$), which are produced under monopolistic competition. Aggregate consumption $C_{j,k}$ of the manufacturing good k (in destination j) thereby is defined as a CES aggregate over the set of horizontally differentiated varieties $\mathbb{V}_k$, which are bundled together according to a sector-specific elasticity of substitution $\sigma_k > 1$.

City j's demand for a sector k's varieties $v_{k,i} \in \mathbb{V}_k$ from origin city i can be derived as:

$$C_{ij,k}(v_{i,k}) = \left[\frac{P_{ij,k}(v_{i,k})}{P_{j,k}} \right]^{-\sigma_k} \frac{\beta_k X_{j,M}}{P_{j,k}}, \tag{A.3}$$

with

$$P_{j,k} \equiv \left[\sum_i \int_{v_{i,k} \in \mathbb{V}_{i,k}} P_{ij,k}(v_{i,k})^{1-\sigma_k} dv_{i,k} \right]^{\frac{1}{1-\sigma_k}} \tag{A.4}$$

as the sectoral price index in city j, $X_{j,M}$ as city j's aggregate expenditure on manufacturing products, and $P_{ij,k}(v_{i,k})$ as the price of sector k's variety $v_{i,k}$ shipped from origin city i to destination city j. Due to a constant price elasticities $\sigma_k > 1$, firms charge constant mark-ups over their marginal costs $w_i/\varphi_{i,k}$, which results in (symmetric) domestic prices:

$$P_{ii,k}(v_{i,k}) = P_{ii,k} = \frac{\sigma_k}{\sigma_k - 1}\frac{w_i}{\varphi_{i,k}}. \tag{A.5}$$

Combining $P_{ij,k} = \tau_{ij,k}P_{ii,k}$ with Eqs. (A.3), (A.4) and (A.5), it is possible to derive the value $X_{ij,k}$ of sector k's bilateral trade from origin city i to destination city j as:

$$X_{ij,k} = \pi_{ij,k}\beta_k X_{j,M} \quad \text{with} \quad \pi_{ij,k} \equiv \frac{\tau_{ij,k}^{1-\sigma_k}(w_i/\varphi_{i,k})^{1-\sigma_k}M_{i,k}}{\sum_l \tau_{lj,k}^{1-\sigma_k}(w_l/\varphi_{l,k})^{1-\sigma_k}M_{l,k}} \in [0,1] \tag{A.6}$$

denoting the share of destination city j's expenditure spend on sector k's goods produced in origin city i, and $M_{i,k} \geq 0$ as the number of sector k's firms/varieties in origin city i. Notably, it holds that $X_{j,k} = \sum_{i=1}^n X_{ij,k} = \beta_k X_{j,M}$, which implies $Y_k = \sum_{j=1}^n X_{j,k} = \beta_k \sum_{j=1}^n X_{j,M} = \beta_k X_M = \beta_k Y_M$ with Y_k as the value of total sectoral production and Y_M as the value of aggregate manufacturing production. Balanced trade implies $Y_{i,k} = \sum_{j=1}^n X_{ij,k}$ such that

$$Y_{i,k} = \sum_{j=1}^n X_{ij,k} = w_i^{1-\sigma_k}M_{i,k}\varphi_{i,k}^{\sigma_k-1}\sum_{j=1}^n \left(\frac{\tau_{ij,k}}{\Omega_{j,k}}\right)^{1-\sigma_k} X_{j,k} = w_i^{1-\sigma_k}M_{i,k}\varphi_{i,k}^{\sigma_k-1}\Phi_{i,k}^{1-\sigma_k}Y_k, \tag{A.7}$$

where $\Omega_{j,k}^{1-\sigma_k} \equiv \sum_{l=1}^n \tau_{lj,k}^{1-\sigma_k} w_l^{1-\sigma_k} M_{l,k}\varphi_{l,k}^{\sigma_k-1}$ and

$$\Phi_{i,k}^{1-\sigma_k} \equiv \sum_{j=1}^n \left(\frac{\tau_{ij,k}}{\Omega_{j,k}}\right)^{1-\sigma_k} \frac{X_{j,k}}{Y_k}. \tag{A.8}$$

