Urban-Biased Structural Change*

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May 2023

PRELIMINARY AND INCOMPLETE: PLEASE DO NOT CITE

Abstract

In recent decades, high-income countries have experienced a structural shift of economic activity from manufacturing towards services. Using rich micro data from France, we document that structural change has been urban-biased – areas with higher population density have seen a faster shift into services than less densely populated locations. The urban bias is entirely accounted for by the location choices of large firms. We find that large services firms are located in large cities while the average size of manufacturing firms are relatively similar across cities. Motivated by these findings, we build and estimate a model of cities and heterogeneous firms to quantify the role of sectoral productivity growth, falling international trade costs, and changing agglomeration economies in shaping urban-biased structural change. We find that changing agglomeration economies shifted the presence of large services firms to large cities and large manufacturing firms to small cities. As a result, large cities increase specialization in services and small cities in goods, leading to urban-biased structural change. Growing manufacturing productivity and falling services trade costs further reinforce urban-biased services growth.

Keywords: Agglomeration, Cities, Exporting, Firms, Manufacturing, Services, Sorting, Structural Change, Trade Costs

JEL Classification: F15, F61, R12, R14

*Chen, Novy and Perroni gratefully acknowledge research support from the Economic and Social Research Council (ESRC grant ES/P00766X/1). Wong gratefully acknowledges financial support from the ERC TRADENET grant (714597). For data access and assistance, we thank DGFiP, INSEE, and CASD. We are grateful for comments from various seminar and conference presentations, in particular by Ernest Liu, Andreas Moxnes, Florian Sniekers, Etienne Wasmer, and Jens Wrona. Chen, Novy and Perroni are affiliated with the Department of Economics, University of Warwick, Coventry CV4 7AL, United Kingdom. Chen is also affiliated with CEPR and CESifo. Novy is also affiliated with CEPR, CEP/LSE and CESifo. Perroni is also affiliated with CESifo. Wong is affiliated with the Department of Economics, Stockholm University, 106 91 Stockholm, Sweden. Email addresses: `n.a.chen@warwick.ac.uk`, `d.novy@warwick.ac.uk`, `c.perroni@warwick.ac.uk`, `horngchernwong@gmail.com`.

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 differential productivity growth across manufacturing and services, a phenomenon related to "Baumol's cost disease" (Ngai and Pissarides, 2007). In an open economy, international trade further accelerates structural change by encouraging countries to specialize in certain sectors, driven by comparative advantage or scale economies (Matsuyama, 2009; 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. For example, the effects of international trade is geographically concentrated within countries (Autor, Dorn, and Hansen, 2013; Fajgelbaum and Redding, 2022). More broadly, the spatial distribution of manufacturing and services activity has changed over time: services firms are increasingly concentrated in densely populated U.S. cities (Desmet and Henderson, 2015). Existing research also shows that agglomeration forces have changed over time depending on the sector (Desmet and Rossi-Hansberg, 2009; Eckert, 2019).

In this paper we ask two related questions. First, to what extent is the structural change from manufacturing to services a phenomenon observed evenly across different regions of a country? Second, what role do productivity growth, falling international trade costs, and changing agglomeration forces play in explaining these regional patterns of structural change?

Section 2 presents newly documented stylized facts about structural change in France between 1995 and 2018. The French microdata contains detailed information about the universe of firms, including their location, size, and exports of both manufacturing *and* services firms. These data allow us to measure structural change across different cities in France and relate those patterns to how firms' location choices vary with their characteristics.

We find that structural change is urban-biased. Whether measured in sales, value-added, exports, or employment, we see that the structural shift from manufacturing to services has been faster in larger cities – the services (manufacturing) share of economic activity within cities increased (declined) more markedly in larger cities. This urban bias is not driven by Paris alone, and cannot be explained by sectors traditionally considered as non-tradable (e.g., catering and hospitality), nor by the shifting comparative advantage away from certain French manufacturing sectors that were more concentrated in large cities in 1995. When we look at sectoral growth, we see that the urban bias reflects a distinct spatial growth pattern of services and manufacturing: the expansion of the services sector is concentrated in large cities, while for manufacturing it is concentrated in small cities.

Urban-biased structural change is largely accounted for by the location choices of large firms. When we look at structural change among large firms, defined as the top 5% of firms in the sales distribution, we see sharp urban bias. However, among the other 95% of firms, we see no evidence of urban bias. Similarly, we see sharp urban bias among exporters, but not among non-exporters. These patterns highlight the role that large firms play in shaping the spatial distribution of economic activity.

Large services firms are heavily concentrated in large cities. Comparing services firms in the largest French cities such as Paris and Lyon, where a fifth of the French workforce is located, to those in the smallest cities that also house 20% of the French workforce, we find that the average services firm in large cities is approximately 50% larger than their small-city counterparts. By contrast, the size of manufacturing firms is more evenly spread out across cities of different sizes, with a slight negative correlation between firm size and city size. The prevalence of large firms in large cities has changed between 1995 and 2018; for example, we see that manufacturing exporters have become less likely to locate in large cities and more likely to locate in small cities, while the opposite is true for services.

In Section 3 we develop a quantitative structural model to decompose urban-biased structural change. The ingredients of our model are motivated by the empirical patterns we see in the detailed French microdata. In particular, the model features heterogeneous sectors and firms that sort into cities of different population sizes while balancing the productivity benefits of larger cities with higher congestion costs (Gaubert, 2018). When more efficient firms benefit disproportionately *more* from locating in large cities, the model predicts positive sorting by firm size and city size (consistent with what we see for French services firms). Conversely, when more efficient firms benefit *less* from locating in large cities, the model predicts negative sorting (consistent with the patterns we see for French manufacturing). The location choice of heterogeneous firms and sectors determines spatial specialization patterns and the exposure of different cities to different drivers of structural change.

Our model combines in a unified framework three main drivers of structural change, each of which operates at the *sector* level. First, sectoral productivity growth leads to overall structural change through complementarities in the consumption of goods and services (Ngai and Pissarides, 2007). Second, our model features international trade costs that differ between manufacturing and services in levels and in changes over time. Variable trade costs determine the intensive margin of exporting while fixed export costs determine the extensive margin (Melitz, 2003). Falling international trade costs reallocate sales and resources from non-exporters to exporters, and the differential sorting patterns of manufacturing and services exporters implies that some cities are more exposed to falling manufacturing trade costs while others are more exposed to falling services trade costs. Third, our model features changing sectoral agglomeration externalities. 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). Higher agglomeration benefits concentrate firms in larger cities.

In Section 4 we calibrate and structurally estimate the model's key parameters – in particular, those that determine sectoral productivity, international trade costs, and agglomeration effects – and how they changed between 1995 and 2018. We calibrate a set of international trade cost parameters for 1995 and another for 2018. The variable trade costs are set to match sectoral export intensity (ratio of domestic sales to exports) among exporters, and fixed export costs are calibrated to match the share of exporters among all firms. To estimate agglomeration effects in 1995 and 2018, we pool data for the two years and estimate agglomeration effects in each year jointly with parameters that are time invariant, such as sorting effects. In our model, agglomeration effects are productivity gains that accrue to all firms within the same sector *in the same way* when firms choose larger cities, while sorting effects determine whether those gains are larger or smaller depending on the firm's idiosyncratic efficiency. Our estimation approach infers positive sorting effects when the correlation between firm size and city size is positive (and vice versa). Agglomeration effects are inferred from a city's share of total sectoral sales. The intuition is that, when there are no sorting effects, greater agglomeration benefits attract more firms to larger cities without changing the composition of firm efficiency types. Finally, we calibrate sectoral productivity to match the increase in real GDP per capita and the falling aggregate manufacturing revenue share.

In Section 5 we use our structural framework to assess the contribution of sectoral productivity growth, falling international trade costs, and changing agglomeration effects to urban-biased structural change (UBSC henceforth). We show that our model is capable of replicating the UBSC we see in the data and the spatial distribution of large and small firms (stylized facts 1 and 3). The model also does well at reproducing stylized fact 2 – large firms account for UBSC – although it is not a targeted moment in the estimation of the model. Finally, the model is able to reproduce the fact that large cities account for the lion's share of services growth. We quantify the role of each of the three drivers of structural change in accounting for UBSC through the following steps. We start from the estimated 1995 equilibrium and introduce one driver in each counterfactual experiment, with the said driver set to 2018 values. We then compare the counterfactual UBSC to the UBSC predicted by the full model.

Between 1995 and 2018, productivity has grown faster in manufacturing than in services, leading to a more than doubling of the productivity gap between the two sectors. While this has been emphasized as a leading driver of aggregate structural change in the literature (Herrendorf, Rogerson, and Valentinyi, 2013), we find that it does not explain the urban bias. Our counterfactual exercises show that the growth of manufacturing productivity relative to services has led to a relative expansion of the services sector, generating a fifteen-percentage-point increase in the aggregate services revenue share. Since large services firms tend to sort into large cities, services growth is more concentrated in large cities, leading to population growth in the largest cities (Paris and Lyon) of 8% at the expense of smaller cities. The resulting growth of large cities raises the productivity of services firms. This highlights a novel interplay between manufacturing productivity growth and services productivity growth through agglomeration externalities, but it still cannot account for UBSC: since services already represented the largest share of economic activity in large cities in 1995, the percentage point increase in the services share of large-city output is no larger than that in small cities. Structural change induced by manufacturing productivity growth thus shows no urban bias.

Our calibrated international trade costs are much higher for services firms than for manufacturing firms, at a tariff-equivalent of 301% for services and 15% for manufacturing in 1995, but trade costs fell considerably more between 1995 and 2018 for services than for manufacturing, standing at a tariff-equivalent of 120% for services compared to 7% for manufacturing in 2018. This is consistent with the fact that export intensity is lower, but increased faster, among services exporters. However, falling international trade costs do not generate UBSC. In both sectors, the fall in trade costs led exporters to expand, reallocating sales, employment, and land from non-exporters to exporters. Although the decline in manufacturing trade costs is relatively small, it generates a 13% decline in manufacturing domestic sales and a 71% export growth for the manufacturing sector concentrated in small cities. The decline in services trade costs leads to a 6% decline in domestic sales of services and a 248% export growth, concentrated in large cities. The fall in manufacturing trade costs increases population size in small cities (0.5%) while the fall in services trade costs increase population in large cities (0.5%) at the expense of medium-sized cities. The large fall in services trade costs imply a reduction in the relative price of services, which trigger two offsetting effects: a lower expenditure share on services due to the complementarity between goods and services, and a higher expenditure share on services due to a higher income elasticity of demand for services (Comin, Lashkari, and Mestieri, 2021). Overall, the decline trade costs deliver little structural change in our model.

Our estimates of agglomeration externalities show that they have changed in opposite directions for services and manufacturing: agglomeration effects have strengthened over time for services, but they have weakened for manufacturing. These estimates are consistent with evidence on the diverging spatial growth of manufacturing and services in the US. Desmet and Henderson (2015) show that services firms have become more spatially more concentrated in the US, whereas manufacturing has become more spatially dispersed. Our estimates are also consistent with Desmet and Rossi-Hansberg's (2009, 2014) finding that local knowledge spillovers are more important for young industries than for mature industries.

We find that this divergence in agglomeration externalities across sectors is a major contributor to UBSC. Services firms experienced a productivity improvement which, at the same time, raised the benefits of locating in larger cities. The stronger services agglomeration effect led to more concentration of services firms in large cities, driving up population, wages, and land prices, thereby crowding out manufacturing firms and leading to UBSC. As large cities have grown larger, services firms have become more productive, particularly large services firms due to positive sorting by firm size and city size. This contributed to overall services growth, leading the manufacturing sector to grow disproportionately due to the resulting increase in expenditure shares on goods. Overall, strengthening services agglomeration externalities leads to UBSC while reducing the aggregate services share of output.

The weakening manufacturing agglomeration externalities further reinforced UBSC and led to a decrease in the aggregate services share. The weakening manufacturing agglomeration effect reduced manufacturing productivity and led to stronger incentives to leave large cities for smaller cities. The rising concentration of manufacturing in smaller cities, and in particular, the relocation of large manufacturing firms away from large cities led to reduced population size, wages, and land prices, making room for small and less efficient services firms to enter large cities while reducing the productivity of larger incumbent services in those locations. The decline in manufacturing productivity thus acts as a drag on services growth. Overall, the weakening manufacturing agglomeration externalities complement the strengthening services agglomeration externalities to give rise to a decrease in the aggregate services share.

