Urban-Biased Structural Change *

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Using rich micro data from France, we document that the shift of economic activity from manufacturing to services over the last few decades has been *urban-biased*: structural change has been more pronounced in areas with higher population density. This bias can be accounted for by the location choices of large services firms that tend to sort into big cities and large manufacturing firms that increasingly locate in suburban and rural areas. Motivated by these findings, we estimate a structural model of city formation with heterogeneous firms and international trade. We find that agglomeration economies have strengthened for services but weakened for manufacturing. This divergence is a key driver of the urban bias but it dampens aggregate structural change. Rising manufacturing productivity and falling international trade costs further contribute to the urban bias and the growth of large services firms in big cities, boosting services productivity, but also land prices, in the densest urban areas.

KEYWORDS: Agglomeration, Cities, Exporting, Firm Sorting, Manufacturing, Productivity, Services, Trade Costs.

JEL CLASSIFICATION: F15, F61, R12, R14

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1 Introduction

Over the past few decades, high-income countries have witnessed a swift rise in the services share of economic activity. Researchers have largely attributed this structural transformation to a combination of differential productivity growth across manufacturing and services and price-inelastic demand for services (Ngai and Pissarides, 2007), a phenomenon related to Baumol's cost disease. In an open economy, international trade can further accelerate structural change by encouraging countries to specialize in certain sectors, driven by comparative advantage or economies of scale (Matsuyama, 2009, 2019; Alessandria, Johnson, and Yi, 2018).

While the literature has focused on explaining trends for economies as a whole, less is known about the patterns of structural transformation *within* countries across urban and rural regions – and the drivers behind those regional patterns. Recent evidence suggests that structural change may play out unevenly across domestic regions, as services have become more spatially concentrated over time (Desmet and Henderson, 2015). Possible causes of uneven structural change within countries include spatially concentrated international trade shocks (Autor, Dorn, and Hansen, 2013; Fajgelbaum and Redding, 2022) and differential changes in agglomeration forces across sectors (Desmet and Rossi-Hansberg, 2009).

In this paper, we ask three related questions. First, to what extent is the structural change from manufacturing to services observed unevenly across different regions of a country? Second, how can we explain the uneven change, and what role do productivity growth, falling international trade costs, and changing agglomeration forces play in explaining this phenomenon? Third, do within-country spatial differences in structural change matter for how we understand aggregate structural change?

We begin our analysis by constructing measures of structural change from manufacturing to services across different commuting zones in France between 1995 and 2018 (we will refer to commuting zones as 'cities'). Using detailed micro data on the universe of French firms, we then relate those measures to firms' characteristics such as their size, exports, and location, unveiling previously undocumented stylized facts about the underpinnings of structural change in France.

First, we find that structural change is urban-biased. That is, the services share of economic activity increases more rapidly in bigger French cities, and the manufacturing share declines more slowly in smaller cities. This is true regardless of whether economic activity is measured as sales, value-added, or employment. The urban bias is not unique to Paris but holds across the distribution of French cities. We rule out potential explanations based on composition effects: we find no evidence of changes in comparative advantage away from the manufacturing sectors that were more concentrated in big cities in 1995, and no evidence that services sectors traditionally considered as non-tradable (such as catering and hospitality) expanded more in urban areas.

Second, the urban bias in structural change can be accounted for by the behavior of large firms. Among these firms, defined as firms in the top 5% of the French sales distribution, we see a sharp expansion of the services share in big cities between 1995 and 2018. Among the remaining 95% of firms we see no such urban bias.

Third, large services firms sort into big cities but large manufacturing firms do not. Comparing services firms in the biggest cities such as Paris and Lyon where one-fifth of the French workforce is located, to those in the smallest cities that also house one-fifth of the French workforce, we find that the average services firm in the biggest cities is approximately 50% larger than its counterpart in the smallest cities. By contrast, the size of manufacturing firms is more evenly spread out across cities, with a slightly negative correlation between firm size and city size.

Fourth, and consistent with the stylized facts above, since exporting firms tend to be large, we see sharp urban-biased structural change among exporters but not among domestic firms. Exporters of services are more likely to locate in big cities, but the opposite is true for manufacturing exporters.

To understand the driving forces behind urban-biased structural change (UBSC henceforth), we develop a quantitative spatial general equilibrium model of city formation whose ingredients are motivated by the patterns we see in the detailed French micro data. The model has two sectors, manufacturing and services, each featuring heterogeneous firms. As the main drivers of aggregate structural change, the model features differential productivity growth (i.e., TFP growth) across the two sectors (Ngai and Pissarides, 2007) as well as non-homothetic preferences (Comin, Lashkari, and Mestieri, 2021). The model generates cities of different sizes through agglomeration externalities that make bigger cities more productive but at the same time more congested due to land constraints.

The model rationalizes the differential sorting of large and small firms by allowing for heterogeneous agglomeration effects across firms of different types and in different sectors. When more efficient firms benefit *more* from locating in big cities (i.e., when the effects of agglomeration and efficiency on firm productivity are log-supermodular; see Gaubert, 2018; Combes, Duranton, Gobillon, Puga, and Roux, 2012), the model predicts positive sorting by firm size and city size – consistent with what we see for French services firms. Large firms in such a sector gain relatively more from Marshallian externalities in big cities. But conversely, when more efficient firms benefit *less* from locating in big cities (log-submodular agglomeration effects), the model predicts negative sorting – consistent with the patterns we see for French manufacturing firms. Large firms in such a sector suffer disproportionately from congestion costs associated with big cities. In addition, we allow services production to be labor intensive and manufacturing to be land intensive. Big cities thus put pressure on manufacturing firms in two ways: log-submodular agglomeration effects give them an incentive to locate in smaller cities where they can be more productive, and higher land prices disproportionately affect their costs, giving them a further incentive to move to smaller, less densely populated locations.[1]

The final ingredient relates to international trade. We model the economy as internationally open. Firms face fixed and variable trade costs and decide whether to become an exporter and how much to export. As we observe differences in export intensities across sectors in the data, we allow trade costs to vary across manufacturing and services.

The model thus combines, in a unified framework, three drivers of structural change each operating at the sectoral level: differential productivity growth, differential changes in agglomeration externalities, and differential changes in international trade costs. In the resulting spatial equilibrium, heterogeneous firms in different sectors locate in different cities, producing endogenous spatial patterns of specialization and export composition across cities of different size. By implication, each city has a distinct exposure to shocks that drive structural change in the model.

First, differential productivity growth across sectors leads to structural change through the conventional complementarities in the consumption of manufacturing goods and services. Non-homothetic income effects further alter the relative demand for services. Second, differential changes in agglomeration externalities across sectors can lead to changes in the concentration of economic activity at dense locations. For example, if agglomeration externalities rise in the services sector, services firms expand in big cities and crowd out manufacturing to suburban and rural areas. Third, falling international trade costs reallocate sales and resources from non-exporters to exporters. The differential sorting patterns across manufacturing and services exporters imply that some cities are more exposed to falling manufacturing trade costs, while others are more exposed to falling services trade costs.

Based on the French micro data, we calibrate and structurally estimate the model's key parameters, in particular those that determine sectoral productivity, agglomeration effects and sorting, and trade costs. Our procedure jointly matches moments of the distribution of firms across city sizes for 1995 and 2018 as well as the falling aggregate manufacturing share, the changes in sectoral trade flows, and the increase in real GDP per capita in the French economy between 1995 and 2018. The estimated model is capable of replicating UBSC and the spatial sorting of large and small firms that differs across sectors (the first and third stylized facts discussed above). It also reflects the fact that big cities account for the lion's share of services growth. The estimated model does also well at

[1] Gaubert (2018) allows for footloose capital as an input that is uniformly priced across space, but land is not an input. In our production function, higher land prices affect firms' production costs both directly and indirectly through higher labor costs as workers need to be compensated for higher housing costs. Sectoral differences in land intensity make it possible for the model to account for why, despite being less labor intensive, manufacturing firms are more likely than services firms to locate in less densely populated cities.

attributing UBSC to the growth of large firms and exporting firms (the second and fourth stylized facts), even though these are not targeted moments in the estimation.

We then use the estimated model to assess the contribution of sectoral productivity growth, changing agglomeration effects, and falling international trade costs to UBSC. To do this, we start from the estimated 1995 equilibrium and switch on each driver one-by-one as a separate counterfactual experiment, setting the driver to its 2018 value and leaving the other drivers at their 1995 values. We then compare each counterfactual UBSC prediction to the UBSC prediction of the estimated model.

First, the model's estimate of growth in manufacturing TFP between 1995 and 2018 is more than double that in services. While we confirm the role of differential productivity growth across sectors as a leading driver of structural change on aggregate (Herrendorf, Rogerson, and Valentinyi, 2014), we find that it does not explain the urban bias. In our corresponding counterfactual experiment, relative manufacturing productivity growth expands the aggregate services share of the economy and shrinks the manufacturing share, consistent with the literature. In big cities, where services already represented the majority of economic activity in 1995 and where services growth is concentrated, the services share naturally rises. But in small cities, where manufacturing was dominant in 1995, the services share also rises because of the relative decline of manufacturing – even though services growth was not concentrated in those cities. On balance, structural change induced by relative manufacturing productivity growth shows no urban bias.

However, in our model with heterogeneous firms operating at different locations, the expansion of services is first and foremost driven by the growth of large services firms, which are labor intensive (not land intensive) and which tend to be concentrated in big cities. As a consequence, population is pulled into big cities, raising the productivity of services firms through agglomeration externalities. Our model thus also incorporates an indirect effect of manufacturing TFP changes on services sector productivity, an effect that is absent in canonical analyses that abstract from firm heterogeneity. In our estimates, this effect is almost exactly offset by an accompanying increase in land prices in big cities, and so has no overall impact on aggregate structural change.

Second, our estimates suggest that agglomeration externalities at the sector level have changed in opposite directions over time, becoming stronger for services but weaker for manufacturing. This result is consistent with evidence based on US and European data of greater spatial concentration in services but de-concentration in manufacturing (Desmet and Henderson, 2015). It is also consistent with the finding that local knowledge spillovers are more important for young industries such as innovative services than for mature industries (Duranton and Puga, 2001; Desmet and Rossi-Hansberg, 2009). In our counterfactual experiment, we find that this divergence in agglomeration externalities across sectors is a major contributor to UBSC. Strengthening agglomeration externalities for services lead to increased concentration of services firms in big cities, driving up wages and land prices, thereby crowding out manufacturing firms to less densely populated areas. Services firms become more productive, especially large services firms due to the positive sorting of firm size and city size. At the same time, weakening agglomeration externalities for manufacturing give firms in that sector a further incentive to leave big cities, leading to a rising concentration of manufacturing in other parts of France. Due to negative sorting, large manufacturing firms in particular relocate towards small cities, making room for small and less efficient services firms to enter big cities.[2] In our estimates, changes in agglomeration externalities lead to a reduction in aggregate structural change by about one-tenth.

Thus, we would understate the inferred change in manufacturing productivity growth – the main driver of aggregate structural change – if we did not account for the differential growth of heterogeneous firms at different locations and if we did not account for changes in agglomeration externalities. In short, we would understate manufacturing productivity growth if we employed a model that abstracts from UBSC.[3]

Related Literature. Our paper falls into the intersection of macroeconomics, urban economics and international trade. We contribute to the macroeconomic literature that studies drivers of aggregate structural change (Ngai and Pissarides, 2007; Herrendorf, Rogerson, and Valentinyi, 2014; Comin, Lashkari, and Mestieri, 2021). This implicitly assumes that any spatial variation in the patterns of structural change can be understood as being orthogonal to changes in the aggregate. But, as discussed above, the indirect mechanisms in our framework can make a non-negligible, negative contribution to aggregate structural change, i.e., a slower transition from manufacturing to services compared to what a conventional macroeconomic model would imply.

At the same time, urban economists have long debated the causes underlying the growth of cities while abstracting from structural change (e.g., Glaeser, Kallal, Scheinkman, and Shleifer, 1992). Our results also contribute to this debate by highlighting a novel interplay between manufacturing productivity growth and city size growth through agglomeration externalities. Structural change on its own may cause cities to grow even if agglomeration forces remained unchanged. Recent studies have stressed the role of heterogeneous preferences for urban amenities across individuals with different incomes in accounting for spatial inequality (see Diamond and Gaubert, 2022, for a survey). Our model abstracts from this potential source of UBSC as it does not distinguish between

[2]This change offsets the relative increase in population at dense locations that is brought about by an increase in manufacturing TFP. As a result, the distribution of city sizes in our model remains stable over time, consistent with the corresponding empirical distribution in the data.

[3]Related to this line of questioning, Davis, Fisher and Whited (2014) have shown that agglomeration contributes to consumption growth.

worker types and thus takes the composition of the workforce as being homogeneous across sectors.[4]

An emerging literature studies the spatial patterns of structural change (Desmet and Rossi-Hansberg, 2009; Desmet and Henderson, 2015). Desmet and Rossi-Hansberg (2014) further show that spatial patterns of technological diffusion can explain the differential spatial growth patterns of manufacturing and services. Our empirical findings are consistent with theirs, while also highlighting the role of large firms' location choices in driving UBSC.[5]

Our paper also relates to the literature studying the spatial impact of trade liberalization. Alessandria, Johnson, and Yi (2021) make the case for international trade as a driver of aggregate structural change, emphasizing the role that comparative advantage and scale economies can play.[6] We find no evidence in our data that this channel plays out unevenly across locations within a country.

Roadmap. Section 2 describes the key data patterns motivating our analysis. In Section 3 we develop our model of differential structural change across locations. In Section 4 we parameterize and estimate our model. In Section 5 we use the model to decompose structural change into the various mechanisms highlighted by our framework. Section 6 concludes.

2 Urban-biased structural change: Evidence from France

In this section, we describe the French firm-level data we use and illustrate the main empirical patterns relating to structural change in France over recent decades. These findings motivate our

[4]If the demand for urban amenities is comparatively more income elastic than the demand for other goods, and if services firms employed comparatively higher-wage workers than do manufacturing firms, then urban bias could arise purely as the result of the differential composition of worker types across the two sectors. In our data, however, it is manufacturing firms that employ higher-wage worker types by comparison with services firms. Another potential explanation for UBSC is differential spending by age group. Cravino, Levchenko, and Rojas (2022) show that population aging explains a sizable share of the observed increase in US services consumption as older households tend to spend more on services. As in other parts of Western Europe, however, there has been no obvious divergence in age structures across French urban and rural regions (see Kashnitsky, De Beer and Van Wissen, 2021).

[5]Eckert, Ganapati, and Walsh (2022) show that the rapid wage growth in large US cities since 1980 has been led by large business services firms, in line with our findings. Ding, Fort, Redding, and Schott (2022) offer a framework of structural change within the firm. They demonstrate that large multi-plant US manufacturers have become more services intensive over recent decades. Eckert and Peters (2022) and Coeurdacier, Oswald, and Teignier (2022) study structural change in historical perspective with a focus on agriculture productivity growth, while we consider the more recent period. Desmet and Rossi-Hansberg (2014) study the evolution of the spatial clustering in the production of goods and services in a model with with sector-specific agglomeration externalities and endogenous technical change. Their analysis, however, does not address UBSC, as it assumes that firms at each location specialize in either services or manufacturing, and it does not allow for systematic variation in population density across locations beyond that which is implied by differences in labor intensity and technology across firms.

[6]Fajgelbaum and Redding (2022) show that increased trade integration led to spatially concentrated patterns of structural change in Argentina in the late nineteenth and early twentieth centuries. Bakker, Garcia-Marin, Potlogea, Voigtländer, and Yang (2022) study the impact of trade on cities (and the reverse) in a quantitative spatial model.

theoretical framework in Section 3 and the structural estimation exercise in Section 4.

2.1 Data description

To document structural change at the aggregate level and the city level across France, we use the FICUS (1995-2007) and FARE (2008-2018) firm balance sheet data from INSEE. These data sets allow us to observe firm-level revenue, value-added, employment, and exports of all active firms, and also provide information about firms' geographic locations. Throughout the analysis we focus on 1995 and 2018 as the initial and final years.[7]

We define a city as a commuting zone ("zone d'emploi") following Combes, Duranton, Gobillon, Puga and Roux (2012) and Gaubert (2018). There are 297 commuting zones covering all of mainland France (excluding Corsica and overseas regions) based on the 2010 revision. To arrive at a measure of population size by commuting zone, we rely on the DADS matched employer-employee data set. This includes information on all employees, their location of work and residence. We use the number of total employees in the initial year as our measure of population size.[8] Figure A.1 in Appendix A.1 shows a map of the population across commuting zones.

Firms may have multiple establishments and those establishments may be located in multiple cities. We restrict attention to firms with one establishment and firms whose establishments are all located in the same city, as we do not want to rely on information on firms' location that may be tainted by headquarter effects whereby firms report activity in places where production may not be happening (see Duranton and Puga, 2005). However, our empirical findings are robust to including all firms.[9] To identify single-establishment and single-city firms, we use the DADS data set, which contains information about the location of each firm's establishments.

A unique feature of the French administrative balance sheet data is that export revenues are observed not only for manufacturing firms but also for services firms. This allows us to measure export intensity for both manufacturing and services firms. The specific sectors included in services are accommodation and catering, administrative and support services, arts and entertainment, construction, finance and insurance, information and communications technology, real estate, specialized

[7]The key data patterns we rely on in our estimation evolve gradually and smoothly over time. In particular, revenue and export shares across city size bins do not jump from year to year.

[8]Total employees include those in manufacturing, services and all other sectors being employed by any firm, including multi-establishment firms. While there is population growth over time, the city size distribution is stable.

[9]In Table A.1 we show that multi-establishment firms represent around 5% of all firms and around half of aggregate economic activity. As we demonstrate further below, the urban-biased patterns we document are not materially affected by including multi-establishment firms.

and technical services, and transportation.[10]

2.2 Empirical patterns

We next describe how structural change occurred across France over the period from 1995 to 2018. We distinguish between cities with different population sizes and present the patterns in terms of city size quintiles. We refer to these quintiles as city size *bins*, with bin 5 containing the largest cities and bin 1 containing the smallest cities. By construction, each bin has roughly the same population, measured as the number of total employees.[11] We define these bins based on population size in 1995 and we do not change the assignment of cities to bins over time. The two largest cities in each bin are: Paris and Lyon (bin 5), Roissy-Sud Picardie and Saclay (bin 4), Rennes and Nice (bin 3), Aix-en-Provence and Troyes (bin 2), Nevers and Boulogne-sur-Mer (bin 1). Tables A.2-A.4 provide descriptive statistics by city size bin for variables of interest such as revenue, value added, employment, and exports.

Stylized fact 1: Aggregate and urban-biased structural change
On aggregate, France experiences the typical structural change from manufacturing towards services. But structural change is uneven across space, with the largest cities experiencing the strongest decline in manufacturing and the strongest rise in services.

Focusing on the aggregate level, Figure 1a illustrates the well-known pattern of structural change from manufacturing towards services in our sample. It shows the aggregate revenue shares of manufacturing and services in 1995 and 2018. While in 1995 the two sectors have roughly the same revenue, in 2018 the services share is almost twice as large as the manufacturing share: the aggregate revenue shares of manufacturing and services are 53% and 47% in 1995, and they stand at 38% and 62% in 2018.[12] When we compute shares based on value added rather than revenue, we arrive at a similar picture. The value-added share of manufacturing declines from 42% in 1995 to 27% in 2018, while the services share increases from 58% to 73%. Corresponding shares based on employment are virtually the same.[13]

Overall, aggregate structural change in France mirrors developments in other high-income

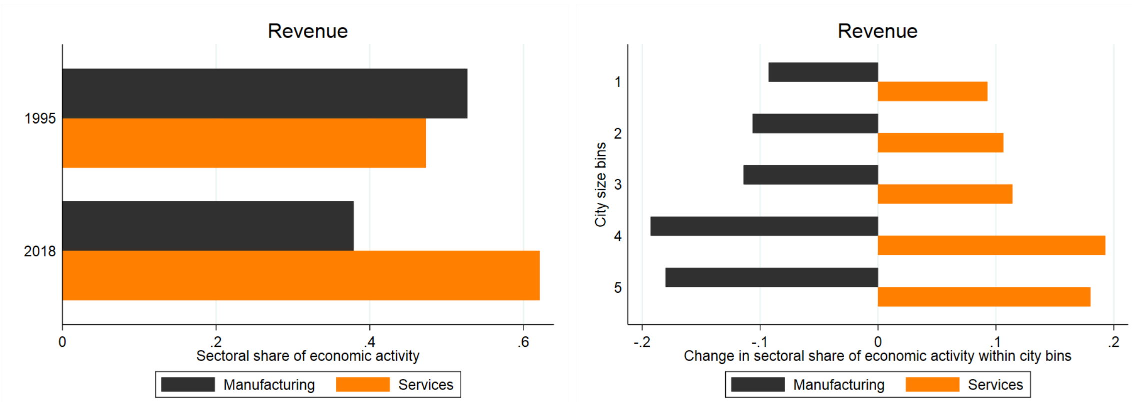
[10]Firms classified as offering retail/wholesale services are not included. Since those firms tend to have multiple establishments and are typically active in multiple locations, they effectively drop out of our single-establishment sample. Adding those firms to our sample does not change our empirical results in any meaningful way.