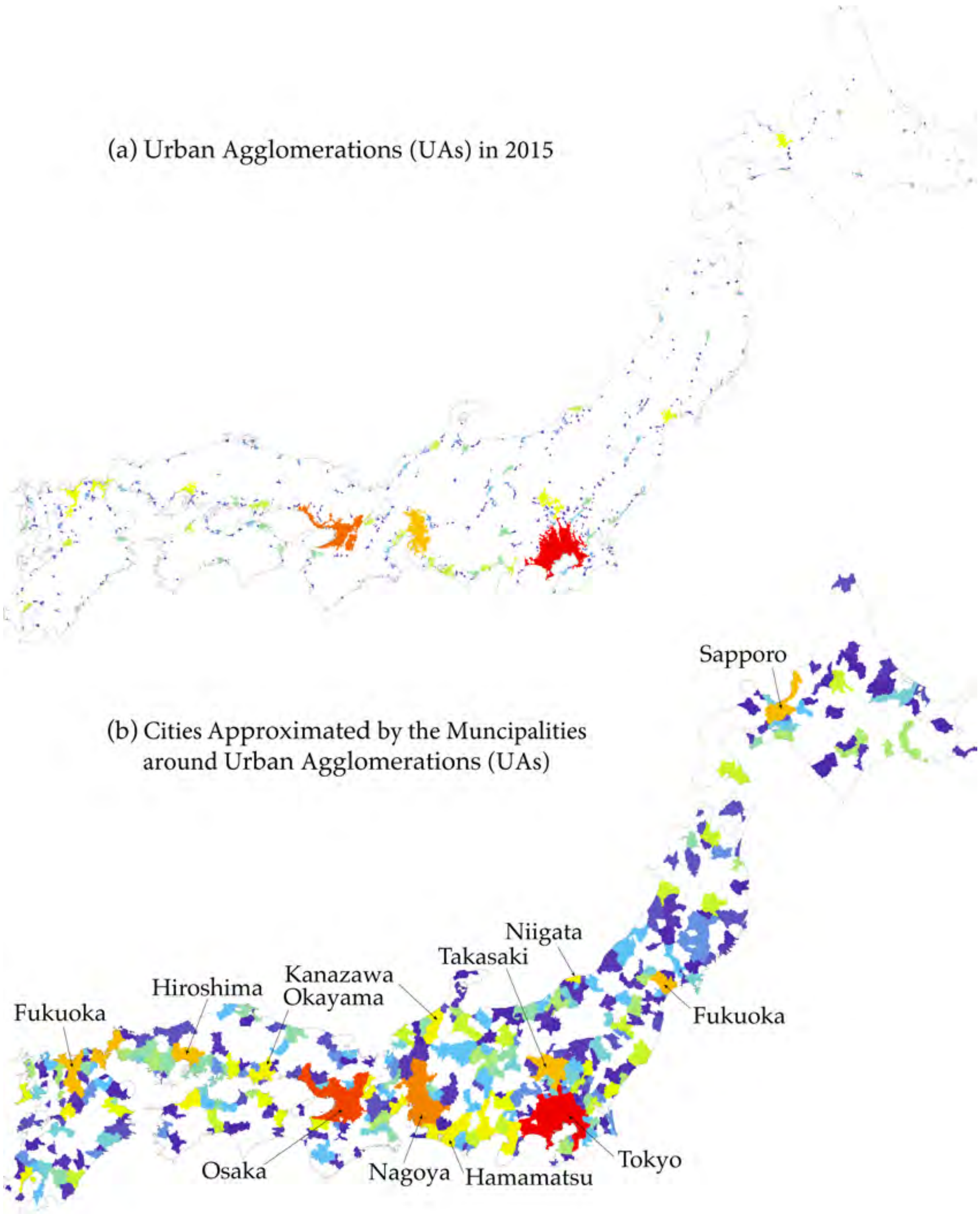
Using the fact that $w_i^{1-\sigma_k}M_{i,k}\varphi_{i,k}^{\sigma_k-1} = (Y_{i,k}/Y_k)/\Phi_{i,k}^{1-\sigma_k}$ we can solve for

$$\Omega_{j,k}^{1-\sigma_k} \equiv \sum_{i=1}^n \tau_{ij,k}^{1-\sigma_k} w_i^{1-\sigma_k} H_{i,k} = \sum_{i=1}^n \left(\frac{\tau_{ij,k}}{\Phi_{i,k}}\right)^{1-\sigma_k} \frac{Y_{i,k}}{Y_k}. \tag{A.9}$$

Finally, replacing $\sum_{l=1}^n \tau_{lj,k}^{1-\sigma_k} w_l^{1-\sigma_k} M_{l,k}\varphi_{l,k}^{\sigma_k-1} = \Omega_{j,k}^{1-\sigma_k}$ and $w_i^{1-\sigma_k}M_{i,k}\varphi_{i,k}^{\sigma_k-1} = (Y_{i,k}/Y_k)/\Phi_{i,k}^{1-\sigma_k}$ in Eq. (A.6) results in the system of structural gravity equations in Eq. (1). ■

B Data Appendix

Figure 7: *Identifying Cities based on Urban Agglomerations*



C Results Appendix

Figure 8: *Central Places and Hinterland Cities at the 2nd and 3rd Layer – 1995-2010*