We contribute to the macroeconomic literature on structural change. Herrendorf, Rogerson and Valentinyi (2014) describe a canonical multi-sector model in which structural transformation can occur through a substitution channel when productivity grows faster in the manufacturing sector, or through an income channel with non-homothetic preferences (Ngai and Pissarides, 2007; Comin et al, 2021).[1] Alessandria, Johnson, and Yi (2021) make the case for international trade as a potentially important driver of aggregate structural change, emphasizing the role that comparative advantage and scale economies could play. While that literature has mostly abstracted from spatial considerations, our empirical findings show that structural change does not play out evenly across locations within a country and point to the role that large firms play in accounting for these

[1] Cravino, Levchenko and Rojas (2022) show that population aging explains a sizeable share of the observed increase in US services consumption as older households tend to spend more on services. Differential spending by age group is unlikely to be a viable explanation for the urban bias in structural change in our data since, as in other parts of Western Europe, there has been no obvious divergence in age structures across French urban and rural regions (see Kashnitsky, De Beer and Van Wissen, 2021). That is, there has been little change in the empirical regularity that large cities in France have a substantially younger population compared to rural areas.

different regional experiences.[2] We show that changes in agglomeration forces are a driver of aggregate structural change. We also show that sectoral TFP growth has important implications for city sizes and the spatial patterns of services growth. Our model highlights a novel productivity spillover effect from manufacturing to services that arises due to an agglomeration feedback effect. Productivity growth in manufacturing leads to an increase in the demand for services. Since services are concentrated in the large cities and are relatively less land intensive (and more labor intensive) this leads to a relative increase in the demand for labor and in the number of workers in larger cities relative to smaller cities, which in turn disproportionately benefits the productivity of services firms (which are disproportionately located in large cities), further adding to overall structural change. Yet, because services already represent the bulk of economic activity in large cities in 1995, we do not find that this channel generates UBSC.

An emerging literature studies the spatial patterns of structural change. The spatial distribution of services and manufacturing firms have changed over time (Desmet and Henderson, 2015). Desmet and Rossi-Hansberg (2009) show that stronger knowledge spillovers in younger sectors may explain this fact. Desmet and Rossi-Hansberg (2014) further show that spatial patterns of technological diffusion can explain the differential spatial growth patterns of manufacturing and services firms. Our empirical findings are consistent with their work. We highlight the role that large firms' location choices play in urban-biased structural change. Eckert and Peters (2022) study the transformation from agriculture to manufacturing across US regions from 1880 to 1920, focusing on the role of technological catch-up and regional specialization. We focus on the relatively recent structural shift from manufacturing to services in high income countries while evaluating the main forces studied by the macro structural change literature. Eckert (2019) examines the uneven rise of the college wage premium across different US labor markets, leveraging the differential roll-out of information and communication technology. 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. We show that large firms account for the urban-biased shift from manufacturing to services and focus on the interplay between manufacturing and services within a quantitative urban model.

Our paper also relates to a literature studying the spatial impact of trade liberalization. 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 century. Bakker, Garcia-Marin, Potlogea, Voigtländer, and Yang (2022) study the impact of trade on cities (and the reverse) in a quantitative spatial model. Our paper shows new channels through which structural change leads to heterogeneous spatial patterns of export growth. In our model, manufacturing productivity growth leads to services export growth through (a) increased foreign demand for French services, and (b) agglomeration forces as the expansion of services in large cities leads to population growth, which further raises services productivity in large cities.

This paper is organized as follows. In Section 2 we describe the key data features motivating our analysis. In Section 3 we develop our model of heterogeneous structural change across locations. In Sections 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]Ding, Fort, Redding and Schott (2022) offer a framework of structural change within the firm. They demonstrate that large multiplant US manufacturers have become more services-intensive over recent decades. 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.

2 Urban-biased structural change: Evidence from France

In this section we describe the French firm-level data we use, and we then illustrate the main empirical patterns relating to structural change in France over recent decades. These findings motivate our theoretical framework in Section 3 and the structural estimation in Section 4.

2.1 Data description

Our data cover the period from 1995 to 2018. 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.[3]

We define a city as a commuting zone ("zone d'emploi") following Combes *et al.* (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 running from 1995 to 2018. This includes information on all employees, their location of work and residence. We use the number of total employees as our measure of population size.[4] Figure 7 in the appendix shows a map of the population across commuting zones.

Firms may have multiple establishments and those establishments may be located in multiple cities. We focus our attention on firms with one establishment and firms whose establishments are all located in the same city as we do not want to capture headquarter effects whereby firms report activity in locations where production may not be happening (see Duranton and Puga (2005)). However, our empirical findings are robust to including all firms.[5] To identify single-establishment and single-city firms, we use the DADS matched employer-employee 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 at the firm level for both manufacturing and services. 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 and technical services, and transportation.[6]

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

[4]Total employees include those in manufacturing, services and all other sectors being employed by any firm, including multi-establishment firms.

[5]In Table 15a in Appendix A, we show that multi-establishment firms represent around 5% of all firms and around half of aggregate economic activity. We also show in Figure 13 that the urban-biased patterns we document are not materially affected by including multi-establishment firms.

[6]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.

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 we present the patterns in terms of city size quintiles (to which we refer as city size bins). Bin 5 contains the largest cities, and bin 1 contains the smallest cities, based on size in 1995. By construction, each bin has roughly the same population, measured as the number of total employees.[7] We define the bins by initial population size in 1995 and do not change them 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 16a-16c in the appendix provide descriptive statistics by city size bin for variables of interest such as revenue, value-added, employment, and exports. We now highlight the key data patterns that motivate our empirical analysis.

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. To be precise, the aggregate revenue shares of manufacturing and services are 49 percent and 51 percent in 1995, and they stand at 35 percent and 65 percent in 2018.[8]

When we compute shares based on value-added rather than revenue, we obtain a similar picture. The value-added share of manufacturing declines from 42 percent in 1995 to 27 percent in 2018, while the services share increases from 58 percent to 73 percent. Corresponding shares based on employment are virtually the same.[9] Overall, aggregate structural change in France mirrors developments in other high-income countries. For example, for the period from 1970 to 2007 Herrendorf, Rogerson and Valentinyi (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.[10]

Next, Figure 1b illustrates a key empirical motivation for our paper, namely the observation

[7]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.

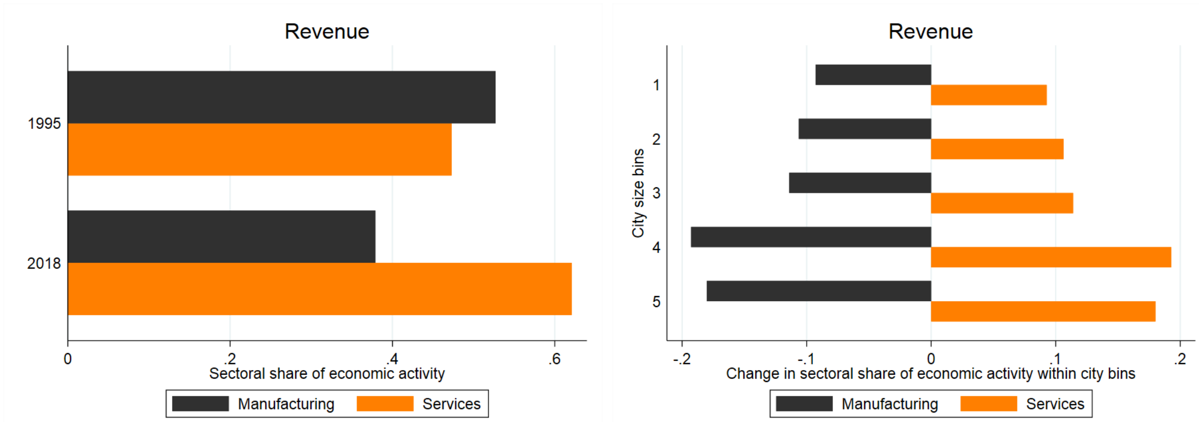
[8]See Table 16a for details. These shares add up to 1 as we exclude agriculture and mining since those sectors were small and their shares hardly changed over time. Specifically, the value-added shares of agriculture, forestry and fishing in the French economy were 2.7 percent in 1995 and 1.9 percent in 2018. The value-added shares for mining and quarrying were 0.2 percent and 0.1 percent.

[9]See Table 16a for details. As shown in Table 16b, manufacturing value-added in our sample declines in real terms by 2 percent between 1995 and 2018. Manufacturing employment (not listed in Table 16b) drops by 22 percent, broadly comparable in magnitude to a decline in US manufacturing employment by 18 percent between 2001 and 2007 as reported by Pierce and Schott (2016).

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

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).

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

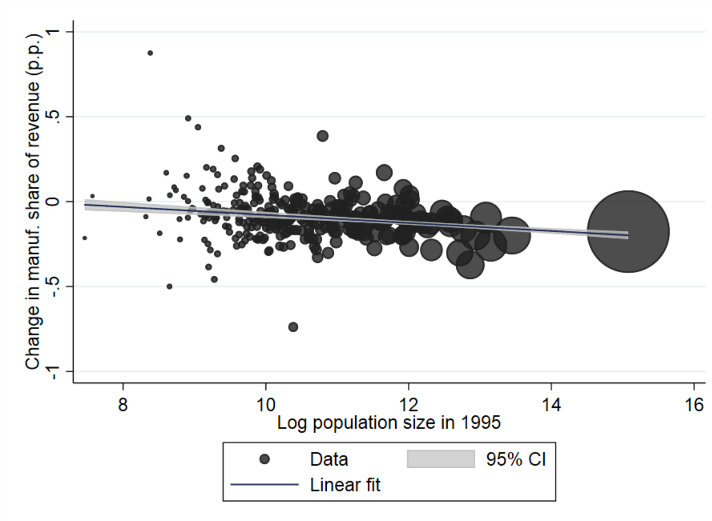
	Manufacturing share of revenue		
City size bin	1995	2018	UBSC
1	0.67	0.58	-0.09
2	0.64	0.53	-0.11
3	0.54	0.42	-0.12
4	0.56	0.37	-0.19
5	0.33	0.15	-0.18

Notes: This 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.

that structural change occurs faster in larger cities. We refer to this observation as *urban-biased structural change*. 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 percent compared to 67 percent in the smallest cities).[11]

[11] In Figure 8 we also show the change in sectoral revenue shares *across* city bins between 1995 and 2018.

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.

We stress that 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.[12] In addition, Figure 10 in Appendix A demonstrates that the urban-biased pattern also holds for different measures of structural change (expressed in terms of exports, value-added, and employment). In Figure 11 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. Conversely, the share of all firms within the 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 be due to a swift decline of the manufacturing sector in those cities, or due to rapid growth in the services sector. We now decompose the growth in the total domestic and export revenues of each sector into the share accounted for by each city size bin:

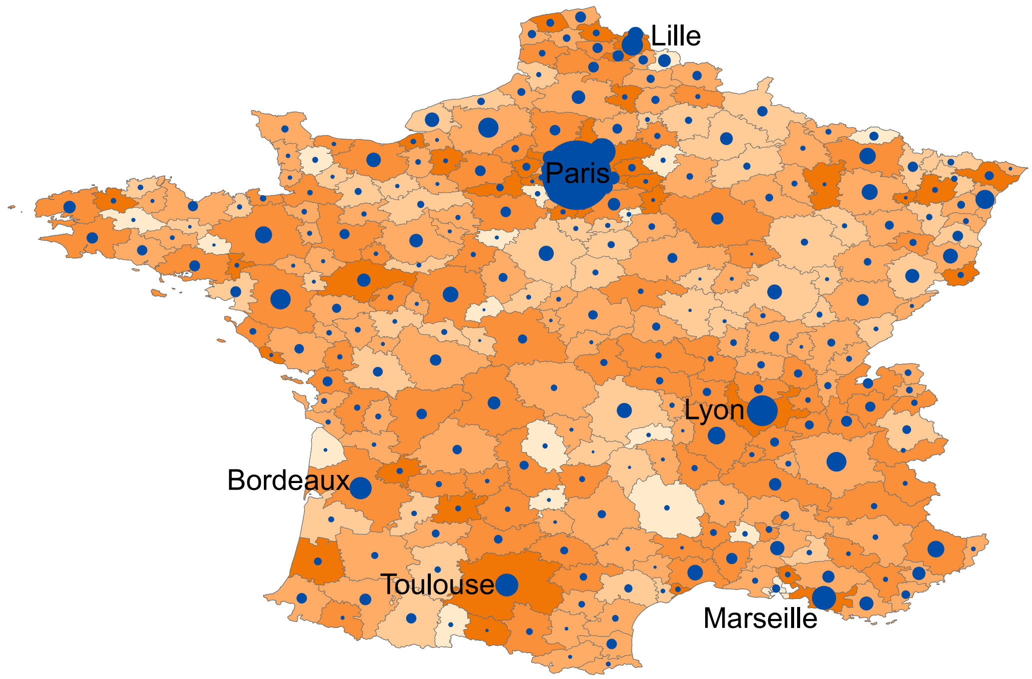
$$g^r_{jt+1} = \sum_i \left(\frac{R^r_{jt}(i)}{\sum_{i'} R^r_{jt}(i')} \right) g^r_{jt+1}(i)$$

where $r = \{\text{domestic, export}\}$, g_{jt+1} is the revenue growth rate of sector j, $g_{jt+1}(i)$ is the same for

Manufacturing shifts away from the largest cities towards smaller cities, and the opposite is true for services.

[12] 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.

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.

city i, and $R^r_{jt}(i)$ is the total domestic or export revenue of sector j in city size bin i.