[11]The number of employees is not exactly the same across bins due to the discrete nature of cities. The city size ranking based on total employees is very highly correlated with the ranking based on working-age population.

[12]See Table A.2 for details. These shares add up to 100% as we exclude agriculture and mining since those sectors were small and their shares hardly changed over time. Specifically, the value-added shares of agriculture, forestry and fishing in the French economy were 2.7% in 1995 and 1.9% in 2018. The value-added shares for mining and quarrying

Figure 1: Aggregate and urban-biased structural change in France, 1995-2018

(a) Aggregate structural change (b) Urban-biased structural change



Notes: In panel (a) the bars show the aggregate sectoral revenue shares for manufacturing and services in 1995 and 2018. The shares of the two sectors add up to 1. Panel (b) shows structural change within French city bins, with city bin 1 representing the smallest cities and bin 5 the largest cities. The bars show the percentage point *change* in sectoral revenue shares for manufacturing and services between 1995 and 2018. For example, −0.1 means a ten percentage point decline. The changes within city bins add to zero as manufacturing and services are the only sectors (agriculture and mining are excluded).

countries. For example, for the period from 1970 to 2007, Herrendorf *et al.* (2014) report an increase in the value-added share of services by about 15 to 20 percentage points in the EU15, Japan and the US.[14]

Next, Figure 1b illustrates a key empirical motivation for our paper, namely the observation that structural change occurs faster in larger cities. We refer to this observation as *urban-biased structural change* (UBSC). The figure shows the change in sectoral revenue shares within city size bins between 1995 and 2018. In each bin, the manufacturing share declines and the services share increases, but the changes are stronger in larger cities, giving rise to a rough 'pyramid' shape. As shown in Table 1, the decrease in the manufacturing share is 18 percentage points in the largest cities but only 9 percentage points in the smallest cities. The stronger decrease comes on top of a lower 1995 baseline share of manufacturing in the largest cities (33% compared to 67% in the smallest

were 0.2% and 0.1%.

[13]See Table A.2 for details. As shown in Table A.3, manufacturing value-added in our sample declines in real terms by 2% between 1995 and 2018. Manufacturing employment (not listed in Table A.3) drops by 22%, broadly comparable in magnitude to a decline in US manufacturing employment by 18% between 2001 and 2007 as reported by Pierce and Schott (2016). In Figure A.2 we show different measures of aggregate structural change (revenue, exports, value-added, employment) including multi-establishment firms.

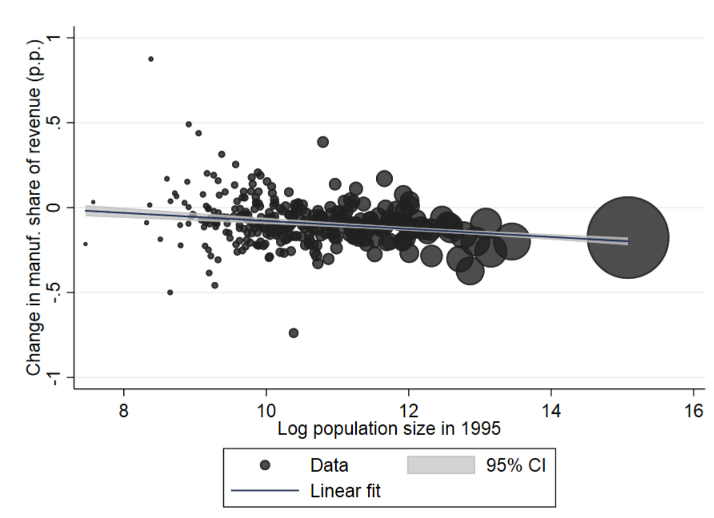
[14]See their Figure 6.2. Specifically, from 1970 to 2007 the nominal value-added share of services rises from roughly 65% to 80% in the US, from roughly 50% to 70% in Japan, and from roughly 55% to 75% in the EU15. The corresponding manufacturing shares fall from roughly 30% to 20% in the US, and from roughly 40% to 25% in Japan and the EU15. The remaining sector is agriculture.

Table 1: Urban-biased structural change across French city size bins, 1995-2018

	Manufacturing share of revenue		
City size bin	1995	2018	UBSC
1	0.67	0.58	−0.09
2	0.64	0.53	−0.11
3	0.54	0.42	−0.12
4	0.56	0.37	−0.19
5	0.33	0.15	−0.18

Notes: The table reports the manufacturing sector revenue shares in each city size bin. Bin 1 represents the smallest cities and bin 5 the largest cities. The column labeled UBSC (which stands for urban-biased structural change) reports the changes in the shares between 1995 and 2018. For example, -0.09 means a nine percentage point decline.

Figure 2: City size and the decrease in the manufacturing share across French cities, 1995-2018



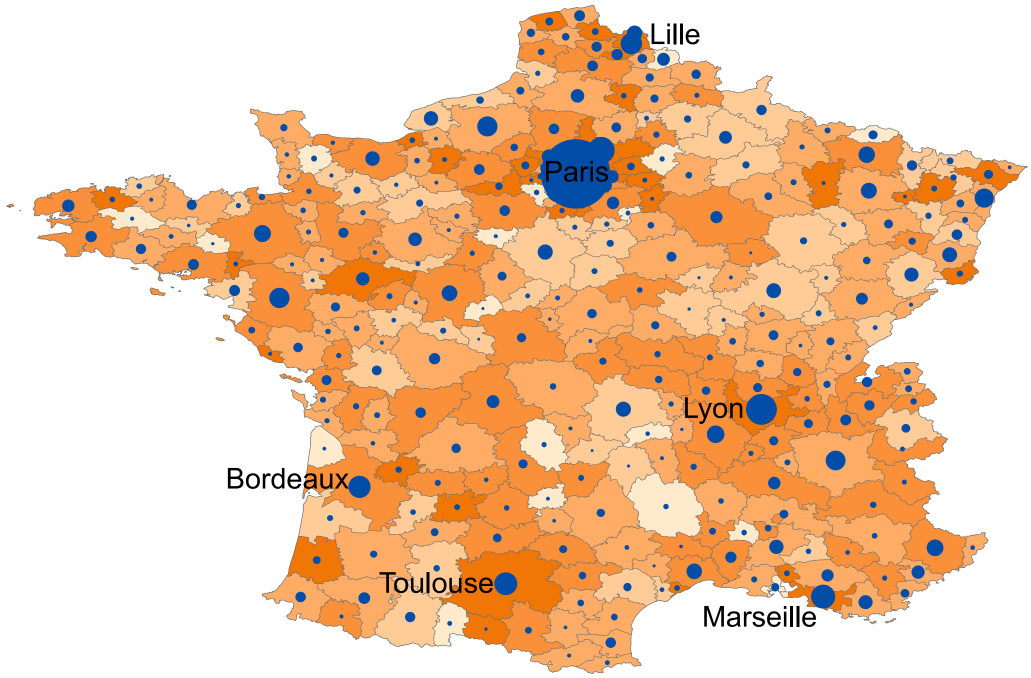
Notes: The figure plots city size (population) against the decrease in the manufacturing share across 297 French cities (commuting zones) between 1995 and 2018. Each dot represents one French city, proportional to city size in 1995. City size is measured as the number of total employees. The largest dot represents Paris. The variable on the vertical axis is the change in the manufacturing share in percentage points. The slope of the regression line is significantly different from zero.

cities).[15]

Consistent with the literature, we measure structural change as the percentage point change in the sector shares of economic activity. Mechanically, this means that a lower baseline share of manufacturing in the largest cities (and thus a higher baseline share of services) makes it relatively hard to find UBSC. The reason is that a given growth rate of services translates into a smaller

[15]In Figure A.3 we also show the change in sectoral revenue shares *across* city bins between 1995 and 2018. Manufacturing shifts away from the largest cities towards smaller cities, and the opposite is true for services.

Figure 3: City size and the increase in the services share across French cities, 1995-2018



Notes: The map illustrates the city size (population) and the increase in the services share across 297 French cities (commuting zones) between 1995 and 2018. The dots are proportional to city size. City size is measured as the number of total employees. The increase in the services share is depicted in five shades of orange, with the darkest shade corresponding to the strongest increase. In addition to the Paris region, the labels indicate the five largest cities outside of the Paris region. Ordered by size these are Lyon, Marseille, Toulouse, Bordeaux, Lille.

percentage point increase in the services share of economic activity of a larger city compared to a smaller city where services were initially less prominent. Our measurement of the urban bias is therefore conservative.

The urban bias of structural change is not merely a 'Paris versus the rest' phenomenon. The scatter plot in Figure 2 shows the systematic negative relationship between city size and the change in the manufacturing share across all 297 cities. The map in Figure 3 illustrates the converse, namely the positive correlation between population size and the increase in the services share across cities. In addition, Figure A.4 demonstrates that the urban-biased pattern also holds for different measures of structural change (expressed in terms of exports, value added, and employment).[16] In Figure A.6 we also show that, consistent with Figure 1b, the share of all firms within the manufacturing sector falls in the largest cities and rises in all other cities. By implication, the share of all firms within the

[16]Figure A.5 shows the corresponding graphs for the sample including multi-establishment firms. Recall that as agriculture and mining are excluded, the decrease in the manufacturing share is by construction the same in absolute value as the increase in the services share.

Table 2: Concentration of sectoral growth across city size bins

City size bin	Domestic revenue		Export revenue	
	Manufacturing	Services	Manufacturing	Services
1	29%	13%	22%	3%
2	26%	15%	25%	4%
3	18%	16%	19%	9%
4	17%	19%	20%	16%
5	10%	38%	14%	68%
Total contribution	100%	100%	100%	100%
Total growth	−14%	74%	40%	181%

Notes: The table decomposes the growth of the manufacturing and services sector into the contributions of each city size bin. Revenues in 2018 are adjusted to 1995 prices. 'Total contribution' refers to the sum of the contribution of each city size bin to the total (domestic/export) revenue growth of each sector. 'Total growth' in the last row refers to the total real (domestic/export) revenue growth of each sector between 1995 and 2018. Bin 1 represents the smallest cities and bin 5 the largest cities.

services sector increases in the largest cities and falls in the smallest cities.

The fact that economic activity experiences a faster shift from manufacturing to services in larger cities may reflect a swift decline of the manufacturing sector in those cities or a rapid growth of the services sector. To determine this, we decompose the growth in the total domestic and export revenues of each sector into the share accounted for by each city size bin:

$$g^r_{jt+1} = \sum_i \left(\frac{R^r_{jt}(i)}{\sum_{i'} R^r_{jt}(i')} \right) g^r_{jt+1}(i), \tag{1}$$

where $r = \{\text{domestic}, \text{export}\}$, g_{jt+1} is the revenue growth rate of sector j, $g_{jt+1}(i)$ is the corresponding growth rate for city i, and $R^r_{jt}(i)$ is the total domestic or export revenue of sector j in city size bin i. The results of this decomposition are reported in Table 2 and show that sectoral growth is highly spatially concentrated. The growth of the services sector is concentrated in large cities, with the largest cities accounting for 38% of domestic revenue growth and 68% of export revenue growth between 1995 and 2018. Conversely, the decline of domestic manufacturing revenue and growth of manufacturing exports are concentrated in small cities. UBSC thus reflects a disproportionate growth of services in large cities, rather than a disproportionate decline of manufacturing in large cities.

The role of non-tradable services. We do not find evidence that non-tradable services explain the urban bias. When we examine subsectors of services, we do not find that the urban bias in structural change is driven by an expansion of local services that cannot be traded nationally or internationally. In Figure A.7, we categorize services subsectors into tradable and non-tradable services. We categorize ICT, professional and business services, and finance and insurance as tradable services and other services sectors as non-tradable. We find no urban bias for non-tradable services but a clear urban bias for tradable services.

Changes in comparative advantage. Our data shows that a shift in manufacturing comparative advantage cannot explain the urban bias in structural change.[17] For comparative advantage to be a driver, the manufacturing sectors whose output is replaced by outsourcing or imports should be those sectors that (i) decline at the fastest rate and (ii) are more concentrated in large cities in 1995 compared to manufacturing sectors that have a smaller (or non-negative) rate of decline. To examine this, we correlate the growth rates of individual manufacturing sectors in large cities with their initial size. Figure A.10 shows that there is no systematic relationship. This suggests that a shift in comparative advantage working against manufacturing sectors that were over-represented in large cities in 1995 cannot explain the urban bias in structural change.

Stylized fact 2: Large firms account for urban-biased structural change

Structural change among large firms is urban-biased, but structural change among other firms displays no urban bias.

To better understand how different firms may contribute to urban-biased structural change, we decompose structural change into the contributions of large firms and other firms, measuring structural change in each city size bin in the same way as discussed in the context of Figure 1b, i.e., as the change in the manufacturing share in a city size bin between 1995 and 2018. This change can be expressed as

$$\Delta\omega_{m,2018}(i) = \Big(\underbrace{\varsigma_{1995}^{\text{non-large}}(i)\,\Delta\omega_{m,2018}^{\text{non-large}}(i)}_{\substack{\text{(a) Structural change}\\ \text{among non-large firms}}} + \underbrace{\omega_{m,2018}^{\text{non-large}}(i)\,\Delta\varsigma_{2018}^{\text{non-large}}(i)}_{\substack{\text{(b) Changing non-large firms'}\\ \text{revenue share}}}\Big)$$
$$+\Big(\underbrace{\varsigma_{1995}^{\text{large}}(i)\,\Delta\omega_{m,2018}^{\text{large}}(i)}_{\substack{\text{(c) Structural change}\\ \text{among large firms}}} + \underbrace{\omega_{m,2018}^{\text{large}}(i)\,\Delta\varsigma_{2018}^{\text{large}}(i)}_{\substack{\text{(d) Changing large firms'}\\ \text{revenue share}}}\Big),$$

where $\omega_{mt}(i) = R_{mt}(i)/\sum_k R_{kt}(i)$ is the manufacturing sector's share of revenue in bin i, $\omega_{mt}^{\text{large}}(i) = R_{mt}^{\text{large}}(i)/\sum_k R_{kt}^{\text{large}}(i)$ is the manufacturing share in the revenue of *large firms'* in bin i (the total revenue of large firms in that bin, including export sales and domestic sales). As previously, the other sector is services ($k = m, s$). The variable $\varsigma_t^{\text{large}}(i) = \sum_k R_{kt}^{\text{large}}(i)/\sum_k R_{kt}(i)$ is the large

[17] In Appendix A.2 we show that aggregate structural change in France cannot be fully explained through changes in comparative advantage over time that may increasingly have led France to specialize in sectors other than manufacturing.

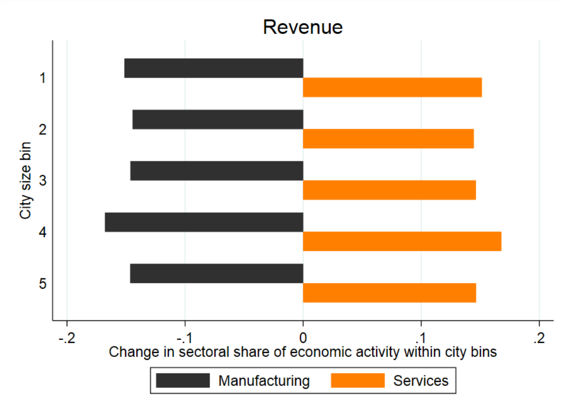
Table 3: Contribution of large firms and non-large firms to urban-biased structural change

		Non-large firms		Large firms	
City size bin	UBSC (total)	Structural change among non-large (a)	Changing non-large revenue share (b)	Structural change among large firms (c)	Changing large-firm revenue share (d)
1	−0.093	−0.066	0.005	−0.021	−0.010
2	−0.106	−0.061	0.014	−0.041	−0.008
3	−0.114	−0.065	−0.001	−0.050	0.003
4	−0.193	−0.069	0.011	−0.112	−0.023
5	−0.180	−0.041	−0.005	−0.142	0.008

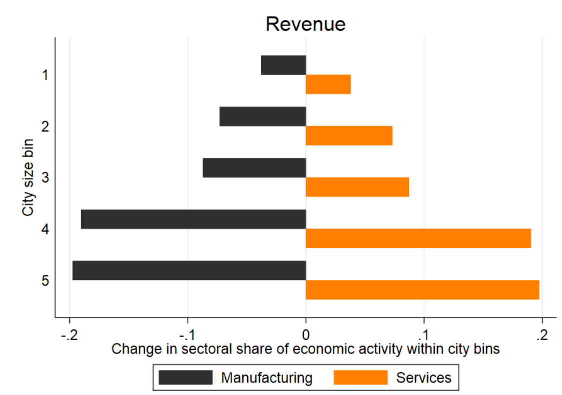
Notes: The table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labeled 'UBSC', which stands for urban-biased structural change). For example, -0.1 means a ten percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities.

Figure 4: Large firms and urban-biased structural change in France, 1995-2018

(a) Structural change among *non-large firms* (bottom 95%)



(b) Structural change among *large firms* (top 5%)

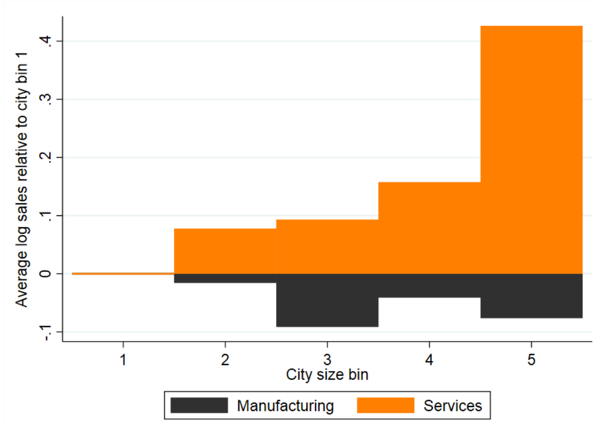


Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. Large firms are defined as those in the top 5% of the log sales distribution (adjusted to 1995 prices). In panel (a) the bars show the percentage point change in sectoral revenue shares within city bins for manufacturing and services between 1995 and 2018 among non-large firms only. The numbers correspond to the red element of the first row in the decomposition formula. Panel (b) does the same among large firms only. The numbers correspond to the red element of the second row in the decomposition formula. For example, −0.1 means a ten percentage point decline. The changes within city bins add to zero.

firms' share of revenue in bin i. The first term (a) on the right-hand side captures structural change among non-large firms, while the third term (c) represents structural change among large firms. The second and fourth terms (b) and (d) capture the contributions to structural change in bin i of the changing relative sizes of non-large and large firms.

Table 3 presents the results of this decomposition. The column labeled 'UBSC' reports the total change in the manufacturing share. It corresponds to the black bars in Figure 1b. What can explain the urban bias in this structural change? We find that it is mostly accounted for by structural change

Figure 5: Sorting patterns between firm size and city size in France



Notes: The table shows the cross-sectional relationship between firm size (measured as log sales) and city size bins. The table pools data for 1995 and 2018. Sales in 2018 are adjusted to 1995 prices. The bars show the average log sales across firms for manufacturing (black) and services (orange) in each city size bin, normalized to zero for city size bin 1. City size bin 1 represents the smallest cities and bin 5 the largest cities.

among large firms, as shown in column (c). This is the only column that exhibits a negative and monotonically declining contribution across city bins. That is, the decline in the manufacturing share accounted for by structural change among large firms has a gradient. It is weakest for the smallest cities (minus 2.1 percentage points in bin 1), and it is strongest for the largest cities (minus 14.2 percentage points in bin 5).[18] Figure 4 demonstrates graphically that there is a clear 'pyramid' pattern for structural change among large, but not among non-large firms. We also find similar patterns among exporters, who tend to be large firms, as shown in Figure A.8.[19]

Stylized fact 3: Differential firm sorting in manufacturing and services

For services, we observe positive sorting between firm size and city size – larger services firms tend to be located in larger cities. For manufacturing, we observe weak negative sorting – larger manufacturing firms tend to be located in smaller cities.

