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On the revealed comparative advantages of Dutch cities

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Abstract

Davis and Dingel explain the distributions of skills, occupations, and sectors across cities. Their model predicts that larger cities will be relatively skill-abundant and specialize in skill-intensive activities. This relates the model to factor-driven comparative advantages. They also develop an elasticity test and pairwise comparison test for the spatial distributional implications of the model. What is not analyzed, however, is the associated structure of trade flows. This next step—the analysis of the structure of trade—is the main contribution of our article. We combine micro-economic data to analyze how the sorting process of factors of production across cities determines the *revealed* comparative advantage (RCA) distributions of Dutch cities. We find that (i) the sorting of factors of production across cities is consistent with Davis and Dingel, (ii) RCA patterns differ significantly across locations, (iii) RCA differences can be explained by the interaction of local skill-abundance and sector skill-intensity (in line with the factor abundance model), and (iv) the RCA analysis relative to the Netherlands mostly, but not always, coincides with that relative to the world.

KEYWORDS
cities, comparative advantage, location characteristics

JEL CLASSIFICATION
F11, F15, R12

1 | INTRODUCTION

Davis and Dingel (2020) combine insights from trade theory and urban economics to explain the sorting of skills, occupations, and sectors across cities. What is not part of their analysis is the connection of the resulting structure to trade flows. In this article, we take this next step and analyze the trade patterns across cities that are the result of this sorting process. In general, we find that the sorting process results in factor-driven comparative advantages.

The uneven spatial distribution of location fundamentals, factors of production, and sectors is an important characteristic of economic activity addressed by Davis and Dingel (2020). In classical trade models countries are modeled as dimensionless points, implicitly assuming that the internal geography of countries can be ignored. This strong assumption obscures important aspects of trade flows, such as the effects of trade on regional development, income inequality, or the local impact of trade on regions within countries (see Autor et al., 2013; Donaldson, 2018; Hirte et al., 2020). In contrast, within the field of urban economics, the uneven spatial distribution of economic activity is central in the analyses, but trade flows are not. Trade flows in urban economics models often illustrate the importance of transport costs but the structure of trade is not central in the analysis (see Redding & Turner, 2015 for a survey). The recent literature, however, stresses the interaction between trade and the spatial distribution of economic activity (see Redding, 2021, for a survey).

The literature on trade models that include internal geography is rapidly growing. Coşar and Fajgelbaum (2016) show that in a Ricardian setting the internal trade costs split locations into two types: export oriented international gates and more distant locations that do not trade. As a result, the sensitivity of locations to trade shocks can differ considerably with the largest effects near borders (see also Brülhart et al., 2018). Courant and Deardorff (1992, 1993) show that in a Heckscher–Ohlin setting of factor abundance, the spatial *uneven* distribution of production factors within a country can affect the national structure of trade in complex ways (see Brakman et al., 2022; Brakman & Van Marrewijk, 2013; Debaere, 2004; Debaere & Demiroglu, 2003 for empirical evidence). Models incorporating production externalities in certain locations combined with trade costs can explain the export orientation of certain sectors in specific locations (Rossi-Hansberg, 2005). This interaction of agglomeration economies and trade costs is crucial in New Economic Geography models and can determine trade patterns between core- and peripheral regions (Redding & Rossi-Hansberg, 2017). The welfare consequences can be substantial. Ramondo et al. (2016) points out that the gains from trade are reduced in large countries because of internal trade frictions between regions. The overall conclusion of this growing body of literature is that the internal geography of countries should be taken on board in trade analyses.

Davis and Dingel (2020) predict that larger cities will be relatively skill-abundant and home to skill-intensive activities. By implication, their model can explain, within a system of internally structured cities, factor-driven comparative advantages at the urban level. They also develop two tests that evaluate whether the sorting of factors of production and sectors is consistent with the model: an elasticity test and a pairwise comparison test. For the United States, the sorting process is consistent with their model. For other countries, such as Brazil, China, and India, similar results are found (Brakman et al., 2021; Dingel et al., 2021). We take the next empirical step, not yet taken by this literature, to establish and compare the distributions of *revealed* comparative advantage (RCA) across cities. This next step—the analysis of the structure of trade for cities—is our main contribution.

The central question that we answer is: can distributions of comparative advantage across cities be explained by the sorting of factors of production and sectors? In addition, we establish the contribution of locational fundamentals to the distribution of comparative advantages. In contrast to most contributions in the literature—that have a more restrictive regional perspective—we focus on 22 cities that cover most of Dutch exports.[1] An exception is Díaz-Lanchas et al. (2018) who also look at city exports. They, however, do not relate their analysis to locational fundamentals, but stress the complexity of products. We analyze the complete distribution of comparative advantage of 83 sectors in each city. This enables us to differentiate between strong and weak sectors in a city and to compare these distributions across cities. By doing so, we can identify—for each city—strong and weak sectors relative to The Netherlands as a nation, as well as relative to the world. We do this in four steps.

First, we use the elasticity test and the pairwise comparison test to show that the sorting of skills, and sectors across cities confirms that larger cities are relatively skill-abundant and specialize in skill-intensive activities. This is consistent with factor-endowment driven comparative advantage.

Second, using local micro data on firms and workers, we establish city distributions of RCA for The Netherlands using the Balassa index based on export value (BI, if abbreviated). For each city we have a distribution of BIs for all sectors that are active in that city and identify sectors with a comparative (dis)advantage relative to the Netherlands and relative to the world. Using the harmonic weighted mass index as a test statistic, we establish that the distributions of the Balassa indices differ significantly between cities. This illustrates that the spatial distribution of economic activity across cities is important for determining comparative advantages.

Third, we link the differences in trade patterns to local circumstances. We focus on the interaction between factor abundance and factor intensity, where a city is *abundant* for a certain skill if it is *relatively* widely available in that city and a sector is *intensive* in a certain skill if it is intensively used in the production process in *relative* terms, see Section 5.1. We also include local characteristics, such as density or market access, to see if local fundamentals are also important for the city distributions of the BIs (see Coşar & Fajgelbaum, 2016; Donaldson, 2018; Rossi-Hansberg, 2005). We find that the interaction of skill-abundance and skill-intensity systematically explains local trade patterns, in line with the work of Davis and Dingel (2020). Local characteristics are also important, but to a lesser extent.

Fourth, we identify city-sector combinations that have a comparative advantage relative to both the Netherlands and the world as well as city-sectors that have a comparative advantage relative to the Netherlands but not relative to the world (and vice versa). A strong regional position of a sector does not always translate to a strong position internationally, while some national exports are so strong that even weak locations prove to be strong international players. For almost all weak sectors at the national level there is a Dutch city which is strong internationally. This implies that there are local strengths not visible at the national level, possibly in line with the empirical evidence of the heterogeneity literature inspired by the Melitz (2003) model.

This article is organized as follows. Section 2 introduces the dataset. We have micro-firm export data, factor endowments, and factor intensities for the period 2007–2017 for 22 Dutch cities (+4 regional areas) and 83 sectors. This enables us to calculate and explain local trade patterns for about 90% of total Dutch exports. Section 3 explains the procedure for calculating comparative advantages. Section 4 analyzes the distributions of comparative advantage for Dutch cities relative to the Netherlands; these distributions differ significantly across locations. Section 5 analyzes the interaction between sector skill-intensities and local factor abundance for explaining international trade flows. Section 6 analyzes the comparative advantages of Dutch cities relative to the world for manufacturing sectors and compares it with the findings of Section 4. Section 7 concludes.

2 | DATA

We construct a disaggregated data set of Dutch exports at the location- and sector level using administrative data. This enables us to calculate RCA, factor intensities and factor endowments for Dutch locations and sectors.

2.1 | Spatial units

Statistics Netherlands defines 22 *cities*, which consist of municipalities with city-status as well as surrounding municipalities that are determined to be economically dependent on the city.[2]

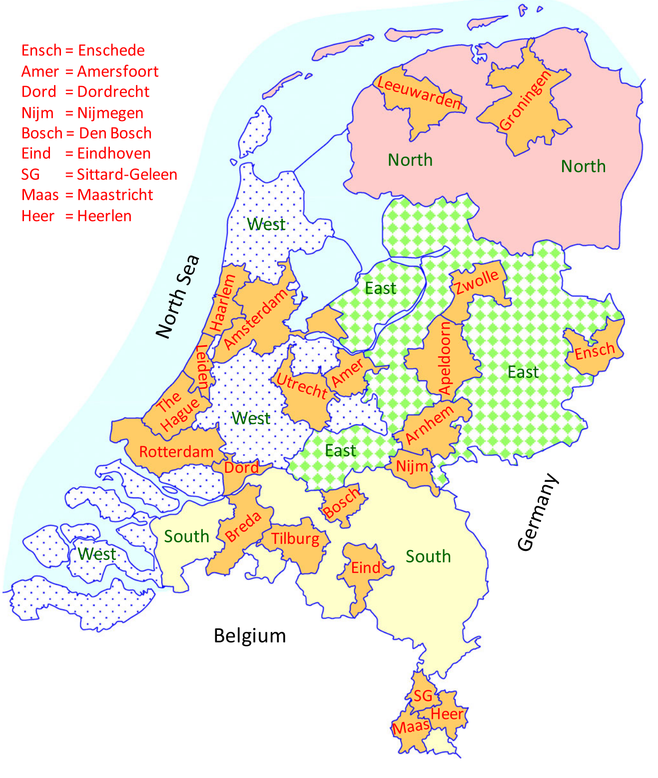

FIGURE 1 Dutch locations; 22 cities and 4 regions. *Source*: Constructed by the authors; based on CBS 2005, Grootstedelijke agglomeraties en stadsgewesten afgebakend. NB regions are only included for sensitivity analyses. NB for all the results presented below we also have results for city-regions; these are available upon request. In general, these results are similar to those presented in the main text for cities. [Colour figure can be viewed at wileyonlinelibrary.com]

To ensure complete coverage, municipalities that do not form part of a city are aggregated at the NUTS 1 regional level into four regions: North, South, West, and East. Our analysis focuses on the 22 cities, but similar results hold if we include the regions as well (available upon request). Figure 1 provides an overview of the location of cities within the Netherlands, see Table A2 in the Appendix for an overview of their size in terms of (working) population. The main cities are in the western part of the country, close to the sea. This includes the largest cities: Amsterdam, Rotterdam, and The Hague, each with a population of more than one million people. Taken together, the 22 cities account for about 56% of the Dutch population.

2.2 | Firms

Throughout this study, export is measured in terms of annual export-revenue generated by Dutch exporting firms. Our initial data set draws on a complete registry of anonymized Dutch firm level value-added tax (VAT) statements for the period 2007–2017, and as such covers all export revenues. We restrict our final dataset to exporting firms.[3] Firms are excluded from the final sample if the reporting is incomplete or illogical, such as zero or negative revenue or for missing location-data. Some location information is not available for firm privacy reasons.

Summary information on exporting firms is provided in Table 1. Our final data set comprises 33,000–42,000 exporting firms per year. This is around 3.5% of all Dutch firms, accounting for about 80%–90% of all Dutch exports in any given year. Exports are highly concentrated within these firms, with 90% of the export-revenue generated by the top 10% of firms (the 90th percentile in Table 1), which is in line with previous studies (Bernard et al., 2012). In 2017 the average firm employed 34 workers (measured in full time equivalents) and 73% of the workers are employed by the top 10% of firms in terms of size. The average firm has about 1.7 local branches, so most firms are small and only active in one location. From 2007 to 2017, the average firm size has been increasing (from 29 to 34 workers), while the share of workers in the largest firms has increased as well (from 67 to 73%). The share of exports of the largest firms has remained constant (about 90%).

TABLE 1 Overview of exporting firm size, 2007–2017

Year	Exporting firms (×1000)	# local branches (mean)	# firm employees (mean)	Share employees 90th percentile (%)	Share exports 90th percentile (%)
2007	33	1.5	29	67	90
2008	33	1.5	31	68	90
2009	33	1.5	31	68	90
2010	34	1.7	33	69	89
2011	36	1.7	32	68	89
2012	37	1.7	32	69	89
2013	37	1.7	31	70	89
2014	38	1.7	34	72	89
2015	40	1.7	33	72	88
2016	41	1.7	33	72	89
2017	42	1.7	34	73	89

2.3 | Sectors and exports

Exports for cities and sectors are constructed using registry data from Statistics Netherlands for the period 2007–2017.[4] Firm level export data distinguish between two destinations: the EU and non-EU. Because export data are reported at the firm level, we match (national) firm exports with cities in four steps.

First, we use the general business register (GBR) and its local counterpart (LGBR) to collect information on the sector classification and location (municipality) of all local branches for all Dutch firms, including self-employed workers. Each firm and branch are assigned a sector code according to the Dutch coding system (SBI 2008) of which the first two digits correspond to the international NACE rev. 2 classification.[5] By this definition, our data set contains a total of 83 two-digit sectors. It should be noted Statistics Netherlands may assign local branches a different sector than their parent firm if their main economic activities differ.[6]

Second, we match the branch location- and sector- data to the firm level VAT data.