Table 2 reports the results of this decomposition and shows 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 percent of domestic revenue growth and 68 percent 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. Urban-biased structural change thus reflects a disproportionate growth of services in large cities, rather than a disproportionate decline of manufacturing in large cities.

Robustness: 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 may be hard to trade nationally or internationally. In Figure 12, 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.

Robustness: changes in comparative advantage. We show that a shift in comparative advantages away from certain French manufacturing sectors also cannot explain the urban bias in structural

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: This 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.

change.[13] For comparative advantage to be a driver, the manufacturing sectors whose output is replaced by outsourcing or imports should be the 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. We therefore correlate the growth rates of manufacturing sectors in large cities with their initial size. Figure 16 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.

Stylized fact 2: Large firms account for urban-biased structural change
Structural change among large firms, such as exporters, 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 exporting firms and non-exporting firms.

For this purpose, we measure 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 written as:

$$\Delta\omega_{m,2018}(i) = \Bigg(\underbrace{\varsigma^{nx}_{1995}(i)\Delta\omega^{nx}_{m,2018}(i)}_{\substack{\text{(a) Structural change} \\ \text{among non-exporters}}} + \underbrace{\omega^{nx}_{m,2018}(i)\Delta\varsigma^{nx}_{2018}(i)}_{\substack{\text{(b) Changing non-exporter} \\ \text{revenue share}}} \Bigg) + \Bigg(\underbrace{\varsigma^{x}_{1995}(i)\Delta\omega^{x}_{m,2018}(i)}_{\substack{\text{(c) Structural change} \\ \text{among exporters}}} + \underbrace{\omega^{x}_{m,2018}(i)\Delta\varsigma^{x}_{2018}(i)}_{\substack{\text{(d) Changing exporter} \\ \text{revenue share}}} \Bigg),$$

where $\omega_{mt}(i) = \frac{R_{mt}(i)}{\sum_k R_{kt}(i)}$ is the manufacturing sector's share of revenue in bin i, $\omega^x_{mt}(i) = \frac{R^x_{mt}(i)}{\sum_k R^x_{kt}(i)}$ is the manufacturing share of *exporter* revenue in bin i, where exporter revenue is the total revenue

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

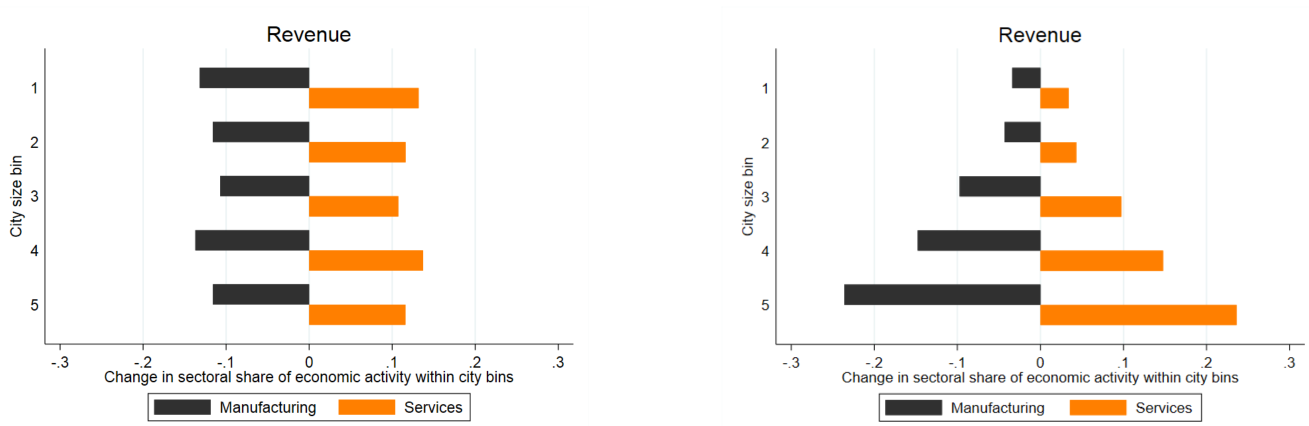
Table 3: Contribution of non-exporters and exporters to urban-biased structural change

City size bin	**UBSC (total)**	Non-exporters: Structural change among non-exp (a)	Non-exporters: Changing non-exp revenue share (b)	Exporters: Structural change among exp (c)	Exporters: 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: This table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labelled '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: Non-exporters, exporters, and urban-biased structural change in France, 1995-2018

(a) Structural change among *non-exporters* (b) Structural change among *exporters*

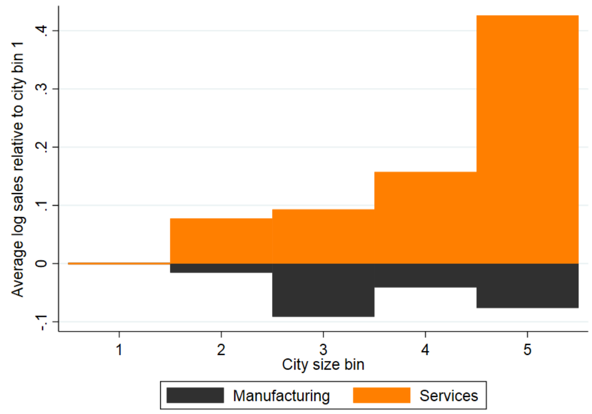


Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. In panel (a) the bars show the percentage point change in sectoral revenue shares within city bins for manufacturing and services between 1995 and 2018 among non-exporters only. The numbers correspond to the red element 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.

of exporting firms in that bin (i.e., including export sales and domestic sales). As previously, the other sector is services ($k = m, s$). The variable $\varsigma_t^x(i) = \frac{\sum_k R_{kt}^x(i)}{\sum_k R_{kt}(i)}$ is the exporter share of revenue in bin i. The first term (a) on the right-hand side captures structural change among non-exporters, while the third term (c) represents structural change among exporters. The second and fourth terms (b) and (d) capture the contributions to structural change in bin i of the changing relative sizes of non-exporters and exporters.

Table 3 presents the results of this decomposition. The column labeled 'UBSC', which stands for urban-biased structural change, 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

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



Notes: This 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.

that it is mostly accounted for by structural change among large firms, which tends to be exporters, 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 exporters has a gradient. It is weakest for the smallest cities (minus 1.7 percentage points in bin 1), and it is strongest for the largest cities (minus 12.2 percentage points in bin 5). Figure 4 demonstrates graphically that there is a clear 'pyramid' pattern for structural change among exporters, but not among non-exporters. We also find similar patterns under alternative definitions of 'large firms', as shown in Figure 9.

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.[14] 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 the bin of smallest cities.

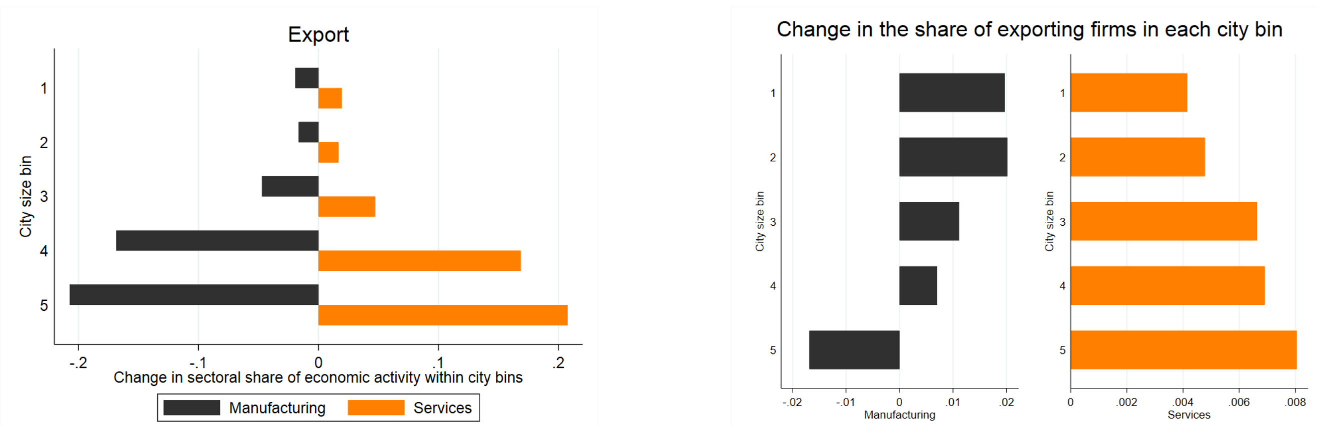
By contrast, we observe an entirely different sorting pattern for manufacturing firms. The average size of manufacturing firms is not as different across city size bins as for services, but nevertheless manufacturing firm revenue is weakly negatively correlated with city size. Firms in the largest cities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

[14]Note that Figure 5 averages log revenue across firms, whereas Table 16b 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.

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 exporters become more concentrated in small cities, while the opposite is true for services exporters.
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 16a 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 percent in 1995, falling only marginally to 95 percent by 2018. In the largest cities, however, while in 1995 the majority of exports (54 percent) was still in manufacturing, by 2018 services dominated exports with a share of 67 percent.

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.[15]

[15]See the top panel of Table 16c for details.

3 A model of urban-biased structural change

Motivated by our empirical findings, we develop a model of urban-biased structural change to better understand and 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 forces for structural change – sectoral TFP growth, changes in sectoral international trade costs, and changes in agglomeration forces (Melitz, 2003; Herrendorf, Rogerson, and Valentinyi, 2014; Desmet and Henderson, 2015; Alessandria, Yi, and Johnson, 2019).

3.1 Countries

There are two countries: Home and Foreign (rest of the world). In what follows, we assume that Home and Foreign are symmetrically identical. We therefore omit country indices. This modelling assumption formally implies that trade balances in manufacturing and services are always equal to zero, which adds considerable tractability. However, as is discussed in Appendix B.3, in practice the model is capable of accommodating changes in the composition of output and trade arising from comparative advantage through productivity and trade costs parameters.

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, let us assume that land is owned by absentee landlords from another country and leased to workers and firms following the price schedule:

$$p_h(i) = L(i)^{\bar{\gamma}}, \tag{1}$$

which solely depends on city size, where $p_h(i)$ is the rental price of land in city i. The parameter $\bar{\gamma}$ governs the elasticity of land prices with respect to population size, following Hsieh and Moretti (2019) and Behrens, Duranton, and Robert-Nicoud (2014).[16]

3.3 Workers and final demand

There is a mass 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

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

i as given. Second, choose i. The first stage of utility maximization is to choose $C(i)$ and $h(i)$ to maximize

$$U(i) = \left(\frac{C(i)}{\eta}\right)^{\eta} \left(\frac{h(i)}{1-\eta}\right)^{1-\eta}, \quad \eta \in (0,1), \tag{2}$$

subject to a budget constraint

$$PC(i) + p_h(i)h(i) = (1+\mu)W(i) \equiv \tilde{W}(i), \tag{3}$$

where the parameter $\eta \in [0,1]$ captures the worker's expenditure share on final goods (and housing), P is the price of the final good composite, $p_h(i)$ is the price of housing 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

$$W(i) = \lambda p_h(i)^{1-\eta}, \tag{4}$$

where $\lambda = UP^{\eta}/(1+\mu)$ is an economy-wide proportionality factor to be determined in general equilibrium. Since denser cities have a higher housing price, wages in denser cities must also be higher to compensate for higher land prices: $W(i) = p_h(i)^{1-\eta}/(1+\mu)$. Housing is therefore a congestion force – larger cities are more expensive for firms to operate in – ensuring a non-degenerate city size distribution.

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

$$\Pi = PQ - \sum_j P_j Q_j, \tag{5}$$

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

$$\sum_j \theta_j^{\frac{1}{\rho}} \left(\frac{Q_j}{Q^{\varsigma_j}}\right)^{\frac{\rho-1}{\rho}} = 1. \tag{6}$$

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

$$\vartheta_j = \frac{P_j Q_j}{\sum_k P_j Q_k} = \frac{\theta_j P_j^{1-\rho} Q^{(1-\rho)(\varsigma_j - 1)}}{\sum_k \theta_k P_k^{1-\rho} Q^{(1-\rho)(\varsigma_k - 1)}}. \tag{7}$$

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 in a sector j are aggregated through a sector-specific, homothetic CES aggregator:

$$Q_j = \left(\int_{\omega \in \Omega_j} q_j(\omega)^{\frac{\sigma_j - 1}{\sigma_j}} \, d\omega \right)^{\frac{\sigma_j}{\sigma_j - 1}}, \tag{8}$$

where $\sigma_j > 0$ captures the elasticity of substitution between differentiated varieties $\omega \in \Omega_j$.