Figure 5 shows average log revenue across firms for manufacturing (in black) and services (in orange) in each city size bin, normalized to zero for the smallest bin.[20] The figure exhibits a distinct positive sorting pattern for services firms – larger firms are located in larger cities. The average services firm in the bin of largest cities has revenue approximately 40 log points larger than the average firm in

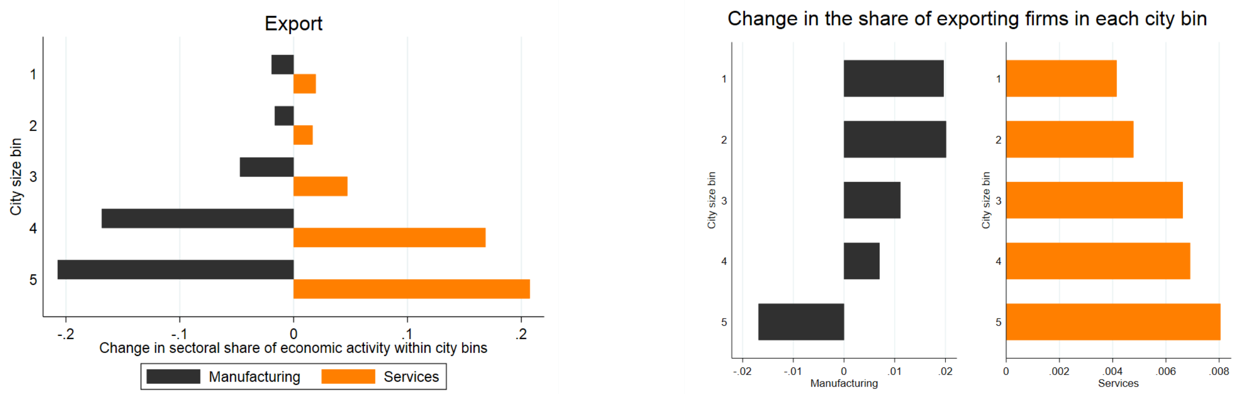
[18]Table A.5 provides a decomposition as in Table 3 but for exporting and non-exporting firms.

[19]Hsieh and Rossi-Hansberg (2023) show that top services firms have grown in the US by opening new establishments predominantly in small and mid-size cities. We focus on single-plant firms, but our results are robust to including all firms.

[20]Note that Figure 5 averages log revenue across firms, whereas Table A.3 reports average revenue in each city size bin.

Figure 6: Urban-biased structural change in French exports, 1995-2018

(a) Change in exports within city bins (b) Change in the share of exporting firms



Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The changes are between 1995 and 2018. In panel (a) the bars show the change in sectoral export revenue shares within city bins for manufacturing (black) and services (orange). The changes within city bins add to zero. In panel (b) the bars show the change in the share of exporting firms.

the bin of smallest cities.

By contrast, we observe an entirely different sorting pattern for manufacturing firms. The average size of manufacturing firms is not as different across city size bins as for services, but nevertheless manufacturing firm revenue is weakly negatively correlated with city size. Firms in the largest cities are on average approximately 10 log points smaller than those in the smallest cities.

Stylized fact 4: Urban-biased structural change in exporting activity

Urban-biased structural change extends to exporting behavior, with the largest cities experiencing the strongest shift in exporting shares from manufacturing to services. At the same time, manufacturing exports become more concentrated in small cities, while the opposite is true for services exports.

Figure 6a has the same structure as Figure 1b, but it focuses on export revenue. That is, it shows the change in sectoral export revenue shares within each city bin between 1995 and 2018. The manufacturing export shares contracted the most in the largest cities and the least in the smallest cities, mirrored by corresponding increases in the services export shares. Within bins we thus observe structural change in exporting behavior that is tilted towards the largest cities. Quantitatively we obtain a steeper 'pyramid' shape than for overall revenue in Figure 1b. As Table A.2 shows, the services export share expanded by 21 percentage points in the largest cities compared to only 2 points in the smallest cities. It is also worthwhile considering the corresponding *levels* of export shares. Exports in the smallest cities were almost exclusively geared towards manufacturing with a share of 97% in 1995, falling only marginally to 95% by 2018. In the largest cities, however, while in 1995 the majority of exports (54%) was still in manufacturing, by 2018 services dominated exports with a share of 67%.

Figure 6b plots the change in the share of exporting firms across city bins, i.e., the change in the extensive margin of exporting. Manufacturing firms became more likely to export in the smallest and medium-sized cities but *less* likely to export in the largest cities. By contrast, services firms became more likely to export across all cities.[21]

3 A model of urban-biased structural change

Motivated by our empirical findings, we develop a model of location decisions by heterogeneous firms in manufacturing and services in the presence of agglomeration externalities that can give rise to urban-biased structural change. We later use the model to quantify the channels through which economic activity shifts from manufacturing to services across French cities. Ours is primarily an economic geography model in which heterogeneous firms sort into cities of various sizes (Behrens, Duranton, and Robert-Nicoud, 2014; Gaubert, 2018). The sorting of heterogeneous firms and sectors to different cities determines the exposure of each city to the forces of structural change. Our model features three main drivers of structural change: sectoral TFP growth, changes in sectoral international trade costs, and changes in agglomeration forces (Melitz, 2003; Herrendorf *et al.*, 2014; Desmet and Henderson, 2015; Alessandria *et al.*, 2019).

3.1 Countries

There are two countries, Home and Foreign. We assume they are symmetrically identical and omit country indices.[22]

3.2 Cities and industries

There is a continuum of *ex-ante* identical cities i, each hosting manufacturing and services firms. The manufacturing and services sectors $j \in \{m, s\}$ are monopolistically competitive. Manufactured goods and services are traded domestically at zero cost.

Let the equilibrium population size be $L(i)$ in city i. For simplicity, we assume that land is owned by absentee landlords from another country and leased to workers and firms. Following

[21] See the top panel of Table A.4 for details.

[22] This modeling assumption implies that trade balances in manufacturing and services are zero, adding considerable tractability. In Appendix B.1 we discuss a version of the model that allows for trade imbalances between manufacturing and services arising from comparative advantage through differential productivity and trade costs parameters.

Hsieh and Moretti (2019) and Behrens *et al.* (2014) the user price of land (and housing) in city i is an increasing function of population size:

$$p_h(i) = \left(\frac{L(i)}{L(1)}\right)^{\gamma}, \tag{2}$$

where γ represents the constant elasticity of land prices with respect to normalized population size.[23]

3.3 Workers and final demand

There is a total mass $\bar{L}$ of identical workers, each endowed with one unit of labor. Workers are freely mobile across cities, with each choosing a location i, a level of consumption of a final goods composite $C(i)$, and housing $h(i)$ to maximize utility subject to a budget constraint. The worker's problem can be solved in two steps. First, choose housing and consumption, taking city i as given. Second, choose i. The first stage of utility maximization is to choose $C(i)$ and $h(i)$ to maximize

$$U(i) = \left(\frac{C(i)}{\eta}\right)^{\eta} \left(\frac{h(i)}{1-\eta}\right)^{1-\eta}, \tag{3}$$

subject to a budget constraint

$$PC(i) + p_h(i)h(i) = (1+\mu)W(i), \tag{4}$$

where the parameter $\eta \in (0,1)$ captures the worker's expenditure share on final goods, P is the price of the final goods composite, $p_h(i)$ is the price of housing (and land use) in city i, $W(i)$ is the wage earned by workers in city i, and μ is a proportional wage subsidy from the redistribution of profits the made by final goods producer.

Workers choose which city i to live in. Free worker mobility equalizes worker utility across cities, i.e., $U(i) = U$ for all i. The city-level equilibrium wage is then

$$W(i) = \lambda p_h(i)^{1-\eta}, \tag{5}$$

where $\lambda = UP^{\eta}/(1+\mu)$ is an economy-wide proportionality factor to be determined in general equilibrium that we take as the numeraire. Since denser cities have higher housing prices, wages in denser cities must also be higher to compensate for higher land prices: $W(i) = p_h(i)^{1-\eta}/(1+\mu)$.

[23]In Appendix B.2 we discuss a model extension in which we introduce a full land market clearing condition. We find that this extension yields quantitatively similar results as those in our baseline simulations in Section 5.

Housing is therefore a congestion force – larger cities are more expensive to operate in – ensuring a non-degenerate city size distribution.

To model non-homothetic preferences, we assume that there is a final goods firm that aggregates output Q_j from the manufacturing and service sectors $j \in \{m, s\}$ to obtain Q units of a final consumption goods composite. The price of the final goods composite is determined competitively. The firm maximizes profits,

$$\Pi = PQ - \sum_{j \in \{m,s\}} P_j Q_j, \tag{6}$$

by choosing Q_j at price P_j, subject to a non-homothetic constant elasticity of substitution (CES) production function over sectors (Comin *et al.*, 2021), implicitly defined as

$$\sum_{j \in \{m,s\}} \theta_j^{\frac{1}{\rho}} \left(\frac{Q_j}{Q^{\varsigma_j}} \right)^{\frac{\rho-1}{\rho}} = 1. \tag{7}$$

The sector-specific parameters $\theta_j > 0$ capture production weights on each sector j's output, the parameter $0 < \rho < 1$ captures the constant elasticity of substitution between the output of each sector implying complementarity, and $\varsigma_j \geq 1$ represents non-homothetic income effects. As Comin *et al.* (2021) show, this allows expenditure shares for each sector to depend not only on their relative prices, but also on the level of aggregate production (income effects). Each sector j's sales share is then

$$\vartheta_j = \frac{P_j Q_j}{\sum_k P_k Q_k} = \frac{\theta_j P_j^{1-\rho} Q^{(1-\rho)(\varsigma_j - 1)}}{\sum_k \theta_k P_k^{1-\rho} Q^{(1-\rho)(\varsigma_k - 1)}}. \tag{8}$$

When $\varsigma_j = 1 \; \forall j$, the production function is homothetic, in which case the sectoral sales shares depend only on sectoral relative prices (Ngai and Pissarides, 2007).

Within sectors, quantities $q_j(\omega)$ of differentiated varieties are aggregated through a sector-specific, homothetic CES aggregator:

$$Q_j = \left(\int_{\omega \in \Omega_j} q_j(\omega)^{\frac{\sigma_j - 1}{\sigma_j}} \, \mathrm{d}\omega \right)^{\frac{\sigma_j}{\sigma_j - 1}}, \tag{9}$$

where $\sigma_j > 0$ captures the elasticity of substitution between differentiated varieties $\omega \in \Omega_j$. The corresponding price index P_j is common across cities as varieties are freely traded within each country.

The non-homothetic CES production function features (weakly) decreasing returns to scale as long as $\varsigma_j \geq 1$. Therefore, the final goods firm makes positive profits, which are entirely redistributed to workers such that $\Pi = \mu \sum_i W(i)\, L(i),\ \mu > 0$.

3.4 Production technologies, agglomeration effects, and trade costs

Firms pay an *ex-ante* entry cost f_j^e, denominated in final goods, to draw an idiosyncratic efficiency type, z, from a sector-specific distribution $G_j(z)$ with support $[1, \infty)$. Goods and services are then produced using labor and land as inputs according to a constant-returns-to-scale technology with a unitary substitution elasticity (Cobb-Douglas technologies):

$$
\begin{aligned}
q_j^d(z,i) &= \Psi_j(z,i)\, \left(l_j^d\right)^{\alpha_j} \left(h_j^d\right)^{1-\alpha_j},\\
q_j^x(z,i) &= \frac{1}{\tau_j} \Psi_j(z,i)\, \left(l_j^x\right)^{\alpha_j} \left(h_j^x\right)^{1-\alpha_j}, \quad \alpha_j \in (0,1),
\end{aligned} \tag{10}
$$

where the d and x subscripts refer to production for the domestic and export markets, respectively, and where $\tau_j > 1$ reflects sector-specific variable iceberg trade costs. A firm's factor-neutral productivity level $\Psi_j(z,i)$ depends on its idiosyncratic efficiency draw z, the sector j in which the firm operates, and the population density in its chosen city $L(i)$. Agglomeration externalities capture the productivity advantage to firms of locating in larger cities, which may arise from knowledge spillovers, labor pooling, inter-firm trade, or demand externalities (Duranton and Puga, 2020; Dauth, Findeisen, Moretti, and Suedekum, 2022).

As in Gaubert (2018), we assume that the composite productivity function $\Psi_j(z,i)$ is not log-modular in z and $L(i)$, i.e., $\partial^2 \log \Psi_j(.)/(\partial \log z\, \partial \log L(i)) \neq 0$. But we extend Gaubert's (2018) specification by allowing for both log-supermodularity and log-submodularity:

$$
\begin{aligned}
\log \Psi_j(z,i) = \;& \log A_j + \log z \\
& + \frac{a_j}{2} \left(\log \frac{L(i)}{L(1)} + \frac{1}{s_j} \left(\frac{(1+\xi_j)\log z + (1-\xi_j)}{1+\log z} \right) \left(\left(1 + \log \frac{L(i)}{L(1)}\right)^{s_j} - 1 \right) \right),
\end{aligned} \tag{11}
$$

where A_j is a sectoral TFP shifter and the parameter $a_j \in [0,1]$ governs the strength of agglomeration externalities in sector j, i.e., it is equal to $\mathrm{d}\log \Psi_j / \mathrm{d}\log(L(i)/L(1))$ when evaluated at $L(i) = L(1)$ for $z = \min\{z\} = 1$ and $\xi_j = 0$.[24]

[24] The normalization $L(i)/L(1)$ ensures that $\log L(i)/L(1) \geq 0$. As discussed by Glaeser, Kallal, Scheinkman and Shleifer (1992), these agglomeration externalities could arise within industries (Marshall, 1890) and across industries (Jacobs, 1969). As in Gaubert (2018), our specification is neutral in that composite productivity depends on city size $L(i)$, not industry size.

The parameter ξ_j determines the direction of the deviation from log modularity in sector j, i.e., the extent to which more efficient firms experience greater or smaller agglomeration effects for a given location, with $-1 \leq \xi_j \leq 1$.[25] This in turn dictates how differentially efficient firms sort across locations of different size. When $\xi_j > 0$, the function is log-supermodular in z and L, implying that more efficient firms benefit relatively more from locating in a larger city. We therefore obtain positive sorting (more efficient firms locating in denser locations). When $\xi_j < 0$, the function is log-submodular in z and L, implying that more efficient firms benefit relatively less from locating in a larger city. We therefore obtain negative sorting (more efficient firms locating in less dense locations). A value of $\xi_j = 0$ gives no sorting.

The parameter $s_j \leq 1$ determines the marginal benefit of choosing a larger city – how the elasticity of $\Psi_j(\cdot)$ with respect to $L(i)$ varies with $L(i)$. This in turn determines the shape of the equilibrium sorting relationship between firm types and location sizes.[26] This gives our model full flexibility for accommodating differences between larger, high-efficiency firms (typically exporters) and smaller, low-efficiency firms (typically non-exporters) in terms of how sharply they sort across differentially dense locations.

We additionally allow for imperfect sorting by making each firm, ω, draw a random, location-specific productivity shock, $\hat{\epsilon}(\omega, i)$, on top of their permanent efficiency z. Define firm-level overall productivity as $\Phi_j(z, i) \equiv \Psi_j(z, i)\, e^{\epsilon(\omega,i)}$. Let the location shock $\epsilon(\omega, i)$ be i.i.d. and distributed Type-I Extreme Value (Gumbel) with mean 0 and variance $\nu_{\epsilon,j}$. Then, $\epsilon(\omega, i) \equiv e^{(\sigma_j - 1)\,\hat{\epsilon}(\omega,i)}$ is distributed Fréchet with shape parameter $\chi_j \equiv \nu_{\epsilon,j}/(\sigma_j - 1)$. Firms with otherwise identical efficiency might thus choose different locations. When $\nu_{\epsilon,j} \to 0$, the model features a perfect (frictionless) sorting equilibrium.

Another difference between our model and Gaubert's (2018) is that firms use land as a factor input. This feature allows us to account for the empirical relationship between sizes of cities and their shares of economic activity in each sector. In the data, this empirical relationship is positive for services and negative for manufacturing (see Table A.2). Conditional on having the same agglomeration and sorting parameters, a model *without* land as a factor of production would predict the *opposite* pattern. The reason would be that services, which are more labor intensive than manufacturing, would effectively also be more land intensive because of workers' demand for housing, suggesting that services would face stronger congestion forces. Instead, our model interprets the empirical relationship as coming from the higher land intensity of manufacturing.[27]

[25]In Appendix B.3, we show that the productivity function $\Psi_j(z, i)$ is only well-behaved within these bounds.

[26]We provide details on how sorting varies with the parameters of (11) in Appendix B.4.

[27]In Gaubert (2018), labor is combined with fully mobile capital, whereas in our model it is combined with a fully immobile factor (land). More generally, non-labor inputs could be modeled as consisting of a combination of mobile

The goods and services produced by firms can be sold domestically and exported. In addition to the variable trade costs τ_j, exports incur sector-specific fixed trade costs f_j^x .

3.5 Firms' choices

To maximize profits, a firm from sector j with efficiency z located in city i chooses the amount of labor and land to employ, taking the input prices as given. Each firm produces a differentiated variety ω. The firm's profit maximization problem is

$$\pi_j(z,i) = \max_{\substack{l^d,l^x,h^d,h^x,\\ q^d,q^x,p^d,p^x,\varkappa}} \quad p^d q^d - W(i)\, l^d - p_h(i) h^d \\ + \varkappa_j(z,i)\left(p^x q^x - W(i)\, l^x - p_h(i) h^x - P f_j^x\right), \tag{12}$$

where $\varkappa_j(z,i) \in \{0,1\}$ denotes the firm's extensive-margin export choice, and the x superscripts refer to the production of exports, subject to the technologies

$$q^d = q_j^d(z,i), \quad q^x = q_j^x(z,i),$$

where $q_j^d(z,i)$ and $q_j^d(z,i)$ are as defined in (10), and subject to firm-specific domestic and export demand curves

$$q_j^d = \left(\frac{p_j^d}{P_j}\right)^{-\sigma_j} Q_j, \quad q_j^x = \left(\frac{p_j^x}{P_j}\right)^{-\sigma_j} Q_j. \tag{13}$$

The firm's profits can be written as $\pi_j(z,i) = \pi_j^d(z,i) + \varkappa_j(z,i)\left(\pi_j^x(z,i) - P f_j^x\right)$, where π_j^d is profits from domestic sales and π_j^x variable profits from exports. Firms will only export (i.e., choose $\varkappa_j(z,i) = 1$) if doing so delivers profits at least as high as the fixed trade costs, i.e., if

$$\pi_j^x(z,i) \geq P f_j^x. \tag{14}$$

Given the above characterization of profits at any given location, firms will choose a location that maximizes their profits. The firm draws a random, location-specific shock to profits $\epsilon(\omega,i)$ so that we can write variable profits as a composite of an idiosyncratic component $\nu_j(z,i)$ and the

and immobile capital. As long as the composition of non-labor inputs in manufacturing is not excessively biased towards mobile capital, the ranking between services and manufacturing in terms of land intensity, and the qualitative implications that follow from it, would remain unchanged.

random shock:

$$\pi_j(z,i) = v_j(z,i)\,\epsilon(\omega,i) - Pf_j^x. \tag{15}$$

Since the fixed trade costs are independent of location, the firm's location choice problem can be expressed as

$$i_j^*(z) = \arg\max_{i\in I}\ v_j(z,i)\,\epsilon(\omega,i). \tag{16}$$

3.6 Equilibrium

The entry cost f_j^e pins down the mass of firms in each sector M_j in equilibrium. There are no fixed operating costs, hence there is no selection upon entry. Following Behrens *et al.* (2014), we assume that firms and workers self-organize in the creation of cities.

An equilibrium is defined by the following conditions:

- *Export selection condition*

$$\Phi_j(z,i) \;\geq\; \tau_j p_h(i)^{1-\eta\alpha_j}\left(\frac{Pf_j^x}{\kappa_j}\right)^{\frac{1}{\sigma_j-1}},$$

  where $\kappa_j \equiv \frac{1}{\sigma_j}\left(\frac{\sigma_j-1}{\sigma_j}\right)^{\sigma_j-1}\tilde{\alpha}_j^{\sigma_j-1}\lambda^{(1-\sigma_j)\alpha_j}P_j^{\sigma_j}Q_j$ and $\tilde{\alpha}_j = \alpha_j^{\alpha_j}(1-\alpha_j)^{1-\alpha_j}$, and where P is an aggregate price index,

$$P = \left(\sum_{j\in\{m,s\}}\epsilon_j\vartheta_j\right)\left(\sum_{j\in\{m,s\}}\theta_j P_j^{1-\rho}Q^{(1-\rho)(\epsilon_j-1)}\right)^{\frac{1}{1-\rho}},$$

  the same across cities within the country (absent intercity trade frictions) and the same in Home and Foreign (because of symmetry).