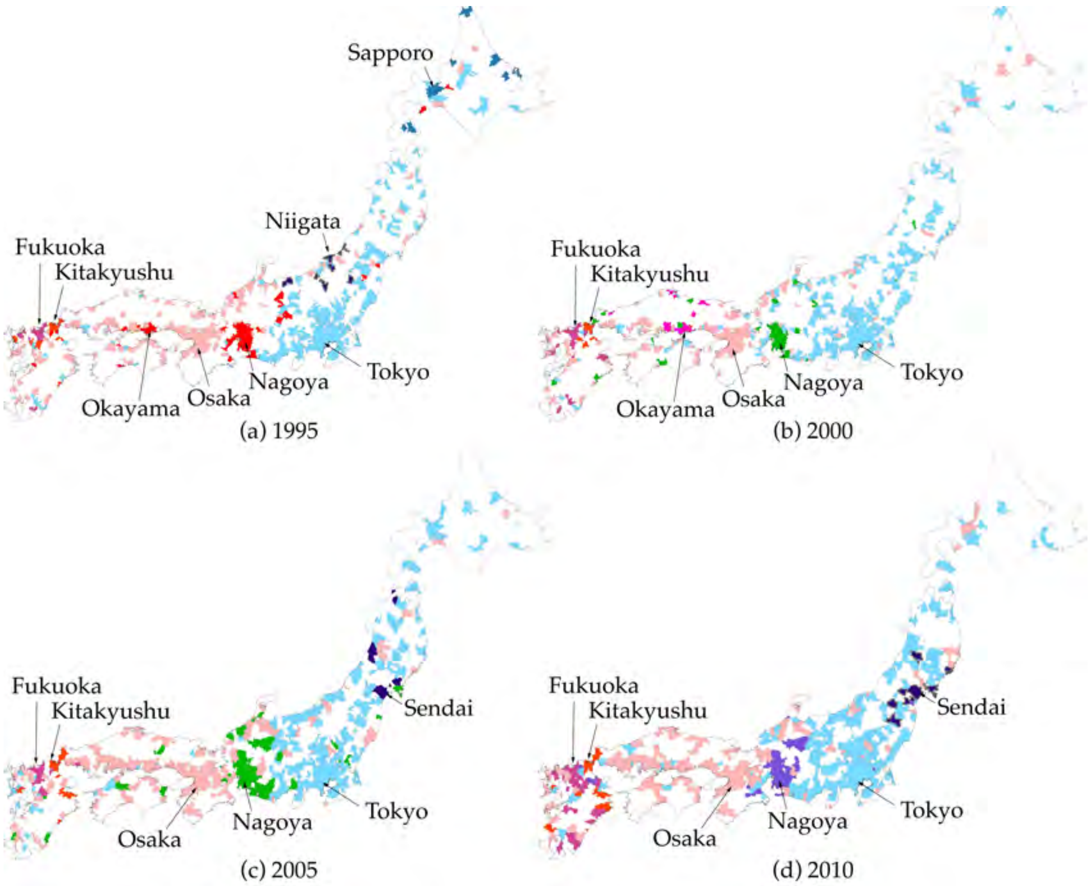
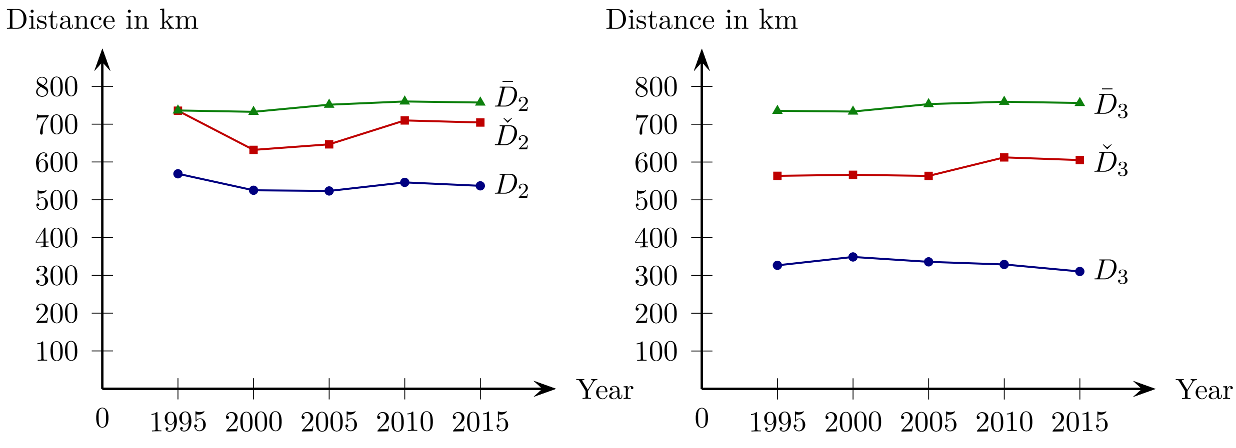


Figure 9: *Testing for the Spatial Clustering of Central Places and their Hinterlands*