The non-homothetic CES production function features 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 productivity z from a sector-specific distribution $G(z; j)$ with support $[1, \infty)$. Goods and services are then produced using labor and land as inputs according to constant-returns-to-scale technology with a constant elasticity of substitution of unity (Cobb-Douglas technologies):

$$\begin{aligned} q_j^d(z,i) &= \Psi_j(z,i)\ (l_j^d)^{\alpha_j} (h_j^d)^{1-\alpha_j}, \\ q_j^x(z,i) &= \frac{1}{\tau_j} \Psi_j(z,i)\ (l_j^x)^{\alpha_j} (h_j^x)^{1-\alpha_j}, \quad \alpha_j \in (0,1), \end{aligned} \tag{9}$$

where the d and x subscripts refer to production for the domestic and export markets, respectively, and where $\tau_j > 1$ reflects, sector-specific iceberg variable trade costs. A firm's factor-neutral productivity level, $\Psi_j(z,i)$, depends on its idiosyncratic productivity draw z, the sector j in which the firm operates, and the population density in its chosen city $L(i)$.

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

$$\begin{aligned} &\log \Psi_j(z,i) \\ &= \log A_j + \log z + \frac{a_j}{2} \left(\log \frac{L(i)}{L(0)} + \frac{1}{s_j} \left(\frac{(1+\xi_j)\log z + (1-\xi_j)}{1+\log z} \right) \left(\left(1 + \log \frac{L(i)}{L(0)} \right)^{s_j} - 1 \right) \right), \end{aligned} \tag{10}$$

where A_j is a sectoral productivity shifter and the parameter $a_j \in [0,1]$ captures the strength of agglomeration externalities in sector j—it is equal to $\mathrm{d} \log \Psi_j / \mathrm{d} \log(L(i)/L(0))$ at $L(i) = L(0)$, $z = \min z = 1$ and $\xi_j = 0$.[17]

The parameter ξ_j determines the direction of the deviation from log modularity in sector j

[17] 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.

(i.e., the extent to which comparatively more productive firms experience comparatively greater agglomeration effect for a given location density), which in turn dictates how differentially productive firms sort across differential dense locations. When $\xi_j > 0$, the function is log supermodular in z and L, implying that more productive firms benefit relatively more from locating in a larger city—and therefore positive sorting (more productive firms locating in denser locations)—whereas when $\xi_j < 0$, it is log submodular in z and L, implying that more productive firms benefit relatively less from locating in a larger city—and therefore negative sorting (more productive firms locating in less dense locations). A value $\xi_j = 0$ gives no sorting.

The parameter $s_j \leq 1$ determines the marginal benefit of choosing a larger city – how the elasticity of Ψ_j with respect to $L(i)$ varies with $L(i)$ – which in turn determines shape of the equilibrium sorting relationship between firm types and location sizes (as shown in Appendix B.2). This gives our model full flexibility for accommodating differences between larger, high-productivity firms (typically exporters) and smaller, lower-productivity firms (typically non-exporters) in terms of how sharply they sort across differentially dense locations.

We additionally allow for imperfect sorting by making firms draw an idiosyncratic, location-specific productivity shock $\hat{\epsilon}(\omega, i)$ on top of their permanent productivity z. Define firm-level overall productivity $\Phi_j(z, i) \equiv \Psi_j(z, i)\, e^{\epsilon(\omega,i)}$. 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 productivity might thus choose different locations. When $\nu_{\epsilon,j} \to 0$, the model features a perfect sorting equilibrium.

Another difference between our model relative to Gaubert's (2018) is that firms use land as a factor input. This feature allows us to capture the differential strength of the empirical relationship between firm size and city size between manufacturing and service firms. In the data, the empirical relationship between firm size and city size is initially weak and then negative for manufacturing and strongly positive for tradable services (see Figure 5). Our model explains this difference between the two sectors as coming from different land intensity.

The goods and services produced by firms can be either sold domestically or exported. Exports incur both a fixed cost, f_j^x, which is sector-specific, and a per-unit variable trade cost, τ_j, which is also sector-specific.

3.5 Profit maximization

To maximize profits, a firm from sector j with productivity 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

$$\pi_j(z, i) = \max_{\substack{l^d, l^x, h^d, h^x, \\ q^d, q^x, p^d, p^x, \xi}} \quad p^d q^d - W(i)\, l^d - p_h(i) h^d + \xi \left(p^x q^x - W(i)\, l^x - p_h(i) h^x - P f_j^x \right), \tag{11}$$

where $\xi \in \{0, 1\}$ denotes the firm's extensive-margin export choice and the x subscripts refers to the production of exportables; 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 (9), and to firm-specific product domestic and export demand curves,

$$q_j^d = \left(\frac{p_j^d}{P_j}\right)^{-\sigma_j} Q_j, \quad q_j^x = \left(\frac{p_j^x}{P_j}\right)^{-\sigma_j} Q_j. \tag{12}$$

3.6 Selection into exporting

The equilibrium profits of the firm can be written as $\pi_j(z,i) = \pi_j^d(z,i) + \pi_j^x(z,i) - P f_j^x$, where π^d represents profits from domestic sales and π^x from exports. Firms will only export (choose $\xi_j(z,i) = 1$) if they make profits at least as high as the fixed export costs, i.e., if

$$\pi_j^x(z,i) \geq P f_j^x. \tag{13}$$

3.7 Firm location choice

Define the permanent component of firm profits as $v_j(z,i)$. Then, firm profits can be written as

$$\hat{\pi}_j(z,i) = v_j(z,i)\,\hat{\epsilon}(\omega,i) - P f_j^x. \tag{14}$$

Since the fixed exporting cost is independent of location, the firm's location choice problem can be expressed as

$$i_j^*(z) = \arg\max_{i \in I} \; v_j(z,i)\,\hat{\epsilon}(\omega,i). \tag{15}$$

3.8 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 no selection upon entry. Following Behrens *et al.* (2014), we assume that firms and workers self-organize in the creation of cities.

The model's equilibrium conditions are fully detailed in Appendix B. There are two equilibria. One is an unstable equilibrium where all cities are of equal size. The stable equilibrium features cities of different sizes and it is the relevant one 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 changes, international trade costs, and agglomeration effects to urban-biased structural change.

4.1 Calibrated parameters

Exogenously specified parameters. Following Comin *et al.* (2021) and Sposi *et al.* (2021), we set the degree of non-homotheticity for manufacturing and services to $\varsigma_{man} = 1$ and $\varsigma_{svc} = 1.3$, and the elasticity of substitution between the two sectors to $\rho = 0.3$. As for the land price elasticity $\bar{\gamma} = 0.7$, we calibrate it to estimates by Combes *et al.* (2019) using French administrative data on land prices.

Parameters obtained through calibration. The sector-specific labor intensity parameter 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, $A_{man}^{1995} = A_{svc}^{1995} = 1$. Changes in sectoral productivity shifters between 1995 and 2018 are potentially key drivers of structural change. We calibrate A_{man}^{2018} and A_{svc}^{2018} to match the growth rate of real GDP per capital and changes in the manufacturing sector share of aggregate sales between 1995 and 2018. The weight on consumption of goods versus services $\theta_{man} = 1 - \theta_{svc}$ 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 export costs are set to match the share of firms that are exporters in each sector. We calibrate one fixed export cost for each sector and year, $\{f_{man}^{x,1995}, f_{man}^{x,2018}, f_{svc}^{x,1995}, f_{svc}^{x,2018}\}$. Finally, consistent with the model, the sector-specific 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): $\tau_j^{1-\sigma_j} = \frac{R_j^x}{R_j^d}$. This gives $\{\tau_{man}^{x,1995}, \tau_{man}^{x,2018}, \tau_{svc}^{x,1995}, \tau_{svc}^{x,2018}\}$.

4.2 Parameters inferred via structural estimation

Parameters to estimate. We assume that firm-specific productivity, $\log z$, 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 (10), the sector-specific parameters to estimate include the agglomeration externality scale parameter, a_j, the sorting parameter, ξ_j, and the rate of diminishing returns to city size, 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 productivity z and their land intensity constant over time. Specifically, the set of parameters we estimate for each sector are:

$$\Theta_j = \left\{ \nu_{z,j}^{scale}, \nu_{z,j}^{shape}, \nu_{\epsilon,j}^{scale}, a_j^{1995}, a_j^{2018}, \xi_j, s_j \right\}. \tag{16}$$

This allows comparison between the 1995 and 2018 equilibria, isolating the effects of those changes we focus on in our analysis, namely changes in agglomeration effects and change in trade costs—alongside the TFP changes, which are exactly identified separately through calibration.

Identification. The parameters Θ_j are estimated in partial equilibrium by solving the firm's location choice problem (17). We estimate these parameters separately for the manufacturing and service sectors to match a set of sector-specific moment conditions detailed below. Given the

Table 4: Exogenously specified parameters

Parameter	Source	Sector	
Income elasticity parameter in consumption (ς_j)	Comin *et al.* (2021)	Manufacturing Services	1 1.3
Elasticity of substitution in consumption (ρ)	Comin *et al.* (2021)	-	0.3
Land price elasticity ($\bar{\gamma}$)	Combes *et al.* (2019)	-	0.7

Table 5: Calibrated parameters

Parameter	Sector	1995	2018
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	
Variable trade cost (τ_j)	Manufacturing	0.148	0.073
	Services	3.009	1.196
Fixed trade cost (f_j^x)	Manufacturing	0.022	0.028
	Services	0.186	0.391
Sectoral TFP (A_j)	Manufacturing	1	2.039
	Services	1	0.838

composite productivity function (10), 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 follows:

$$\begin{aligned} \log R_j(z,i) - E[\log R_j(1)] = \quad & (\sigma_j - 1)\,\log \Psi_j(z,i) - (\sigma_j - 1)\,E\Big[\log \Psi_j(z,1)\,\Big|\, z \in \mathcal{Z}_j(1)\Big] \\ & + \log\Big(1 + \varrho_j(z,i)\,\tau_j^{1-\sigma_j}\Big) - E\Big[\log\Big(1 + \varrho_j(z,i)\,\tau_j^{1-\sigma_j}\Big)\,\Big|\, z \in \mathcal{Z}_j(1)\Big] \\ & + (\sigma_j - 1)\hat{\epsilon}_i, \end{aligned} \tag{17}$$

where $\varrho_j(z,i) \in \{0,1\}$ is an indicator function that takes the value 1 if firm of type z in sector j is an exporter and 0 otherwise. 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 moments of the data that are informative about the underlying Θ_j.

Intuition behind identification. The agglomeration externality parameter a_j can be identified from proportional shifts in the distribution of $\log R_j(z,i) - E\Big[\log R_j(1)\Big]$ across city sizes. This is because the agglomeration parameter affects all firms within a given sector equally. On the other hand, 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 in terms of productivity from moving to a larger city. The sorting parameter can therefore be identified from differences in the skewness of $\log R_j(z,i) - E\Big[\log R_j(1)\Big]$ across city sizes, i.e., how the firm size-city size gradient changes for firms at different points of the distribution of firm sizes. The parameter s_j can be identified from variation, across the distribution of firm sizes, in the intensity of sorting of firms by size and locations.[18]

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

Targeted moments. Given the above discussion of what moments are informative about each parameter, we target the following 14 moments for each sector:

1. The 50-10, 75-25, 90-50, 90-10, and 95-90 differences of the log normalized revenue distributions for each sector.[19]

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

3. The share of each sector's revenues that originate from a city size quintile $i \in \mathcal{I}$.

Estimation is carried out by the Method of Simulated Moments using a pooled specification for 1995 and 2018; i.e., letting $\Theta \equiv \Big(\Theta_{man}, \Theta_{svc}\Big)$, and denoting with m the combined vector of empirical moments for 1995 and 2018 (a vector of dimension $14 \times 2 = 28$), with $\widehat{m}(\Theta)$ the corresponding vector of model moments, and with $\mathcal{W}$ an estimate of the matrix of variances and covariances of the empirical moments (obtained by bootstrapping), we derive an estimate $\widehat{\Theta}$ as

$$\widehat{\Theta} = \arg\min_{\Theta} \ \Big(m - \widehat{m}(\Theta)\Big)' \mathcal{W}^{-1}\Big(m - \widehat{m}(\Theta)\Big). \tag{18}$$

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

Parameter values and model fit. The parameter values obtained via this calibration/estimation procedure are shown in Tables 5 and 6. The model accommodates the observed changes in production patterns across locations mainly through a relative change in the relative decline of TFP in services (A_j), an increase in the strength of agglomeration gains in services (a_j),[20] and a

[18] As detailed in Appendix B.2, s_j determines how the elasticity of L with respect to z varies with z.

[19] Our choice of targeted moments is aligns with that of Gaubert (2018).

[20] As discussed in section 2.2, the data shows a relative increase in the share of smaller services firms in dense locations. This is consistent with a rise in the share of high-productivity, high-quality, low-revenue services firms. The model accommodates this fact through an increase in a_{svc}. This raises agglomeration incentives for all services firms, and in relative terms it weakens the sorting incentives for services firms of different sizes.

Table 6: Parameter estimates

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.

substantially larger fall in trade costs in services by comparison with manufacturing.[21]

In Tables 18 and 19 in Appendix C we report the values of the targeted empirical moments and the corresponding values predicted by the model.