- *Optimal firm location choice condition (free movement of firms)*

$$i_j^*(z) = \arg\max_{i\in I}\ v_j(z,i)\,\epsilon(\omega,i).$$

  This allows us to derive the share of firms that choose location i, and the share of firms choose location i and are exporters:

$$\delta_j(i) = \Pr(\text{choose } i) \quad \text{and} \quad \delta_j^x(i) = \Pr(\text{choose } i \cap \text{exporter}).$$

- *Utility equalization across locations (free worker mobility)*

$$W(i) = \frac{p_h(i)^{1-\eta}}{1+\mu}.$$

- *Aggregate labor market clearing*

$$\int \varrho(i)\,\mathrm{d}i = 1,$$

  where $\varrho(i)$ is the share of the population living in city i.

- *Zero profit for the marginal entrant in each sector (free entry of firms)*

$$M_j = \frac{1}{\sigma_j}\left(\frac{P_j Q_j}{P f_j^e + P f_j^x \sum_i \delta_j^x(i)}\right).$$

- *Goods market clearing*

$$P_j^{1-\sigma_j} = \left(\frac{\sigma_j - 1}{\sigma_j}\,\tilde{\alpha}_j \left(UP^{\eta}\right)^{-\alpha_j}\right)^{\sigma_j - 1} M_j \mathcal{G}_j,$$

  where

$$\mathcal{G}_j(i) = \frac{E\left[\Phi_j(z,i)^{\sigma_j-1} \mid i, j\right]}{p_h(i)^{(1-\eta\alpha_j)(\sigma_j-1)}} + \frac{\delta_j^x(i)}{\delta_j(i)}\,\frac{E\left[\left(\Phi_j(z,i)/\tau_j\right)^{\sigma_j-1} \mid i, j, \varkappa_j(z,i) = 1\right]}{p_h(i)^{(1-\eta\alpha_j)(\sigma_j-1)}},$$

  and

$$\mathcal{G}_j = \int \delta_j(i)\,\mathcal{G}_j(i)\,\mathrm{d}i.$$

- *Local labor market clearing*

$$W(i)u(i)\bar{L} = \sum_{j\in\{m,s\}} \delta_j(i) M_j (\sigma_j - 1)\,\alpha_j E\left[\pi_j(z,i) \mid j\right],$$

  where $\bar{L}$ is total population.

- *Final goods market clearing*

$$Q = C + \sum_{j\in\{m,s\}} M_j\left(f_j^e + f_j^x \int \delta_j^x(i)\,\mathrm{d}i\right),$$

  where $C \equiv \int C(i)\,\mathrm{d}i$.

There are two equilibria. One is an unstable equilibrium where all cities are of equal size. The other is a stable equilibrium which features cities of different sizes and which is relevant for our purposes.

4 Parameterization and estimation

To quantify the channels that lead to structural change across French cities, we first derive the model's parameters from the data through a procedure that combines calibration and structural estimation. In Section 5 we then use the parameterized model to carry out counterfactual simulations. Our purpose is to decompose the contributions of sectoral TFP growth, international trade costs, and agglomeration effects to urban-biased structural change. In this section, we explain how we obtain the values of these key parameters.

The parameters $\{A_j^{1995}, A_j^{2018}\}$ are sectoral TFP shifters, $\{\tau_j^{1995}, \tau_j^{2018}, f_j^{x,1995}, f_j^{x,2018}\}$ represent sector-specific variable and fixed trade costs, and $\{a_j^{1995}, a_j^{2018}\}$ determine the strength of sectoral agglomeration externalities. As we discuss below, our approach to quantifying these parameters requires first measuring variable trade costs and then incorporating them into the structural estimation routine to estimate agglomeration externalities. However, we show that our approach to estimating agglomeration externalities does not require measuring sectoral TFP shifters as a first step.

4.1 Calibrated parameters

Exogenously specified parameters. Following Lewis, Monarch, Sposi, and Zhang (2022), we set the degree of non-homotheticity for manufacturing and services to $\varsigma_m = 1$ and $\varsigma_s = 1.62$, and the elasticity of substitution between the two sectors to $\rho = 0.16$. As for the land price elasticity, we calibrate it to estimates by Combes, Duranton and Gobillon (2019) who use French administrative data on land prices, setting it to $\gamma = 0.7$. Table 4 summarizes the exogenously specified parameters.[28]

Parameters obtained through calibration. The sector-specific labor intensity parameter α_j is set to match the sector-level wage bill share of total expenditure (wage bill, materials, and capital expenditure) under the assumption of constant returns to scale production technologies. We calibrate the elasticity of substitution across varieties within sectors σ_j to match the sector-specific ratio of revenues to total expenditure. The household non-housing consumption share in utility η is set to match French households' expenditure share on housing related costs.

The aggregate sectoral productivity shifters for manufacturing and services are set to unity in 1995, $A_m^{1995} = A_s^{1995} = 1$. Changes in sectoral productivity shifters between 1995 and 2018 are

[28]Comin, Lashkari, and Mestieri (2021) estimate a somewhat lower value for ς_s of around 1.3 and a higher value for ρ of around 0.3, based on household expenditure data and a model featuring agriculture, manufacturing, and services sectors. Our quantitative results in Section 5 are robust to those parameter values. We draw parameter values from Lewis *et al.* (2022) because they estimate those values using data for the manufacturing and services sectors only, which are the two sectors we model. We provide robustness checks for alternative values of the land price elasticity (see Section 4.2).

Table 4: Exogenously specified and calibrated parameters

Parameter	Source	Sector	Value	
Income elasticity parameter in consumption (ς_j)	Lewis *et al.* (2022)	Manufacturing	1	
		Services	1.62	
Elasticity of substitution in consumption (ρ)	Lewis *et al.* (2022)	-	0.16	
Land price elasticity (γ)	Combes *et al.* (2019)	-	0.7	
Elasticity of substitution across varieties (σ_j)		Manufacturing	11	
		Services	2.96	
Share parameters in consumption (θ_j)		Manufacturing	0.41	
		Services	0.59	
Sectoral labor intensity (α_j)		Manufacturing	0.35	
		Services	0.47	
Non-housing consumption share in utility (η)			0.8	
Sectoral TFP (A_j)		Manufacturing	1	2.357
		Services	1	1.027
Variable trade costs (τ_j)		Manufacturing	0.148	0.073
		Services	3.009	1.196
Fixed trade costs (f_j^x)		Manufacturing	0.022	0.028
		Services	0.186	0.391

potential key drivers of structural change. We calibrate A_m^{2018} and A_s^{2018} to match the growth rate of real GDP per capita and changes in the manufacturing sector share of aggregate sales between 1995 and 2018. The weight on consumption of goods versus services $\theta_m = 1 - \theta_s$ is calibrated to match the manufacturing sector share of aggregate sales in 1995. The fixed entry cost f_j^e for services is normalized to unity and that for manufacturing is set to match the average firm size (average revenue) in manufacturing relative to services. The fixed trade costs are set to match the share of firms that are exporters in each sector. We calibrate one fixed trade cost for each sector and year, $\{f_m^{x,1995}, f_m^{x,2018}, f_s^{x,1995}, f_s^{x,2018}\}$. Finally, consistent with the model, the variable trade costs are calibrated to match the sector-specific export intensity, defined as total export revenues among exporters R_j^x divided by the total domestic revenues among exporters $R_j^{d,\varkappa=1}$: $\tau_j^{1-\sigma_j} = R_j^x / R_j^{d,\varkappa=1}$. This gives $\{\tau_m^{x,1995}, \tau_m^{x,2018}, \tau_s^{x,1995}, \tau_s^{x,2018}\}$. Table 4 lists the calibrated parameters.

4.2 Parameters inferred via structural estimation

PARAMETERS TO ESTIMATE. We assume that firm-specific efficiency, $\log z$, is drawn from a Gamma distribution with scale parameter $\nu_{z,j}^{scale}$ and shape parameter $\nu_{z,j}^{shape}$. Firm and location-specific shocks $\epsilon(\omega, i)$ are drawn from a Gumbel distribution with scale parameter $\nu_{\epsilon,j}^{scale}$. Given the functional form for firms' composite productivity $\Psi_j(z, i)$ in equation (11), the sector-specific parameters to estimate include the agglomeration externality scale parameter a_j, the sorting parameter ξ_j, and the agglomeration curvature s_j.

For each sector, we allow the agglomeration externality parameters and the trade cost parameters to differ between 1995 and 2018. We keep the scale and shape parameters for firms' idiosyncratic efficiency z and their land intensity constant over time. Specifically, the set of parameters we estimate for each sector are

$$\mathbf{\Theta}_j = \left(\nu_{z,j}^{scale}, \nu_{z,j}^{shape}, \nu_{\epsilon,j}^{scale}, a_j^{1995}, a_j^{2018}, \xi_j, s_j\right). \tag{17}$$

This allows us to compare the 1995 and 2018 equilibria, and we can isolate the effects of the drivers we focus on in our analysis, namely changes in agglomeration effects, changes in trade costs, and changes in TFP, the latter of which are exactly identified through calibration.

IDENTIFICATION. The parameters Θ_j are estimated in partial equilibrium by solving the firm's location choice problem (16).[29] We estimate these parameters separately for the manufacturing and services sectors to match a set of sector-specific moment conditions detailed below. Given the composite productivity function (11), we first write the log of firms' total revenues, normalized by the average log revenue of firms in the same sector in the least populated city ($i = 1$), as

$$\begin{aligned}\log R_j(z,i) - E[\log R_j(1)] = \;& (\sigma_j - 1)\log\Psi_j(z,i) - (\sigma_j - 1)\,E\big[\log\Psi_j(z,1)\,\big|\,z \in \mathcal{Z}_j(1)\big] \\ & + \log\left(1 + \varkappa_j(z,i)\tau_j^{1-\sigma_j}\right) - E\left[\log\left(1 + \varkappa_j(z,i)\tau_j^{1-\sigma_j}\right)\,\Big|\,z \in \mathcal{Z}_j(1)\right] \\ & + (\sigma_j - 1)(1 - \eta\alpha_j)\big(\log p_h(i) - \log p_h(1)\big) + (\sigma_j - 1)\,\hat{\epsilon}_i, \end{aligned} \tag{18}$$

where $\varkappa_j(z,i) \in \{0,1\}$ is an indicator function that takes the value 1 if firm of type z in sector j is an exporter and 0 otherwise. $\mathcal{Z}_j(1)$ is the set of firms that belong to sector j and locate in the least populated city. Variable trade costs τ_j therefore need to be measured before implementing the estimation routine. However, given the assumption that sectoral TFP shifters A_j are Hicks-neutral, these TFP shifters are differenced away by comparing firms *not* in the smallest cities to those in

[29] See Appendix B.5 for an outline of the solution algorithm.

the smallest cities. In the data, we observe the difference between a firm's revenue and the average revenue in the smallest city $\log R_j(z,i) - E[\log R_j(1)]$, and the relative city size $L(i)/L(1)$. For a given set of calibrated parameters and observed firm size and city size distributions, we estimate the set of parameters Θ_j to match data moments that are informative about their underlying values.

Intuition behind identification. The agglomeration externality parameter a_j can be identified from proportional shifts in the distribution of $\log R_j(z,i) - E[\log R_j(1)]$ across city sizes. This is because the agglomeration parameter affects all firms within a given sector equally. By contrast, the sorting parameter ξ_j determines the gains from moving to a larger city depending on the efficiency z of the firm. For $\xi_j > 0$, firms with a higher z gain disproportionately in terms of productivity from moving to a larger city. For $\xi_j < 0$, firms with a higher z lose disproportionately from moving to a larger city. The sorting parameter can therefore be identified from differences in the skewness of $\log R_j(z,i) - E[\log R_j(1)]$ across city sizes, i.e., how the firm size-city size gradient changes for firms at different points of the firm size distribution. The parameter s_j can be identified from how the intensity of firm sorting by size and locations varies across the distribution of firm sizes.[30]

The variance of firm efficiency draws, related to $\nu_{z,j}^{scale}$ and $\nu_{z,j}^{shape}$, can be identified from the overall, non-location-specific variance of $\log R_j(z,i) - E[\log R_j(1)]$. The variance of firm-location-specific shocks $\nu_{\epsilon,j}^{scale}$ introduces imperfect sorting between firm size and city size, which can be identified from the correlation between $\log R_j(z,i) - E[\log R_j(1)]$ and $\log(L(i)/L(1))$.

Targeted moments. Given the above discussion of which moments are informative about each parameter, we target the following thirteen moments for each sector, with the choice of targeted moments the same as that of Gaubert (2018):

1. The 50-10, 75-25, 90-50, and 90-10 differences of the log normalized revenue distributions.

2. The average (normalized) log revenue by city size quintiles $i \in \mathcal{I}$.

3. The share of revenue that originates from a city size quintile $i \in \mathcal{I}$.[31]

Estimation is carried out by the Method of Simulated Moments using a pooled specification for 1995 and 2018, i.e., letting $\boldsymbol{\Theta} \equiv (\boldsymbol{\Theta}_m, \boldsymbol{\Theta}_s)$. We denote the combined vector of empirical moments for 1995 and 2018 (a vector of dimension $13 \times 2 = 26$) by $\boldsymbol{m}$, with $\widehat{\boldsymbol{m}}(\boldsymbol{\Theta})$ the corresponding vector of model moments. With $\mathcal{W}$ an estimate of the matrix of variances and covariances of the empirical

[30]As explained in Appendix B.4, s_j is a determinant of the sorting condition, i.e., how the elasticity of L with respect to z varies with z.

[31]We do not target any moments of the export revenue distribution beyond those used to calibrate the trade cost parameters as discussed above.

Table 5: Estimated parameter values

Parameter	Sector	1995	2018
Shape of Gamma productivity ($\nu_{z,j}^{shape}$)	Manufacturing	0.548	0.548
		(0.019)	(0.019)
	Services	1.465	1.465
		(0.025)	(0.025)
Scale of Gamma productivity ($\nu_{z,j}^{scale}$)	Manufacturing	0.163	0.163
		(0.011)	(0.011)
	Services	0.319	0.319
		(0.012)	(0.012)
Scale of Gumbel shock ($\nu_{\epsilon,j}^{scale}$)	Manufacturing	0.069	0.069
		(0.000)	(0.000)
	Services	0.257	0.257
		(0.014)	(0.014)
Agglomeration curvature (s_j)	Manufacturing	0.668	0.668
		(0.023)	(0.023)
	Services	0.912	0.912
		(0.063)	(0.063)
Agglomeration effect (a_j)	Manufacturing	0.718	0.694
		(0.010)	(0.004)
	Services	0.703	0.712
		(0.015)	(0.011)
Sorting effect (ξ_j)	Manufacturing	−0.104	−0.104
		(0.021)	(0.021)
	Services	0.420	0.420
		(0.114)	(0.114)

Notes: Asymptotic standard errors in parentheses.

moments (obtained by bootstrapping), we derive an estimate $\widehat{\boldsymbol{\Theta}}$ as

$$\widehat{\boldsymbol{\Theta}} = \arg\min_{\boldsymbol{\Theta}} \left(\boldsymbol{m} - \widehat{\boldsymbol{m}}(\boldsymbol{\Theta})\right)' \mathcal{W}^{-1}\left(\boldsymbol{m} - \widehat{\boldsymbol{m}}(\boldsymbol{\Theta})\right). \tag{19}$$

By using this estimation strategy, we can obtain time-invariant estimates for those parameters that are constrained to remain the same across the two periods while allowing other parameters of interest to change.

Parameter values and model fit. The parameter values obtained via this estimation procedure are shown in Table 5. The model accommodates the observed changes in production patterns across locations mainly through a relative decline of TFP in services (A_j), a substantially larger fall of trade costs in services than in manufacturing, as well as an increase in the strength of agglomeration

Table 6: Model fit

Moment	Data 1995 m	Data 1995 s	Data 2018 m	Data 2018 s	Model 1995 m	Model 1995 s	Model 2018 m	Model 2018 s
Firm size 50-10 ratio	1.14	1.05	*1.26*	*1.61*	1.17	1.02	*1.19*	*1.03*
Firm size 75-25 ratio	1.75	1.31	*1.82*	*1.45*	1.75	1.35	*2.09*	*1.36*
Firm size 90-50 ratio	2.19	1.60	*2.31*	*1.62*	2.41	1.59	*2.57*	*1.60*
Firm size 90-10 ratio	3.33	2.65	*3.57*	*2.93*	3.58	2.61	*3.76*	*2.63*
Normalized mean log sales in city bin 2	0.02	0.07	0.02	0.07	0.05	0.09	0.01	0.08
Normalized mean log sales in city bin 3	−0.04	0.09	−0.05	0.08	0.01	0.09	−0.02	0.08
Normalized mean log sales in city bin 4	0.07	0.18	−0.12	0.10	0.01	0.17	−0.04	0.16
Normalized mean log sales in city bin 5	0.07	0.47	−0.17	0.31	0.02	0.36	−0.10	0.34
City bin 1 share of sectoral revenue	0.26	0.14	0.31	0.13	0.23	0.14	0.29	0.13
City bin 2 share of sectoral revenue	0.23	0.15	0.24	0.14	0.23	0.13	0.28	0.12
City bin 3 share of sectoral revenue	0.17	0.16	0.19	0.17	0.19	0.18	0.18	0.17
City bin 4 share of sectoral revenue	0.16	0.17	0.15	0.18	0.14	0.19	0.12	0.19
City bin 5 share of sectoral revenue	0.18	0.38	0.11	0.39	0.21	0.36	0.13	0.39

Notes: The table reports the model's fit to the moments used in the structural estimation routine. Normalized mean log sales in each city size bin are defined relative to city size bin 1 (smallest cities). See Section 4 for more information. The numbers in *italics* are not targeted in the estimation routine because the distribution of firm-level efficiency draws is kept constant over time. '*m*' refers to manufacturing and '*s*' refers to services.

externalities for services and a decrease in those for manufacturing (a_j).[32] The estimated sorting parameter ξ_j is negative for manufacturing and positive for services.[33]

Table 6 reports the values of the targeted empirical moments and the corresponding values predicted by the model. The model generally performs well in matching the targeted moments. It is able to closely match the firm size distribution. It also captures the mostly negative sorting patterns by firm size and city size of manufacturing firms, and the relatively strong positive sorting patterns for services firms. The model also matches each city size bin's share of sectoral revenue reasonably well. In particular, the model replicates the positive relationship in the data between city size and the revenue share of the services sector. It also does well in matching the opposite pattern for manufacturing.[34]

[32]In light of the observed change in the manufacturing balance of trade between 1995 and 2018, the small fall in manufacturing trade costs we infer through our calibration procedure can be partly accounted for by a change in manufacturing comparative advantage. Given its symmetric structure, the model interprets a fall in the manufacturing trade balance as an increase in manufacturing trade costs such that our inferred decline in manufacturing trade costs would appear understated.

[33]Table A.6 in Appendix A.3 shows estimated parameters for alternative values of the land price elasticity γ. The alternative values correspond to those reported by Combes *et al.* (2019) based on housing price data as opposed to land price data.

[34]In Appendix B.6 we derive values for agglomeration elasticities as implied by our model. These values are in line

Table 7: Data vs. model: Decomposition of the change in manufacturing revenue shares by firm size

City size bin	UBSC (total)		Contribution of bottom 95% of sales: Direct contribution		Contribution of bottom 95% of sales: Contribution from change in rev. share		Contribution of top 5% of sales: Direct contribution		Contribution of top 5% of sales: Contribution from change in rev. share	
	Data (1)	Model (2)	Data (3)	Model (4)	Data (5)	Model (6)	Data (7)	Model (8)	Data (9)	Model (10)
1	−0.093	−0.066	−0.068	−0.003	0.006	0.002	−0.017	−0.060	−0.014	−0.005
2	−0.106	−0.077	−0.061	−0.020	0.014	0.002	−0.020	−0.055	−0.039	−0.004
3	−0.114	−0.144	−0.061	−0.024	0.004	0.004	−0.043	−0.116	−0.015	−0.008
4	−0.193	−0.166	−0.079	−0.031	0.025	0.004	−0.063	−0.129	−0.076	−0.010
5	−0.180	−0.241	−0.056	−0.013	0.001	0.001	−0.122	−0.219	−0.003	−0.010
Aggregate	−0.145	−0.151	-	-	-	-	-	-	-	-

Notes: The table decomposes percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labeled 'UBSC', which stands for urban-biased structural change). For example, −0.1 means a ten percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities. The columns 'Model' show the predictions of the 2018 estimated model. Columns 3, 5, 7, 9 add to column 1. Columns 4, 6, 8, 10 add to column 2.

5 What drives the urban bias in structural change?

We use our estimated model to assess the contribution of the different drivers of the urban-biased structural change we observe in the data from 1995 to 2018. We proceed as follows. First, in Section 5.1 we assess the model's ability to reproduce the urban-biased patterns presented in Section 2.2. Next, in Section 5.2 we carry out counterfactual experiments to decompose this urban bias into the contributions of three driving forces: sectoral TFP growth, falling international trade costs, and changes in agglomeration externalities.