Third, we allocate the annual export revenues of each firm to its local branches, using wages as weights.[7] Each branch b can be associated with a share of the total firm export revenue E_b equal to the percentage of wages earned in that specific branch. This is calculated on an annual basis as given in Equation (1), where E_b and E_F are the export revenues of a branch and its firm, w_b and w_F are the branch and firm wage sums, and $fb \in F$ is the set of branches belonging to the same firm as branch b.

$$E_b = E_F \frac{w_b}{\sum_{fb \in F} \left(w_{fb} \right)} = E_F \frac{w_b}{w_F}. \tag{1}$$

Wages are taken from a monthly registry of all jobs performed at each Dutch firm, which also contains information about the municipalities in which jobs are performed.[8] If a firm has multiple local branches within a municipality, we cannot allocate wages to a specific branch. We therefore aggregate firm branches at the municipal level. Aggregated branches are assigned to the same sector as the largest firm branch in the municipality.

Fourth, we aggregate the municipal data for all sectors within the 22 cities. Our data set thus contains export information for 22 cities and 83 two-digit sectors for a period of 10 years. In view of the relatively small spatial units of our study (cities within a country, rather than the country as a whole), our measure of RCA is volatile on an annual basis (Hinloopen & Van Marrewijk, 2001). To avoid excess volatility, we therefore analyze two longer time periods (2007–2012 and 2012–2017) and calculate the *average* BI of a sector for each sub-period. The first period includes the Great Recession, with profound consequences for global trade and most of the recovery. The second period (2012–2017) represents a more stable economic regime. Our discussion, therefore, focuses on the most recent second period, using the first period as a robustness check for our main conclusions. Graphs use the most recent year (2017) for illustration purposes. Figure 2, for example, shows that larger cities in terms of population also tend to have larger export flows (this explains 84% of the variance in exports), starting with Amsterdam, followed by Rotterdam and The Hague.

Our analysis uses gross export data and thus produces RCA results most often reported in the literature. Value added data are not available for cities and for most sectors tends to produce similar results. Brakman and Van Marrewijk (2017), for example, analyze gross export and value-added data for 40 countries and find the same strong and weak sectors in 78% of all cases. A further analysis of the source of comparative advantage is warranted for both types of data.

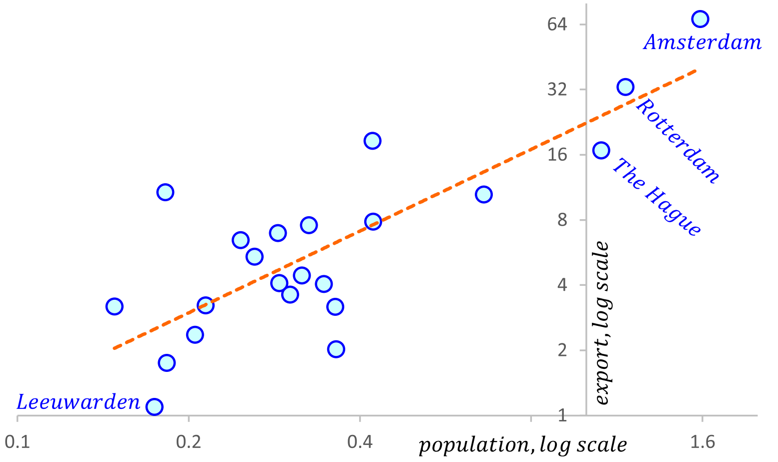

FIGURE 2 Population and exports of Dutch cities, 2017. *Source*: Author construction; population in million, exports in billion euro; both scales in logs; dashed line is regression with slope 1.04, it explains 69.1% of the variance; regions denoted by squares. [Colour figure can be viewed at wileyonlinelibrary.com]

2.4 | Skills, abundance, and intensity

Regarding factors of production, our analysis focuses on human capital in terms of skills from schooling for cities as well as sectors. We use annual registry data on the highest attained level of education for Dutch citizens to identify three skill levels for general schooling, namely high skilled, medium skilled, and low skilled (with subindices *high*, *med*, and *low*, respectively). In addition, we differentiate between technical and non-technical types of schooling using the same classification (identified by subindices *tec-high*, *tec-med*, and *tec-low*). The correlation between the types of skill-levels is shown in Table A5 in the Appendix. Note, that the regular skills classification shares add to one, while this is not the case for technical skill shares; we thus use the sub-index *tech* to refer to the sum of *low*, *medium*, and *high* technical skill.[9]

We analyze differences in human skills from two perspectives: From a cities perspective (we refer to this as the *abundance* of skills in a location), and from a sector perspective (we refer to this as the *intensity* of skills in a sector). Citizens are assigned to cities using their registered home addresses, and to sectors using their work locations from firm-level job data.[10] Our analysis in Section 6 focuses on the *interaction* between abundance and intensity for determining RCA, which is consistent with the Heckscher–Ohlin (factor abundance) trade model.[11]

Regarding skill abundance, Table 2a provides some information for 2017 for the top five and bottom five locations by the share of high skill workers. The highest share for Utrecht is 44.5%, while the lowest share for Heerlen is 20.5%. It is worth noting that relatively large shares of high skill workers is not only reserved for the largest cities. Mid-sized cities that house a university, such as Nijmegen, Groningen, and Leiden also have a relatively large high skill share (see also Glaeser & Resseger, 2010). Obviously, if the share of high skilled workers is relatively high, the share of low skilled workers tends to be low (correlation is −0.89). Table 2a also provides information on the abundance of technical skills. Regarding technical high skilled workers, Eindhoven ranks highest (9.3%), followed by Utrecht and The Hague, while Heerlen and Leeuwarden (3.3%) rank lowest. Although there is substantial variation in the ordering of high skilled workers and technical high skilled workers, the correlation between these two variables is strongly positive (0.60). Clearly, cities are diverse in terms of the skill abundance of their inhabitants.

Regarding skill intensity, Table 2b provides some information for 2017 for the top five and bottom five sectors in terms of high skill worker shares, where workers are counted in full time equivalents (fte). The top sectors employ around 80% of high skill workers, starting with (not surprisingly) education and R&D. The bottom sectors have around 10% of high skilled workers, including wellness and security. A large sector in terms of the number of workers at the top is education (515,000), whereas the food sector is large at the bottom (504,000). There are substantial differences in terms of the technical intensities of the sectors. Education and R&D both require about 80% of high skill workers, but in terms of technical skills, education requires only 5.7% of technical high skilled workers compared to 41.8% for R&D (more than seven times as much). When comparing part a and part b of Table 2, it is clear that the sectors are more diverse in terms of their skill intensities than the cities in terms of their skill abundance. We return to this issue in Section 3.

2.5 | The sorting of skills in Dutch cities

Davis and Dingel (2020) and Dingel et al. (2021) develop and apply two statistical tests for their theoretical model (an elasticity test and a bilateral comparison test) to analyze the sorting of skills into larger locations in the USA, Brazil, China, and India. Brakman et al. (2021) apply these tests to China using different datasets for sensitivity analyses. In all cases there is strong support for the sorting of skills into larger locations. We briefly evaluate the sorting of skills in Dutch cities using both methods reported in Section 2.3.[12] Although in contrast to the above studies we only have a limited number of observations (22) as the Netherlands is a small country, which affects statistical power and significance of the tests, we *do* find support for the sorting of skills using both methods. We first report the results regarding the elasticity test, and then those for the pairwise comparison test.

The elasticity test performs a simple OLS regression that compares the slope elasticities β_{1i} in the following regression: $\ln S_{ij} = \beta_{0i} + \beta_{1i} \ln \left(W_j\right) + \eta_{ij}$, where the index i refers to the skill type of workers (high, med, low) and the index j to the city ($j = 1, .., 22$), the variable S_{ij} is a measure of the population with skill level of type i at location j, the variable W_j is the size of a city j (measured in working population). The β's are parameters to be estimated and η_{ij} is an error term. The test asks, whether the elasticity β_{1i} is larger for the higher skill levels. The intuition is simple. If the sorting is according to the model then for higher skill levels, increasing city sizes should have a larger effect on the number of higher skilled workers in that city than for lower skilled workers.

As Table 3 shows, the working-population elasticity of high skill workers is above one, namely 1.09 (with SE 0.0608), which is significantly higher than the population elasticities of the two other skill types, which are both below one. This supports the sorting of skills in larger locations as the number of high skill workers tends to rise faster than the working population, while the number of medium- and low skill workers tends to rise slower.

Figure 3 reports the success rate for the sorting of skills in the *bilateral comparisons*. In this test, we compare any two arbitrary cities and check if the larger city (measured by population size) has relatively more higher skilled workers than the smaller city. A “success” (value = 1) arises if the larger city has relatively more higher-skilled workers than the smaller city and a “failure”

TABLE 2 Skill abundance in cities and skill intensity in sectors; percent, 2017

(a) Skill abundance in cities; top 5 and bottom 5 by high skill intensity

City	Size # work	General schooling High skill	General schooling Low skill	Technical schooling High skill	Technical schooling Low skill
Top 5 locations high skill abundance					
Utrecht	373	44.5	22.4	7.6	1.8
Nijmegen	151	39.3	24.1	6.2	2.4
Groningen	209	38.4	20.1	5.2	2.0
Amsterdam	863	37.0	26.4	5.0	2.2
Leiden	175	36.9	25.3	6.3	2.3
Bottom 5 locations high skill abundance					
Apeldoorn	103	26.7	30.9	4.4	3.3
Leeuwarden	94	26.6	27.2	3.4	3.1
Rotterdam	581	26.1	34.0	4.0	3.0
Dordrecht	135	23.6	32.5	4.0	3.7
Heerlen	123	20.5	36.5	3.6	4.6

(b) Sector skill intensity; top 5 and bottom 5 by high skill intensity

SBI	Sector	Size # work	General schooling High skill	General schooling Low skill	Technical schooling High skill	Technical schooling Low skill
Top 5 sectors high skilled intensity						
85	Education	515	80.8	3.3	5.7	1.0
72	R&D	31	78.2	3.1	41.8	0.5
60	Program and broadcasting	8	73.4	2.9	2.5	0.4
64	Financial institutions	86	71.8	3.5	8.6	0.4
70	Holding companies	116	71.1	4.4	16.1	0.7
Bottom 5 sectors high skilled intensity						
49	Land transport	139	10.5	29.8	1.6	6.2
56	Food services	504	10.4	33.8	0.9	3.1
81	Facility management	172	9.5	46.8	1.7	5.0
96	Wellness; funeral activity	59	9.5	24.0	0.8	2.0
80	Security and investigation	34	8.9	19.0	1.2	2.0

Source: Author calculations; size by working population (thousands); skill distribution as percent of working population (15–75 years) based on place of residence; see Table A1 in the Appendix for sector description. See Table A5 for a correlation matrix between Schooling skills, and technical skills.

TABLE 3 Working population elasticity estimates, 22 Dutch cities

Skill type	Coefficient	Standard error	R^2
High skilled	1.0896	0.0608	0.941
Medium skilled	0.9392	0.0219	0.989
Low skilled	0.9806	0.0468	0.956

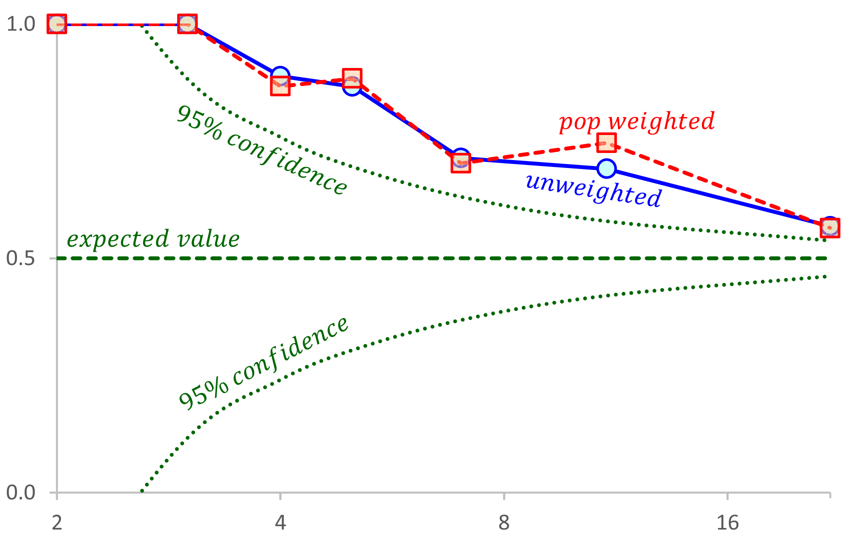

FIGURE 3 Pairwise comparison of three educational attainment levels, 2017. *Source*: Author construction; bins are 2, 3, 4, 5, 7, 11, and 22 with size 11, 7, 5, 4, 3, 2, 1; the figure includes bilateral comparisons for high versus medium, high versus low, and high versus medium-low; total number of bilateral comparisons is 981; the 95% confidence intervals are based on tossing a fair coin. [Colour figure can be viewed at wileyonlinelibrary.com]

arises if this is not the case (value = 0). The intuition is again simple. If the sorting of skills across cities is as predicted by the model, the larger city should have a relatively higher share of higher skilled workers than the smaller city. For each individual city, for a specific skill-type, we make this comparison relative to all the other cities. So, each city is compared to the other 21 cities giving 21 bilateral comparisons for that city for that skill-type. To determine the extent to which the average success rate exceeds a random distribution a benchmark of 0.5 can be taken as an indication regarding the sorting-predictive power of the model. In doing so we, in fact, compare the outcome of the pairwise comparisons to the flip of a coin. If the predictions of the model are valid, the outcomes of these comparisons should systematically differ from the random outcome of "flipping a fair coin"; we expect significantly more "successes" than predicted for a random outcome.