5 What drives the urban bias in structural change?

We now carry out counterfactual experiments with our estimated model to assess the contribution of the different channels to the urban-biased pattern of structural change we observe in the data

[21]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. In other words, given its symmetric structure the model interprets an increase in the price of domestic manufactured goods relative to that of imported manufactured goods (leading to a fall in the manufacturing balance of trade) as a partially offsetting increase in manufacturing export costs.

Table 7: Data vs. model: change in the share of manufacturing revenue within city size bins

City size bin	**UBSC (total)**		Non-exporters: Structural change among non-exp		Non-exporters: Changing non-exp revenue share		Exporters: Structural change among exp		Exporters: Changing exp revenue share	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
1	-0.093	-0.062	-0.068	-0.003	0.006	-0.001	-0.017	-0.069	-0.014	0.011
2	-0.106	-0.073	-0.061	-0.006	0.014	-0.001	-0.020	-0.080	-0.039	0.013
3	-0.114	-0.137	-0.061	-0.007	0.004	-0.000	-0.043	-0.132	-0.015	0.003
4	-0.193	-0.154	-0.079	-0.008	0.025	-0.000	-0.063	-0.147	-0.076	0.001
5	-0.180	-0.222	-0.056	-0.003	0.001	0.000	-0.122	-0.218	-0.003	-0.001

Notes: This table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labelled 'UBSC', which stands for urban-biased structural change). For example, -0.1 means a 10 percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities. The columns 'Model' show the predictions of the full estimated model.

from 1995 to 2018. We proceed as follows. We first assess the model's ability to reproduce the urban-biased patterns presented in section 2.2. Next, we use the model to decompose this urban bias into the contributions of three forces: sectoral TFP growth, falling international trade costs, and changes in agglomeration externalities. To do so, we set all parameters at their 1995 level and change one set of parameters at a time, with each set pertaining to one of the three forces. The change in the parameters associated with each counterfactual experiment is as follows:

(i) Sectoral TFP: $\{A_j^{1995}\}_{j\in\{man,svc\}} \quad \rightarrow \quad \{A_j^{2018}\}_{j\in\{man,svc\}}$

(ii) Trade costs: $\{\tau_j^{1995}, f_j^{x,1995}\}_{j\in\{man,svc\}} \quad \rightarrow \quad \{\tau_j^{2018}, f_j^{x,2018}\}_{j\in\{man,svc\}}$

(iii) Agglomeration: $\{a_j^{1995}\}_{j\in\{man,svc\}} \quad \rightarrow \quad \{a_j^{2018}\}_{j\in\{man,svc\}}$

We then compare the counterfactual equilibrium to the estimated 2018 equilibrium to assess the quantitative importance of the three forces.

Urban-biased structural change in the model. The model does well at reproducing the key urban-biased patterns of structural change presented in section 2.2. Table 7 compares the full estimated model to the data. Columns 2 and 3 show that model is capable of reproducing the 'pyramid' pattern of structural change – stylized fact (i). We next decompose this pattern into the contributions of large firms (exporters) and small firms (non-exporters). Although this decomposition is not a target of the calibration and structural estimation of the model, columns 3 through 11 show that, just as in the data, the urban bias is fully accounted for by large firms – stylized fact (iii). However, comparing columns 8 and 9 (and similarly columns 4 and 5) shows that the model does overstate the contribution of exporters to overall structural change relative to the data.

The fact that economic activity took a faster 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. We next decompose the growth in the total domestic and export revenue of each sector into the individual contributions of each city size bin:

$$g_{jt+1}^r = \sum_i \left(\frac{R_{jt}^r(i)}{\sum_{i'} R_{jt}^r(i')} \right) g_{j+1}^r(i),$$

Table 8: Data vs. model: contributions of city size bins to the growth of the manufacturing and services sectors

City size bin	Domestic revenue				Export revenue			
	Manufacturing		Services		Manufacturing		Services	
	Data	Model	Data	Model	Data	Model	Data	Model
1	29%	29%	13%	10%	22%	29%	3%	12%
2	26%	29%	15%	13%	25%	29%	4%	14%
3	18%	18%	16%	16%	19%	18%	9%	18%
4	17%	12%	19%	21%	20%	12%	16%	21%
5	10%	11%	38%	40%	14%	12%	68%	35%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	-14%	-11%	74%	77%	40%	77%	181%	492%

Notes: This table decomposes the growth of total revenue 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.

where $r = \{\text{domestic, export}\}$, g_{jt+1} is the revenue growth rate of sector j, $g_{jt+1}(i)$ is the same for city i, $R^r_{jt}(i)$ is the total domestic or export revenue of sector j in city size bin i.

Table 8 reports the real domestic and export revenue growth of the manufacturing and services sectors in the data and in the model. These growth rates are not targeted in the quantification of the model. Column 2 shows that the model closely replicates the real decline in the domestic revenue of the manufacturing sector: -14% in the data compared to -11% in the model. The model also closely replicates the contribution of each city size bin to the decline in domestic revenue. Column 3 shows that the model also reproduces 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 for 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 ($\frac{\text{sum of export rev. across exporters in sector } j}{\text{sum of domestic rev. across exporters in sector } j}$), which gives a higher weight to larger exporters. In the data, however, export intensity is higher and increased more among large firms.

The role of sectoral TFP growth. We now show that sectoral TFP growth is the main driver of aggregate structural change, but it does not explain the urban bias. In our calibration, we find that TFP in manufacturing has grown substantially relative to services. TFP growth in the model is global: it happens both in the home country (France) and the foreign country (rest of the world). It also occurs at the same rate in both countries, given our symmetry assumption.[22] Table

[22] As mentioned earlier, this assumption rules out changing comparative advantage in driving the size of the French manufacturing sector. This assumption is motivated by three features of the data: (i) the manufacturing level and increase in the trade deficit are relatively small, (ii) the services trade surplus is small and constant over time, and (iii) the manufacturing sectors that declines the most were not more concentrated in large cities in 1995. In the

Table 9: TFP counterfactual: change in the share of manufacturing revenue within city size bins

City size bin	**UBSC (total)**		Non-exporters: Structural change among non-exp		Non-exporters: Changing non-exp revenue share		Exporters: Structural change among exp		Exporters: Changing exp revenue share	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	-0.062	-0.150	-0.003	-0.004	-0.001	0.002	-0.069	-0.113	0.011	-0.035
2	-0.073	-0.144	-0.006	-0.006	-0.001	0.003	-0.080	-0.085	0.013	-0.055
3	-0.137	-0.151	-0.007	-0.006	-0.000	0.002	-0.132	-0.114	0.003	-0.033
4	-0.154	-0.146	-0.008	-0.006	-0.000	0.002	-0.147	-0.109	0.001	-0.032
5	-0.222	-0.142	-0.003	-0.002	0.000	0.000	-0.218	-0.121	-0.001	-0.019

Notes: This table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labelled 'UBSC', which stands for urban-biased structural change). For example, -0.1 means a 10 percentage point decline. Bin 1 represents the smallest cities and bin 5 the largest cities. The columns 'Model' show the predictions of the full estimated model.

9 compares the UBSC in the counterfactual simulation, where we introduce only 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 (column 3), but there is no urban bias. When we look at the role of exporters and non-exporters, we again see that exporters account for the bulk of the TFP-induced structural change. Indeed, column 9 shows a slight urban bias in structural change among exporters. The last column shows that TFP growth induced a reallocation of revenues from exporters to non-exporters. This reallocation from exporters to non-exporters reflects the between industry reallocation from manufacturing exporters to services non-exporters. It occurs at a slower rate in large cities than in smaller cities since there are more manufacturing exporters in smaller cities.

While TFP growth explains the expansion of the size of the services sector, it does not explain the decline in the size of the manufacturing sector. Table 10 reports the growth of the manufacturing and services sectors in the estimated equilibrium and counterfactual equilibrium. Columns 1 and 2 show that while manufacturing domestic revenue has declined by 11% in the full model, it has increased by 2% in the counterfactual simulation. Manufacturing export revenue, on the other hand, has increased by 77% in the full model, while it has only increased by 3% in the counterfactual. In contrast, the TFP-induced services growth in domestic revenue is comparable to that of the full model. The increase in global manufacturing TFP also increased the demand for French services exports, leading to a 152% increase in services exports, with the largest share of growth coming from the largest French cities.

What we can take away from this exercise is that, while TFP growth cannot explain UBSC, it accounts for the bulk of aggregate structural change. TFP growth explains the growth of domestic sales and exports of the services sector, but does not explain the manufacturing sector's decline in

appendix, we discuss how abstracting from shifting comparative advantage may affect our quantitative exercises.

Table 10: TFP counterfactual: contributions of city size bins to the growth of the manufacturing and services sectors

City size bin	Domestic revenue				Export revenue			
	Manufacturing		Services		Manufacturing		Services	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	29%	23%	10%	14%	29%	23%	12%	15%
2	29%	24%	13%	13%	29%	24%	14%	12%
3	18%	19%	16%	18%	18%	19%	18%	17%
4	12%	14%	21%	19%	12%	14%	21%	17%
5	11%	20%	40%	36%	12%	20%	35%	39%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	-11%	2%	77%	90%	77%	3%	492%	152%

Notes: This table decomposes the impact of TFP growth on the growth of total revenue of the manufacturing and services sector into the contributions of each city size bin. '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.

Table 11: Trade cost counterfactual: change in the share of manufacturing revenue within city size bins

City size bin	UBSC (total)		Non-exporters				Exporters			
			Structural change among non-exp		Changing non-exp revenue share		Structural change among exp		Changing exp revenue share	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	-0.062	0.005	-0.003	0.000	-0.001	-0.005	-0.069	-0.044	0.011	0.053
2	-0.073	0.006	-0.006	0.001	-0.001	-0.007	-0.080	-0.062	0.013	0.074
3	-0.137	0.005	-0.007	0.001	-0.000	-0.008	-0.132	-0.058	0.003	0.070
4	-0.154	0.005	-0.008	0.002	-0.000	-0.007	-0.147	-0.068	0.001	0.079
5	-0.222	0.003	-0.003	0.001	0.000	-0.002	-0.218	-0.059	-0.001	0.063

Notes: This table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labelled '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.

domestic sales and increase in exports.

The role of falling international trade costs. Counterfactual simulations show that falling international trade costs did not drive aggregate and urban-biased structural change in our model. Our measure of manufacturing variable trade costs (τ_{man}) declines from 14.8% in 1995 to 7.3% in 2018, while for services (τ_{svc}) it declines from a high level of 300.9% to 119.6%. Columns 2 and 3 in table 11 show that the decline in trade costs increased the manufacturing revenue share across city size bins slightly, by around 0.5 percentage points. When we break down the response of structural change among exporters and non-exporters in columns 5 and 9, we see that falling trade costs led to little structural change among non-exporters, but significant structural change among exporters, although it is not urban-biased. The trade-cost-induced decline in the manufacturing share of exporter revenue contributes to around a six-percentage-point decline in the manufacturing revenue share within city size bins. However, this is offset by an increase in the exporter share of revenue within city size bins as revenues reallocate from non-exporters to exporters in both sectors.

How has the decline in trade costs affected the size of the manufacturing and services sectors?

Table 12: Trade cost counterfactual: contributions of city size bins to the growth of the manufacturing and services sectors

City size bin	Domestic revenue				Export revenue			
	Manufacturing		Services		Manufacturing		Services	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	29%	23%	10%	14%	29%	23%	12%	15%
2	29%	23%	13%	13%	29%	23%	14%	12%
3	18%	19%	16%	18%	18%	19%	18%	18%
4	12%	14%	21%	19%	12%	14%	21%	17%
5	11%	21%	40%	36%	12%	21%	35%	38%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	-11%	-13%	77%	-6%	77%	71%	492%	248%

Notes: This table decomposes the impact of falling international trade costs on the growth of total revenue of the manufacturing and services sector into the contributions of each city size bin. '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.

Table 12 reports our results. We find that the fall in τ_{man} reduced the size of manufacturing domestic revenues by 13% and increased the size of manufacturing exports by 71%, driven by a reallocation of sales from non-exporters to exporters. These numbers are similar to the corresponding numbers for the full model, which are -11% and 77%. For the services sector, falling trade costs generates a 6% decline in domestic sales compared to a 77% increase in the full model. However, it generates a 248% increase in services exports, explaining the bulk of the export growth predicted by the full model.

Our main takeaways are as follows. Falling international trade costs in our model do not generate large aggregate or urban-biased structural change. However, they provide an important explanation for the decline in the size of the manufacturing sector's domestic sales and the increase in its exports. They also explain the fast growth of services exports.

The role of changing agglomeration externalities. We now show that changing agglomeration externalities account for UBSC in our model. Our structural estimates suggest that agglomeration externalities – the elasticity of productivity with respect to city size – for manufacturing declined from 0.72 in 1995 to 0.70 in 2018, while for services it increased from 0.69 to 0.71. Table 13 shows the results of the counterfactual simulation where we introduce only changes in agglomeration externalities.