5.1 Urban-biased structural change: Data vs. model

The model does well at reproducing the key urban-biased patterns of structural change presented in Section 2.2. Columns 1 and 2 of Table 7 compare the full estimated model to the data. They show that the model is capable of reproducing the 'pyramid' pattern of structural change – our first stylized fact – as well as the magnitude of aggregate structural change. The remaining columns in the table decompose this pattern into the contributions of non-large firms (firms in the bottom 95% of the sales distribution, columns 3-6) and large firms (firms in the top 5%, columns 7-10). Although this decomposition is not a target of the estimated model, the table shows that, just as in the data, the urban bias is fully accounted for by large firms – our third stylized fact.

with reduced-form estimates from the literature.

Table 8: Data vs. model: Contributions of city size bins to sectoral growth

	Domestic revenue				Export revenue			
	Manufacturing		Services		Manufacturing		Services	
City size bin	Data (1)	Model (2)	Data (3)	Model (4)	Data (5)	Model (6)	Data (7)	Model (8)
1	29%	29%	13%	13%	22%	29%	3%	14%
2	26%	28%	15%	12%	25%	28%	4%	11%
3	18%	18%	16%	17%	19%	18%	9%	17%
4	17%	13%	19%	19%	20%	13%	16%	17%
5	10%	12%	38%	39%	14%	12%	68%	42%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	−14%	−14%	74%	75%	40%	71%	181%	551%

Notes: The table decomposes the growth of total revenue of the manufacturing and services sectors into the contributions of each city size bin. Revenues in 2018 are adjusted to 1995 prices. The columns 'Model' show the predictions of the 2018 estimated model. 'Total contribution' refers to the sum of the contributions of each city size bin to the total (domestic and export) revenue growth of each sector. 'Total growth' in the last row refers to the total real (domestic and export) revenue growth of each sector between 1995 and 2018.

The fact that economic activity took a sharper shift from manufacturing to services in larger cities may be due to a decline in the size of the manufacturing sector, or a relatively faster increase in the size of the services sector. Table 8 reports the real domestic and export revenue growth of the manufacturing and services sectors in the data and in the model, based on the decomposition described in equation (1). These growth rates are not targeted in the quantification of the model. Columns 2 and 3 show that the model closely replicates the decline in domestic revenue of the manufacturing sector: −14% both in the data and in the model. The model also closely replicates the contribution of each city size bin to the decline in domestic revenue. Columns 4 and 5 show that the model can also reproduce the growth of domestic revenues for the services sector. The model performs less well in capturing the growth of export revenues for manufacturing and services. In particular, the model overstates the growth rate of export revenues for both sectors. For the manufacturing sector, the model over-predicts rural bias in the contribution of city size bins to export revenue growth. For the services sector, the model understates the urban bias in the contribution of city size bins to export revenue growth. One reason why the model overstates export growth is that trade costs are constant across firms within a given sector, as is standard in Melitz-style trade models. As discussed in Section 4, variable trade costs are measured using the average export intensity of exporters, defined as total export revenue among exporters over total domestic revenue among exporters in each sector, which downweights smaller exporters. In the data, however, export intensity is higher and increased more among larger firms.

5.2 Assessing the drivers of urban-biased structural change

We now turn to counterfactual experiments that examine the three driving forces of structural change in our model – sectoral TFP growth, falling international trade costs, and changes in agglomeration externalities. For this purpose, we set all parameters to their 1995 levels and change them one set at a time to their estimated 2018 level, with each set pertaining to one of the driving forces. The parameters associated with each of these "partial-counterfactual" experiments are as follows:

(i)	Sectoral TFP:	$\{A_j^{1995}\}_{j\in\{m,s\}}$	$\rightarrow$	$\{A_j^{2018}\}_{j\in\{m,s\}}$
(ii)	Trade costs:	$\{\tau_j^{1995}, f_j^{x,1995}\}_{j\in\{m,s\}}$	$\rightarrow$	$\{\tau_j^{2018}, f_j^{x,2018}\}_{j\in\{m,s\}}$
(iii)	Agglomeration:	$\{a_j^{1995}\}_{j\in\{m,s\}}$	$\rightarrow$	$\{a_j^{2018}\}_{j\in\{m,s\}}$

To assess the quantitative importance of each driving force, we then compare each of these partial counterfactuals to the baseline 2018 estimated equilibrium, which combines all changes and which is shown in Tables 7 and 8.

The role of sectoral TFP growth. In our calibration, we find that TFP in manufacturing grew substantially relative to services.[35] Columns 3 and 4 in Table 9 compare UBSC in the counterfactual simulation that only allows for TFP growth to UBSC in the full estimated model. As is standard in the structural change literature, the increase in manufacturing TFP has two aggregate effects in our model. First, it reduces goods prices and shifts the consumption expenditure share towards services due to strong complementarities between goods and services (Ngai and Pissarides, 2007). Second, the consumption expenditure share also shifts towards services due to non-homothetic demand effects (Comin *et al.*, 2021). As a result, TFP growth generates rapid structural change in the model, but there is no urban bias. When we look at the role of large and non-large firms, we again see that large firms account for the bulk of the TFP-induced structural change. Indeed, column 4 shows that large firms account for the bulk of structural change within each city size bin.

We can conclude from this counterfactual experiment that sectoral TFP growth accounts for the bulk of aggregate structural change but does explain UBSC. Although TFP growth generates a larger expansion of services in large cities, it does not translate into a larger *percentage point* increase in the services revenue share in large cities since the initial share is already high. Explanations of structural change that focus only on sectoral TFP growth abstract from heterogeneity in the way

[35] TFP growth in the model is global: given our symmetry assumption, it occurs at the same rate in the Home country (France) and the Foreign country (rest of the world). As explained in Appendix A.2, this assumption is motivated by three features of the data: (i) the level and the increase in the manufacturing trade deficit are relatively small, (ii) the services trade surplus is small and constant over time, and (iii) the manufacturing sectors that decline the most were not more concentrated in large cities in 1995. In Appendix B.1, we explicitly model shifting comparative advantage and find that while it plays a non-negligible role in aggregate structural change, it cannot explain the urban bias.

Table 9: Counterfactual changes in the share of manufacturing revenue within city size bins

City size bin	Counterfactuals							
	All changes		TFP		Trade costs		Agglomeration	
	all	contribution of top 5%	all	contribution of top 5%	all	contribution of top 5%	all	contribution of top 5%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	−0.066	98%	−0.154	92%	0.001	−300%	0.069	87%
2	−0.077	77%	−0.147	86%	0.003	0%	0.054	109%
3	−0.144	86%	−0.160	85%	0.002	0%	0.014	71%
4	−0.166	84%	−0.158	82%	0.004	25%	−0.010	60%
5	−0.241	95%	−0.157	95%	0.000	0%	−0.104	96%
Overall	−0.151	96%	−0.162	98%	0.002	150%	0.010	83%

Notes: The table indicates the percentage point changes in the manufacturing sector revenue share in each city size bin. For example, −0.1 means a ten percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities. The columns 'All changes' show the predictions of the estimated 2018 model (see column 2 of Table 7). The columns 'TFP', 'Trade costs', and 'Agglomeration' show the predictions of the partial counterfactuals. The columns 'All' refer to all firms. The columns 'Contribution of top 5%' show the contribution of firms in the top 5% of the sales distribution to structural change in each city size bin.

changes in economic fundamentals affect different firm types at different locations, and are thus incapable of accounting for the bias the urban that results from this heterogeneity.

Table 10 reports the growth of the manufacturing and services sectors in the estimated 2018 equilibrium and the partial counterfactual. Columns 1 and 2 show that while manufacturing real domestic revenue declines by 14% in the estimated model, it declines by only 1% in the partial counterfactual. Manufacturing export revenue, on the other hand, increases by 71% in the estimated model, while it remains unchanged in the partial counterfactual. The reason for this gap is that changes in TFP have little effect on the relative price of exported vs. domestic goods. As shown below, the strongest determinant of the change in this relative price from 1995 to 2018 is a change in trade costs. In contrast, the TFP-induced services growth in domestic revenue is comparable to that of the estimated model. The increase in global manufacturing TFP also increases the demand for French services exports, leading to a 152% increase in services exports in the partial counterfactual, with the largest share of growth coming from the largest French cities. On the extensive margin of trade, exports get some boost from TFP changes from manufacturing firms vacating large cities and making it possible for large services firms in those cities to grow and start exporting. However, the bulk of the expansion in services exports we observe in 2018 could not have occurred if trade costs for services had not also fallen.

The role of falling international trade costs. Our second counterfactual experiment isolates the effects of changes in trade costs. Our measure of manufacturing variable trade costs (τ_m) declines from 14.8% in 1995 to 7.3% in 2018, while for services (τ_s) it declines from a high level of 300.9%

Table 10: Counterfactuals: Contributions of city size bins to sectoral growth

	TFP COUNTERFACTUAL							
	DOMESTIC REVENUE				EXPORT REVENUE			
	Manufacturing		Services		Manufacturing		Services	
CITY SIZE BIN	Model (1)	Cntrf (2)	Model (3)	Cntrf (4)	Model (5)	Cntrf (6)	Model (7)	Cntrf (8)
1	29%	23%	13%	14%	29%	23%	14%	15%
2	28%	24%	12%	13%	28%	24%	11%	12%
3	18%	19%	17%	18%	18%	19%	17%	17%
4	13%	14%	19%	19%	13%	14%	17%	17%
5	12%	20%	39%	36%	12%	20%	42%	39%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	−14%	−1%	75%	90%	71%	0%	551%	152%
	TRADE COST COUNTERFACTUAL							
1	29%	23%	13%	14%	29%	23%	14%	15%
2	28%	23%	12%	14%	28%	23%	11%	12%
3	18%	19%	17%	18%	18%	19%	17%	18%
4	13%	14%	19%	19%	13%	14%	17%	17%
5	12%	21%	39%	36%	12%	21%	42%	38%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	−14%	−14%	75%	−6%	71%	70%	551%	247%
	AGGLOMERATION COUNTERFACTUAL							
1	29%	28%	13%	13%	29%	28%	14%	14%
2	28%	27%	12%	13%	28%	27%	11%	11%
3	18%	18%	17%	17%	18%	18%	17%	16%
4	13%	13%	19%	19%	13%	13%	17%	17%
5	12%	14%	39%	38%	12%	14%	42%	42%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	−14%	−3%	75%	−8%	71%	−2%	551%	21%

Notes: The table decomposes the impact of TFP growth, changing international trade costs, and changing agglomeration externalities on the growth of total revenue of the manufacturing and services sectors into the contributions of each city size bin. 'Total contribution' refers to the sum of the contributions of each city size bin to the total (domestic and export) revenue growth of each sector. 'Total growth' in the last row refers to the total real (domestic and export) revenue growth of each sector between 1995 and 2018.

to 119.6%. Column 5 in Table 9 shows that the decline in trade costs increased the manufacturing revenue share across city size bins slightly, by around 0.2 percentage points.

How does the decline in trade costs affect the size of the manufacturing and services sectors? Table 10 reports our results. We find that the fall in τ_m reduces the size of manufacturing domestic revenues by 14% and increases the size of manufacturing exports by 70%, driven by a reallocation of sales from non-exporters to exporters. These numbers are similar to the corresponding numbers for the estimated 2018 equilibrium, which are −14% and 71%. For the services sector, falling trade costs generate a 6% decline in domestic sales compared to a 75% increase in the estimated model.

However, they generate a 247% increase in services exports, explaining a large fraction of the export growth predicted by the estimated model.

Our main takeaways from this exercise are as follows. Falling international trade costs do not generate large aggregate or urban-biased structural change but provide an important explanation for the (rural-biased) decline in the manufacturing sector's domestic sales and its increase in exports. They also explain the fast (urban-biased) growth of services exports.

The role of changing agglomeration externalities. In our third counterfactual experiment, we show that changing agglomeration externalities can account for UBSC in our model and also play a non-trivial role for aggregate structural change. Our structural estimates in Table 5 suggest that the agglomeration parameter a_j – the sensitivity of productivity with respect to city size – declined from 0.718 in 1995 to 0.694 in 2018 for manufacturing, while it increased from 0.703 to 0.712 for services. Table 9 shows the results of the counterfactual simulation where we only introduce changes in these two agglomeration parameters.

Changes in agglomeration externalities lead to a substantial decline in the manufacturing share of revenue in large cities but an increase in small cities (column 7). These effects are driven by large firms (column 8). Recall that the manufacturing sector is characterized by negative sorting (i.e., log-submodularity of Ψ_m between firm efficiency z and city size). That is, more efficient manufacturing firms tend to prefer smaller cities. While the decline in agglomeration externalities reduces the attractiveness of large cities for all manufacturing firms, log-submodularity implies that large manufacturing firms in large cities are relatively more likely to respond by locating in small cities.[36] This relocation of manufacturing towards smaller cities makes room for services firms to enter large cities, leading to strong UBSC.

The services sector, by contrast, is characterized by positive sorting (i.e., log-supermodularity of Ψ_s). The increase in agglomeration externalities for services pushes services firms into large cities, with large services firms in small cities relatively more likely to move. This relocation of services firms crowds out manufacturing firms, pushing them into smaller cities. This further generates UBSC.

The diverging agglomeration externalities between the two sectors also have a sizable impact on aggregate structural change. Taken together, they effectively represent a relative productivity boost for services, increasing the manufacturing share of revenue by one percentage point (see the final row of Table 9). But overall, both manufacturing and services decline in absolute size. As Table 10 shows, the domestic and export revenues in the manufacturing sector shrink by 3% and 2%, meaning

[36]Highly efficient manufacturing firms with a random productivity draw ϵ that favors large cities are more likely to respond by moving to small cities compared to less efficient manufacturing firms with the same ϵ draw.

that the manufacturing sector declines in absolute size. Given that the share of manufacturing in total output rises, this implies an even stronger decline of services production. While services export revenue increases by 21% as large services exporters in large cities become more productive, this is more than offset by the 8% drop in domestic services revenue.

How could the decline in manufacturing agglomeration externalities and the increase in services agglomeration externalities be rationalized? A possible interpretation relates to land markets. To see this, we must start by noting that firms' location choices in the model are determined by the net benefits they receive from agglomeration at any given location. That is, firms consider the gross agglomeration productivity benefits at a location minus any cost premium for using land directly as a production input or indirectly by hiring workers who need to be compensated for housing price differentials across locations.

In our estimation exercise, we have assumed that the elasticity of land prices with respect to population size γ remained unchanged between 1995 and 2018. The model can therefore only interpret sectoral changes in net agglomeration benefits as reflecting changes in gross agglomeration benefits, i.e., changes in the agglomeration productivity parameters a_m and a_s. However, since manufacturing is more land intensive than services, the benefits of operating at denser locations could also have changed differentially for manufacturing and services between 1995 and 2018 because of a change in γ. Specifically, if land prices become more sensitive to population size over time (a rise in γ), this increases the attractiveness of smaller, less densely populated areas for manufacturing and in turn frees up space for services firms in larger, more densely populated locations.

Evidence on housing price indices across French communes for 1995 and 2018 is consistent with a rising elasticity of land prices with respect to population density.[37] In a log-linear regression of housing prices on population, we find that the elasticity increases by 17% between 1995 and 2018.[38] To gauge the extent to which a change in the relationship between density and land prices is capable of accounting for UBSC, we then carry out a counterfactual exercise where we increase the value of γ between 1995 and 2018 by the same proportion – from 0.7 to 0.82 – while leaving all

[37] The data are proprietary and were provided by ADNOV, a private organization that collaborates with INSEE to produce price indices, based on the PERVAL database, of all housing transactions for existing apartments and houses combined (i.e., new constructions are excluded) recorded by solicitors in France, with the exception of Ile de France and Corsica. As the price indices are hedonic and control for the characteristics of each dwelling and therefore for differences in quality, the indices are comparable over time. We use data for the years 1995 and 2018, available on a quarterly basis for 33,192 French communes.

[38] The point estimates are 0.350 and 0.412, respectively. The level of these estimates is lower than the value for γ taken from Combes *et al.* (2019) and reported in Table 4. The reason is that the higher value is based on land price data as opposed to housing price data. Combes *et al.* (2019) also report housing price elasticities which fall into the same ballpark as our estimates (see their Tables 4 and 5).

other parameters unchanged.[39] The counterfactual exercise shows that this change generates even stronger UBSC than reported in Table 7 for the baseline model. The rise in the land price elasticity generates a 28 percentage point decline in the manufacturing share in city bin 5 (largest cities), and a 7 percentage point increase in city bin 1. For comparison, the baseline model generates a 24.1 percentage point decline in the manufacturing share in bin 5 and a 6.6 percentage point decline in bin 1.[40]

5.3 Implications for local and aggregate productivity

The above counterfactual experiments show how various sector-specific shocks – sectoral TFP growth, falling international trade costs, and changing agglomeration externalities – shape local and aggregate structural change. Agglomeration effects and the spatial sorting patterns of heterogeneous firms imply that different cities are differentially exposed to shocks. We now quantify how agglomeration and sorting shape the impact of those shocks on local and aggregate sectoral productivity. We also quantify the impact of those shocks on marginal costs.

In Appendix B.7, we show that the *local* (i.e., location-specific) sectoral productivity growth between time $t' > t$ and t is

$$\frac{\Phi_{jt'}^{\text{local}}(i)}{\Phi_{jt}^{\text{local}}(i)} = \underbrace{\frac{A_{jt'}}{A_{jt}}}_{\text{exogenous}} \; \underbrace{\frac{\tilde{\Psi}_{jt'}^{\text{local}}(i)}{\tilde{\Psi}_{jt}^{\text{local}}(i)}}_{\text{endogenous}} . \tag{20}$$

The first component of the above equation is the exogenous TFP growth. The second component is the local sectoral productivity index,

$$\tilde{\Psi}_{jt'}^{\text{local}}(i) \equiv \left(\frac{1}{M_{jt'}(i)} \int_{z \in \mathcal{Z}_{jt'}(i)} \tilde{\Psi}_{jt'}(z,i)^{\sigma_j - 1} \mathrm{d}z + \frac{M_j^x(i)}{M_j(i)} \tau_j^{1-\sigma_j} \int_{z \in \mathcal{Z}_{jt'}^x(i)} \tilde{\Psi}_j(z,i)^{\sigma_j - 1} dz \right)^{\frac{1}{\sigma_j - 1}},$$

where $\Psi_j(z,i) \equiv A_j \tilde{\Psi}_j(z,i)$ and $M_{jt'}(i)$ is the mass of firms in sector j and city i at time t'. It is a harmonic mean of firm-specific productivity and depends on endogenous agglomeration effects. This definition of sectoral productivity follows from the CES sectoral price index, obtained from

[39]Formally, in our model this corresponds to a decrease in the land supply parameter ν (see Appendix B.2).

[40]Another possible cause for the decline in agglomeration effects in manufacturing, leading to relocation of manufacturing from big to small cities, would be a tightening of environmental pollution standards at densely populated locations. However, if we compare changes in location sorting across different manufacturing industries in the French data, we find no evidence that the change was greater in more pollution intensive industries.

sectoral goods (and services) market clearing conditions.[41] Using the exact same market clearing conditions, we can write *aggregate* sectoral productivity growth as

$$\frac{\Phi_{jt'}^{\text{agg}}}{\Phi_{jt}^{\text{agg}}} \equiv \frac{A_{jt'}}{A_{jt}} \left(\frac{\sum_i \frac{M_{jt'}(i)}{M_{jt'}} \, \tilde{\Psi}_{jt'}^{\text{local}}(i)^{\sigma_j - 1} \, \mathrm{d}i}{\sum_i \frac{M_{jt}(i)}{M_{jt}} \, \tilde{\Psi}_{jt}^{\text{local}}(i)^{\sigma_j - 1} \, \mathrm{d}i} \right)^{\frac{1}{\sigma_j - 1}} . \tag{21}$$

Similarly, the growth of local marginal costs, *net* of firm productivity $\Phi_j(z,i)$ for firms in sector j and location i, is given by[42]

$$\frac{\tilde{c}_{jt'}^{\text{local}}(i)}{\tilde{c}_{jt}^{\text{local}}(i)} \equiv \left(\frac{W_{t'}(i)}{W_t(i)} \right)^{\alpha_j} \left(\frac{p_{h,t'}(i)}{p_{h,t}(i)} \right)^{1-\alpha_j} , \tag{22}$$

which are shaped directly by land prices because land is a factor input, and indirectly through wages due to the need to compensate workers for higher land prices. Given the expression for local marginal costs, we can then define the growth of *aggregate* sectoral marginal costs as

$$\frac{\tilde{c}_{jt'}^{\text{agg}}}{\tilde{c}_{jt}^{\text{agg}}} \equiv \left(\frac{\sum_i \left(\frac{M_{jt'}(i)}{M_{jt'}} \frac{\Phi_{jt'}^{\text{agg}}}{\Phi_{jt'}^{\text{local}}(i)} \tilde{c}_{jt'}^{\text{local}}(i) \right)^{1-\sigma_j}}{\sum_i \left(\frac{M_{jt}(i)}{M_{jt}} \frac{\Phi_{jt}^{\text{agg}}}{\Phi_{jt}^{\text{local}}(i)} \tilde{c}_{jt}^{\text{local}}(i) \right)^{1-\sigma_j}} \right)^{\frac{1}{1-\sigma_j}} . \tag{23}$$

This equation shows that aggregate sectoral marginal costs give more weight to cities where (i) more firms of that sector locate in, and where (ii) firms of that sector are relatively *less* productive compared to the average firm in the same sector.