We also report, as a sensitivity analysis, the results for city "bins" in which cities are grouped together in an aggregate group. For 2 bins, for example, we compare the combination of the 11 largest cities with the combination of the 11 smallest cities, and so on. Figure 3 shows whether the success rate for these comparisons is random or not. If sorting of skills systematically favors the bigger city, the outcome of this comparison should not be comparable to a random outcome (in our case the tossing of a fair coin).

In view of our focus on the sorting of high skilled workers and the limited number of cities (implying that we have only a limited number of bilateral comparisons), we combine the results of the bilateral comparisons for the high- versus medium skilled workers, for the high- versus low skilled workers, and for the high- versus medium-low skilled workers in Figure 3. Since the comparison between a large city (such as Amsterdam with 1.6 million inhabitants) and a much smaller city (such as Zwolle with 182 k inhabitants) is more revealing to test the prediction of the model than a comparison between two similar-sized cities, such as Zwolle (182,000 inhabitants) and Maastricht (183,000 inhabitants) we also report "weighted" success rates, where we use the difference in log population as weight. Using either unweighted or weighted bilateral comparisons, Figure 3 shows that the bilateral comparison test supports the sorting of skills in larger locations as the results are above the random coin toss confidence interval.[13] This outcome is consistent with the model of Davis and Dingel (2020).

2.6 | International exports

At the *national* level, our export data come from the UN Comtrade database, which classifies exports by product category using the Harmonized System (HS2017). In order to compare international product data with our regional sector data we perform a concordance analysis, matching HS2017 product classifications with Dutch sector classifications (SBI2008), as explained in Section 3.3 (see Table A3 in the Appendix).

3 | REVEALED COMPARATIVE ADVANTAGE

The discussion below proceeds in three steps. First, we determine the comparative advantage of Dutch cities relative to the Netherlands based on the Balassa index. Second, we determine the comparative advantage of The Netherlands relative to the World. Third, we determine the comparative advantage of Dutch cities relative to the World.

3.1 | Step one: Comparative advantage of Dutch cities relative to the Netherlands

Our measure of RCA is the Balassa index, denoted by BI. As noted above, for city c and sector i in period t this is a normalized export share relative to an appropriate reference group of countries (ref), see the first equality sign in Equation (2).[14]

$$\mathrm{BI}_{i,t}^{c,\mathrm{NL}} = \frac{\text{export share}_{i,t}^{c}}{\text{export share}_{i,t}^{\mathrm{ref}}} = \frac{E_{i,t}^{c}/E_{t}^{c}}{E_{i,t}^{\mathrm{NL}}/E_{t}^{\mathrm{NL}}}. \tag{2}$$

Exports E for city c and sector i in period t is denoted by $E_{i,t}^{c}$. Total exports for city c in period t are denoted by E_{t}^{c} and is simply the sum over all sectors: $E_{t}^{c} \equiv \sum_i E_{i,t}^{c}$. This implies that the export share for sector i in city c at time t is equal to: export $\text{share}_{i,t}^{c} = E_{i,t}^{c}/E_{t}^{c}$. As explained in Section 2, we calculate the average of annual BIs for the two sub-periods, 2007–2012 and 2012–2017, for 83 different sectors at the city level, in order to avoid excess volatility.

If the Netherlands is the reference group, we have ref = NL in the sup-index of the equation. It implies that if $\mathrm{BI}_{i,t}^{c,\mathrm{NL}} > 1$, for example for the export of tobacco from Groningen, then Groningen has an RCA *within* the Netherlands (which is the case).[15] It is the most direct way to determine a location's relatively strong and weak sectors within a country. Obviously, Dutch exports for sector i in period t, denoted by $E_{i,t}^{\mathrm{NL}}$, is simply the sum over all cities: $E_{i,t}^{\mathrm{NL}} \equiv \sum_c E_{i,t}^c$. Similarly, total Dutch exports in period t, denoted by E_t^{NL}, is then the sum over all sectors: $E_t^{\mathrm{NL}} \equiv \sum_i E_{i,t}^{\mathrm{NL}}$. The reference export *share* for sector i at time t is thus: export share$_{i,t}^{\mathrm{ref}} = E_{i,t}^{\mathrm{NL}}/E_t^{\mathrm{NL}}$, hence the second equality sign in Equation (2).

Note that the Balassa index for cities defined in Equation (2) differs slightly from the regular definition at the country level as it focuses on exports outside of the Netherlands as a whole, instead of exports outside the city only. In this respect, the country thus serves as a double benchmark, which has advantages when we go to step 3 in Section 3.3. In addition, note that the range of $B_{i,t}^{c,\mathrm{NL}}$ (which starts at zero) is limited from above by the inverse of a city's trade share. The maximum for a good i is reached if city c is the only city that exports good i in period t, in which case: $E_{i,t}^c = E_{i,t}^{\mathrm{NL}}$ and $B_{i,t}^{c,\mathrm{NL}} = \frac{E_{i,t}^c/E_t^c}{E_{i,t}^{\mathrm{NL}}/E_t^{\mathrm{NL}}} = \frac{E_{i,t}^{\mathrm{NL}}/E_t^c}{E_{i,t}^{\mathrm{NL}}/E_t^{\mathrm{NL}}} = \frac{E_t^{\mathrm{NL}}}{E_t^c} = \frac{1}{s_{c,t}} > 1$, where $s_{c,t}$ is the share of city c in Dutch exports in period t.

3.2 | Step two: Comparative advantage of the Netherlands relative to the world

To determine the relatively strong and weak sectors for the Netherlands as a whole, we apply the regular Balassa index using UN Comtrade data with the *world* as reference group. At the Dutch national level, the export share of sector i in period t is equal to $E_{i,t}^{\mathrm{NL}}/E_t^{\mathrm{NL}}$. We denote world variables with a superscript w, hence the world export share of sector i in period t is equal to $E_{i,t}^w/E_t^w$ and the Balassa index at the national level is provided in Equation (3).

$$\mathrm{BI}_{i,t}^{\mathrm{NL},w} = \frac{E_{i,t}^{\mathrm{NL}}/E_t^{\mathrm{NL}}}{E_{i,t}^w/E_t^w}. \tag{3}$$

To determine the comparative advantage for Dutch cities in step one, we use 83 SBI sectors. To determine the comparative advantage for the Netherlands in step 2, we use international trade data based on the Harmonized System (HS, 2017 classification). For goods sectors we can make an adequate concordance between these two data sets using the NACE and ISIC classifications as intermediate steps. As summarized in Table A3 in the Appendix, this means that we can classify 5304 HS2017 products at the 5-digit level to correspond to 42 SBI goods sectors, which is then used to determine comparative advantage for these 42 sectors for the Netherlands as a whole.[16] Unfortunately, we cannot perform a sufficiently reliable similar correspondence exercise for services sectors, which means that step 2 in this subsection and step 3 in the next subsection can only be performed for the 42 goods sectors.

3.3 | Step three: Comparative advantage of Dutch cities relative to the world

Once we have determined the comparative advantage of Dutch cities relative to the Netherlands $\mathrm{BI}_{i,t}^{c,\mathrm{NL}}$ in step 1 and the comparative advantage of the Netherlands as a whole relative to the world

$BI_{i,t}^{NL,w}$ in step 2, simple multiplication suffices to determine the comparative advantage of Dutch cities relative to the world $BI_{i,t}^{c,w}$ for the sectors listed in Table A3:

$$BI_{i,t}^{c,w} = BI_{i,t}^{c,NL} \cdot BI_{i,t}^{NL,w} = \left(\frac{E_{i,t}^{c}/E_{t}^{c}}{E_{i,t}^{NL}/E_{t}^{NL}} \right) \left(\frac{E_{i,t}^{NL}/E_{t}^{NL}}{E_{i,t}^{w}/E_{t}^{w}} \right) = \frac{E_{i,t}^{c}/E_{t}^{c}}{E_{i,t}^{w}/E_{t}^{w}}. \tag{4}$$

City c thus has an RCA relative to the world in sector i in period t if $BI_{i,t}^{c,w} = BI_{i,t}^{c,NL} \cdot BI_{i,t}^{NL,w} > 1$. Note that it is possible for city c to be relatively strong in sector i within the Netherlands, but not relative to the world, namely if $BI_{i,t}^{c,NL} > 1$ and $BI_{i,t}^{c,w} < 1$ $\left(\text{note: this requires } BI_{i,t}^{NL,w} < 1\right)$. Similarly, it is possible for city c to be relatively weak in sector i within the Netherlands, but strong compared to the world if $BI_{i,t}^{c,NL} < 1$ and $BI_{i,t}^{c,w} > 1$ $\left(\text{note: this requires } BI_{i,t}^{NL,w} > 1\right)$. We return to these issues in Section 6.

4 | COMPARATIVE ADVANTAGE OF DUTCH CITIES RELATIVE TO THE NETHERLANDS

The information in this section is based on average Balassa indices per sector and location over the years 2012–2017 relative to The Netherlands.[17] We use the period 2007–2012 for comparison throughout our discussion. We start with an overview of the main characteristics of the Balassa index in Section 4.1, followed by a discussion on the comparability of the distribution for different locations in Section 4.2 and a first analysis on the link between factor abundance and comparative advantage in Section 4.3. A more detailed analysis of the connection between abundance, intensity, and comparative advantage is provided in Section 5.

4.1 | Characteristics of the Balassa index

Table 4 provides summary statistics for the Balassa index of Cities relative to The Netherlands. In the period 2012–2017, the average Balassa index is 1.13 and the median is 0.46, which indicates the overall distribution is skewed to the right, with skewness of 8.44 and a maximum of 44.2. The share of sectors with a Balassa index higher than one (and thus an RCA) is 28.9%. These observations are like the findings in Hinloopen and Van Marrewijk (2001) and for the 2007–2012 period, see Table 4.

TABLE 4 Summary statistics of the Balassa index, 22 Dutch cities relative to NL

Variable	Period 2012–2017	Period 2007–2012
Number of observations	1607	1563
Average Balassa index	1.13	1.25
Median Balassa index	0.46	0.46
Skewness	8.44	10.67
Maximum Balassa index	44.2	69.9
Number BI > 1	464	459
Percent BI > 1	28.9	29.4

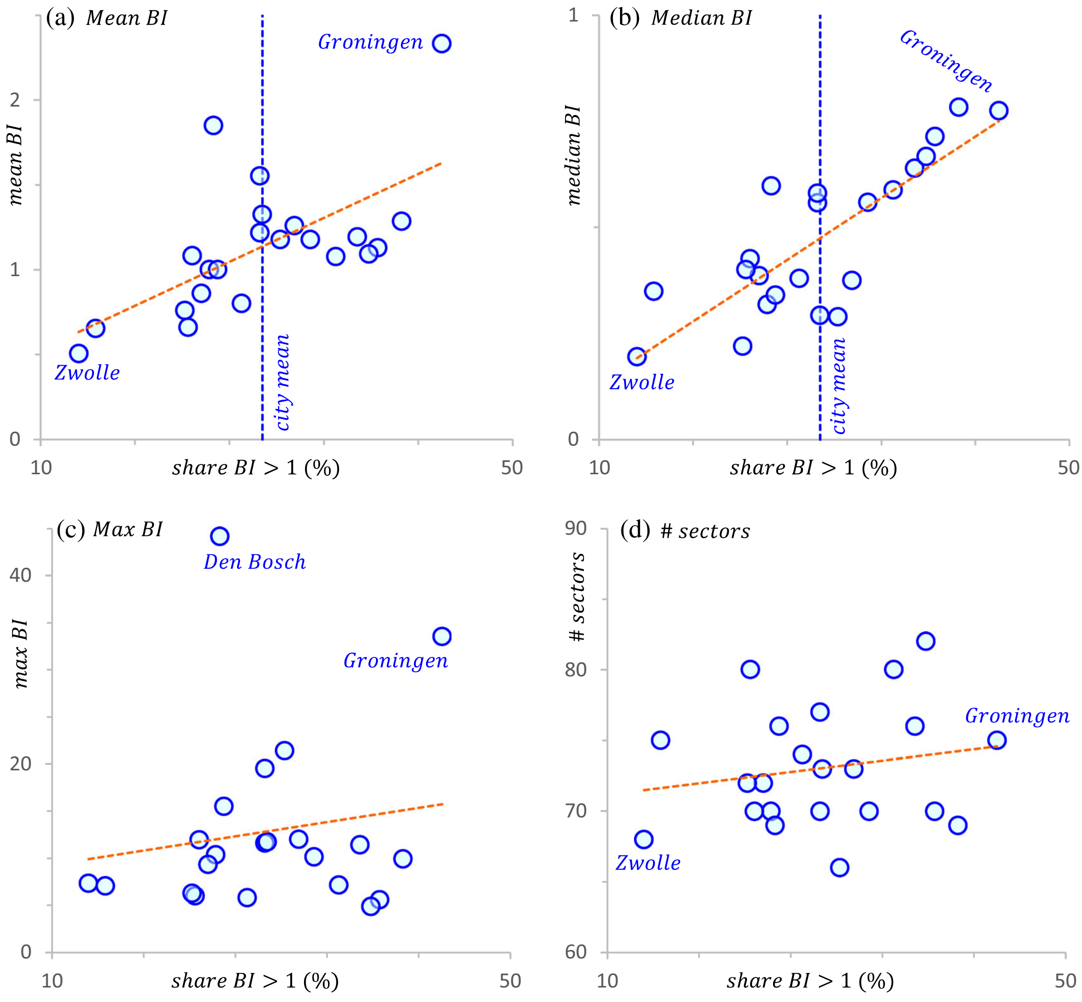

FIGURE 4 Balassa index cities characteristics, 2012–2017. *Source*: Authors; see Section 2 for data info; BI, Balassa index; share of variance explained is 31.4; 82.0; 0.0; and 29.6% in panels (a)–(d), respectively. For complete coverage, we also include regions. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 4 illustrates the differences in distribution characteristics for the individual cities in four panels. The horizontal axis always displays the share of sectors with an RCA (BI > 1) in percentage points. The vertical axis in panels *a*–*d* depict the relationship with the mean, median, maximum, and the number of included sectors, respectively. Panels *a* and *b* display the mean and median for the cities.