Changing agglomeration externalities lead to a substantial decline in the manufacturing share of revenue in large cities, but an increase in small cities (column 3). These effects are driven by large firms, who also tend to be exporters, as column 9 shows. Recall that the manufacturing sector is characterized by negative sorting (log-submodularity of $\Psi_{man}(.)$): more efficient (high z) firms in our model tend to prefer smaller cities. The decline in agglomeration externalities for the manufacturing sector reduces all manufacturing firms' incentives to locate in large cities. However, large manufacturing firms in large cities are disproportionately more likely to move to small cities in response to the decrease in a_{man} than small manufacturing firms due to the log-submodularity between z and city size in this sector.[23] The relocation of manufacturing towards smaller cities

[23] Highly efficient manufacturing firms with an idiosyncratic productivity draw ϵ that favors large cities are more

Table 13: Agglomeration counterfactual: change in the share of manufacturing revenue within city size bins

City size bin	**UBSC (total)**		Non-exporters: Structural change among non-exp		Non-exporters: Changing non-exp revenue share		Exporters: Structural change among exp		Exporters: Changing exp revenue share	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	-0.062	0.071	-0.003	0.004	-0.001	-0.002	-0.069	0.046	0.011	0.023
2	-0.073	0.056	-0.006	0.002	-0.001	-0.002	-0.080	0.035	0.013	0.021
3	-0.137	0.011	-0.007	0.000	-0.000	-0.000	-0.132	0.009	0.003	0.001
4	-0.154	-0.013	-0.008	-0.001	-0.000	0.000	-0.147	-0.007	0.001	-0.005
5	-0.222	-0.105	-0.003	-0.001	0.000	0.000	-0.218	-0.086	-0.001	-0.018

Notes: This table decomposes the percentage point changes in the manufacturing sector revenue share in each city size bin (see the column labelled '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.

Table 14: Agglomeration counterfactual: contributions of city size bins to the growth of the manufacturing and services sectors

City size bin	Domestic revenue: Manufacturing		Domestic revenue: Services		Export revenue: Manufacturing		Export revenue: Services	
	Model	Cntrf	Model	Cntrf	Model	Cntrf	Model	Cntrf
1	29%	28%	10%	13%	29%	28%	12%	14%
2	29%	27%	13%	13%	29%	27%	14%	11%
3	18%	18%	16%	17%	18%	18%	18%	16%
4	12%	13%	21%	19%	12%	13%	21%	17%
5	11%	13%	40%	38%	12%	14%	35%	42%
Total contribution	100%	100%	100%	100%	100%	100%	100%	100%
Total growth	-11%	-6%	77%	-7%	77%	-4%	492%	21%

Notes: This table decomposes the impact of changing agglomeration externalities on the growth of total revenue of the manufacturing and services sector into the contributions of each city size bin. '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.

makes room for services firms to enter large cities, leading to UBSC. The services sector, on the other hand, is characterized by positive sorting (log-supermodularity of $\Psi_{svc}(.)$). Analogously, the increase in agglomeration externalities for services pushes service firms into large cities, with large services firms in small cities disproportionately more likely to move to large cities. The relocation of services firms to large cities crowds out manufacturing firms, pushing them into smaller cities.

The change in agglomeration externalities also affected sector sizes. The decrease in a_{man} represents a reduction in manufacturing productivity, while the increase in a_{svc} represents an increase in services productivity. Table 14 shows that domestic and export revenue in the manufacturing sector declined by 6% and 4%. The domestic revenue of services also decreased by 4%. The decrease in domestic revenues in both sectors shows that the impact of reduced manufacturing productivity on aggregate output dominates the effects of increased services productivity, leading to an overall decrease in demand for both goods and services. However, services exports do increase by 21% as

likely to respond by moving to small cities than a less efficient manufacturing firm with the same ϵ draw.

large services exporters become more productive and relocate into larger cities.

Taken together, our results show that changing agglomeration forces are important drivers of urban-biased structural change, because they relocate large manufacturing firms to small cities and large services firms to large cities. However, the estimated changes in agglomeration forces in France has reduced the size of the manufacturing sector as well as a size of domestic service sales. Overall, the changing agglomeration forces generate an approximate 6% decline in aggregate output.

6 Conclusion

We document heterogeneous spatial patterns of structural change in France from 1995 to 2018. We show that while the country has experienced an aggregate shift from manufacturing to services, this shift is predominantly reflected in the largest cities with the highest density of economic activity. The services sector has grown disproportionately in large cities while manufacturing firms have reoriented towards less populous locations. In those cities employment and value-added are more than twice as large in services compared to manufacturing, whereas manufacturing continues to be the dominant industry in the smallest cities. These urban-biased patterns of structural change are led by large firms. Using an estimated structural model of cities and heterogeneous firms' location choices, we find that changing sectoral agglomeration externalities are a major force behind the urban bias. Sectoral productivity growth and declining international trade costs further reinforce urban-biased structural change.

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Appendix

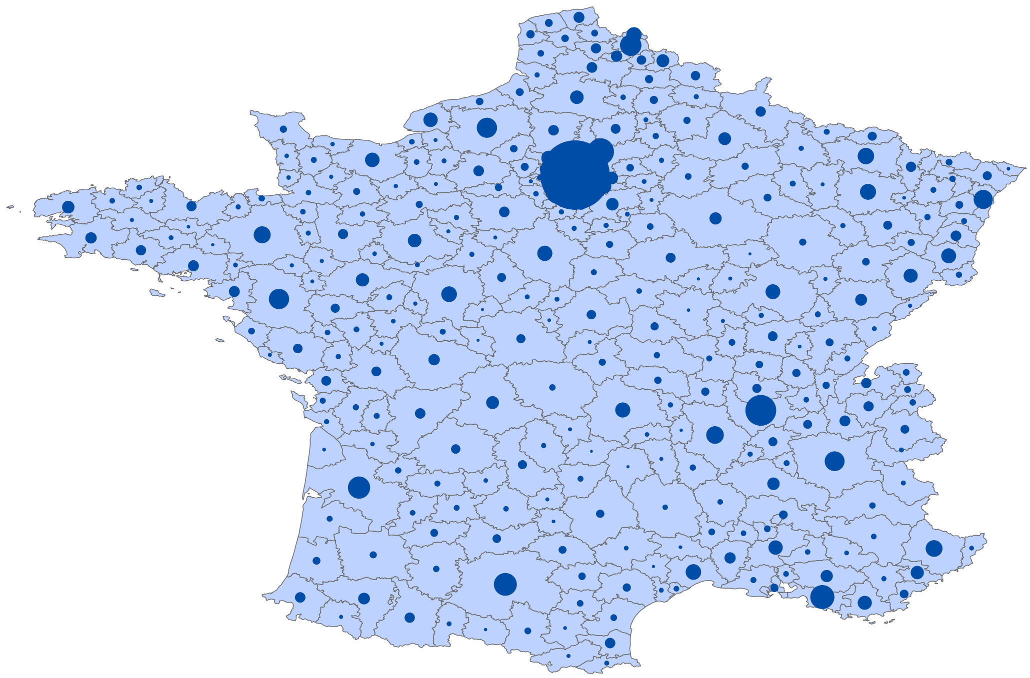
A Data appendix

Descriptive statistics

Figure 7 shows a map of the population across French cities (commuting zones). Figure 8 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 9 shows that the urban bias in structural change is associated with large firms. Figure 10 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 11 shows for each manufacturing and services the change in the share of firms across city bins between 1995 and 2018. Figure 12 illustrates the role of tradable vs. non-tradable services.

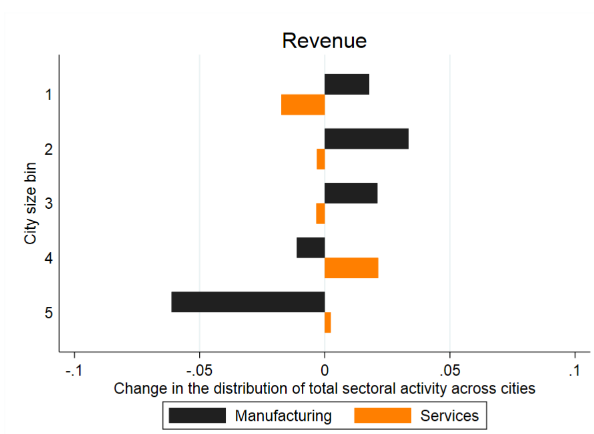
Tables 16a-16c report descriptive statistics for key variables.

Figure 7: 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.

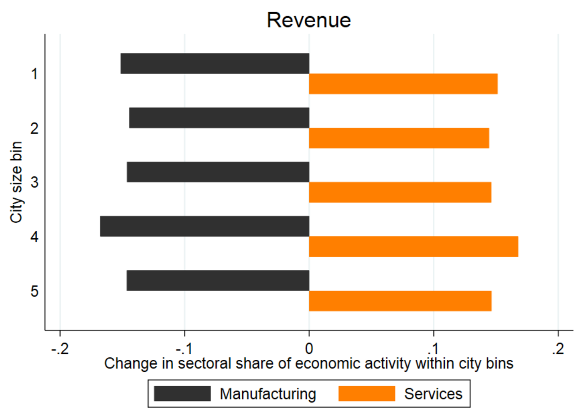
Figure 8: Structural change across French city bins, 1995-2018



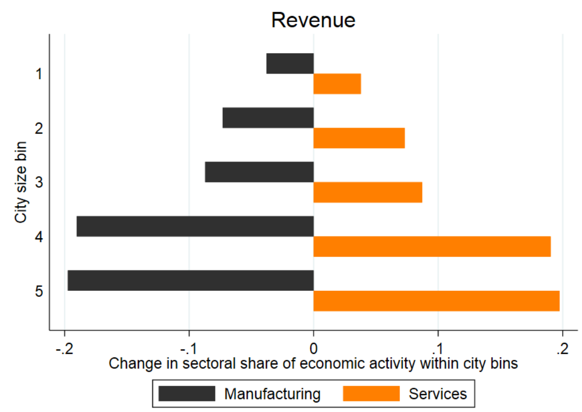
Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The bars show the percentage point change in sectoral revenue shares across city bins between 1995 and 2018. The changes within each sector add to zero.

Figure 9: 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 10 percentage point decline. The changes within city bins add to zero.

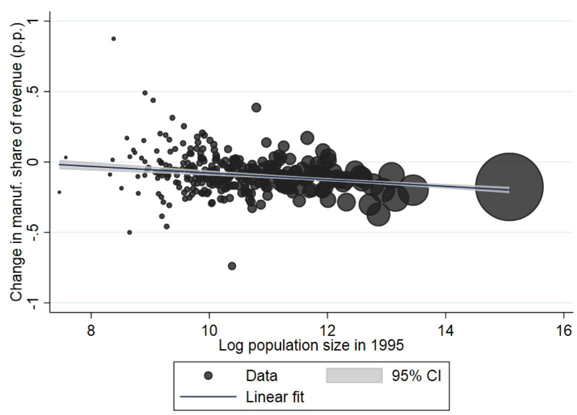
Table 15a: Multi-establishment firms' share of the French economy

	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

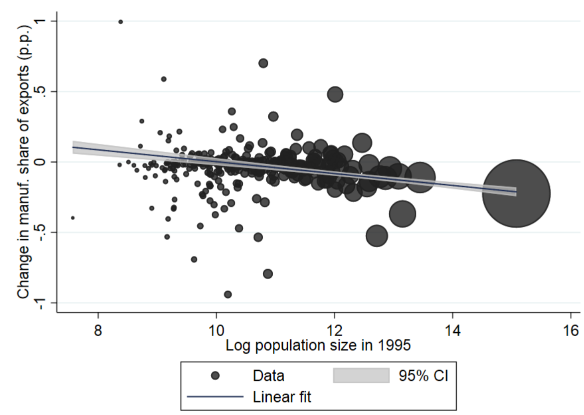
Notes: This table reports the size of multi-establishment firms relative to the aggregate French economy.