(a) *2nd-layer Randomisation Test* **(b)** *3rd-layer Randomisation Test*

Table 12: *Centrality and Central Places in 2015*

			Rank		Central Place	
	City	**Prefecture**	**Centrality**	**Population**	**2^{nd} Layer**	**3^{rd} Layer**
(1)	Tokyo	Tokyo	1	1	Tokyo	Tokyo
(2)	Osaka	Osaka	2	2	Osaka	Osaka
(3)	Nagoya	Aichi	3	3	Osaka	Nagoya
(4)	Fukuoka	Fukuoka	4	4	Osaka	Fukuoka
(5)	Kitakyushu	Fukuoka	5	7	Tokyo	Kitakyushu
(6)	Sapporo	Hokkaido	6	5	Tokyo	Sapporo
(7)	Okayama	Okayama	7	10	Osaka	Okayama
(8)	Takasaki	Gunma	8	6	Tokyo	Takasaki
(9)	Oita	Oita	9	24	Tokyo	Kitakyushu
(10)	Matsuyama	Ehime	10	18	Osaka	Osaka
(11)	Toyohashi	Aichi	11	17	Osaka	Osaka
(12)	Koyama	Tochigi	12	41	Tokyo	Tokyo
(13)	Yokkaichi	Mie	13	16	Tokyo	Tokyo
(14)	Satsumasendai	Kagoshima	14	158	Osaka	Nagoya
(15)	Miyakonjo	Miyazaki	15	83	Osaka	Okayama
(16)	Nobeoka	Miyazaki	16	92	Osaka	Osaka
(17)	Hamamatsu	Shizuoka	17	11	Osaka	Osaka
(18)	Miyazaki	Miyazaki	18	36	Tokyo	Tokyo
(19)	Wakayama	Wakayama	19	22	Osaka	Osaka
(20)	Matsue	Shimane	20	66	Osaka	Osaka
(21)	Takaoka	Toyama	21	56	Tokyo	Tokyo
(22)	Niigata	Niigata	22	20	Tokyo	Tokyo
(23)	Isahaya	Nagasaki	23	102	Osaka	Fukuoka
(24)	Shunan	Yamaguchi	24	64	Osaka	Osaka
(25)	Komatsu	Ishikawa	25	74	Osaka	Osaka
(26)	Sano	Tochigi	26	101	Tokyo	Tokyo
(27)	Sendai	Miyagi	27	9	Tokyo	Tokyo
(28)	Niigata (Kita)	Niigata	28	188	Osaka	Osaka
(29)	Tanabe	Wakayama	29	144	Osaka	Nagoya
(30)	Kanoya	Kagoshima	30	140	Osaka	Osaka
(31)	Kagoshima	Kagoshima	31	21	Osaka	Nagoya
(32)	Kirishima	Kagoshima	32	106	Osaka	Osaka
(33)	Aira	Kagoshima	33	135	Osaka	Nagoya
(34)	Kobayashi	Miyazaki	34	244	Osaka	Okayama
(35)	Minamata	Kumamoto	35	267	Osaka	Osaka
(36)	Yashiro	Kumamoto	36	108	Tokyo	Kitakyushu
(37)	Uki	Kumamoto	37	197	Osaka	Okayama
(38)	Hyuga	Miyazaki	38	156	Osaka	Osaka
(39)	Nagasaki	Nagasaki	39	25	Osaka	Osaka
(40)	Ohmura	Nagasaki	40	105	Osaka	Fukuoka
(41)	Sasebo	Nagasaki	41	59	Osaka	Fukuoka
(42)	Imari	Saga	42	220	Osaka	Osaka
(43)	Shimabara	Nagasaki	43	212	Osaka	Osaka
(44)	Kumamoto	Kumamoto	44	12	Tokyo	Tokyo
(45)	Tamana	Kumamoto	45	206	Osaka	Fukuoka
(46)	Kikuchi	Kumamoto	46	272	Osaka	Nagoya
(47)	Ohmuta	Fukuoka	47	63	Osaka	Fukuoka
(48)	Yamaga	Kumamoto	48	246	Tokyo	Tokyo
(49)	Takeo	Saga	49	255	Tokyo	Kitakyushu
(50)	Saga	Saga	50	61	Osaka	Osaka

Table 13: *Centrality and Central Places in 2010*

			Rank		Central Place	
	City	**Prefecture**	**Centrality**	**Population**	**2nd Layer**	**3rd Layer**
(1)	Tokyo	Tokyo	1	1	Tokyo	Tokyo
(2)	Osaka	Osaka	2	2	Osaka	Osaka
(3)	Fukuoka	Fukuoka	3	4	Osaka	Fukuoka
(4)	Nagoya	Aichi	4	3	Tokyo	Nagoya
(5)	Sendai	Miyagi	5	9	Tokyo	Sendai
(6)	Kitakyushu	Fukuoka	6	7	Osaka	Kitakyushu
(7)	Takasaki	Saitama	7	6	Tokyo	Tokyo
(8)	Okayama	Okayama	8	10	Osaka	Osaka
(9)	Hachinohe	Aomori	9	49	Tokyo	Tokyo
(10)	Kagoshima	Kagoshima	10	20	Osaka	Osaka
(11)	Matsuyama	Ehime	11	16	Osaka	Osaka
(12)	Nobeoka	Miyazaki	12	86	Osaka	Fukuoka
(13)	Kanazawa	Ishikawa	13	14	Osaka	Osaka
(14)	Ube	Yamaguchi	14	50	Tokyo	Tokyo
(15)	Oita	Oita	15	25	Osaka	Kitakyushu
(16)	Kanoya	Kagoshima	16	134	Osaka	Fukuoka
(17)	Kirishima	Kagoshima	17	100	Tokyo	Tokyo
(18)	Satsumasendai	Kagoshima	18	153	Osaka	Kitakyushu
(19)	Kobayashi	Miyazaki	19	235	Osaka	Osaka
(20)	Nichinan	Miyazaki	20	206	Osaka	Fukuoka
(21)	Miyakonjo	Miyazaki	21	79	Osaka	Fukuoka
(22)	Miyazaki	Miyazaki	22	37	Osaka	Osaka
(23)	Izumi	Kagoshima	23	245	Osaka	Osaka
(24)	Minamata	Kumamoto	24	258	Osaka	Osaka
(25)	Amakusa	Kumamoto	25	207	Osaka	Osaka
(26)	Yashiro	Kumamoto	26	98	Osaka	Fukuoka
(27)	Takanabe	Miyazaki	27	256	Osaka	Kitakyushu
(28)	Hyuga	Miyazaki	28	149	Osaka	Fukuoka
(29)	Nagasaki	Nagasaki	29	24	Osaka	Osaka
(30)	Ohmura	Nagasaki	30	99	Osaka	Kitakyushu
(31)	Sasebo	Nagasaki	31	56	Osaka	Osaka
(32)	Imari	Saga	32	222	Osaka	Fukuoka
(33)	Shimabara	Nagasaki	33	203	Osaka	Osaka
(34)	Kumamoto	Kumamoto	34	12	Tokyo	Tokyo
(35)	Isahaya	Nagasaki	35	96	Tokyo	Tokyo
(36)	Kikuchi	Kumamoto	36	260	Osaka	Kitakyushu
(37)	Ohmuta	Fukuoka	37	57	Osaka	Fukuoka
(38)	Yamaga	Kumamoto	38	233	Osaka	Osaka
(39)	Takeo	Saga	39	252	Osaka	Fukuoka
(40)	Saga	Saga	40	59	Osaka	Osaka
(41)	Hita	Oita	41	154	Osaka	Fukuoka
(42)	Saiki	Oita	42	192	Osaka	Kitakyushu
(43)	Beppu	Oita	43	72	Tokyo	Tokyo
(44)	Karatsu	Saga	44	125	Osaka	Osaka
(45)	Asakura	Fukuoka	45	212	Osaka	Fukuoka
(46)	Iizuka	Fukuoka	46	70	Tokyo	Tokyo
(47)	Tagawa	Fukuoka	47	107	Osaka	Kitakyushu
(48)	Nakatsu	Oita	48	122	Tokyo	Nagoya
(49)	Shimonoseki	Yamaguchi	49	163	Osaka	Osaka
(50)	Kochi	Kochi	50	36	Osaka	Osaka