There is no relationship between the share of the Balassa index above one and the maximum observation for a city, see panel *c*. The maximum is particularly high for Groningen (sector 06; oil and gas extraction, which results in a violation of the Hillman condition) and Den Bosch (sector 65; insurance and pensions). The highest share of explained variance (66%) is for the median Balassa index, see panel *b*. The relationship with the mean is less tight (40%, see panel *a*) because it is influenced by the maximum observations. Finally, if the number of included sectors is high, the share of sectors with RCA (BI > 1) is barely affected (see panel *d*). Section 4.2 analyzes the extent to which the distribution differs between locations.

TABLE 5 Strongest export sectors; Dutch cities relative to NL, 2012–2017

City	Strongest SBI sector	Second strongest SBI sector
Groningen	06; Extract gas	86; Human health
Leeuwarden	17; Paper prod	25; Fabricated metal
Zwolle	70; Holding comp	74; Industrial design
Enschede	31; Furniture	30; Other transport eq
Apeldoorn	24; Basic metals	17; Paper products
Arnhem	16; Wood prod	84; Public services
Nijmegen	27; Electrical eq	86; Human health
Amersfoort	73; Advertising	65; Insurance and pension
Utrecht	88; Social work	85; Education
Amsterdam	79; Travel agencies	63; Information services
Haarlem	09; Mining support	18; Printing
Leiden	21; Pharmaceutical prod	72; R&D
The Hague	41; Construction	93; Sports and recreation
Rotterdam	50; Water transport	52; Warehousing
Dordrecht	19; Man oil prod	81; Facility man
Breda	42; Civil engineering	22; Rubber and plastic
Tilburg	15; Leather	29; Motor vehicles
Den Bosch	65; Insurance and pension	37; Sewerage
Eindhoven	28; Machinery n.e.c.	26; Man computers
Geleen-Sittard	96; Wellness and funeral	29; Motor vehicles
Heerlen	11; Beverages	96; Wellness and funeral
Maastricht	17; Paper prod	82; Other business serv

Source: Author calculations; see Section 2 for data details; ranking based on Balassa index; see Table A1 in the Appendix for sector description.

Table 5 provides an overview of the two strongest export sectors as identified by the Balassa index for each city. For readers familiar with the economic structure of the Netherlands, some of these are in accordance with expectations. Groningen, for example, has sector 06 (extraction of oil and gas) as its strongest sector. Similarly, Amsterdam (where the national airport is located) is strong in sector 79 (travel) and Rotterdam (where the largest port is located) is strong in sector 50 (water transport). Other noteworthy observations are that Eindhoven is strong in sectors 28 (machinery not elsewhere classified) and 26 (computers and electronics), Utrecht is strong in sector 85 (education), and Dordrecht is strong in sector 81 (facility management). We will argue below that this is related to the skill requirements (intensity) of sectors in combination with the skill abundance in locations. Sectors 26 and 28 are relatively intensive in the use of technical high skill workers and Eindhoven is relatively abundant in technical high skill workers. Similarly, sector 85 is most intensive in the use of high skill workers and Utrecht is most abundant in high skill workers, while sector 81 is most intensive in low skill workers and Dordrecht is relatively abundant in low skill workers.

4.2 | Comparing distributions

The firm-sector export data allows us to calculate the Balassa index for each sector in each city to identify strong export sectors, as discussed in Section 4.1. For a given city we have a sector-based distribution of Balassa indices, which allows us to order or rank the sectors in terms of RCA within the city. The question arises to what extent we can compare values of the Balassa index in different locations. Can we conclude, for example, that a Balassa index of 4 for a sector in Amsterdam is stronger than a Balassa index of 2 for another sector in Eindhoven? To be able to do so, the observations should be based on a similar underlying distribution. We thus require a test to conclude whether the observations from two different cities are drawn from the same distribution, or not.[18]

The method we use is the 2-sample Harmonic Weighted Mass (HWM) index developed by Hinloopen et al. (2012). The essence of this method is the comparison of two entire distributions based on so-called probability–probability plots for the (empirical) cumulative distributions.[19] This is illustrated in Figure 5 for The Hague and Rotterdam in the period 2012–2017. If the draws are from the same underlying distribution, the expected value of the pp-plot coincides with the diagonal. The HWM index takes the deviation between the actual pp-plot and the diagonal (the shaded area in Figure 5) corrected for the number of observations as a measure to determine if the underlying distributions are the same (if the area is sufficiently small) or not (if the area exceeds a

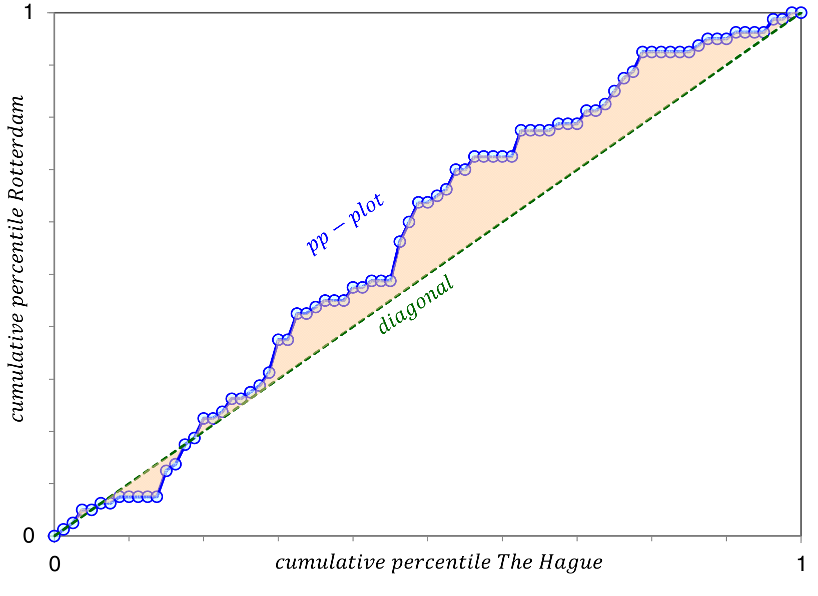

FIGURE 5 PP-plot and HWM index; the Hague and Rotterdam, 2012–2017. *Source*: Authors; see Section 2 for data details; HWM index is based on shaded area between diagonal and pp-plot. [Colour figure can be viewed at wileyonlinelibrary.com]

critical value). In the case of The Hague and Rotterdam, the underlying distributions are *not* the same (beyond the 1% significance level).

Table A4 in the Appendix provides a summary of all possible bilateral comparisons (at the 10% significance level). The conclusion is that, in general, the Balassa index distributions differ from each other. For example, in the period 2012–2017 the Balassa index distribution of Groningen differs from the Balassa index distribution in all other locations (100% of the cases) while Geleen-Sittard (which has the highest number of similar distributions) still differs in 62% of all comparisons. On average, the distributions are significantly different for 85% of all cases in the 2012–2017 period and for 80% of the cases in the 2007–2012 period. We therefore conclude that it is not appropriate to compare the value of the Balassa index for corresponding sectors in different cities, because the same value could represent a different ranking and a different value a similar ranking. It is only appropriate to compare the order within the same city, or the ranking of sectors in different cities (see also Sections 4.3 and 5).[20]

A question that might arise at this point is whether significant different patterns of comparative advantage across locations affect the overall pattern of comparative advantage of The Netherlands. Following the neo-classical methodology of Courant and Deardorff (1992) on the regional "lumpiness" of factors of production, the answer is that in The Netherlands this is not the case, see Brakman et al. (2022).

4.3 | The sorting of sectors and workers across cities

How can we explain the strengths and weaknesses of a sector across cities? In Section 4.1 we already suggested that this is related to the skill intensity of sectors and the skill abundance in cities. An explanation closely related to the factor endowments trade model. We develop this line of reasoning in this section in two steps. The first step is to show the link between sector skill intensity and a city's strong export sectors in terms of a correlation for that city. The second step is to show the link between this correlation and a city's relative factor abundance. Section 5 provides a more detailed statistical analysis of these interaction effects.

The first step (relating strong sectors to skill intensity) is illustrated for Tilburg in Figure 6. We motivated in Section 4.2 why we prefer to compare the ranking of sectors in different locations over comparing the value of the Balassa index in different locations. The vertical axis in Figure 6 therefore shows the rank of a sector in Tilburg's Balassa index (where 1 is highest, the strongest export sector), while the horizontal axis shows the rank of that sector in terms of high skill intensity. Sector 85 (education), for example, has rank 1 in terms of high skill intensity and rank 53 in terms of Tilburg's Balassa index, while sector 49 (land transport) has rank 79 in terms of high skill intensity and rank 10 in terms of Tilburg's Balassa index. The figure illustrates that, in general there is a negative association for Tilburg between its strong export sectors and high skill intensity (rank correlation is −0.393). In Tilburg, therefore, relatively strong export sectors tend to have relatively low high skill intensity (the BI – high correlation is negative). Please note that this outcome is not robust, because if we perform a similar calculation for other cities the BI – high correlation is positive in some cases and negative in other cases. This brings us to the next step.

Step 2, relating correlations between strong sectors and skill intensity to factor abundance, is illustrated in Figure 7. On the vertical axis we depict the correlation between strong sectors (the Balassa index) and high skill intensity in a city (the BI – high correlation). This is related on the horizontal axis to the share of high skill workers in a city. The sloping dashed line is a trendline

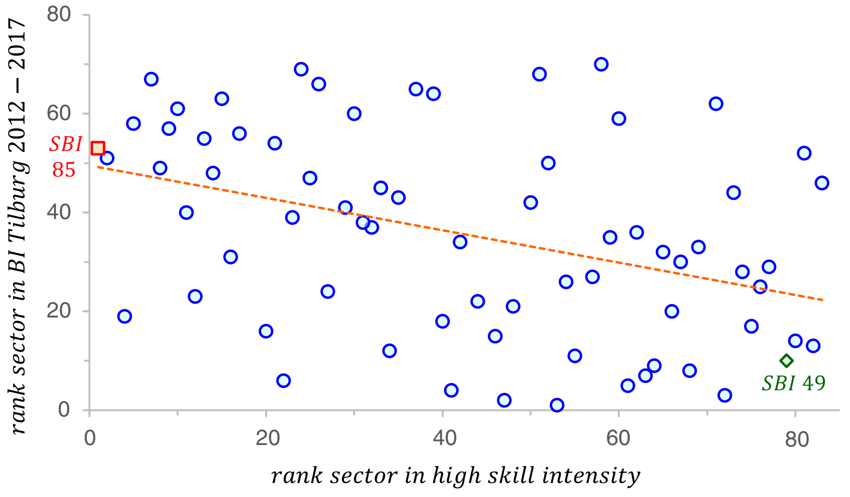

FIGURE 6 Rank correlation Balassa index and high skill share; Tilburg, 2012–2017. *Source*: Authors; see Section 2 for data info; rank correlation is −0.4596; dotted line is a trendline. [Colour figure can be viewed at wileyonlinelibrary.com]

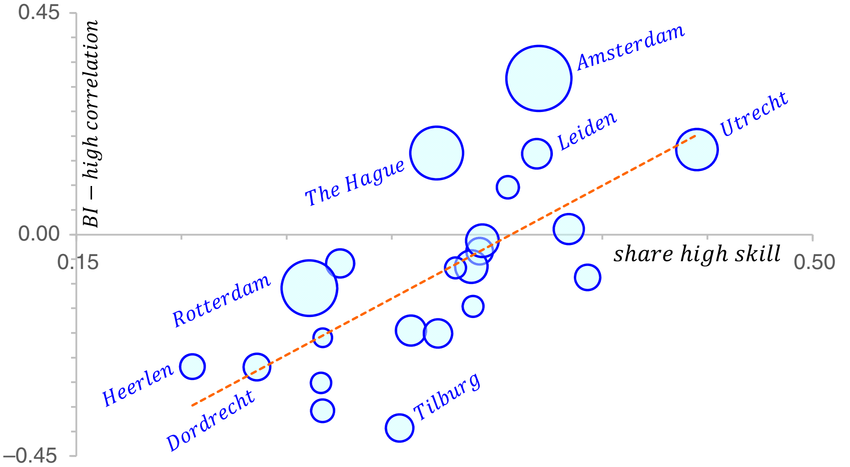

FIGURE 7 Relationship between share high skill and BI-high correlation, 2012–2017. *Source*: Authors; see Section 2 for data info; bubbles proportional to population size; dashed line is a trendline; share of (unweighted) variance explained is 48.4%. [Colour figure can be viewed at wileyonlinelibrary.com]

and the size of the bubbles is proportional to population. Figure 7 illustrates that cities with a relatively *low* share of high skill workers, like Heerlen, Dordrecht, Rotterdam, and Tilburg, have a *negative* BI – high correlation, while cities with a relatively *high* share of high skill workers, like The Hague, Leiden, Amsterdam, and Utrecht, have a *positive* BI – high correlation.[21] The share of high skills available in cities explains 48.4% of the variance in BI – high correlation in Figure 7. In other words, this correlation is related to the factor abundance in a city (in this case of high skill workers), which indicates that strong export sectors are related to the interaction of sector skill intensity with a city's factor abundance.