Figure 10: Structural change across French cities, 1995-2018

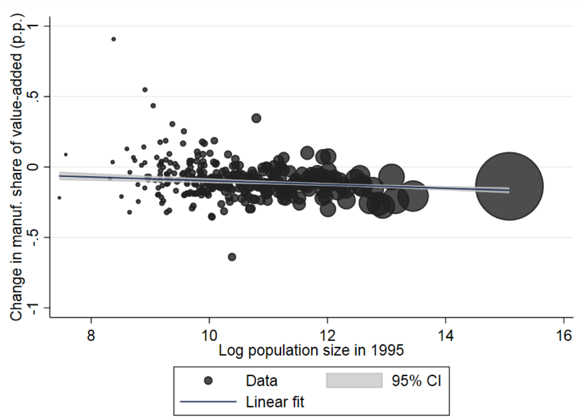
(a) Structural change in revenue



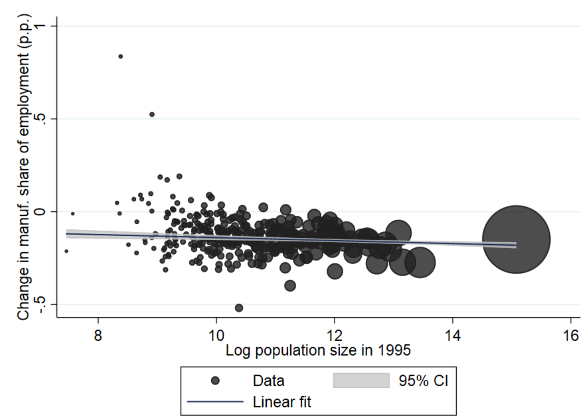
(b) Structural change in exports



(c) Structural change in value-added

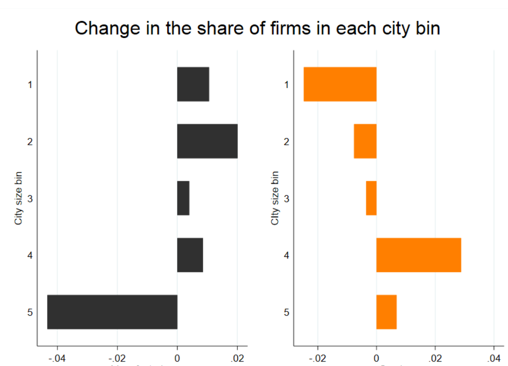


(d) Structural change in employment



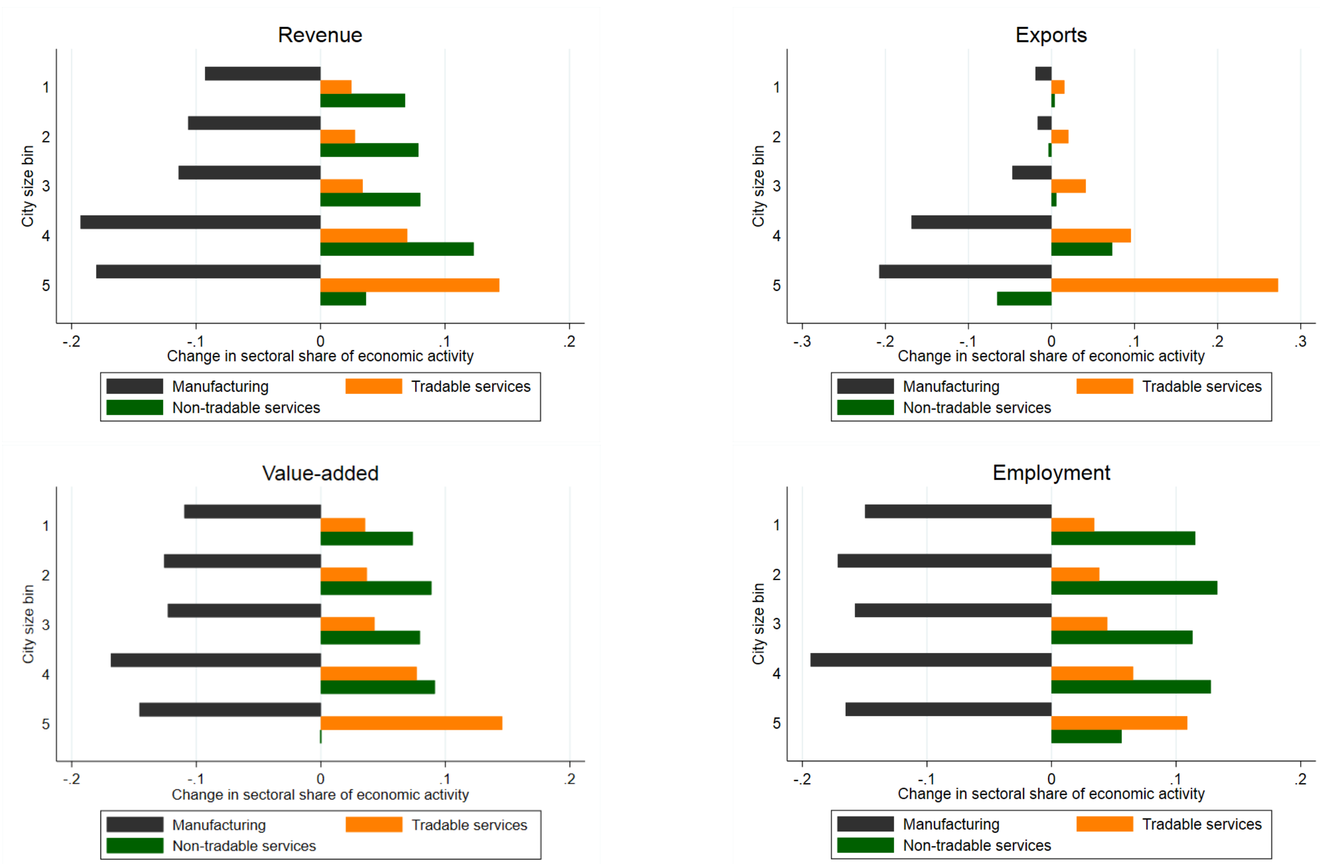
Notes: Each dot represents one French city (commuting zone), proportional to population size in 1995. The largest dot represents Paris. The variable on the vertical axis is the change in the manufacturing share in percentage points. The slope of the regression line is significantly different from zero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

Figure 11: 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.

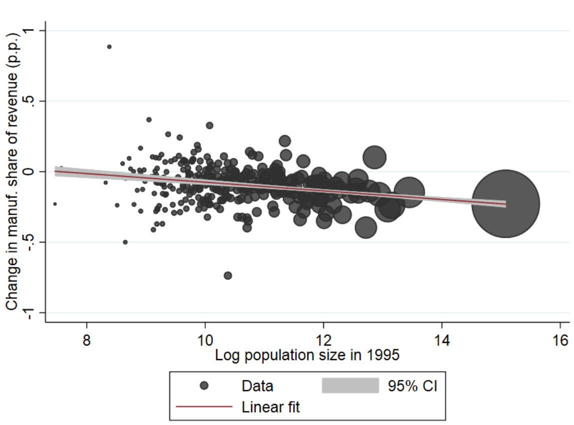
Figure 12: Tradable vs. non-tradable services and urban-biased structural change, 1995-2018



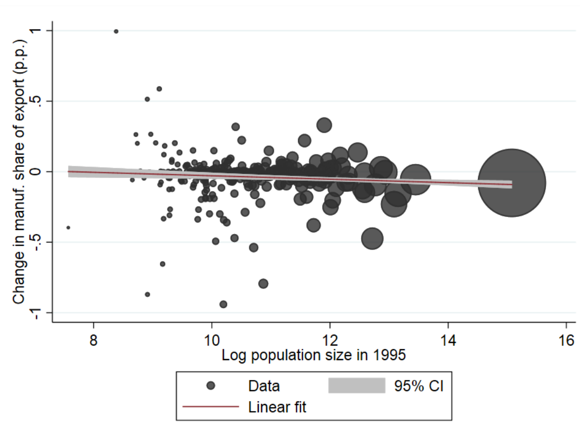
Notes: City size bin 1 represents the smallest cities and bin 5 the largest cities. The changes are across French city bins between 1995 and 2018 and add to zero. Black denotes manufacturing, orange denotes tradable services, and green denotes non-tradable services. The panels show the change in a sector's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

Figure 13: Structural change across French cities, 1995-2018 (inc. multi-establishment firms)

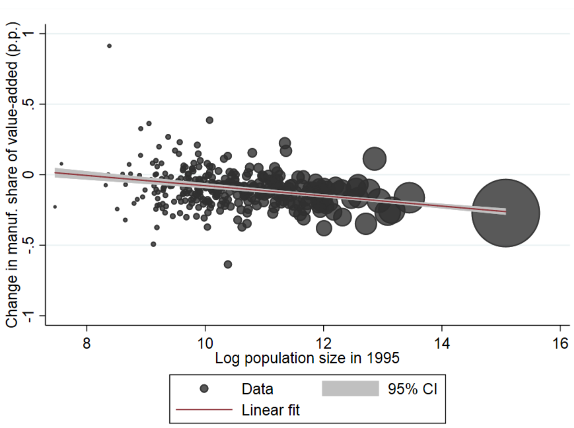
(a) Structural change in revenue



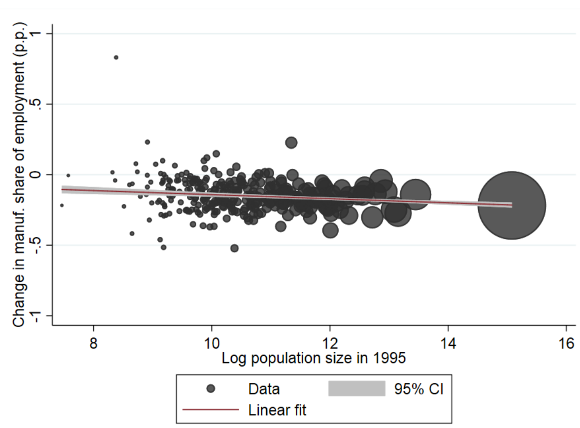
(b) Structural change in exports



(c) Structural change in value-added



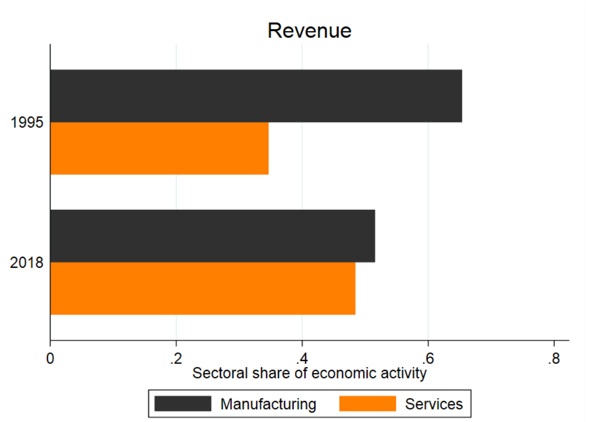
(d) Structural change in employment



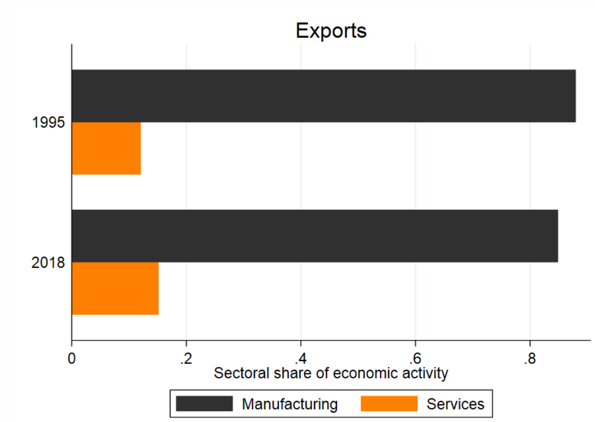
Notes: Each dot represents one French city (commuting zone), proportional to population size in 1995. The largest dot represents Paris. The variable on the vertical axis is the change in the manufacturing share in percentage points. Compared to Figure 10, this figure includes multi-establishment firms 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 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 14: Aggregate structural change in France, 1995-2018 (inc. multi-establishment firms)

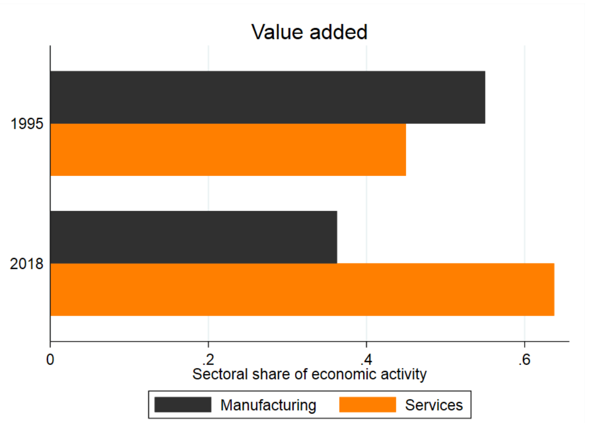
(a) Structural change in revenue



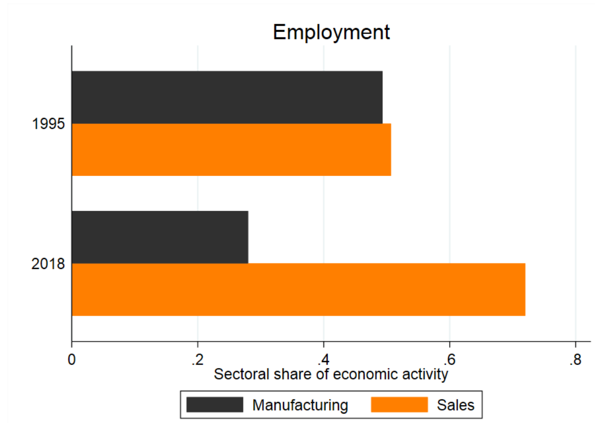
(b) Structural change in exports



(c) Structural change in value-added



(d) Structural change in employment



Notes: Compared to Figure 1, this figure includes multi-establishment firms whose establishments are located in different commuting zones.