Panel A of Table 11 reports how local and aggregate sectoral productivity growth responds to each shock. The last two rows of column 1 indicate that manufacturing productivity grew by 120% between 1995 and 2018 compared to 15% for services. Column 3 shows that the *endogenous* component of sectoral productivity dampened the manufacturing productivity advantage over services: it reduced manufacturing productivity by 9% and boosted services productivity by 12%.[43] Column

[41] The intuition for it being a harmonic mean rather than an arithmetic mean is that the productivities of any two firms are not perfect substitutes since firms produce differentiated goods.

[42] To see this, notice that the firm's optimal price is given by a constant markup over marginal costs: $p_j(z,i) = \frac{\sigma_j}{\sigma_j-1} \frac{1}{\Phi_j(z,i)} \tilde{c}_j^{\text{local}}(i)$.

[43] Notice that, in column 3 of panel A, *aggregate* productivity growth is larger than *local* productivity growth. The reason for this can be seen by comparing the corresponding equations (21) and (20). The *local* measure of productivity growth considers how the (harmonic) average firm productivity in a given location i changes in response to shocks. The *aggregate* measure further considers the shifting distribution of firms across space, $M_j(i)/M_j$. The same reason applies

Table 11: Local and aggregate productivity and marginal cost growth in manufacturing and services

Panel A: Productivity growth								
					Counterfactual			
		Combined changes			$\Delta A_m, \Delta A_s$	$\Delta \tau_m, \Delta \tau_s$	Δa_m	Δa_s
	City size bin	Total	Exogenous	Endogenous		Endogenous		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Manufacturing	1	140%	142%	−1%	0%	0%	−1%	0%
	2	137%	142%	−2%	0%	0%	−2%	0%
	3	129%	142%	−5%	3%	0%	−9%	1%
	4	137%	142%	−2%	5%	0%	−10%	1%
	5	132%	142%	−4%	6%	0%	−17%	3%
	Aggregate	120%	142%	−9%	5%	0%	−19%	3%
Services	1	3%	3%	0%	0%	0%	0%	0%
	2	3%	3%	0%	0%	0%	0%	2%
	3	2%	3%	−1%	3%	0%	−6%	2%
	4	6%	3%	3%	5%	0%	−7%	4%
	5	10%	3%	7%	7%	0%	−13%	9%
	Aggregate	15%	3%	12%	7%	0%	−13%	14%
Panel B: Marginal cost growth								
Manufacturing	1	0%	-	0%	0%	0%	0%	0%
	2	0%	-	0%	−1%	0%	0%	1%
	3	−3%	-	−3	3%	0%	−7%	1%
	4	0%	-	0%	5%	0%	−7%	1%
	5	2%	-	2%	7%	0%	−12%	4%
	Aggregate	37%	-	37%	3%	2%	−35%	3%
Services	1	0%	-	0%	0%	0%	0%	0%
	2	0%	-	0%	0%	0%	0%	1%
	3	−2%	-	−2%	3%	0%	−6%	1%
	4	0%	-	0%	4%	0%	−6%	1%
	5	2%	-	2%	6%	0%	−11%	3%
	Aggregate	6%	-	6%	7%	0%	−13%	7%

Notes: The table decomposes the impact of exogenous TFP growth, falling international trade costs, and changing agglomeration externalities on local and aggregate productivity as well as marginal costs in the manufacturing and services sectors between 1995 and 2018. In panel A, 'Exogenous' refers to the exogenous component of productivity, whereas 'Endogenous' refers to the endogenous component that depends on agglomeration externalities. The corresponding equations for local and aggregate productivity growth are (20) and (21). In panel B, marginal costs are *net* of productivity $\Phi_j(z,i)$. The corresponding equations for local and aggregate marginal cost growth are (22) and (23).

3 in panel B shows that the manufacturing productivity advantage is further dampened by a larger increase in manufacturing marginal costs than in services.

When we introduce only *exogenous* TFP growth into the model's 1995 equilibrium, holding constant other drivers of structural change, we find that it leads to sizable productivity spillovers

to columns 6 and 7, as well as the results for local and aggregate marginal cost growth in the same columns of panel B.

both within and across sectors through agglomeration and sorting effects. Column 4 in panel A shows the results of this counterfactual experiment: the endogenous components of manufacturing and services productivity growth induced by TFP growth contribute 5% and 7%. These effects do not play out evenly across space. Productivity grows more in large cities because exogenous TFP growth leads to an expansion of the services sector, which is concentrated in large cities. Population growth in large cities leads to higher productivity through agglomeration externalities (recall that in 1995 agglomeration externalities were larger for manufacturing than for services). Why then do services firms in large cities experience a larger productivity boost (7%) than manufacturing firms (5%) in the same cities? This is because highly efficient services firms, which were already located in large cities in 1995, benefit disproportionately more from agglomeration externalities. As population grows more in large cities, however, land prices also increase, driving marginal costs of production higher in large cities. Column 4 in panel B shows that, for both manufacturing and services, the associated rise in marginal costs almost entirely offsets the productivity gains due to agglomeration externalities. Therefore, although large cities are relatively more exposed to a common manufacturing TFP boost due to the sorting of large services firms to large cities, the changes in agglomeration and congestion effects approximately cancel out.

The decline of only the manufacturing agglomeration externality (a_m) generates a large productivity spillover effect on services. Column 6 in panel A shows that services productivity declines by 13%, with the decline concentrated in large cities. This decline in the manufacturing agglomeration externality leads to a shift of manufacturing firms away from large cities towards small cities, reducing the population size of large cities. The decline in large-city population mainly affects large services firms (in a negative way), as they are concentrated in large cities. The departure of manufacturing firms from large cities additionally reduces services productivity in large cities as it leads to an inflow of less productive services firms. Similarly, an increase in services agglomeration externalities (a_s) generates productivity gains for both manufacturing and services, particularly for large services firms in large cities (see column 7). However, as column 7 of panel B shows, the gains of 14% for the services sector are partially offset by a corresponding rise in marginal costs (due to rising land prices) of 7%, with the result that the net productivity growth is dampened by half.

6 Conclusion

We document uneven spatial patterns of structural change in France from 1995 to 2018. We show that while the country experienced a shift from manufacturing to services on aggregate, this shift was concentrated in the largest cities with the highest density of economic activity. The services sector grew disproportionately in such cities, while manufacturing reoriented towards less populous locations. In the largest cities, the services sector became more than five times as prominent as manufacturing in terms of revenue, value-added, and employment, whereas in the smallest cities the split is more even. This urban-biased pattern of structural change was driven by the behavior of large firms, with large services firms expanding in urban areas and large manufacturing firms expanding in other parts of the country. The expansion of large services firms in large cities was also accompanied by a rapid increase in services exports.

To understand these patterns of structural change, we estimate a structural model of city formation with location choices by heterogeneous firms in an open economy setting. We find that strengthening agglomeration externalities in services relative to manufacturing are a major driving force behind the urban bias. Rapidly declining international trade costs for services further reinforce urban-biased services growth. Strong TFP growth in manufacturing also increases the share of services in the economy but evenly across locations. Sectoral TFP growth thus does not explain the urban bias, although it is a crucial determinant of structural change at the aggregate level.

Differences in structural change across locations, driven by the behavior of heterogeneous firms, also have implications for understanding structural change at the aggregate level. Rising manufacturing TFP encourages the concentration of large services firms in big cities, raising their productivity through agglomeration externalities. This cross-sector effect on services sector productivity dampens the aggregate impact of manufacturing TFP on aggregate structural change and is absent in canonical analyses that abstract from firm heterogeneity and urban agglomeration externalities.

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Online Appendix
"Urban-Biased Structural Change"

by Natalie Chen, Dennis Novy, Carlo Perroni, and Horng Chern Wong

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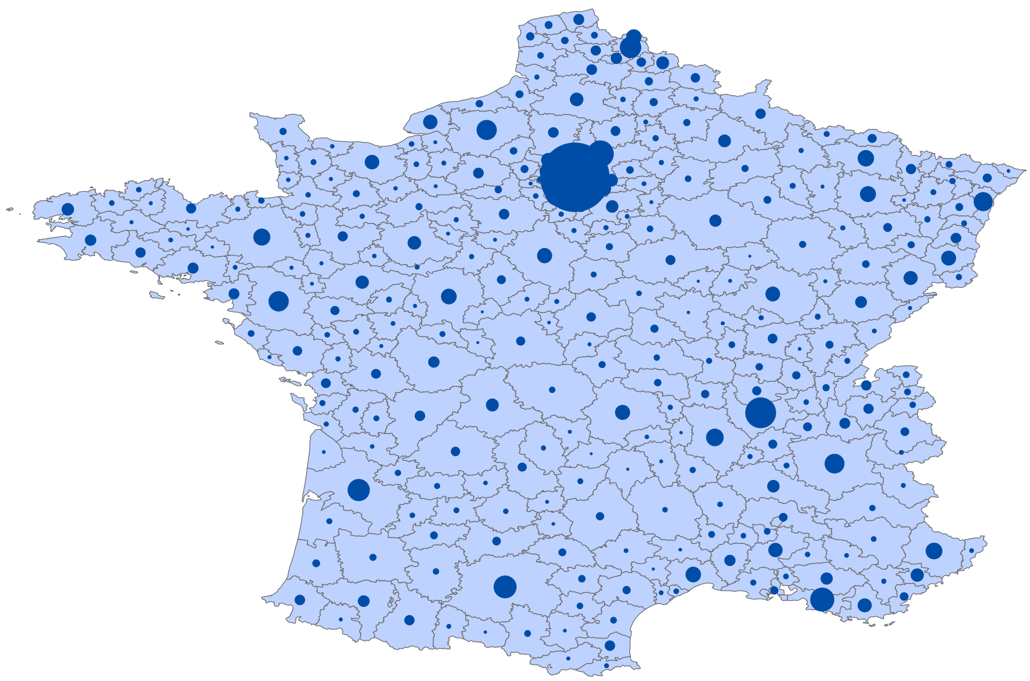
A Data appendix

A.1 Descriptive statistics

Figure A.1 shows a map of the population across French cities (commuting zones). Figure A.2 shows different measures of aggregate structural change (revenue, exports, value-added, employment) including multi-establishment firms. Figure A.3 shows the change in sectoral revenue shares *across* city bins between 1995 and 2018. For manufacturing we observe a redistribution of activity from the largest to the smallest cities. For services we see a shift in the opposition direction (albeit weaker), with the services shares declining in the three smallest bins and rising in the two largest bins. Figure A.4 illustrates that the urban-biased pattern of structural change holds across individual cities and for different measures of structural change (revenue, exports, value-added, employment). Figure A.5 also illustrates that the urban-biased pattern of structural change holds across individual cities and for different measures of structural change (revenue, exports, value-added, employment) but including multi-establishment firms. Figure A.6 shows, for manufacturing and services each, the change in the share of firms across city bins between 1995 and 2018. Figure A.7 illustrates the role of tradable vs. non-tradable services. Figure A.8 shows the urban bias in structural change associated with non-exporting and exporting firms.

Table A.1 reports the size of multi-establishment firms relative to the aggregate French economy. Based on the main sample in Section 2, Tables A.2-A.4 report descriptive statistics for key variables. Table A.5 decomposes the contribution of non-exporters and exporters to urban-biased structural change.

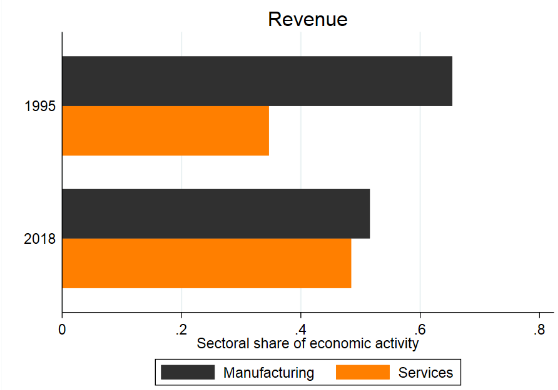
Figure A.1: Population across French cities



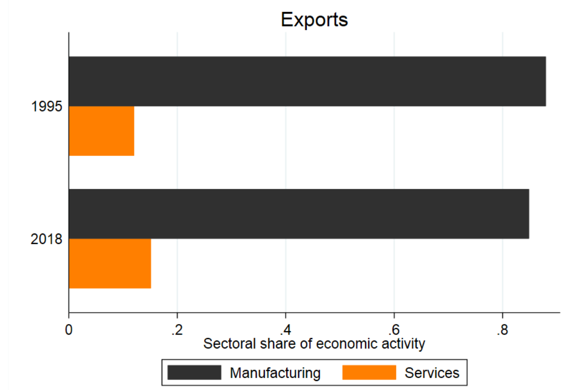
Notes: The map illustrates the population across 297 French cities (commuting zones). Population (city size) is measured as the number of total employees. The dots are proportional to population. See Section 2 for more information.

Figure A.2: Aggregate structural change in France, 1995-2018 (incl. multi-establishment firms)

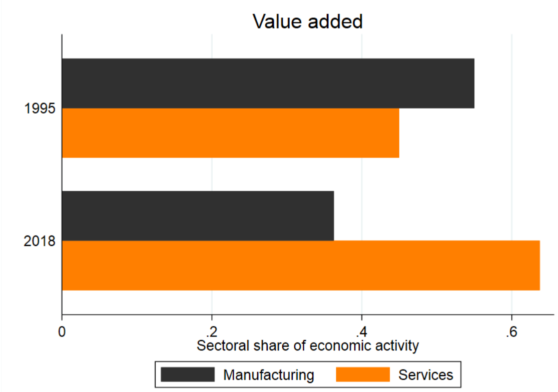
(a) Structural change in revenue



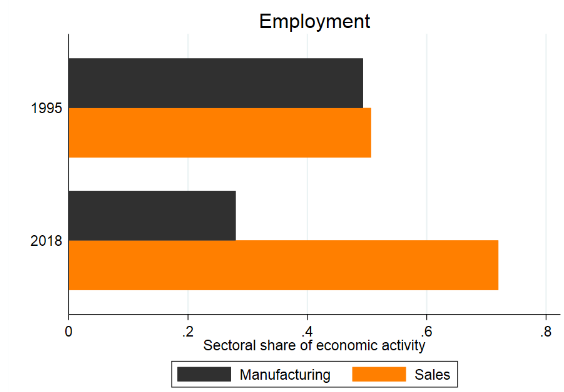
(b) Structural change in exports



(c) Structural change in value-added

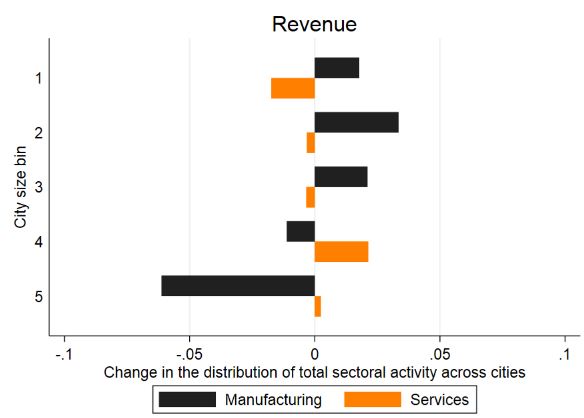


(d) Structural change in employment



Notes: Compared to Figure 1a and other data in Section 2, this figure includes multi-establishment firms whose establishments are located in different commuting zones.

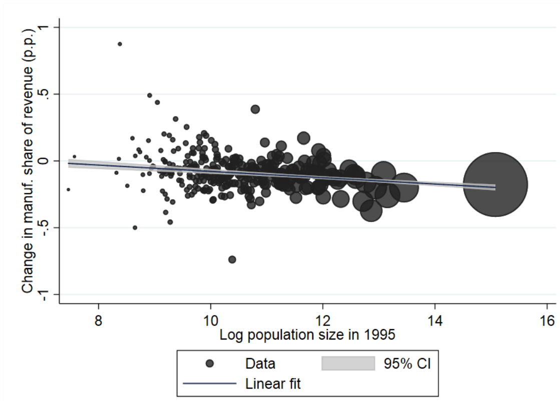
Figure A.3: Structural change across French city bins, 1995-2018



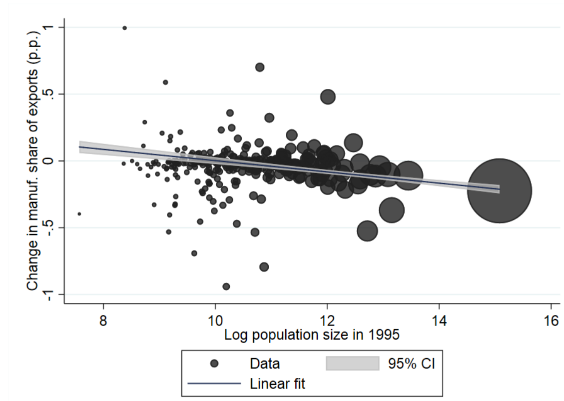
Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The bars show the percentage point change in sectoral revenue shares across city bins between 1995 and 2018. The changes within each sector add to zero.

Figure A.4: Structural change across French cities, 1995-2018

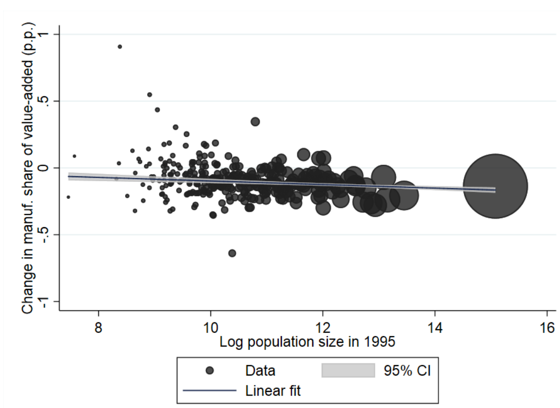
(a) Structural change in revenue



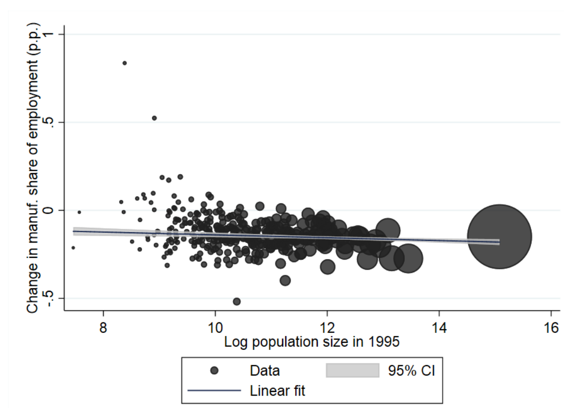
(b) Structural change in exports



(c) Structural change in value-added



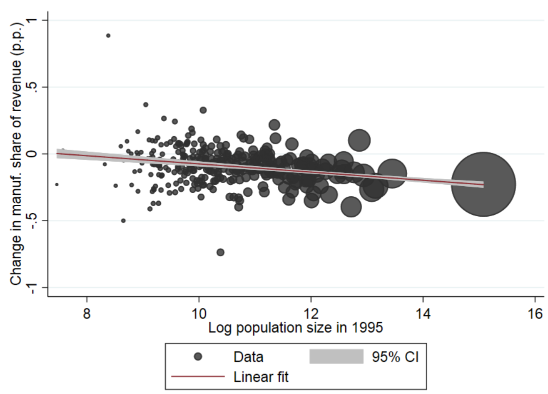
(d) Structural change in employment



Notes: Each dot represents one French city (commuting zone), proportional to population size in 1995. The largest dot represents Paris. The variable on the vertical axis is the change in the manufacturing share in percentage points. The slope of the regression line is significantly different from zero in each panel.