This section has illustrated, using high skill workers as an example, that strong sectors in a city are determined by the interaction between sector skill intensity and city skill abundance. The next section will analyze this in more detail, extending the analysis to include other skills and technical skills, to show that low skill intensive sectors thrive in low skill abundant cities and technical skill intensive sectors thrive in technical skill abundant cities. As such the analyses link factor abundance, skill intensity, and RCA at the city level within The Netherlands.

5 | ABUNDANCE, INTENSITY, AND COMPARATIVE ADVANTAGE

As explained in Section 2.3, we identify two types of human skills (general and technical) at three levels (high, medium, and low). We have information available regarding the availability of skills in cities and regarding the use of skills in sectors. In Section 4.3, we argued that the distribution of strong sectors across cities is related to the interaction between the abundance of skills in cities and the intensity of the use of skills in sectors. Before we can analyze this interaction in more detail in Section 5.2, we must specify how we define abundance and intensity in Section 5.1.

5.1 | Abundance and intensity

A city is *abundant* in a certain skill if this skill is *relatively* widely available in that city. Similarly, a sector is *intensive* in a certain skill if this skill is intensively used in *relative* terms. To determine the abundance of skills in cities or the intensity of skills in sectors we therefore need an appropriate measure to compare to, for which we take the average of this skill for the Netherlands as a whole. As indicated in Section 2.3, we use simple mnemonics for our variables. We use abun for abundance, int for intensity, and share for shares. In addition, we use subindices high, med, and low for high-, medium-, and low general skill levels, subindices tec – high, tec – med, and tec – low for high, medium, and low technical skill levels, and a subindex t for time. Finally, we use a sup-index c for cities, a sup-index i for sectors, and a supindex NL for The Netherlands as a whole.

$$\text{Abun}_{\text{high}}^{c} = \frac{1}{6}\left\{\left(\sum_{t=2012}^{2017} \text{share}_{\text{high},t}^{c}\right) - \left(\sum_{t=2012}^{2017} \text{share}_{\text{high},t}^{\text{NL}}\right)\right\}, \tag{5}$$

$$\text{Int}_{\text{high}}^{i} = \frac{1}{6}\left\{\left(\sum_{t=2012}^{2017} \text{share}_{\text{high},t}^{i}\right) - \left(\sum_{t=2012}^{2017} \text{share}_{\text{high},t}^{\text{NL}}\right)\right\}. \tag{6}$$

Equation (5) provides the definition of high skill abundance for cities in 2012–2017 and Equation (6) provides a similar definition of high skill intensity for sectors. Similar definitions apply to all other types and levels of skills. The definition implies that abundance is *positive* in a city if the period-average share in the city is *higher* than the period-average share for the Netherlands as a whole, and negative otherwise. Similarly, intensity is *positive* for a sector if the period-average share in the sector is *higher* than the period-average share for the Netherlands as a whole, and negative otherwise.

5.2 | Interaction and comparative advantage

Our regression analysis focuses on the interaction between factor abundance for cities and factor intensity for sectors to determine a city's strong sectors. We do not analyze the causality of the sorting problem if sectors decide to produce in cities abundant in the skills that the sector uses intensively, or if workers decide to locate in cities with sectors that intensively use their skills. To provide a "clean" regression analysis, we focus on cities and "tradable" sectors only. We classify 22 sectors as non-tradable (see Table A1 in the Appendix) if the export share of total revenue is less than 1%.[22] The median export share for these 22 sectors is 0.2%. Similar results as reported below hold if all sectors are included and if the analysis is extended to include the four regions as well (results available upon request).

$$\text{rank}_i^c\left(\text{BI}_{i,t}^{c,\text{NL}}\right) = \beta_0 + \beta_1 \text{Abun}_{\text{high}}^c \times \text{Int}_{\text{high}}^i + \text{controls} + \text{fixed effects (city and sector)} + \epsilon_{ict}. \quad (7)$$

Our regression estimates explain strong export sectors as identified by the Balassa index in three ways. First, we use the *rank* of sector i within city c, $\text{rank}_i^c\left(\text{BI}_{i,t}^{c,\text{NL}}\right)$, to determine the city-specific order of strong export sectors. This eliminates any city-specific distribution issues related to the *value* of the BI as discussed in Section 4.2. Our focus is on determining the interaction effects for city abundance and sector intensity, such as parameter β_1 for high skills in Equation (7), taking into consideration location specific control variables, as discussed below. Second, we analyze strong export sectors that have a RCA $\left(\text{BI}_{i,t}^{c,\text{NL}} > 1\right)$ using a probit analysis to determine the probability that $\text{BI}_{i,t}^{c,\text{NL}} > 1$ in a structure similar to Equation (7). Third, we use $\ln\left(\text{BI}_{i,t}^{c,\text{NL}}\right)$ as a measure of export strength for sector i in city c in period t. Note that this variable suffers from the limitations discussed in Section 4.2 and is provided as a robustness check only.

Table 6 provides an overview of the individual interaction effects for all three types of analyses. Each analysis considers one of the six skill classes discussed in Section 2.3. To focus on the abundance-intensity interaction effects, we correct for sector fixed effects and cities fixed effects. In general, the abundance-intensity interaction effects are negative and highly significant, except for low skilled workers (schooling), and high technical skills, which are not significant for all three panels. A negative coefficient indicates that an increase in abundance-intensity interaction relates to a higher place in the local BI ranking.[23] This is in accordance with the factor-driven comparative advantage, which states that a region will export the goods for which the required production factors are available in abundance.

The proportion of variance explained in Table 6 is around 20% for the BI rank and close to 30% for log of BI. For general schooling, the high and med skill variables have most explanatory power. For technical schooling, the med and low skill variable have most explanatory power. Panel *a* presents our preferred specifications, Panels *b* and *c* can be seen as sensitivity analyses. Panel *b* provides a probit analysis; what is the probability of finding a BI >1 based on the same variable as in panel *a*. The results are in line with those in panel *a*. The same holds for panel *c*. Here we use the log of the BI as dependent variable in order to reduce the influence of outliers in the value of BIs. In general, we conclude from Table 6 that location specific comparative advantage is to a fair extent explained by the combination of location-specific factor abundance and sector-specific skill intensity. This interaction also positively affects the probability of export success, as illustrated by the probit results.

TABLE 6 Abundance, intensity, and comparative advantage for Dutch cities, 2012–2017

(a) OLS regression on rank of Balassa index, 2012–2017						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Abun^c_{high} \times Int^i_{high}$	−242.5*** (46.82)					
$Abun^c_{med} \times Int^i_{med}$		−836.8*** (151.5)				
$Abun^c_{low} \times Int^i_{low}$			−146.4 (143.7)			
$Abun^c_{tec-high} \times Int^i_{tec-high}$				−832.0 (522.9)		
$Abun^c_{tec-med} \times Int^i_{tec-med}$					−2225*** (345.6)	
$Abun^c_{tec-low} \times Int^i_{tec-low}$						−16,678*** (2580)
R-squared	0.201	0.204	0.179	0.180	0.217	0.220
(b) Probit regression on Balassa Index, 2012–2017						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Abun^c_{high} \times Int^i_{high}$	17.68*** (4.584)					
$Abun^c_{med} \times Int^i_{med}$		62.04*** (15.15)				
$Abun^c_{low} \times Int^i_{low}$			8.95 (12.51)			
$Abun^c_{tec-high} \times Int^i_{tec-high}$				55.29 (44.36)		
$Abun^c_{tec-med} \times Int^i_{tec-med}$					164.6*** (35.36)	
$Abun^c_{tec-low} \times Int^i_{tec-low}$						1256*** (257.7)
(c) OLS regression on natural logarithm Balassa Index, 2012–2017						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Abun^c_{high} \times Int^i_{high}$	25.35*** (4.659)					
$Abun^c_{med} \times Int^i_{med}$		82.99*** (16.13)				
$Abun^c_{low} \times Int^i_{low}$			24.49* (14.35)			
$Abun^c_{tec-high} \times Int^i_{tec-high}$				72.21 (55.19)		
$Abun^c_{tec-med} \times Int^i_{tec-med}$					194.0*** (37.71)	
$Abun^c_{tec-low} \times Int^i_{tec-low}$						1617*** (274.8)
R-squared	0.294	0.294	0.275	0.274	0.298	0.306

Source: Author calculations; see Section 2 for data details; standard errors in parentheses, clustered on cities as well as sectors; ***$p < .01$; **$p < .05$; *$p < .1$; all regressions include sector fixed effects and city fixed effects; 61 tradable sectors included; panels (a) and (c) have 835 observations, panel (b) has 818 observations. See Table A5 for a correlation matrix of Abundance of Cities and Intensity of Sectors.

5.3 | Locational characteristics and comparative advantage

Next, we look at how locational characteristics affect RCA. We use four explanatory variables that capture relevant location specific characteristics. First, *density* measures the average population per square km in a city and captures the net effects of local costs-of-living aspects as well as possible (knowledge) spillovers. The market access variable, *markaccexp*, is defined as a population-weighted exponential distance decay function, and is a proxy for the size of the local- and nearby markets within The Netherlands.[24] The distance to Schiphol (*schiphroad*) and to the port of Rotterdam (*portroad*) capture the distance of a city to the main international airport and main international port in the Netherlands by road in km.[25] Cities closer to these international distribution points are considered to have greater *international* market access. These variables also correlate positively with local market access, see Table A6 in the Appendix for a correlation matrix for these location characteristics and the factor-abundance and skill-intensity interactions. Table A7 repeats the analysis of Table 6 with these additional control variables. We find that the factor-abundance interaction with skill-intensity results is robust for these control variables and that locational characteristics only marginally contribute to local comparative advantage (with the exception of market access, which is significantly positive in panel *c* of Table A7).

6 | COMPARATIVE ADVANTAGE OF DUTCH CITIES RELATIVE TO THE WORLD

The main objective of calculating the Balassa index is to determine which sectors are relatively strong or weak in a certain city. In this section, we classify as "weak" all sectors with a Balassa index below one and as "strong" all sectors with a Balassa index above one.

An important aspect of calculating the Balassa index is choosing the reference group for determining strong and weak sectors. As discussed in Section 3.3, the decomposition of Equation (4): $BI_{i,t}^{c,w} = BI_{i,t}^{c,NL} \cdot BI_{i,t}^{NL,w}$ allows us to determine strong and weak sectors for Dutch cities relative to the *world*, rather than for The Netherlands only. To do so, we limit attention to 42 sectors (see Table A3 in the Appendix and the discussion in Section 4.2). We first determine strong and weak sectors for the Netherlands as a whole relative to the world in Section 6.1, that is, $BI_{i,t}^{NL,w}$. In Section 6.2, we determine strong and weak sectors for Dutch cities relative to the world, that is $BI_{i,t}^{c,w}$. The results for $BI_{i,t}^{c,NL}$, are already presented in Section 5. This enables us to identify sectors in cities that are strong relative to the world and to The Netherlands. We can also identify sectors that are weak relative to one benchmark, but strong relative to the other: the switching sectors. From a policy perspective, these switches are potentially interesting. It is, for example, possible that The Netherlands is strong in a specific sector, whereas that sector is weak in a particular city. The question arises whether policy action is called for. In addition, the reverse is possible: a city can have a strong sector that is weak for The Netherlands relative to the world; is it useful to support such a sector?

6.1 | The Netherlands relative to the world

Using the methodology outlined above, we determine strong and weak sectors for the Netherlands as a whole relative to the World for 42 SBI sectors. We focus the discussion on the period 2012–2017, but results for 2007–2012 are similar.[26] The Balassa index ranges from a minimum of

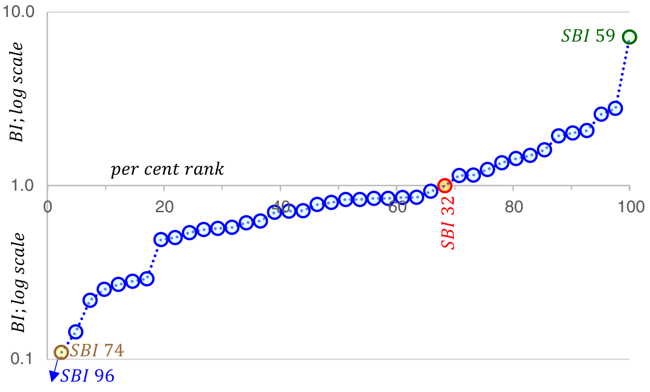

FIGURE 8 Balassa index; percent rank, Netherlands relative to world, 2012–2017. *Source*: Authors; see Section 2 for data info; see Table A1 in the Appendix for sector description; 42 SBI sectors [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 7 Strong SBI sectors; BI Netherlands relative to world, 2012–2017

SBI	BI	# HS	Short name	SBI	BI	# HS	Short name
59	7.18	3	Movies and television	95	1.49	5	Repair computer
12	2.78	7	Tobacco	11	1.43	19	Beverages
62	2.58	10	ICT support	41	1.36	3	Construction
19	2.08	22	Refined oil	21	1.24	122	Pharmaceutical
10	2.01	537	Food products	58	1.15	15	Publishing
01	1.94	289	Agriculture	26	1.14	257	Computers
20	1.61	717	Chemicals	32	1.00	297	Oth manufactures

Source: Authors; see Section 2 for data info; SBI refers to sector number; BI is the Balassa Index; # HS refers to the number of 5-digit HS subsectors; see Table A1 in the Appendix for sector description.