Table 14: *Centrality and Central Places in 2005*

	City	Prefecture	Rank Centrality	Rank Population	Central Place 2nd Layer	Central Place 3rd Layer
(1)	Tokyo	Tokyo	1	1	Tokyo	Tokyo
(2)	Osaka	Osaka	2	2	Osaka	Osaka
(3)	Nagoya	Aichi	3	3	Nagoya	Nagoya
(4)	Fukuoka	Fukuoka	4	4	Osaka	Fukuoka
(5)	Kitakyushu	Fukuoka	5	6	Osaka	Kitakyushu
(6)	Yokkaichi	Mie	6	13	Osaka	Osaka
(7)	Sapporo	Hokkaido	7	5	Tokyo	Tokyo
(8)	Sakade	Kagawa	8	55	Osaka	Osaka
(9)	Sendai	Miyagi	9	9	Tokyo	Sendai
(10)	Kumagaya	Saitama	10	14	Tokyo	Tokyo
(11)	Fukuyama	Hiroshima	11	32	Osaka	Osaka
(12)	Kumamoto	Kumamoto	12	15	Osaka	Osaka
(13)	Toyama	Toyama	13	40	Osaka	Osaka
(14)	Niigata	Niigata	14	17	Tokyo	Tokyo
(15)	Sanjo	Niigata	15	89	Osaka	Osaka
(16)	Takasaki	Gunma	16	11	Tokyo	Tokyo
(17)	Yamagata	Yamagata	17	49	Tokyo	Tokyo
(18)	Nobeoka	Miyazaki	18	87	Osaka	Osaka
(19)	Ohmuta	Fukuoka	19	59	Tokyo	Tokyo
(20)	Kure	Hiroshima	20	64	Osaka	Osaka
(21)	Toyohashi	Aichi	21	21	Nagoya	Nagoya
(22)	Kanoya	Kagoshima	22	138	Tokyo	Tokyo
(23)	Kagoshima	Kagoshima	23	22	Osaka	Osaka
(24)	Kirishima	Kagoshima	24	107	Tokyo	Tokyo
(25)	Satsumasendai	Kagoshima	25	146	Osaka	Osaka
(26)	Nichinan	Miyazaki	26	203	Osaka	Osaka
(27)	Miyakonjo	Miyazaki	27	86	Osaka	Osaka
(28)	Miyazaki	Miyazaki	28	41	Nagoya	Nagoya
(29)	Minamata	Kumamoto	29	259	Osaka	Osaka
(30)	Amakusa	Kumamoto	30	208	Tokyo	Tokyo
(31)	Yashiro	Kumamoto	31	102	Tokyo	Tokyo
(32)	Uki	Kumamoto	32	198	Osaka	Osaka
(33)	Hyuga	Miyazaki	33	143	Osaka	Kitakyushu
(34)	Nagasaki	Nagasaki	34	25	Tokyo	Tokyo
(35)	Ohmura	Nagasaki	35	109	Tokyo	Tokyo
(36)	Sasebo	Nagasaki	36	58	Osaka	Osaka
(37)	Imari	Saga	37	226	Tokyo	Tokyo
(38)	Isahaya	Nagasaki	38	98	Osaka	Kitakyushu
(39)	Tamana	Kumamoto	39	235	Osaka	Osaka
(40)	Kikuchi	Kumamoto	40	267	Osaka	Fukuoka
(41)	Yamaga	Kumamoto	41	240	Osaka	Fukuoka
(42)	Takeo	Saga	42	266	Osaka	Osaka
(43)	Saga	Saga	43	51	Osaka	Osaka
(44)	Yanagawa	Fukuoka	44	159	Osaka	Fukuoka
(45)	Hita	Oita	45	148	Osaka	Osaka
(46)	Oita	Oita	46	28	Osaka	Kitakyushu
(47)	Uwajima	Ehime	47	152	Osaka	Osaka
(48)	Karatsu	Saga	48	145	Osaka	Osaka
(49)	Asakura	Fukuoka	49	223	Osaka	Osaka
(50)	Tagawa	Fukuoka	50	100	Osaka	Fukuoka