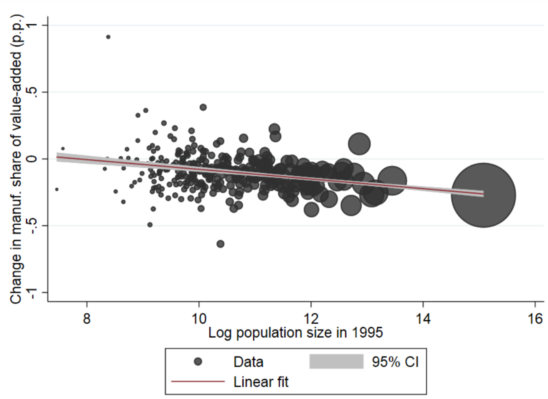
Figure A.5: Structural change across French cities, 1995-2018 (incl. multi-establishment firms)

(a) Structural change in revenue

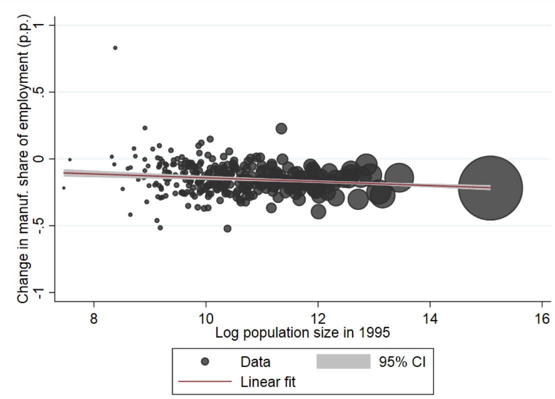


(b) Structural change in exports

(c) Structural change in value-added

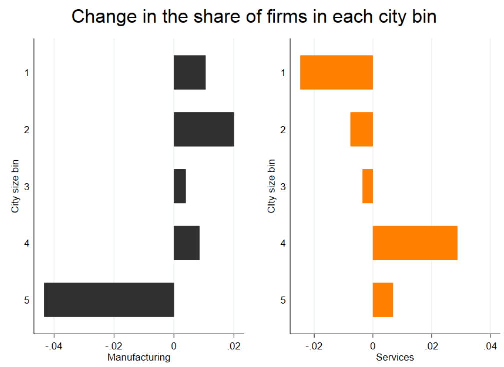


(d) Structural change in employment



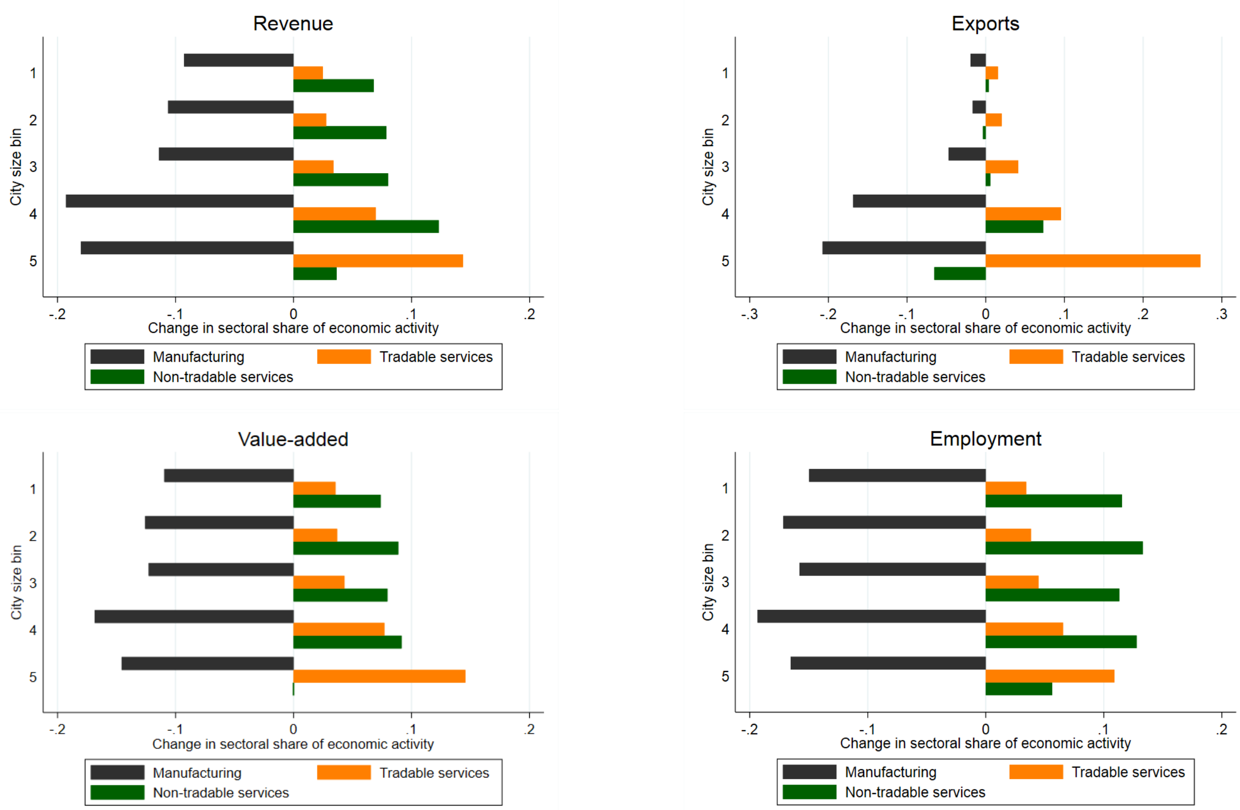
Notes: Each dot represents one French city (commuting zone), proportional to population size in 1995. The largest dot represents Paris. The variable on the vertical axis is the change in the manufacturing share in percentage points. Compared to Figure A.4, this figure includes multi-establishment firms whose establishments are located in different commuting zones. Establishment-level employment is directly measured from the French DADS dataset. However, establishment-level revenue, exports, and value-added are not directly observed in the data. To compute these variables, we split firm-level revenue into establishment-level revenue using each establishment's share of the firm-level wage bill. This way of allocating firm-level output to each establishment works under the assumption of firm-level Cobb-Douglas production technologies and constant markups. The slope of the regression line is statistically significantly different from zero in each panel.

Figure A.6: Change in the share of manufacturing and services firms across city bins, 1995-2018



Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The figure shows the change across city bins in the share of manufacturing firms (black) and services firms (orange). The changes are between 1995 and 2018 and in each sector add to zero.

Figure A.7: Tradable vs. non-tradable services and urban-biased structural change, 1995-2018

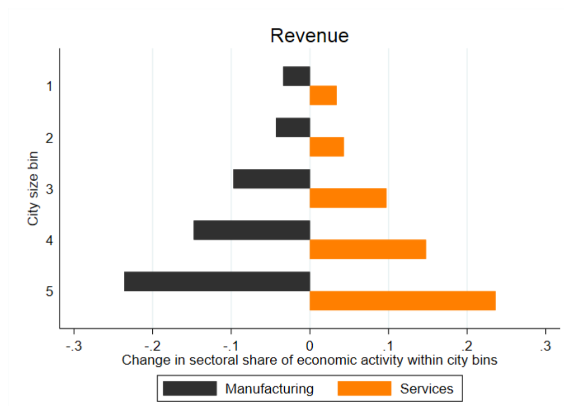


Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The changes are across French city bins between 1995 and 2018 and add to zero. Black denotes manufacturing, orange denotes tradable services, and green denotes non-tradable services. The panels show the change in a sector's share of economic activity, measured in terms of revenue, export, value-added, and employment.

Figure A.8: Non-exporters, exporters, and urban-biased structural change in France, 1995-2018

(a) Structural change among *non-exporters*

(b) Structural change among *exporters*



Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. In panel (a) the bars show the percentage point change in sectoral revenue shares within city bins for manufacturing and services between 1995 and 2018 among non-exporters only. The numbers correspond to the red element of the first row in the decomposition formula. Panel (b) does the same among exporters only. The numbers correspond to the red element of the second row in the decomposition formula. For example, -0.1 means a ten percentage point decline. The changes within city bins add to zero.

Table A.1: Multi-establishment firms' share of the French economy

	Manufacturing		Services		Overall	
Statistic	1995	2018	1995	2018	1995	2018
Fraction of all firms	0.055	0.065	0.031	0.047	0.040	0.051
Share of revenue	0.615	0.664	0.349	0.413	0.523	0.542
Share of exports	0.690	0.750	0.539	0.427	0.671	0.701
Share of value-added	0.623	0.628	0.355	0.425	0.502	0.499
Share of employment	0.489	0.474	0.348	0.409	0.418	0.427

Notes: The table reports the size of multi-establishment firms relative to the aggregate French economy.

Table A.2: Descriptive statistics by city size bin (shares)

		Manufacturing		Services	
Statistic	City size bin	1995	2018	1995	2018
Share of revenue	1	0.67	0.58	0.33	0.42
	2	0.64	0.53	0.36	0.47
	3	0.54	0.42	0.46	0.58
	4	0.56	0.37	0.44	0.63
	5	0.33	0.15	0.67	0.85
	overall	0.53	0.38	0.47	0.62
Share of value-added	1	0.58	0.47	0.42	0.53
	2	0.54	0.42	0.46	0.58
	3	0.43	0.31	0.57	0.69
	4	0.44	0.27	0.56	0.73
	5	0.24	0.10	0.76	0.90
	overall	0.42	0.27	0.58	0.73
Share of employment	1	0.55	0.40	0.45	0.60
	2	0.51	0.34	0.49	0.66
	3	0.42	0.26	0.58	0.74
	4	0.42	0.22	0.58	0.78
	5	0.26	0.10	0.74	0.90
	overall	0.43	0.26	0.57	0.74
Share of exports	1	0.97	0.95	0.03	0.05
	2	0.96	0.94	0.04	0.06
	3	0.88	0.84	0.12	0.16
	4	0.92	0.75	0.08	0.25
	5	0.54	0.33	0.46	0.67
	overall	0.83	0.71	0.17	0.29

Notes: The table reports descriptive statistics for the sample of firms with one establishment and firms whose establishments are all located in the same commuting zone. See Section 2 for more information. Revenue, value-added and exports are in real terms (in 1995 values).

Table A.3: Descriptive statistics by city size bin (totals and averages)

		Manufacturing		Services	
Statistic	City size bin	1995	2018	1995	2018
Total revenue ('000)	1	57594	60479	28268	44160
	2	52016	58562	29119	50942
	3	37613	41624	32667	57202
	4	43168	39796	33896	68537
	5	40032	25426	82806	149034
	sum	230423	225887	206756	369875
Total value-added ('000)	1	28837	30256	20952	34161
	2	26636	29165	22272	40465
	3	19338	20849	25645	47049
	4	21469	21337	27170	56871
	5	22253	14357	70089	136219
	sum	118533	115964	166128	314765
Total exports ('000)	1	11310	15580	330	781
	2	10398	17934	488	1173
	3	6251	13291	829	2613
	4	13737	13817	1191	4565
	5	8640	9743	7401	19675
	overall	50336	70365	10239	28807
Average revenue ('000)	1	1899	2796	465	551
	2	2016	2705	529	643
	3	1791	2510	600	754
	4	1904	2421	741	820
	5	2381	2734	1421	1661
	overall	1976	2633	746	894
Average value-added ('000)	1	947	1417	345	426
	2	1038	1357	404	509
	3	936	1270	471	623
	4	1025	1298	595	678
	5	1308	1526	1218	1518
	overall	1031	1366	601	759

Notes: The table reports descriptive statistics for the sample of firms with one establishment and firms whose establishments are all located in the same commuting zone. See Section 2 for more information. Revenue, value-added and exports are in real terms (in 1995 values). 'Average' refers to the average over firms in each bin.

Table A.4: Descriptive statistics by city size bin (firm shares)

		Manufacturing		Services	
Statistic	City size bin	1995	2018	1995	2018
Share of exporting firms	1	0.25	0.31	0.02	0.05
	2	0.25	0.31	0.03	0.06
	3	0.24	0.30	0.04	0.08
	4	0.26	0.29	0.06	0.08
	5	0.35	0.33	0.13	0.17
	overall	0.25	0.30	0.05	0.08
Share of firms	1	0.27	0.28	0.23	0.20
	2	0.23	0.25	0.20	0.19
	3	0.19	0.19	0.20	0.20
	4	0.17	0.18	0.17	0.20
	5	0.15	0.10	0.21	0.21
	sum	1.00	1.00	1.00	1.00
Share of firms (above median log sales)	1	0.26	0.28	0.20	0.18
	2	0.22	0.25	0.19	0.19
	3	0.18	0.19	0.19	0.19
	4	0.18	0.18	0.17	0.20
	5	0.16	0.10	0.25	0.24
	sum	1.00	1.00	1.00	1.00
Share of firms (below median log sales)	1	0.28	0.28	0.25	0.22
	2	0.23	0.24	0.21	0.20
	3	0.20	0.20	0.21	0.20
	4	0.16	0.18	0.17	0.20
	5	0.14	0.11	0.16	0.19
	sum	1.00	1.00	1.00	1.00

Notes: The table reports descriptive statistics for the sample of firms with one establishment and firms whose establishments are all located in the same commuting zone. See Section 2 for more information.

Table A.5: Contribution of non-exporters and exporters to urban-biased structural change

		Non-exporters		Exporters	
City size bin	UBSC (total)	Structural change among non-exp. (a)	Changing non-exp. revenue share (b)	Structural change among exp. (c)	Changing exp. revenue share (d)
1	−0.093	−0.068	0.006	−0.017	−0.014
2	−0.106	−0.061	0.014	−0.020	−0.039
3	−0.114	−0.061	0.004	−0.043	−0.015
4	−0.193	−0.079	0.025	−0.063	−0.076
5	−0.180	−0.056	0.001	−0.122	−0.003

Notes: The table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labeled ‘UBSC’, which stands for urban-biased structural change). For example, -0.1 means a ten percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities.

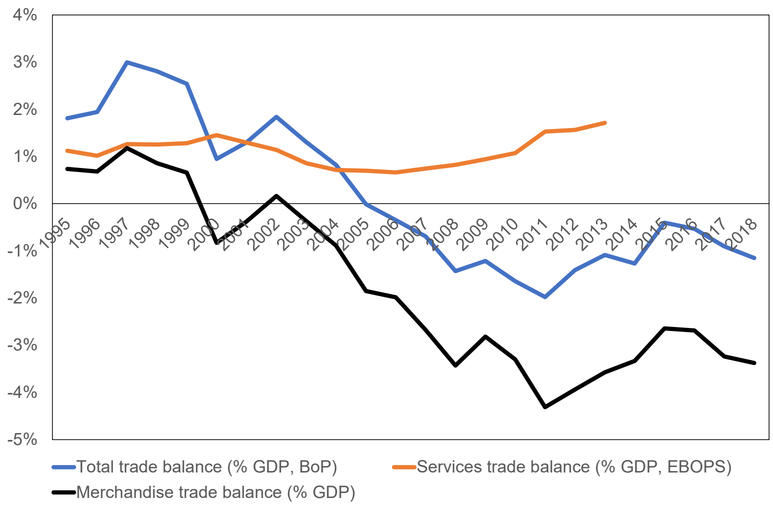
A.2 The trade balance and comparative advantage

Figure A.9 plots the aggregate French trade balance over time. It moved from a surplus of around 2.5% of GDP in the late 1990s to a deficit of around minus 1% by 2018. This decline in the aggregate trade balance is driven by a commensurate decline in the manufacturing trade balance, while the services trade balance remained constant at roughly 1% on average. The change in the trade balance is therefore not sizable enough to explain the decline in the manufacturing value-added share from 42% to 27%.

In addition, we explore whether the manufacturing trade balance evolved differentially across 2-digit manufacturing industries, mapping these industries to city size bins. We find a slightly stronger decline in the manufacturing trade balance of smaller cities. The intuition is that high-tech French manufacturing, which is attractive on international markets, tends to be more strongly represented in larger cities. This trade balance pattern across cities of different sizes goes in the opposite direction of the relatively strong decline of manufacturing in the largest cities documented in Figure 1b.

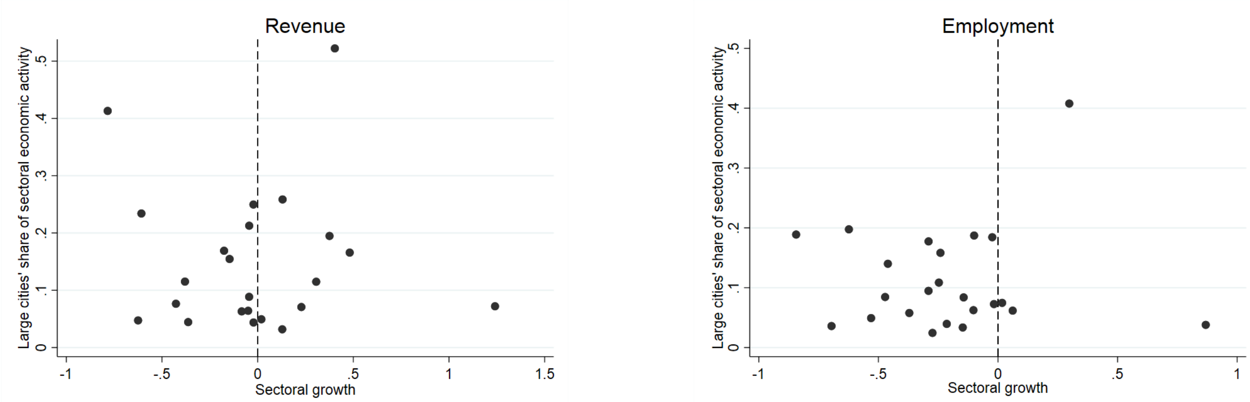
Can a shift in comparative advantage away from certain French manufacturing sectors explain the urban bias in structural change? For this to be a driver, the manufacturing sectors whose output was replaced by outsourcing or imports should be the sectors that (i) declined at the fastest rate and (ii) were more concentrated in large cities in 1995 compared to manufacturing sectors that had a smaller (or non-negative) rate of decline. We therefore correlate the growth rates of manufacturing sectors in large cities with their initial size. Figure A.10 shows that there is no systematic relationship. This finding suggests that a shift in comparative advantage away from certain manufacturing sectors cannot explain the urban bias in structural change. Nevertheless, in Appendix B.1 we extend our quantitative framework to assess whether a decline in the price of imported manufactured goods relative to domestically produced goods can quantitatively account for aggregate and urban-biased structural change.

Figure A.9: French trade balance



Notes: The figure shows the French merchandise trade balance from 1995 to 2018 (black), the French services trade balance from 1995 to 2013 (orange) and the total trade balance (blue) as a fraction of GDP. Data sources: Services total exports and imports (million USD) and merchandise total exports and imports (million USD) are from the World Trade Organization (WTO). The term 'merchandise' has the same meaning as the terms 'goods' and 'commodities.' The services data are available between 1995 and 2013 according to the Extended Balance of Payments Services Classification (EBOPS) 2002 (this classification was replaced by EBOPS 2010 but data for EBOPS 2010 are only available from 2005 and not reported here). Nominal GDP (USD) and total exports and imports of goods and services (USD, from the Balance of Payments, BoP) are from the World Bank World Development Indicators.

Figure A.10: Manufacturing growth and large cities' share of manufacturing activity, 1995-2018



Notes: The left panel shows the relationship between the growth of two-digit manufacturing sectors (1995-2018) and the initial share of revenue of that sector accounted for by large cities (city size bin 5). The right panel does the same for employment.

A.3 Parameter estimates under alternative land price elasticity values

Table A.6 shows estimated model parameters for alternative values of the land price elasticity γ. See Section 4.2 for details.

Table A.6: Estimated parameter values under alternative values of γ

		$\gamma = 0.35$		$\gamma = 0.20$	
Parameter	Sector	1995	2018	1995	2018
Shape of Gamma productivity ($\nu_{z,j}^{shape}$)	Manufacturing	0.549	0.549	0.466	0.466
		(0.007)	(0.007)	(0.031)	(0.031)
	Services	1.454	1.454	2.546	2.546
		(0.054)	(0.054)	(1.116)	(1.116)
Scale of Gamma productivity ($\nu_{z,j}^{scale}$)	Manufacturing	0.173	0.173	0.159	0.159
		(0.001)	(0.001)	(0.001)	(0.001)
	Services	0.274	0.274	0.297	0.297
		(0.017)	(0.017)	(0.067)	(0.067)
Scale of Gumbel shock ($\nu_{\epsilon,j}^{scale}$)	Manufacturing	0.072	0.072	0.077	0.077
		(0.000)	(0.000)	(0.000)	(0.000)
	Services	0.289	0.289	0.153	0.153
		(0.005)	(0.005)	(0.024)	(0.024)
Agglomeration curvature (s_j)	Manufacturing	0.491	0.491	0.694	0.694
		(0.022)	(0.022)	(0.051)	(0.051)
	Services	0.990	0.990	0.903	0.903
		(0.079)	(0.079)	(0.971)	(0.971)
Agglomeration effect (a_j)	Manufacturing	0.290	0.283	0.159	0.148
		(0.005)	(0.004)	(0.007)	(0.003)
	Services	0.320	0.327	0.166	0.164
		(0.020)	(0.024)	(0.039)	(0.036)
Sorting effect (ξ_j)	Manufacturing	−0.139	−0.139	−0.139	−0.139
		(0.043)	(0.043)	(0.067)	(0.067)
	Services	0.554	0.554	0.607	0.607
		(0.108)	(0.108)	(0.949)	(0.949)

Notes: Asymptotic standard errors in parentheses.