0.004 to a maximum of 7.18. This is illustrated in Figure 8 using a log scale for the ordered sectors by percent rank. There are 14 strong sectors (1/3rd of the total) with a Balassa index above one, starting from SBI 32 (other manufactures) up to SBI 59 (movies and television), see Table 7 for all strong sectors. Equivalently, there are 28 weak sectors (two-thirds of the total), with SBI 96 (wellness) and SBI 74 (industrial design) as weakest sectors.

People familiar with the Dutch economy will not be surprised to see that refined oil, food products, agriculture, and chemicals are among the strong export sectors. The relatively high score for movies and television (mainly because of television), tobacco, ICT support, computer repair, and construction may be more surprising. People looking for the export of flowers in the list of strong sectors will be disappointed to see that it is not there. It is included in the *agriculture* sector, which combines no less than 289 HS products. Food products and Chemicals include even more HS subsectors (537 and 717, respectively). It is thus important to keep in mind that the concordance table is lop-sided in terms of the number of HS subsectors an SBI sector represents. It is for that reason that movies and television, tobacco, and ICT support can more easily score high Balassa indices as they represent a concentration of HS subsectors only (viz., 3, 7, and 10, respectively). Similarly for the low-scoring SBI sectors in Figure 8 at the other extreme, where

TABLE 8 Overview of strong-weak and weak-strong reference switches; by sector, 2012–2017

From strong$_{NL}$ to weak$_{WLD}$				**From weak$_{NL}$ to strong$_{WLD}$**			
# observations ($BI_i^{c,NL} > 1$)			**230**	**# observations ($BI_i^{c,NL} < 1$)**			**573**
# reference switches ($BI_i^{c,w} < 1$)			**60**	**# reference switches ($BI_i^{c,w} > 1$)**			**29**
Switches percent of total			**26**	**Switches percent of total**			**5**
SBI	**$BI_i^{NL,w}$**	**Sector**	**# sw**	**SBI**	**$BI_i^{NL,w}$**	**Sector**	**# sw**
96	0.004	Wellness	9	62	2.58	ICT support	6
16	0.28	Wood	5	20	1.61	Chemicals	6
14	0.57	Apparel	5	59	7.18	Movies and television	5
90	0.25	Arts	5	10	2.01	Food products	5
74	0.11	Industrial design	5	95	1.49	Repair computer	3
23	0.49	Non-metal mineral	4	01	1.94	Agriculture	1
08	0.14	Mining	4	21	1.24	Pharmaceutical	1
35	0.83	Air cond	3	41	1.36	Construction	1
29	0.29	Cars	2	58	1.15	Publishing	1
30	0.56	Oth transport	2				
38	0.63	Waste	2				
27	0.85	Electrical eq	2				
09	0.27	Mine sup	2				
24	0.54	Basic metal	2				
02	0.70	Forestry	2				
06	0.22	Oil gas	1				
43	0.58	Spec construct	1				
18	0.83	Printing	1				
28	0.80	Machinery	1				
22	0.85	Rubber plastic	1				
33	0.78	Repair machine	1				
Total number of reference switches			60	Total number of reference switches			29

Source: Author calculations; see Section 2 for data details; see Table A1 in the Appendix for sector description; # sw = number of reference switches. Table A8 provides a detailed description of switches.

wellness consists of only 1 HS subsector and industrial design of only 3 HS subsectors. With these caveats in mind, it is now time to discuss the strong and weak sectors for Dutch cities relative to the world.

6.2 | Dutch cities relative to the world

As explained in Section 3.3, we can calculate the comparative advantage of a Dutch city c relative to the world w for sector i in period t by multiplication: $BI_{i,t}^{c,w} = BI_{i,t}^{c,NL} \cdot BI_{i,t}^{NL,w}$. As a city for a

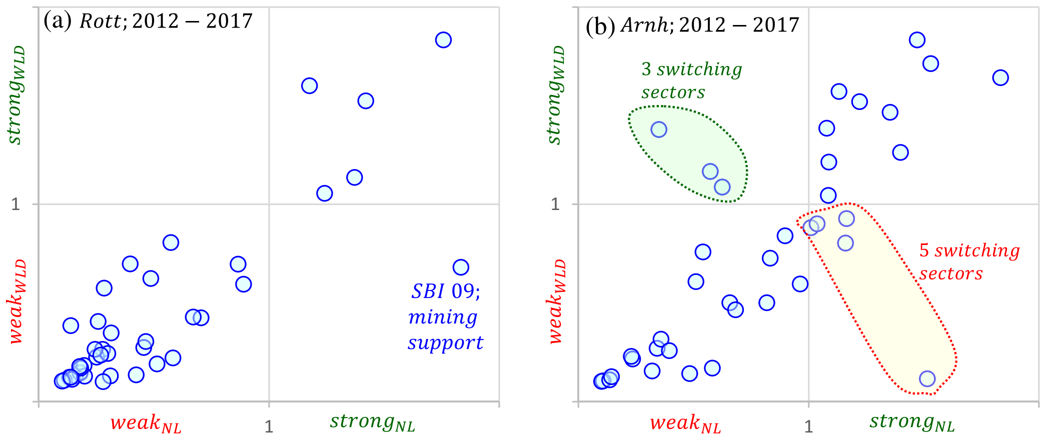

FIGURE 9 Strong and weak sectors, relative to NL and WLD; Rotterdam and Arnhem, 2012–2017. *Source*: Authors; see Section 2 for data info; Rott, Rotterdam; Arnh, Arnhem; see Table A1 in the Appendix for sector description; 40 sectors for Rotterdam and 38 sectors for Arnhem [Colour figure can be viewed at wileyonlinelibrary.com]

sector can be either strong or weak relative to either the Netherlands or the World, we arrive at four logical possibilities identified as weak or strong with a subindex NL relative to the Netherlands and WLD relative to the world. Table A8 in the Appendix provides a complete overview of all strong sectors for all cities. We follow Brakman and Van Marrewijk (2017) by presenting the information in a table-like graph using a monotone transformation (to ensure all variables range from 0 to 2) that does not affect the weak or strong classification.[27] We say a "reference switch" occurs if a sector either goes from weak to strong or from strong to weak. Table 8 provides a complete overview of all sectors that reference switch from weak to strong or from strong to weak for all cities. Figure 9 shows the classification for the locations with the lowest and highest number of reference switches.

Four cities, namely Eindhoven, Geleen-Sittard, Groningen, and Rotterdam have only one reference switch. In all cases it involves a reference switch from strong$_{\mathrm{NL}}$ to weak$_{\mathrm{WLD}}$. It is a different sector for each city. This is illustrated in panel *a* of Figure 9 for Rotterdam, which shows one observation (SBI 09, mining support) in the off-diagonal parts and all other observations in the diagonal parts. There are 34 sectors both weak$_{\mathrm{NL}}$ and weak$_{\mathrm{WLD}}$ and 5 sectors both strong$_{\mathrm{NL}}$ and strong$_{\mathrm{WLD}}$. For Rotterdam (and the other cities above) it thus does not really matter if the sector classification is relative to the world or the Netherlands.

As shown in panel *b* of Figure 9, Arnhem has the highest number of reference switches: namely 8 in total (5 from strong$_{\mathrm{NL}}$ to weak$_{\mathrm{WLD}}$ and 3 from weak$_{\mathrm{NL}}$ to strong$_{\mathrm{WLD}}$). There are 20 sectors both weak$_{\mathrm{NL}}$ and weak$_{\mathrm{WLD}}$ and 10 sectors both strong$_{\mathrm{NL}}$ and strong$_{\mathrm{WLD}}$. Since a reference switch occurs for about one-in-five sectors for Arnhem it *does* matter if the classification is relative to the world or to the Netherlands.

The two examples in Figure 9 are special because they show the lowest and highest number of reference switches. The examples suggest that the number of reference switches is higher from strong$_{\mathrm{NL}}$ to weak$_{\mathrm{WLD}}$ than the other way around. This is confirmed in Figure 10, where we illustrate the switches by showing the number of sectors (and percent of the total) in each part of a panel with centered bubbles proportional to the number of sectors. Panel *a* shows this for 2007–2012 and panel *b* for 2012–2017. As is clear from the panels, the distribution is very stable for

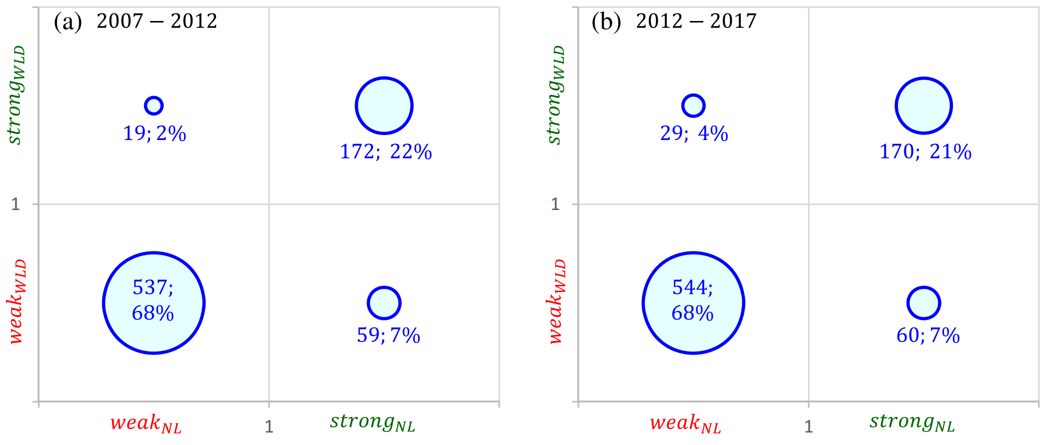

FIGURE 10 Strong and weak sectors, Dutch cities relative to NL and WLD. *Source*: Authors; see Section 2 for data info; see Table A1 in the Appendix for sector description; bubbles proportional to number of sectors in that panel; number of sectors and percent of total listed in each panel [Colour figure can be viewed at wileyonlinelibrary.com]

the two periods and most observations (68%) are in the weak_{NL} – weak_{WLD} part of the diagram, followed by about 22% of the observations in the $\text{strong}_{\text{NL}}$ – $\text{strong}_{\text{WLD}}$ part of the diagram. Most sectors (about 90% of the total) therefore have the same classification relative to both the Netherlands and the world.[28] Of the switching sectors, most switch from $\text{strong}_{\text{NL}}$ to weak_{WLD} (7% of the total), rather than the other way around (2–4% of the total). This points toward firm specific characteristics that determine export success. An individual firm can be productive enough to be competitive on a world scale despite being part of a weak sector, consistent with Melitz (2003).

7 | CONCLUSIONS

The uneven spatial distribution of location fundamentals, factors of production, and sectors is an important aspect of economic activity. Recent developments in the literature show that the interaction between trade and the spatial distribution of economic activity cannot be ignored.

Davis and Dingel (2020) combine insights from trade models and urban economics to address the interaction between trade and the uneven distribution of economic activity. They analyze the sorting of skills, occupations, and sectors across cities. Their model predicts that larger cities will be relatively skill-abundant and home to skill-intensive activities. However, they—and other papers based on their model—do not take the next step, that is they do not analyze the structure of trade that follows from this sorting process. Taking this next step is the main contribution of our article.

Using Dutch micro-firm data we study local trade patterns in 22 cities and 83 sectors for the period 2007–2017 and determine the characteristics of local trade patterns in relation to the sorting of economic activity across cities. We have four main findings.

First we confirm that the sorting of economic activity is such that bigger cities are relatively more skill-abundant and house more skill-intensive activities than smaller cities.

Second, we establish city specific distributions of RCA (Balassa Index; BI). For each city we calculate the distribution of BIs for all sectors that are active in that city and identify sectors with a comparative (dis)advantage relative to the Netherlands and relative to the world. We find that these distributions differ significantly from each other, illustrating that comparative advantage has a local origin.

Third, we find that the interaction of local factor-abundance and sector skill-intensity systematically explains a substantial share of the local trade patterns. This is consistent with (local) factor-driven comparative advantages. Control variables, such as local market access, density, or the distance to international airports or ports, have limited explanatory power.

Fourth, we identify sectors in cities that have a comparative (dis)advantage relative to the Netherlands and relative to the world (90% of all cases), as well as switching sectors that have a comparative advantage relative to the Netherlands but not relative to the world (and vice versa; 10% of all cases). Our method for identifying switching cases can be important from a policy perspective in order to determine if a specific policy action is called for.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Netherlands Bureau of Statistics (CBS). Restrictions apply to the availability of these data, which were used under license for this study. Derived data are available from the authors at request with the permission of CBS.

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ENDNOTES

[1] For complete coverage of The Netherlands, we also add four remaining regions as a sensitivity analysis.