Table 15: *Centrality and Central Places in 2000*

			Rank		Central Place	
	City	**Prefecture**	**Centrality**	**Population**	**2nd Layer**	**3rd Layer**
(1)	Tokyo	Tokyo	1	1	Tokyo	Tokyo
(2)	Osaka	Osaka	2	2	Osaka	Osaka
(3)	Nagoya	Aichi	3	3	Nagoya	Nagoya
(4)	Fukuoka	Fukuoka	4	4	Osaka	Fukuoka
(5)	Okayama	Okayama	5	9	Osaka	Okayama
(6)	Kitakyushu	Fukuoka	6	8	Osaka	Kitakyushu
(7)	Hiroshima	Hiroshima	7	6	Osaka	Osaka
(8)	Sakade	Kagawa	8	56	Osaka	Osaka
(9)	Mishima	Shizuoka	9	11	Tokyo	Tokyo
(10)	Rittou	Shiga	10	20	Osaka	Osaka
(11)	Sapporo	Hokkaido	11	5	Tokyo	Tokyo
(12)	Kochi	Kochi	12	30	Nagoya	Nagoya
(13)	Wakayama	Wakayama	13	23	Osaka	Osaka
(14)	Ohmuta	Kumamoto	14	53	Osaka	Osaka
(15)	Kure	Hiroshima	15	59	Osaka	Osaka
(16)	Oita	Oita	16	26	Osaka	Fukuoka
(17)	Bofu	Yamaguchi	17	92	Osaka	Osaka
(18)	Tokushima	Tokushima	18	29	Osaka	Osaka
(19)	Iwaki	Fukushima	19	44	Tokyo	Tokyo
(20)	Shimonoseki	Yamaguchi	20	43	Nagoya	Nagoya
(21)	Kumamoto	Kumamoto	21	14	Osaka	Osaka
(22)	Hita	Oita	22	157	Osaka	Kitakyushu
(23)	Matsuyama	Ehime	23	18	Osaka	Osaka
(24)	Shunan	Yamaguchi	24	63	Tokyo	Tokyo
(25)	Minakuchi	Shiga	25	199	Tokyo	Tokyo
(26)	Hachinohe	Aomori	26	50	Tokyo	Tokyo
(27)	Asahikawa	Hokkaido	27	32	Osaka	Osaka
(28)	Kagoshima	Kagoshima	28	19	Osaka	Osaka
(29)	Minamata	Kumamoto	29	248	Tokyo	Tokyo
(30)	Kanoya	Kagoshima	30	142	Osaka	Fukuoka
(31)	Kirishima	Kagoshima	31	98	Tokyo	Tokyo
(32)	Satsumasendai	Kagoshima	32	152	Osaka	Osaka
(33)	Nichinan	Miyazaki	33	250	Tokyo	Tokyo
(34)	Miyakonjo	Miyazaki	34	84	Osaka	Fukuoka
(35)	Miyazaki	Miyazaki	35	39	Osaka	Osaka
(36)	Izumi	Kagoshima	36	261	Nagoya	Nagoya
(37)	Yashiro	Kumamoto	37	96	Osaka	Osaka
(38)	Uki	Kumamoto	38	161	Osaka	Osaka
(39)	Hyuga	Miyazaki	39	139	Osaka	Osaka
(40)	Nobeoka	Miyazaki	40	82	Nagoya	Nagoya
(41)	Nagasaki	Nagasaki	41	24	Osaka	Osaka
(42)	Ohmura	Nagasaki	42	105	Osaka	Osaka
(43)	Sasebo	Nagasaki	43	48	Osaka	Osaka
(44)	Imari	Saga	44	224	Osaka	Osaka
(45)	Isahaya	Nagasaki	45	72	Osaka	Fukuoka
(46)	Tamana	Kumamoto	46	233	Osaka	Osaka
(47)	Yamaga	Kumamoto	47	249	Osaka	Osaka
(48)	Kashima	Saga	48	238	Osaka	Fukuoka
(49)	Saga	Saga	49	62	Osaka	Osaka
(50)	Yanagawa	Fukuoka	50	88	Osaka	Osaka