B Model appendix

B.1 Shifting comparative advantage

In our baseline structural framework, the Home and Foreign countries are symmetrically identical. This means that the trade balances for both goods and services are zero. However, as shown in Figure A.9, the French trade balance for goods has declined from about 1% of GDP to minus 3% of GDP between 1995 and 2018. For services, the trade surplus remains at about 1% of GDP. This section quantitatively addresses how shifting comparative advantage away from French manufacturing affects our main findings.

Changes to the baseline model. In this section, we abstract from non-homothetic income effects by working with homothetic CES preferences ($\epsilon_j = 1$). We model the Home country (France) as a small open economy, i.e., Home takes the Foreign price of goods and services as given. Let P_j^F be the exogenous Foreign price of manufactured goods. The Home price index for sector j is now:

$$P_j = \left(\sum_i \int_{z \in \mathcal{Z}_j(i)} p_j^d(z,i)^{1-\sigma_j} \, \mathrm{d}z + \left(P_j^F\right)^{1-\sigma_j} \right)^{\frac{1}{1-\sigma_j}},$$

where $p_j^d(z,i)$ is the domestic price of a Home producer with efficiency z located in city i. A decline in P_j^F implies that Home firms in sector j face stronger import competition.

Quantification of the extended model. In our baseline model, we rely on the assumption that the Home and Foreign countries are symmetrically identical to measure variable international trade costs (τ_j) using data on sectoral export intensity. In the extended framework in this section in which the Home country is a small open economy, sectoral export intensity is now:

$$\frac{p_j^x(z,i)\, q_j^x(z,i)}{p_j^d(z,i)\, q_j^d(z,i)} = \tau_j^{1-\sigma_j} \frac{D_j^F}{P_j^{\sigma_j} Q_j},$$

where D_j^F is a demand shifter capturing exogenous shifts in Foreign's demand for Home sector j's output. We assume that in 1995, Home and Foreign are symmetrically identical: $D_j^F = P_j^{\sigma_j} Q_j$. Trade costs ($\tau_j$) in 1995 therefore retain the same values as in the baseline model.

We calibrate the changes in the price of Foreign manufactured goods (P_j^F) relative to Home manufactured goods to replicate changes in the manufacturing trade balance as a percentage of GDP between 1995 and 2018 – a 5 percentage point decline in the manufacturing trade balance share of GDP.

Main finding. We run a counterfactual simulation in which introduce the calibrated change in the price of imported goods into the estimated 1995 Home equilibrium. We find that the decline in the price of imported goods relative to Home goods can explain around 11% (or 1.7 percentage points) of the increase in the aggregate services share of revenue (aggregate structural change), but very little in terms of the urban bias: the increase in the services share of revenue is 0.002 percentage points higher along the largest cities (city size bin 5) compared to the smallest cities (city size bin 1).

B.2 Extension: Land market clearing

In the baseline version of our model, we represent the relationship between population density and land price in terms of an ad-hoc "equilibrium" land price schedule that depends on population size: $p_h(i) = L(i)^\gamma$. Below we relax this assumption by introducing an explicit land market clearing condition that determines equilibrium land prices.

Assume that the land supply function for city i is given by $h^s(i) = p_h(i)^\nu$. The total demand for land in city i is the aggregate demand for by firms in both the manufacturing and services sectors, as well as workers' demand. The land market clearing condition for city i is

$$\sum_{j\in\{m,s\}} \left(\int_{z\in\mathcal{Z}_j(i)} p_h(i) h_j(z,i)\,\mathrm{d}z \right) + (1-\eta)\, W(i)\, L(i) = p_h(i)\, h^s(i).$$

where $\mathcal{Z}_j(i)$ is the set of firms from sector j located in city i. Using firms' first-order conditions for an optimal input choice, we obtain $p_h(i)\, h_j(z,i) = \frac{1-\alpha_j}{\alpha_j} W(i)\, l_j(z,i)$. Substituting this into the land market clearing condition gives

$$\sum_{j\in\{m,s\}} \frac{1-\alpha_j}{\alpha_j} \left(\int_{z\in\mathcal{Z}_j(i)} W(i)\, l_j(z,i)\,\mathrm{d}z \right) + (1-\eta)\, W(i)\, L(i) = p_h(i)\, h^s(i).$$

Dividing each side of the equality by $W(i)$ and using the free worker mobility condition $W(i) = p_h(i)^{1-\eta}$, we can rewrite this as

$$\sum_{j\in\{m,s\}} \frac{1-\alpha_j}{\alpha_j} L_j(i) + (1-\eta) L(i) = p_h(i)^{\nu+\eta},$$

where $L_j(i)$ is the total employment of sector j in city i. We can now write the equilibrium land price schedule as

$$p_h(i) = \left(1-\eta + \sum_{j\in\{m,s\}} \frac{1-\alpha_j}{\alpha_j} \frac{L_j(i)}{L(i)} \right)^{\frac{1}{\nu+\eta}} L(i)^{\frac{1}{\nu+\eta}}. \tag{24}$$

Note that if all sectors have the same labor and land intensity, then equation (24) converges to the land price schedule in our baseline model (up to a constant). In the estimation approach of our baseline model, firms solve the location choice problem taking population size $L(i)$ as given. With a land market clearing condition as in equation (24), firms would additionally take as given the within-city sectoral share of employment $L_j(i)/L(i)$. Equation (24) also shows that, with an explicit land market clearing condition, and since that manufacturing is more land intensive than services ($\alpha_m < \alpha_s$), structural change can offset the effect of population size on land price as it shifts land demand from the more land intensive sector to the less land intensive sector. Overall, when we estimate the model using equation (24) and use it to run counterfactual experiments, we obtain similar estimated sectoral agglomeration externalities and similar quantitative findings.

B.3 Bounds on the sorting parameter (ξ_j)

We show in this section that the productivity function $\Psi_j(z,i)$ is only well-behaved when the sorting parameter ξ_j lies between -1 and 1. From (11), and denoting $L(i)/L(0)$ by L, the elasticity of firm productivity with respect to city size is then

$$\frac{\partial \log \Psi_j(z,i)}{\partial \log L} = \frac{a_j}{2}\left(1 + \frac{(1+\xi_j \log z) + (1-\xi_j)}{1+\log z}\ (1+\log L)^{s_j - 1}\right),$$

where $s_j \in [0,1]$. This elasticity determines the marginal benefit to the firm of choosing a city of a given population size. The marginal cost of choosing that same city is the elasticity of the firm's marginal production costs with respect to city size: $MC_j(z,i) = (1-\eta\alpha_j)\gamma$. Equating the marginal benefit and marginal cost of choosing a city i gives the following optimality condition:

$$\frac{(1+\xi_j)\log z + (1-\xi_j)}{1+\log z} = \left(2\frac{(1-\eta\alpha_j)\gamma}{a_j} - 1\right)(1+\log L)^{1-s_j}\,.$$

To ensure that no firms prefer a negative city size, we first impose the following parameter restriction $2(1-\eta\alpha_j)\gamma/a_j > 1$. We now show that, when $\xi_j > 1$ or $\xi_j < -1$, the productivity function is not well-behaved: firms would prefer negative city sizes.

For firms to always prefer a positive city size, we require that $\log z \geq -(1-\xi_j)/(1+\xi_j)$. Consider the least efficient firm, with $z_{min} = 1$. The requirement reduces to $0 \geq -(1-\xi_j)/(1+\xi_j) \equiv \tilde{\xi}_j$. This condition is always satisfied when $\xi_j \in [-1,1]$. However, this condition does not hold outside this range:

$\lim_{\xi_j \to -1^-}\ \tilde{\xi}_j\ =\ \infty;$

$\lim_{\xi_j \to 1^+}\ \tilde{\xi}_j\ \geq\ 0;$

$\lim_{\xi_j \to +\infty}\ \tilde{\xi}_j\ =\ 1 > 0;$

$\lim_{\xi_j \to -\infty}\ \tilde{\xi}_j\ =\ 1 > 0.$

We therefore impose the parameter restriction $\xi_j \in [-1,1]$.

B.4 The elasticity of firms' location choices with respect to their efficiency type

Below we discuss how the elasticity of firm's location choices varies with the parameters in (11). In what follows, L denotes $L(i)/L(0) \geq 1$, and for simplicity and we omit the sector j subscript. The first-order condition for a sorting equilibrium yields the following closed-form solution for $z(L)$:

$$\log z = -\frac{\gamma(1+\log L) - a(1+\log L)^s(1-\xi)}{\gamma(1+\log L) - a(1+\log L)^s(1+\xi)},$$

where γ is the elasticity of land prices with respect to city size. The above expression must be non-negative for $z \geq 1$ (as we assume), i.e., the expressions in the numerator (NUM) and the denominator (DEN) must have opposite signs (with NUM $= 0$ at $z = 1$). For $\xi > 0$, we have NUM $>$ DEN, whereas for $\xi < 0$ we have NUM $<$ DEN. Therefore:

$$\begin{array}{lll} \xi > 0 & \Rightarrow & \text{NUM} \geq 0,\ \text{DEN} < 0, \\ \xi < 0 & \Rightarrow & \text{NUM} \leq 0,\ \text{DEN} > 0. \end{array}$$

The expression for $d\log L/d\log z = 1/(d\log z/d\log L) \equiv \eta_z^L$ is

$$\eta_z^L = \frac{\text{DEN}^2}{2\xi(1-s)a\gamma(1+\log L)^s}.$$

For $s < 1$, the sign of η_z^L agrees with the sign of ξ. Consider next how η_z^L varies with L (and thus z):

$$\frac{d\eta_z^L}{dL} = \frac{\text{DEN}}{2\xi(1-s)a\gamma(1+\log L)^{1+s}}\Big((2-s)\gamma(1+\log L) - sa(1+\log L)^s(1+\xi)\Big).$$

- Case $\xi > 0$:
  In this case, we have DEN < 0. The limit of the last expression in within the large parentheses for $s < 1$ and $s \rightarrow 1$ equals DEN < 0 (making the whole expression positive); so, in the neighborhood of $s = 1$, η_z^L (which is positive in this case) must be increasing in L and thus decreasing in z (since L is increasing in z in this case). The limit of the same expression for $s \rightarrow 0$ equals $(2-s)\gamma(1+\log L)$, which is positive; so, for s sufficiently low, η_z^L must be decreasing in L (and in z). Note that a decreasing elasticity implies that $\log L(z)$ is concave in $\log z$, *not* that $L(z)$ is concave in z.

- Case $\xi < 0$:
  In this case, we have DEN > 0. The limit of the numerator in the expression for $s < 1$ and $s \rightarrow 1$ equals DEN, which is positive in this case (making the whole expression positive); so, in the neighborhood of $s = 1$, η_z^L (which is negative in this case) must be increasing in L and thus increasing in z (since L is decreasing in z in this case). The numerator in the expression remains positive for all values of $s < 1$, and so η_z^L remains increasing in z (decreasing in absolute value) for any value $s < 1$.

B.5 Solution algorithm

Preliminaries.

- Define parameter values.
- Permanently draw firm idiosyncratic efficiency z and firm-location-specific productivity ϵ.
- Let $UP^{\eta} = 1$ be the numeraire.

Outer loop. Guess the population distribution $\{u^0(i)\}_{i\in I}$:

- Obtain $\{p_h^n(i)\}_{i\in I}$ in the n^{th} iteration from the land price schedule.
- Obtain composite productivity $\{\Psi_j^n(z,i)\}_{i\in I}$.
- Compute the optimal city choice of firms $i^* = \arg\max_{i\in I} \hat{\pi}_j(z,i)$.
- Compute the share of firms in each location for each sector $\{\delta_j^n(i)\}_{i\in I, j\in J}$ as well as the associated mean composite productivity $\{\bar{\Psi}_j^n(i)\}_{i\in I, j\in J}$.
- Inner loop. Guess sectoral price indices $\{P_j^{n,0}\}_{j\in J}$ and aggregate output Q:
  - Compute sectoral sales shares ω_j, then the final goods price index P, then the final goods firm profits Π.
  - Compute the shares of exporters in each location for each sector $\{\delta_j^{x,n}(i)\}_{i\in I, j\in J}$ as well as the associated mean productivity of exporters $E\big[\big(\frac{\Phi_j^x(z,i)}{\tau_j}\big)^{\sigma_j - 1}\big]$.
  - Compute the sectoral mass of firms M_j and the E_j function.
  - Use the sectoral goods market clearing condition to iterate on $\{P_j^{n,0}\}_{j\in J}$. Use the final goods market clearing condition to iterate on Q.
  - Repeat until convergence.
- Use the local labor market clearing technology to update $\{u^{n+1}(i)\}_{i\in I}$.

Iterate until the equilibrium labor allocation across cities is achieved.

B.6 Estimates of agglomeration elasticities and model-implied elasticities

To relate the agglomeration elasticities of sectoral productivity implied by our estimates with corresponding estimates from the literature, we compute two elasticity measures. The first measure, based on the CES aggregator across firms within sectors, is (see B.7 for the derivation)

$$\frac{\partial \log \Psi_j^{\text{local}}(i)}{\partial \log(L(i)/L(1))} = \int_{z \in \mathcal{Z}_j(i)} \Omega_j(z,i) \, \frac{\partial \log \Psi_j(z,i)}{\partial \log(L(i)/L(1))} \, \mathrm{d}z, \tag{25}$$

where

$$\Omega_j(z,i) \equiv \frac{\left(1 + \varkappa_j(z,i)\, \tau_j^{1-\sigma_j}\right) \Psi(z,i)_j{}^{\sigma_j - 1}}{\int_{z \in \mathcal{Z}_j(i)} \left(1 + \varkappa_j(z,i)\, \tau_j^{1-\sigma_j}\right) \Psi_j(z,i)^{\sigma_j - 1} \, \mathrm{d}z}$$

is the weight placed on firms with efficiency z in sector j and location i. The aggregated local (i.e., location-specific) elasticity is a weighted average of firm-location-specific elasticities that fully accounts for equilibrium selection effects with respect to the productivity types of firms operating at different locations. While this is the theory-consistent measure of the elasticity of sectoral productivity with respect to city size, it is not observable in the data. As such, the literature has often focused on the estimation of firm-level productivity $\Psi_j(z,i)$.

The literature has also typically abstracted from land as a factor input because land use in production is not observed (Rosenthal, S., Strange, W., 2004. Evidence on the Nature and Sources of Agglomeration Economies. In: Henderson, V., Thisse, J. (Eds), *Handbook of Regional and Urban Economics*, Vol. 4, Elsevier, Amsterdam, pp. 2119-2171; Melo, P., Graham, D., Noland, R., 2009. A Meta-Analysis of Estimates of Urban Agglomeration Economies. *Regional Science and Urban Economics* 39(3), pp. 332-342; Graham, D., Gibbons, S., 2019. Quantifying Wider Economic Impacts of Agglomeration for Transport Appraisal: Existing Evidence and Future Directions. *Economics of Transportation* 19, 100121). In these estimates, just as in expression (25), land prices do not affect firms' marginal costs other than through wages, as wages compensate workers for higher local land prices. In contrast, the second measure we compute also accounts for how the elasticity of land prices with respect to city size affects *net* productivity through the cost of land use:

$$\frac{\partial \log \Psi_j^{\text{net, local}}(i)}{\partial \log(L(i)/L(1))} = \frac{\partial \log \Psi_j^{\text{local}}(i)}{\partial \log(L(i)/L(1))} - (1 - \alpha_j)\, \gamma, \tag{26}$$

where the first term on the right-hand side is the sectoral elasticity of *gross* firm productivity with respect to city size. The values of these two measures implied by our estimates are reported in Table B.1. Our estimates of the net elasticities are in the range of those reported elsewhere in the literature. For example, Combes *et al.* (2012) report that estimates of the elasticity of productivity with respect to city size range between 0.02 and 0.10, depending on the sector and the details of the estimation procedure.

Table B.1: Elasticity of sectoral productivity with respect to city size

	Gross				Net of land prices			
	Manufacturing		Services		Manufacturing		Services	
City size bin	1995	2018	1995	2018	1995	2018	1995	2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2	0.50	0.49	0.53	0.54	0.05	0.04	0.15	0.17
3	0.49	0.48	0.52	0.54	0.03	0.02	0.15	0.16
4	0.48	0.47	0.52	0.53	0.02	0.01	0.15	0.16
5	0.46	0.45	0.52	0.53	0.01	0.00	0.14	0.16

Notes: The table shows the elasticity of sectoral productivity (gross and net of land prices) with respect to city population size. The values in columns (1)-(4) correspond to expression (25), those in columns (5)-(8) correspond to expression (26). The values reported are elasticities relative to bin 1 as described in (25) and (26).

B.7 Aggregating firm productivity

In this section, we derive the theory-consistent sector-location-level and sector-level productivity used in Section 5.3. To proceed, first note that the sector-level price index can be written as

$$P_j = \left(\sum_i \int_{z \in \mathcal{Z}_j(i)} p_j^d(z,i)^{1-\sigma_j} \left(1 + \varkappa_j(z,i)\, \tau_j^{1-\sigma_j}\right) dz \right)^{\frac{1}{1-\sigma_j}} = \left(\sum_i P_j(i)^{1-\sigma_j} \right)^{\frac{1}{1-\sigma_j}}, \tag{27}$$

where $P_j(i) \equiv \left(\int_{z \in \mathcal{Z}_j(i)} p_j^d(z,i)^{1-\sigma_j} \left(1 + \varkappa_j(z,i)\, \tau_j^{1-\sigma_j}\right) dz \right)^{\frac{1}{1-\sigma_j}}$ is the sector-location-specific price index. Note that the welfare-relevant equilibrium sectoral price index is P_j since goods and services are traded costlessly across cities within a given country. Define the marginal production cost copula $\tilde{c}_j(i) \equiv \left(\frac{W(i)}{\alpha_j} \right)^{\alpha_j} \left(\frac{p_h(i)}{1-\alpha_j} \right)^{1-\alpha_j}$. Then, the sector-location-specific price index can be written as

$$P_j(i) = \frac{\sigma_j}{\sigma_j - 1}\, \tilde{c}_j(i)\, M_j(i)\, \frac{1}{\Phi_j^{\text{local}}(i)}, \tag{28}$$

where the sector-location-specific productivity index is

$$\Phi_j^{\text{local}}(i) \equiv \left(\Phi_j^{\text{local, D}}(i)^{\sigma_j - 1} + \frac{M_j^x(i)}{M_j(i)}\, \tau_j^{1-\sigma_j}\, \Phi_j^{\text{local, X}}(i)^{\sigma_j - 1} \right)^{\frac{1}{\sigma_j - 1}}, \tag{29}$$

the sector-location-specific productivity index across exporters is

$$\Phi_j^{\text{local, X}}(i) \equiv \left(\frac{1}{M_j^x(i)} \int_{z \in \mathcal{Z}_j^x(i)} \Phi_j^{\sigma_j - 1}(z,i)\, dz \right)^{\frac{1}{\sigma_j - 1}}, \tag{30}$$

and the sector-location-specific productivity index across both exporters and non-exporters is

$$\Phi_j^{\text{local, D}}(i) \equiv \left(\frac{1}{M_j(i)} \int_{z \in \mathcal{Z}_j(i)} \Phi_j^{\sigma_j - 1}(z,i)\, dz \right)^{\frac{1}{\sigma_j - 1}}. \tag{31}$$

Substituting equation (28) into equation (27), we can define the following expression for sectoral productivity:

$$\Phi_j^{\text{agg}} \equiv \left(\sum_i \frac{M_j(i)}{M_j}\, \Phi_j^{\text{local}}(i)^{\sigma_j - 1} \right)^{\frac{1}{\sigma_j - 1}}. \tag{32}$$

Given this definition of sectoral productivity, we can also define sectoral marginal cost copulas as:

$$\tilde{c}_j \equiv \left[\sum_i \left(\frac{M_j(i)}{M_j} \frac{\Phi_j^{\text{agg}}}{\Phi_j^{\text{local}}(i)} \tilde{c}_j(i) \right)^{1-\sigma_j} \right]^{\frac{1}{1-\sigma_j}} \tag{33}$$