[2] For a description (in Dutch), see https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/gemeente/gemeenten-en-regionale-indelingen/niet-landelijk-dekkende-indelingen

[3] In line with the reporting convention of Statistics Netherlands, we label a firm "exporter" if its annual export revenue exceeds 5000 euro.

[4] For privacy reasons these data are not publicly available. The Netherlands Bureau of Statistics manages the micro data, which can be obtained for research purposes upon request: https://www.cbs.nl/en-gb/our-services/customised-services-microdata/microdata-conducting-your-own-research

[5] SBI = Standaard Bedrijfs Indeling (Standard Firm Classification); see the Appendix, TA1, for a list of sectors. We discard SBI sectors 97–99, since these are unused categories not containing any firms.

[6] For example, a web retailer with an IT development branch and a logistics branch in a different location.

[7] To account for the earnings of top management, we exclude the top percentile of wages from the analysis.

[8] Each wage record represents the monthly wage of a single job of a single worker performed at a firm. If workers are employed at multiple firms, they have multiple records. Wage data are categorized by the type of work (such as employed, civil servant, self-employed, temporary) and the type of wage (wage, unemployment benefits, old-age pension). We remove records if they contain unemployment benefits or old-age pensions, keeping records of wages for overtime, payments in kind and bonuses. Information on the location of jobs is only collected for the month of December in any given year. This implies that the wages of about 30% of jobs not held in the month of December cannot be matched to a municipality.

[9] Unfortunately, we do not have reliable information on the capital abundance in cities, nor on the capital intensity in sectors, so, like land, this factor of production is excluded from the analysis. Citizens that have no registered education are excluded from our analysis, as are citizens that are not of working age as defined by Statistics Netherlands (working age is between 15–75 years old). For "technical," we use the categorization of education programmes created by Statistic Netherlands, namely, "Natural Sciences, Mathematics, and Statistics," "Information and Communication Technologies," or "Engineering, Manufacturing, and Construction." Total factor abundance at the city level is corrected for the use in non-tradable sectors, see also Section 5.

[10] Note that the sectors of employees are defined on the firm (national) level and not the local branch level in this part of the analysis.

[11] A motivation to use national skill-intensities is provided by the so-called lens condition. It can be shown that the "lumpiness" of factors of production within The Netherlands is not extreme enough to violate the lens condition. This implies that the integrated equilibrium can still be reproduced through trade (see Courant & Deardorff, 1992, 1993 for a discussion, and Brakman et al., 2022 for empirical evidence for The Netherlands).

[12] We cannot include the sorting of sectors as we have no information at the city-sectoral level of production.

[13] Except for bin 2, which is has only three comparisons and thus cannot possibly be outside the confidence interval.

[14] Note that due to data protection regulations on the microdata of Statistics Netherlands, we refrain from reporting sectoral export levels and shares on a national level. This measure allows us to present Balassa Indices for all city-sectors in the Netherlands without revealing city-sector export figures. The latter can contain sensitive information if the number of active firm branches in a city-sector is small.

[15] Before proceeding with our empirical analysis of the Balassa Indices, we exclude city-sectors that do not satisfy the Hillman-condition (Hillman, 1980). This condition evaluates the correspondence between the empirical revealed comparative advantage and the theory of comparative advantage based on pre-trade relative prices (which are not observed). In general, the Hillman condition is violated if a country has an extreme market share in the supply of a particular commodity in combination with a "high enough" degree of export specialization. The condition is satisfied for virtually all our city-sectors, "extraction of crude petroleum and natural gas" in Groningen being the only notable exception. This finding is in accordance with Hinloopen and Van Marrewijk (2008), who find that "Hillman violations" are small in number and occur mostly in natural-resource intensive sectors.

[16] A summary and complete overview of the concordance is available upon request. See also Table A3.

[17] If a sector does not export from a location in all years, it is excluded from the analysis; we thus only have non-zero Balassa indices, which allows us to use the log BI for our analysis in Section 5. To verify that excluding zeroes does not bias our results and conclusions, we repeat the regressions using Poisson pseudo-maximum likelihood (PPML) estimation, see Silva and Tenreyro (2006). PPML provides similar results (available upon request).

[18] Differences can subsequently be related to explanatory variables to explain Balassa index patterns (see also Deardorff, 2011; Kowalski & Bottini, 2011).

[19] The HWM-index has many attractive properties for applied research: it is not susceptible to outliers in the data, is scale-invariant and there is no need for discrete approximations, such as in applications using Markov transition matrices. Hinloopen et al. (2012) also analytically derive exact, finite-sample critical values for the HWM-index, which makes it more attractive than (variants) of kernel estimates.

[20] Furthermore, the BI is a ratio and values are susceptible to nominator and denominator effects.

[21] Note that Rotterdam stands out in the "Randstad" area (which also includes Utrecht, Amsterdam, Leiden, and The Hague), as it is relatively low skill abundant instead of high skill abundant.

[22] Total factor abundance at the city level is corrected for the use in non-tradable sectors (sector intensity × production) to determine the relevant factor endowments for tradables for the regression analysis.

[23] Note, the sector with the highest BI has rank = 1, the sector with the lowest BI has the highest rank in a city (the number of exporting sectors differs per city).

[24] Distance decay is $\exp\left(-d_{ij}\right)$, where d_{ij} is the distance between the economic centres of cities-regions *i* and *j* in 100 km.

[25] Note that for some peripheral regions other airports might be more relevant; for example, for Maastricht the airports of Brussels or Maastricht/Aachen may be an alternative for Amsterdam airport. To address this, we have identified six city districts for which Schiphol and Rotterdam might not be the main transport hubs, based on road distances. These are: Tilburg, 's-Hertogenbosch, Eindhoven, Geleen/Sittard, Heerlen, and Maastricht. If we exclude these cities and repeat the analysis we arrive at similar results. One difference is that the market access variable shifts from weakly significant to insignificant for services.

[26] All SBI sectors with BI > 1 in 2007–2012 also had BI > 1 in 2012–2017, while two marginally weak sectors in 2007–2012 (SBI 26 and 58, with BI = 0.98 and BI = 0.97, respectively) switched to strong in 2012–2017.

[27] More specifically, if $BI_i \leq 1$ the transformed variable is $0.1 + 0.9BI_i$, where the 0.1 avoids cluttering the diagram at the lower-left corner. If $BI_i > 1$ the transformed variable is $1 + \ln(BI_i) / \left(1.2 \max_j \left(\ln\left(BI_j\right)\right)\right)$, where the 1.2 avoids cluttering the diagram at the upper-right corner.

[28] This confirms our assumption that the regional "lumpiness" of factors of production does not affect the national structure of trade, see Brakman et al. (2022).

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APPENDIX

TABLE A1 Overview of Dutch sectors

Code	Description *(brief reference name)*; NT = non-tradable
A	*Agriculture, forestry and fishing (agriculture)*
01	Agriculture and related service activities
02	Forestry and logging
03	Fishing and aquaculture
B	*Mining and quarrying (mining)*
06	Extraction of crude petroleum and natural gas
08	Mining and quarrying (no oil and gas)
09	Mining support activities
C	*Manufacturing (manufacturing)*
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather, products of leather and footwear
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computers, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers

TABLE A1 Continued

Code	Description *(brief reference name)*; NT = non-tradable
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Manufacture of other products n.e.c.
33	Repair and installation of machinery and equipment
D	*Electricity, gas, steam and air conditioning supply (electricity)*
35	Electricity, gas, steam and air conditioning supply; NT
E	*Water supply (water)*
36	Collection, purification and distribution of water; NT
37	Sewerage; NT
38	Waste collection, treatment and disposal activities; materials recovery
39	Remediation activities and other waste management; NT
F	*Construction (construction)*
41	Construction of buildings and development of building projects; NT
42	Civil engineering
43	Specialized construction activities
G	*Wholesale and retail trade (wholesale)*
45	Sale and repair of motor vehicles, motorcycles and trailers
46	Wholesale trade (no motor vehicles and motorcycles)
47	Retail trade (not in motor vehicles)
H	*Transportation and storage (transportation)*
49	Land transport
50	Water transport
51	Air transport; NT
52	Warehousing and support activities for transportation
53	Postal and courier activities
I	*Accommodation and food service activities (accommodation)*
55	Accommodation; NT
56	Food and beverage service activities
J	*Information and communication (info-com)*
58	Publishing
59	Motion picture and television programme production and distribution; sound recording and music publishing
60	Programming and broadcasting; NT

TABLE A1 Continued

Code	Description *(brief reference name)*; NT = non-tradable
61	Telecommunications; NT
62	Support activities in the field of information technology
63	Information service activities
K	*Financial institutions (fin-inst)*
64	Financial institutions, except insurance and pension funding
65	Insurance and pension funding (no compulsory social security); NT
66	Other financial services
L	*Renting, buying and selling of real estate (real estate)*
68	Renting and buying and selling of real estate
M	*Consultancy, research and other specialized business services (consultancy)*
69	Legal services, accounting, tax consultancy, administration
70	Holding companies (not financial)
71	Architects, engineers and technical design and consultancy; testing and analysis
72	Research and development
73	Advertising and market research
74	Industrial design, photography, translation and other consultancy
75	Veterinary activities; NT
N	*Renting and leasing of tangible goods and other business support services (rent-lease)*
77	Renting and leasing of motor vehicles, consumer goods, machines, and other tangible goods
78	Employment placement, provision of temporary employment and payrolling; NT
79	Travel agencies, tour operators, tourist information and reservation services; NT
80	Security and investigation; NT
81	Facility management; NT
82	Other business services
O	*Public administration, public services and compulsory social security (public admin)*
84	Public administration, public services and compulsory social security; NT
P	*Education (education)*
85	Education
Q	*Human health and social work activities (health)*
86	Human health activities
87	Residential care and guidance; NT
88	Social work activities without accommodation; NT
R	*Culture, sports and recreation (culture)*
90	Arts
91	Lending of cultural goods, public archives, museums, botanical and zoological gardens and nature reserves activities
92	Lotteries and betting
93	Sports and recreation; NT

TABLE A1 Continued

Code	Description *(brief reference name)*; NT = non-tradable
S	*Other service activities (other services)*
94	World view and political organizations, interest and ideological organizations, hobby clubs
95	Repair of computers and consumer goods
96	Wellness and other services; funeral activities; NT
T	*Household activities (household)*
97	Activities of households as employers of domestic personnel; NT
98	Undifferentiated goods- and services-producing activities of private households for own use
U	*Extraterritorial organizations and bodies (extraterritorial)*
99	Extraterritorial organizations and bodies; NT

TABLE A2 Overview of population and working population; ranked by size, 2017

		Population		Working population	
City	Code	Size	% total	Size	% total
Amsterdam	SG10	1586	9.4	863	10.3
Rotterdam	SG14	1172	6.9	581	6.9
The Hague	SG13	1062	6.3	542	6.5
Utrecht	SG09	661	3.9	373	4.4
Haarlem	SG11	422	2.5	207	2.5
Eindhoven	SG19	421	2.5	222	2.6
Groningen	SG01	363	2.1	209	2.5
Arnhem	SG06	362	2.1	193	2.3
Leiden	SG12	346	2.0	175	2.1
Breda	SG16	325	1.9	170	2.0
Enschede	SG04	316	1.9	169	2.0
Tilburg	SG17	302	1.8	161	1.9
Amersfoort	SG08	289	1.7	149	1.8
Dordrecht	SG15	287	1.7	135	1.6
Nijmegen	SG07	261	1.5	151	1.8
Heerlen	SG21	247	1.5	123	1.5
Apeldoorn	SG05	214	1.3	103	1.2
Den Bosch	SG18	205	1.2	109	1.3
Maastricht	SG22	183	1.1	93	1.1
Zwolle	SG03	182	1.1	96	1.1
Leeuwarden	SG02	174	1.0	94	1.1
Geleen/Sittard	SG20	148	0.9	74	0.9

Source: Author calculations; size in thousands; % relative to Dutch total.

TABLE A3 Overview of included SBI sectors and number of HS2017 concordance subsectors

SBI code	# HS products	SBI code	# HS products	SBI code	# HS products
01	288	18	27	32	382
02	39	19	21	33	518
03	71	20	862	35	2
06	4	21	4	38	4
08	37	22	50	41	4
09	53	23	148	43	8
10	537	24	364	58	12
11	18	25	124	59	3
12	7	26	211	71	1
13	470	27	75	74	2
14	276	28	295	79	1
15	48	29	47	90	6
16	90	30	74	95	4
17	95	31	21	96	1

Source: Author calculations; concordance includes 42 SBI sectors with 5304 corresponding HS2017 products; see Table A1 for SBI sector description; the table lists the number of HS2017 products corresponding to a given SBI sector; for example: SBI sector 08 consists of 37 HS2017 products.