Table 16: *Centrality and Central Places in 1995*

			Rank		Central Place	
	City	**Prefecture**	**Centrality**	**Population**	**2nd Layer**	**3rd Layer**
(1)	Tokyo	Tokyo	1	1	Tokyo	Tokyo
(2)	Osaka	Osaka	2	2	Osaka	Osaka
(3)	Nagoya	Aichi	3	3	Osaka	Nagoya
(4)	Kitakyushu	Fukuoka	4	6	Osaka	Kitakyushu
(5)	Niigata	Niigata	5	16	Tokyo	Niigata
(6)	Fukuoka	Fukuoka	6	4	Osaka	Fukuoka
(7)	Oita	Oita	7	28	Osaka	Osaka
(8)	Sapporo	Hokkaido	8	5	Osaka	Sapporo
(9)	Okayama	Okayama	9	9	Osaka	Nagoya
(10)	Hiroshima	Hiroshima	10	7	Osaka	Osaka
(11)	Sakade	Kagawa	11	56	Osaka	Osaka
(12)	Kurume	Fukuoka	12	35	Osaka	Kitakyushu
(13)	Shunan	Yamaguchi	13	61	Tokyo	Tokyo
(14)	Miyakonjo	Miyazaki	14	85	Tokyo	Tokyo
(15)	Sendai	Miyagi	15	8	Tokyo	Tokyo
(16)	Noboribetsu	Hokkaido	16	68	Osaka	Nagoya
(17)	Fukuyama	Hiroshima	17	29	Osaka	Osaka
(18)	Toyama	Toyama	18	37	Osaka	Osaka
(19)	Ube	Yamaguchi	19	53	Osaka	Osaka
(20)	Kirishima	Kagoshima	20	107	Osaka	Osaka
(21)	Kochi	Kochi	21	31	Osaka	Osaka
(22)	Arida	Wakayama	22	228	Osaka	Osaka
(23)	Wakayama	Wakayama	23	23	Osaka	Osaka
(24)	Matsumoto	Nagano	24	49	Tokyo	Tokyo
(25)	Ishimaki	Miyagi	25	78	Tokyo	Tokyo
(26)	Satsumasendai	Kagoshima	26	156	Osaka	Osaka
(27)	Kagoshima	Kagoshima	27	19	Osaka	Osaka
(28)	Kobayashi	Miyazaki	28	257	Osaka	Osaka
(29)	Nichinan	Miyazaki	29	285	Tokyo	Tokyo
(30)	Miyazaki	Miyazaki	30	38	Osaka	Osaka
(31)	Izumi	Kagoshima	31	290	Osaka	Osaka
(32)	Yashiro	Kumamoto	32	98	Osaka	Osaka
(33)	Uki	Kumamoto	33	174	Osaka	Nagoya
(34)	Hyuga	Miyazaki	34	141	Osaka	Kitakyushu
(35)	Nobeoka	Miyazaki	35	82	Tokyo	Tokyo
(36)	Nagasaki	Nagasaki	36	24	Osaka	Osaka
(37)	Ohmura	Nagasaki	37	119	Osaka	Osaka
(38)	Sasebo	Nagasaki	38	48	Osaka	Kitakyushu
(39)	Imari	Saga	39	240	Osaka	Fukuoka
(40)	Kumamoto	Kumamoto	40	14	Osaka	Osaka
(41)	Isahaya	Nagasaki	41	73	Osaka	Osaka
(42)	Tamana	Kumamoto	42	254	Osaka	Osaka
(43)	Kikuchi	Kumamoto	43	311	Tokyo	Tokyo
(44)	Ohmuta	Kumamoto	44	55	Osaka	Osaka
(45)	Yamaga	Kumamoto	45	271	Osaka	Osaka
(46)	Kashima	Saga	46	251	Osaka	Osaka
(47)	Setaka	Fukuoka	47	300	Osaka	Nagoya
(48)	Takeo	Saga	48	296	Osaka	Osaka
(49)	Saga	Saga	49	60	Osaka	Kitakyushu
(50)	Yanagawa	Fukuoka	50	80	Tokyo	Tokyo

Table 17: *Robustness Checks – Industry-level Inter-city Trade*

Dependent variable: Industry-level exports from city i to city j										
Year:	**2015**	**2010**	**2005**	**2000**	**1995**	**2015**	**2010**	**2005**	**2000**	**1995**
Model:	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**	**OLS-FE**
Specification:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
2^{nd} Layer:										
Exports CP $\rightarrow$ HC	0.3433^{**}	0.1447	0.1312	0.2014	0.4015^{***}	0.3223^{**}	0.2499	0.1885	0.1605	0.3713^{**}
	(.1656)	(.1516)	(.1349)	(.1490)	(.1558)	(.1492)	(.1565)	(.1248)	(.1337)	(.1473)
Imports CP $\leftarrow$ HC	0.3169	0.1323	0.02669	0.3662^{*}	0.2193	0.3003	0.0958	0.0670	0.2895	0.1801
	(.2056)	(.2054)	(.1839)	(.1963)	(.1929)	(.1962)	(.1881)	(.1737)	(.1846)	(.1806)
3^{rd} Layer:										
Exports CP $\rightarrow$ HC	0.4155^{**}	-0.02187	0.5405^{*}	0.2559	0.3391^{**}	0.3933^{**}	-0.0565	0.4881	0.4081^{*}	0.3320^{**}
	(.1952)	(.1917)	(.3217)	(.2015)	(.1695)	(.1813)	(.1747)	(.3001)	(.2112)	(.1533)
Imports CP $\leftarrow$ HC	0.0433	0.4705	-0.2642	-0.2043	-0.0423	0.0343	0.4859^{*}	-0.2563	-0.2850	-0.0474
	(.2324)	(.3013)	(.2990)	(.2233)	(.2157)	(.2155)	(.2755)	(.3347)	(.2317)	(.1966)
Controls:										
ln Distance$_{ij}$	-0.4228^{***}	-0.4201^{***}	-0.3874^{***}	-0.3864^{***}	-0.3883^{***}	-0.2530^{***}	-0.2273^{***}	-0.2082^{***}	-0.1902^{***}	-0.2166^{***}
	(.0239)	(.0239)	(.0231)	(.0235)	(.0198)	(.0222)	(.0230)	(.0213)	(.0217)	(.0182)
Intra-city trade	0.6974^{***}	0.6671^{***}	0.3959	0.7085^{***}	0.8458^{***}	0.8099^{***}	0.8373^{***}	0.6082^{***}	0.9712^{***}	1.0360^{***}
	(.2061)	(.2119)	(.2492)	(.2547)	(.2181)	(.2057)	(.2069)	(.2326)	(.2384)	(.2081)
Intra-island trade	-0.0333	0.0563	-0.0454	0.0704	0.0618	-0.0600	0.0287	-0.0455	0.0624	0.0173
	(.0761)	(.0720)	(.0613)	(.0645)	(.0521)	(.0651)	(.0632)	(.0521)	(.0571)	(.0463)
Additional controls:										
ln Transportation costs$_{ijk}$:	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓
Fixed effects:										
Exporter×industry ($i \times k$):	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Importer×industry ($j \times k$):	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Summary statistics:										
Number of observations:	26,134	29,066	33,591	32,026	47,648	26,134	29,066	33,591	32,026	47,648
R^2	0.649	0.632	0.621	0.620	0.599	0.734	0.723	0.716	0.717	0.697