TABLE A4 Comparison of Dutch BI distributions between locations

Balassa index 2007–2012 distribution					Balassa index 2012–2017 distribution				
City	**# similar**	**%**	**# different**	**%**	**City**	**# similar**	**%**	**# different**	**%**
Gron	0	0	21	100	Gron	0	0	21	100
Leeuw	3	14	18	86	Leeuw	4	19	17	81
Zwol	0	0	21	100	Zwol	0	0	21	100
Ensch	8	38	13	62	Ensch	4	19	17	81
Apel	4	19	17	81	Apel	3	14	18	86
Arnh	6	29	15	71	Arnh	4	19	17	81
Nijm	6	29	15	71	Nijm	5	24	16	76
Amer	5	24	16	76	Amer	3	14	18	86
Utr	6	29	15	71	Utr	4	19	17	81
Amst	6	29	15	71	Amst	4	19	17	81
Haar	4	19	17	81	Haar	1	5	20	95
Leid	6	29	15	71	Leid	5	24	16	76
Haag	6	29	15	71	Haag	5	24	16	76
Rott	1	5	20	95	Rott	3	14	18	86
Dord	2	10	19	90	Dord	3	14	18	86
Breda	3	14	18	86	Breda	2	10	19	90
Tilb	5	24	16	76	Tilb	5	24	16	76
Bosch	6	29	15	71	Bosch	1	5	20	95
Eind	0	0	21	100	Eind	3	14	18	86
GelSit	8	38	13	62	GelSit	5	24	16	76
Heer	3	14	18	86	Heer	0	0	21	100
Maas	4	19	17	81	Maas	6	29	15	71
Average	4.2	20	16.8	80	Average	3.2	15	17.8	85

Source: Author calculations, based on critical values of the 2-sample HWM, 10% significance.

TABLE A5 Abundance of cities and intensity of sectors; correlation, 2012–2017

	$Abun_{low}$	$Abun_{med}$	$Abun_{high}$	$Abun_{tec-low}$	$Abun_{tec-med}$
(a) Correlation abundance in 22 cities, observations, 2012–2017					
$Abun_{low}$	1.000				
$Abun_{med}$	0.354	1.000			
$Abun_{high}$	−0.889	−0.744	1.000		
$Abun_{tec-low}$	0.843	0.563	−0.879	1.000	
$Abun_{tec-med}$	0.683	0.724	−0.843	0.884	1.000
$Abun_{tec-high}$	−0.380	−0.660	0.596	−0.410	−0.455
(b) Correlation intensity for sectors; 83 observations, 2012–2017					
	Int_{low}	**Int_{med}**	**Int_{high}**	**$Int_{tec-low}$**	**$Int_{tec-med}$**
Int_{low}	1.000				
Int_{med}	0.603	1.000			
Int_{high}	−0.887	−0.903	1.000		
$Int_{tec-low}$	0.669	0.461	−0.627	1.000	
$Int_{tec-med}$	0.267	0.387	−0.367	0.794	1.000
$Int_{tec-high}$	−0.429	−0.468	0.502	−0.050	0.284

Source: Author calculations; see Section 2 for data details; shaded cells have negative correlation.

TABLE A6 Correlation matrix, 2012–2017 [Colour table can be viewed at wileyonlinelibrary.com]

	1	2	3	4	5	6	7	8	9
1 Market access	1.000								
2 Density	0.382	1.000							
3 Schiphol road	−0.817	−0.548	1.000						
4 Port road	−0.863	−0.654	0.818	1.000					
5 $Abun^{c}_{low} \times Int^{i}_{low}$	−0.076	0.027	−0.120	0.090	1.000				
6 $Abun^{c}_{med} \times Int^{i}_{med}$	−0.204	−0.280	0.257	0.226	0.014	1.000			
7 $Abun^{c}_{high} \times Int^{i}_{high}$	0.077	0.141	−0.161	−0.083	0.734	0.498	1.000		
8 $Abun^{c}_{tec-low} \times Int^{i}_{tec-low}$	−0.047	−0.121	0.155	0.068	0.124	0.375	0.390	1.000	
9 $Abun^{c}_{tec-med} \times Int^{i}_{tec-med}$	−0.120	−0.311	0.275	0.196	−0.173	0.427	0.099	0.763	1.000
10 $Abun^{c}_{tec-high} \times Int^{i}_{tec-high}$	0.130	0.231	−0.156	−0.140	0.277	0.165	0.399	−0.048	−0.227

Source: Author calculations; see Section 2 for data details; shaded cells above 0.7 in absolute value; 1886 obs.

TABLE A7 Additional controls for Balassa index analysis, 2012–2017

(a) Rank analysis of Balassa index

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Abun^{c}_{high} \times Int^{i}_{high}$	−258.0*** (41.21)					
$Abun^{c}_{med} \times Int^{i}_{med}$		−776.6*** (139.0)				
$Abun^{c}_{low} \times Int^{i}_{low}$			−438.1*** (117.7)			
$Abun^{c}_{tec-high} \times Int^{i}_{tec-high}$				−772.2** (324.7)		
$Abun^{c}_{tec-med} \times Int^{i}_{tec-med}$					−1767*** (243.1)	
$Abun^{c}_{tec-low} \times Int^{i}_{tec-low}$						−13,312*** (1551)
Density	8.03e−05 (0.00208)	−0.000955 (0.00207)	−0.00123 (0.00211)	0.000389 (0.00210)	−0.00107 (0.00207)	−5.98e−05 (0.00206)
Market access	−1.737 (1.682)	0.345 (1.719)	−3.501* (1.850)	−0.536 (1.720)	2.027 (1.702)	1.489 (1.705)
Schiphol road	−0.0385 (0.0469)	0.0180 (0.0477)	−0.0576 (0.0491)	−0.00396 (0.0483)	0.0424 (0.0461)	0.0234 (0.0448)
Port road	−0.00940 (0.0541)	−0.00734 (0.0544)	−0.0263 (0.0550)	−0.0124 (0.0554)	0.00683 (0.0524)	0.0102 (0.0522)
R-squared	0.175	0.171	0.163	0.159	0.181	0.191

(b) Probit analysis of Balassa index

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Abun^{c}_{high} \times Int^{i}_{high}$	15.89*** (2.847)					
$Abun^{c}_{med} \times Int^{i}_{med}$		42.37*** (9.723)				
$Abun^{c}_{low} \times Int^{i}_{low}$			31.22*** (8.583)			
$Abun^{c}_{tec-high} \times Int^{i}_{tec-high}$				52.64** (22.84)		
$Abun^{c}_{tec-med} \times Int^{i}_{tec-med}$					121.5*** (17.74)	
$Abun^{c}_{tec-low} \times Int^{i}_{tec-low}$						890.9*** (114.5)
Density	−0.000562 (0.000964)	−0.000738 (0.000949)	−0.000304 (0.000967)	−0.000760 (0.000950)	−0.000592 (0.000990)	−0.00109 (0.00103)
Market access	0.930 (1.018)	0.663 (1.013)	1.338 (1.034)	0.668 (1.012)	−0.206 (1.051)	0.479 (1.048)
Schiphol road	−0.00595 (0.0287)	−0.00712 (0.0285)	−0.00707 (0.0288)	−0.0145 (0.0288)	−0.0191 (0.0295)	−0.00509 (0.0300)
Port road	0.0545** (0.0231)	0.0411* (0.0229)	0.0757*** (0.0249)	0.0526** (0.0233)	0.0169 (0.0235)	0.0289 (0.0237)

TABLE A7 Continued

(c) Natural logarithm analysis of Balassa index						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\text{Abun}^c_{\text{high}} \times \text{Int}^i_{\text{high}}$	20.72 (3.501)					
$\text{Abun}^c_{\text{med}} \times \text{Int}^i_{\text{med}}$		60.05 (11.14)				
$\text{Abun}^c_{\text{low}} \times \text{Int}^i_{\text{low}}$			33.84 (11.16)			
$\text{Abun}^c_{\text{tec-high}} \times \text{Int}^i_{\text{tec-high}}$				41.29 (18.84)		
$\text{Abun}^c_{\text{tec-med}} \times \text{Int}^i_{\text{tec-med}}$					104.9 (18.84)	
$\text{Abun}^c_{\text{tec-low}} \times \text{Int}^i_{\text{tec-low}}$						845.2 (131.4)
Density	2.92e−05 (0.000145)	0.000176 (0.000145)	9.97e−05 (0.000145)	5.26e−05 (0.000148)	0.000186 (0.000146)	0.000116 (0.000143)
Market access	0.406 (0.117)	0.421 (0.119)	0.454 (0.118)	0.404 (0.118)	0.385 (0.116)	0.382 (0.116)
Schiphol road	0.00863** (0.00340)	0.00476 (0.00345)	0.00974 (0.00352)	0.00626 (0.00350)	0.00392 (0.00344)	0.00484 (0.00337)
Port road	0.00221 (0.00370)	0.00458 (0.00371)	0.00232 (0.00374)	0.00364 (0.00376)	0.00440 (0.00365)	0.00376 (0.00361)
R-squared	0.241	0.236	0.231	0.227	0.237	0.243

Source: Author calculations; see Section 2 for data details; robust standard errors in parentheses; ***$p < .01$; **$p < .05$; *$p < .1$; all regressions have 1886 observations and include sector- and city-fixed effects.

TABLE A8 Overview of strong and reference switching sectors

(a) Overview of strong SBI sectors, 2012–2017

Cities	SBI sector strong$_{NL}$	SBI sector strong$_{WLD}$
Groningen	06; 10; 11; 12; 17; 18; 22; 23; 25; 26; 31; 32; 33; 35; 38; 43; 58; 62; 90	06; 10; 11; 12; 17; 18; 22; 23; 25; 26; 31; 32; 33; 35; 38; 43; 58; 62
Leeuwarden	01; 02; 10; 17; 22; 23; 25; 30; 32; 38; 58; 90; 95; 96	01; 10; 17; 20; 22; 25; 32; 38; 58; 62; 95
Zwolle	10; 14; 31; 33; 74	10; 31; 33
Enschede	09; 13; 14; 16; 18; 22; 26; 27; 28; 30; 31; 32; 35; 38; 43; 74; 95	10; 13; 14; 22; 26; 27; 28; 30; 31; 32; 38; 95
Apeldoorn	01; 10; 16; 17; 21; 22; 23; 24; 25; 28; 96	01; 10; 17; 21; 22; 23; 24; 25; 28; 62
Arnhem	01; 13; 14; 16; 20; 23; 26; 27; 28; 31; 33; 35; 41; 58; 96	01; 10; 13; 16; 20; 26; 31; 33; 35; 41; 58; 59; 62
Nijmegen	08; 10; 16; 23; 26; 27; 28; 29; 38; 95	10; 26; 27; 28; 95
Amersfoort	10; 18; 20; 22; 24; 25; 26; 27; 30; 31; 32; 33; 58; 90; 96	10; 18; 20; 25; 26; 27; 31; 32; 33; 58; 59; 62
Utrecht	21; 27; 32; 43; 58; 62	10; 20; 21; 27; 32; 43; 58; 59; 62
Amsterdam	14; 29; 35; 58; 59; 62; 74; 79; 90	58; 59; 62; 79; 95
Haarlem	03; 09; 14; 17; 18; 35	03; 09; 10; 17; 18; 20; 41; 59
Leiden	01; 21; 30; 32; 35; 58; 74; 95	01; 21; 30; 32; 35; 58; 62; 95
Den Haag	01; 06; 09; 18; 26; 32; 41; 43; 62; 90; 95	01; 09; 18; 21; 26; 32; 41; 43; 62; 95
Rotterdam	09; 11; 19; 20; 27; 35	11; 19; 20; 27; 35
Dordrecht	08; 10; 19; 24; 26; 30; 33; 38; 41; 43	10; 19; 20; 24; 26; 30; 33; 41; 43; 95
Breda	01; 10; 14; 22; 23; 26; 33; 59; 62; 96	01; 10; 14; 20; 22; 26; 33; 59; 62
Tilburg	02; 10; 11; 13; 14; 15; 16; 22; 23; 25; 29; 31; 32; 90; 95; 96	10; 11; 13; 14; 15; 22; 23; 25; 29; 31; 32; 58; 90; 95
Den Bosch	14; 26; 33; 41; 62; 74; 96	01; 10; 20; 26; 41; 62
Eindhoven	15; 26; 27; 28; 62; 95	15; 26; 28; 62; 95
Geleen-Sittard	10; 11; 20; 23; 29; 32; 33; 35; 38; 96	10; 11; 20; 23; 29; 32; 33; 35; 38
Heerlen	02; 08; 11; 16; 17; 20; 22; 24; 25; 32; 95; 96	02; 11; 17; 20; 22; 24; 25; 32; 62; 95
Maastricht	08; 17; 20; 23; 24; 38; 41	17; 20; 23; 38; 41; 59; 95

TABLE A8 Continued

(b) Overview of reference switching sectors, 2012–2017		
Location	**SBI weak$_{NL}$ and strong$_{WLD}$**	**SBI strong$_{NL}$ and weak$_{WLD}$**
Groningen		90
Leeuwarden	20; 62	02; 23; 30; 90; 96
Zwolle		14; 74
Enschede	10	09; 16; 18; 35; 43; 74
Apeldoorn	62	16; 96
Arnhem	10; 59; 62	14; 23; 27; 28; 96
Nijmegen		08; 16; 23; 29; 38
Amersfoort	59; 62	22; 24; 30; 90; 96
Utrecht	10; 20; 59	
Amsterdam	95	14; 29; 35; 74; 90
Haarlem	10; 20; 41; 59	14; 35
Leiden	62	74
Den Haag	21	06; 90
Rotterdam		09
Dordrecht	20; 95	08; 38
Breda	20	23; 96
Tilburg	58	02; 16; 96
Den Bosch	01; 10; 20	14; 33; 74; 96
Eindhoven		27
Geleen-Sittard		96
Heerlen	62	08; 16; 96
Maastricht	59; 95	08; 24

Source: Author calculations, see Section 2 for data details; see Table A1 for sector description.