Notes: Robust standard errors are clustered at the city-pair level; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 18: *Inter-City Trade Decomposition for 1995-2015 (Double Demeaning Approach)*

Explanatory Variable:	**Exports 3^{rd} Layer Central Place $\rightarrow$ Hinterland**									
Dependent Variable:	$\ln X_{ij}$	$\ln S_{ij}$	$\ln K_{ij}$	$\ln \bar{S}_{ij}$	$\ln \bar{R}_{ij}$	$\ln \bar{P}_{ij}$	$\ln \bar{C}_{ij}$	N	$\frac{\beta^{K}_{\text{EXP\_3}}}{\beta^{X}_{\text{EXP\_3}}}$	$\frac{\beta^{\bar{S}}_{\text{EXP\_3}}}{\beta^{X}_{\text{EXP\_3}}}$
Column:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Year:										
2015	1.4339^{***}	0.8173^{***}	0.7144^{***}	0.1030^{***}	0.6166^{***}	-0.3926^{***}	1.0093^{***}	15,261	49.82%	7.18%
	(.2526)	(.0909)	(.0770)	(.0311)	(.2109)	(.1197)	(.2247)			
	[.08]	[.14]	[.13]	[.03]	[.05]	[.05]	[.10]			
2010	1.9919^{***}	1.0398^{***}	0.8958^{***}	0.1440^{***}	0.9521^{***}	-0.6692^{***}	1.6213^{***}	16,184	44.97%	7.23%
	(.2030)	(.0816)	(.0597)	(.0395)	(.1654)	(.1342)	(.1734)			
	[.08]	[.13]	[.13]	[.03]	[.05]	[.06]	[.09]			
2005	2.1729^{***}	0.8616^{***}	0.8220^{***}	0.0396	1.3113^{***}	-0.4740	1.7853^{***}	18,098	37.82%	1.82%
	(.5038)	(.1414)	(.1204)	(.0319)	(.4006)	(.2884)	(.3415)			
	[.06]	[.10]	[.10]	[.02]	[.03]	[.04]	[.07]			
2000	1.6638^{***}	0.9376^{***}	0.8605^{***}	0.0770^{**}	0.7263^{**}	-0.9031^{***}	1.6294^{***}	17,146	51.72%	4.74%
	(.4033)	(.1477)	(.1275)	(.0369)	(.2861)	(.2308)	(.2729)			
	[.06]	[.10]	[.10]	[.02]	[.04]	[.04]	[.08]			
1995	1.2994^{***}	0.7400^{***}	0.6345^{***}	0.1056^{**}	0.5594^{***}	-0.6297^{***}	1.1891^{***}	22,138	48.83%	8.88%
	(.2194)	(.1194)	(.0858)	(.0449)	(.1533)	(.1244)	(.1647)			
	[.07]	[.11]	[.11]	[.02]	[.04]	[.05]	[.08]			
Double Demaning:										
Demeaned by:	$\frac{1}{N}\sum_i X_{ij}$	$\frac{1}{N}\sum_i S_{ij}$	$\frac{1}{N}\sum_i K_{ij}$	$\frac{1}{N}\sum_i \bar{S}_{ij}$	$\frac{1}{N}\sum_i \bar{R}_{ij}$	$\frac{1}{N}\sum_i \bar{P}_{ij}$	$\frac{1}{N}\sum_i \bar{C}_{ij}$			
Demeaned by:	$\frac{1}{N}\sum_j X_{ij}$	$\frac{1}{N}\sum_j S_{ij}$	$\frac{1}{N}\sum_{ij} K_{ij}$	$\frac{1}{N}\sum_{ij} \bar{S}_{ij}$	$\frac{1}{N}\sum_j \bar{R}_{ij}$	$\frac{1}{N}\sum_j \bar{P}_{ij}$	$\frac{1}{N}\sum_j \bar{C}_{ij}$			

Notes: R^2 of the underlying regression reported in squared brackets. Robust standard errors in parenthesis; significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.