Table 16a: 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: This 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 16b: 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

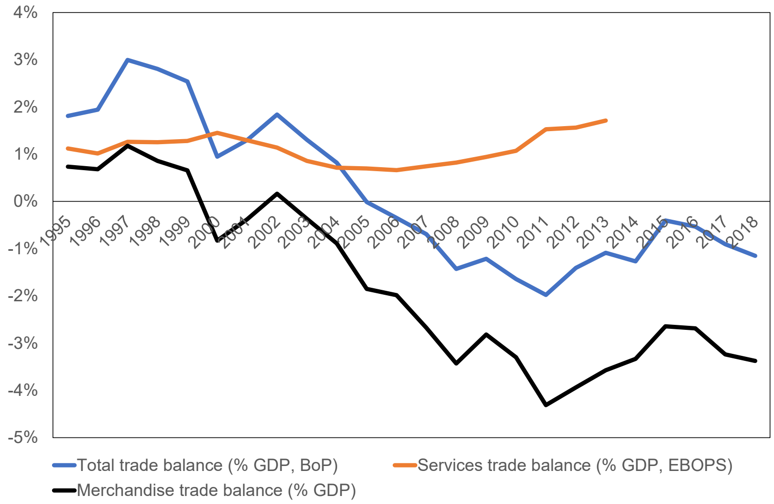
Notes: This table reports descriptive statistics for the sample of firms with one establishment and firms whose establishments are all located in the same commuting zone. See Section 2 for more information. Revenue, value-added and exports are in real terms (in 1995 values). 'Average' refers to the average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

Table 16c: 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: This 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.

Figure 15: 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.

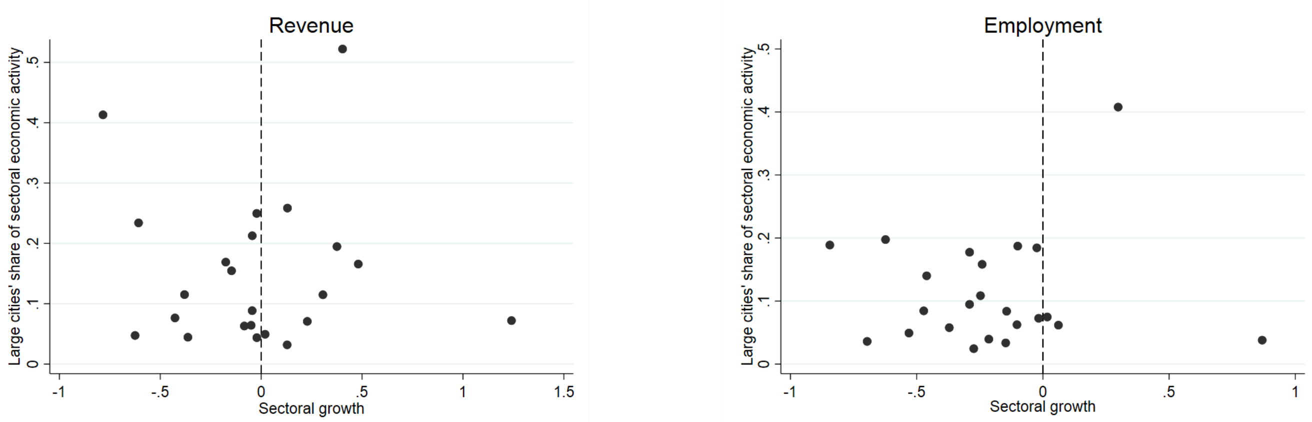
The trade balance and comparative advantage

Figure 15 plots the aggregate French trade balance over time. It moved from a surplus of around 2.5 percent of GDP in the late 1990s to a deficit of around minus 1 percent 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 percent on average. The change in the trade balance is therefore not sizeable enough to explain the decline in the manufacturing value-added share from 42 percent to 27 percent.

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 16 shows that there is no systematic relationship. This finding suggests that a shift in comparative advantage away from certain manufacturing sectors cannot explain

Figure 16: 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.

the urban bias in structural change.

Change in sectoral characteristics over time

Table 17: Descriptive statistics for manufacturing firms by year and city size bin

Averages	**Small cities (city size bin 1)**			**Medium-sized cities (city size bin 3)**			**Large cities (city size bin 5)**		
	1995	**2018**	**% Change**	**1995**	**2018**	**% Change**	**1995**	**2018**	**% Change**
Sales	6.29	6.50	21%	6.26	6.44	19%	6.37	6.37	0%
Employment	1.99	2.09	10%	1.96	2.06	10%	1.93	1.99	5%
Sales per worker	3.81	3.94	13%	3.84	3.95	10%	4.03	3.99	-4%
Physical capital per worker	2.97	3.42	45%	2.79	3.14	35%	2.65	2.88	23%
Intangible capital per worker	0.85	1.21	36%	1.03	1.34	31%	1.23	1.86	63%
Material input per worker	3.09	3.17	8%	3.00	3.08	8%	2.96	2.98	3%
Skill intensity (in levels)	0.18	0.22	22%	0.22	0.27	23%	0.30	0.33	10%
Export intensity	-2.52	-2.40	12%	-2.65	-2.32	33%	-2.46	-2.05	42%
Share of exporters	0.25	0.31	0.06 (p.p)	0.24	0.30	0.05 (p.p)	0.35	0.33	-0.02 (p.p)
Median firm age	9	18	9	8	16	8	9	14	5

Notes: This table reports descriptive statistics for manufacturing firms in 1995 and 2018. All the reported statistics are means of log(variable), except skill intensity and the share of exporting firms. All revenue-related variables are converted to 1995 values. Skill intensity is defined as ratio of the total employment of skilled workers to the total employment of unskilled workers, where unskilled workers are defined as blue-collar workers and low-wage administrative workers, and skilled workers are defined as those in technical professions (e.g., lawyers, engineers) or middle management and higher. Export intensity is the ratio of export revenues to domestic revenues.

Table 18: Descriptive statistics for services firms by year and city size bin

Averages	**Small cities (city size bin 1)**			**Medium-sized cities (city size bin 3)**			**Large cities (city size bin 5)**		
	1995	**2018**	**% Change**	**1995**	**2018**	**% Change**	**1995**	**2018**	**% Change**
Sales	5.50	5.63	13%	5.59	5.69	11%	5.99	5.95	-4%
Employment	1.45	1.52	7%	1.53	1.61	8%	1.72	1.76	4%
Sales per worker	3.73	3.82	9%	3.79	3.86	7%	4.10	4.04	-6%
Physical capital per worker	2.62	2.69	7%	2.39	2.29	-10%	2.33	1.97	-36%
Intangible capital per worker	1.09	1.08	-1%	1.16	1.16	-0%	1.39	1.65	26%
Material input per worker	2.54	2.45	-9%	2.36	2.21	-16%	2.12	1.78	-33%
Skill intensity	0.18	0.23	28%	0.25	0.30	20%	0.40	0.43	8%
Export intensity	-3.16	-2.64	51%	-2.97	-2.48	50%	-2.52	-2.08	44%
Share of exporters	0.03	0.05	0.02 (p.p)	0.04	0.07	0.03 (p.p)	0.13	0.17	0.04 (p.p)
Median firm age	8	11	3	7	10	3	7	9	2

Notes: This table reports descriptive statistics for services firms in 1995 and 2018. All the reported statistics are means of log(variable), except skill intensity and the share of exporting firms. All revenue-related variables are converted to 1995 values. Skill intensity is defined as ratio of the total employment of skilled workers to the total employment of unskilled workers, where unskilled workers are defined as blue-collar workers and low-wage administrative workers, and skilled workers are defined as those in technical professions (e.g., lawyers, engineers) or middle management and higher. Export intensity is the ratio of export revenues to domestic revenues.

B Model appendix

B.1 Equilibrium conditions

Export selection condition

$$\Phi(z,j,i) \geq \tau_j p_h(i)^{1-\eta\alpha_j} \left(\frac{P f_j^x}{\hat{\kappa}(j)}\right)^{\frac{1}{\sigma_j-1}}$$

where $\hat{\kappa}(j) \equiv \frac{1}{\sigma_j}\left(\frac{\sigma_j-1}{\sigma_j}\right)^{\sigma_j-1} \tilde{\alpha}_j^{\sigma_j-1} \lambda^{(1-\sigma_j)\alpha_j} P(j)^{\sigma_j} Q(j)$ and $\tilde{\alpha}_j = \alpha_j^{\alpha_j}(1-\alpha_j)^{1-\alpha_j}$.

Firm location choice condition

$$i^*(z,j) = \arg\max_{i\in I}\ v(z,j,i)\epsilon_i.$$

This gives the probability that a firm chooses location i and the probability that a firm that chooses location i is an exporter: $\delta(j,i) = \Pr(\textit{choose } i)$ and $\delta^x(j,i) = \Pr(j \text{ exports} \mid j \text{ chooses } i)$.

Utility equalization (free worker mobility)

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

Land price schedule

$$p_h(i) = H(L(i)) = \gamma_{0,i} L(i)^{\bar{\gamma}}$$

Note that the parameter γ_0 can be made city-specific to capture level differences across similarly-sized cities, e.g. due to local geography or zoning regulations. Similarly, the elasticity of land prices to city size $\bar{\gamma}$ can be made city-specific.

Aggregate price index

$$P = \Big(\sum_{j=m,s} \epsilon_j \omega_j\Big)\Big(\sum_{j=m,s} \theta_j P(j)^{1-\rho} Q^{(1-\rho)(\epsilon_j - 1)}\Big)^{\frac{1}{1-\rho}}.$$

Note that the aggregate price index is the same across cities within the country because we have assumed away intercity trade frictions. The aggregate price index is also identical between Home and Foreign because we have assumed that the two countries are not only symmetric but also identical.

Aggregate labor market clearing

$$L = L \int_i u(i)\, \mathrm{d}i,$$

where $u(i)$ is the share of the population living in a city of size $L(i)$.

Free entry of firms in each sector

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

Goods market clearing

$$P_j^{1-\sigma_j} = \kappa_{2,j} M_j G_j;$$

where

$$\kappa_{2,j} = \left(\left(\frac{\sigma_j - 1}{\sigma_j}\right)\tilde{\alpha}_j (U P^{\eta})^{-\alpha_j}\right)^{\sigma_j - 1},$$

$$G_j(i) = \frac{E\Big[\Phi_j(z,i)^{\sigma_j - 1} \mid i, j\Big]}{p_h(i)^{(1-\eta\alpha_j)(\sigma_j - 1)}} + \frac{\delta_j^x(i)}{\delta_j(i)} \frac{E\Big[\Big(\frac{\Phi_j^x(z,i)}{\tau_j}\Big)^{\sigma_j - 1} \mid i, j\Big]}{p_h(i)^{(1-\eta\alpha_j)(\sigma_j - 1)}},$$

and

$$G_j = \int_i \delta_j(i) G_j(i)\, \mathrm{d}i.$$

Local labor market clearing

$$W(i) u(i) L = \sum_j \delta_j(i) M_j (\sigma_j - 1) \alpha_j E[\hat{\pi}_j(z,i) \,|\, j].$$

Final goods market clearing

$$Q = C + \sum_j M_j \Big(f_j^e + f_j^x \Big(\int_i^I \delta_j^x(i)\, \mathrm{d}i\Big)\Big),$$

where $C \equiv \int_i C(i)\,\mathrm{d}i = \int_i L(i)c(i)\,\mathrm{d}i = (L/P)\eta \int_i \tilde{W}(i)u(i)\,\mathrm{d}i = (L/P)\eta \int_i UP^{\eta}p_h(i)^{1-\eta}u(i)\,\mathrm{d}i$.

B.2 Behavior of $d\log L/d\log z \equiv \eta_z^L$

In the following, L denotes $L(i)/L(0) \geq 1$ for simplicity and we omit the sector (j) subscript. The FOC for a sorting equilibrium yields the following closed-form solution for $z(L)$:

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

The above must be non-negative for $z \geq 1$ (as we assume), i.e., the expression at the numerator (NUM) and that at 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:

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

The expression for $d\log L/d\log z = 1/\left(d\log z/d\log L\right) \equiv \eta_z^L$ 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 numerator in large brackets for $s < 1$ and $s \to 1$ 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 $s \to 0$ 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).[24]

– Case $\xi < 0$:
  In this case, we have DEN > 0. The limit of the numerator in the expression for $s < 1$ and $s \to 1$ 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.3 Shifting comparative advantage

In our 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 15, the French trade balance for goods has declined from about 1% of GDP to minus 3% of GDP between 1995 and

[24] Note that a decreasing elasticity implies that $\log L(z)$ is concave in $\log z$, *not* that $L(z)$ is concave in z.

2018. For services, the trade surplus remains at about 1% of GDP. This section addresses how shifting comparative advantage affects our main findings.

Can a shift in comparative advantage away from French manufacturing account for the urban bias of structural change in the data? Changing comparative advantage may explain our empirical findings if sectors for which French manufacturing has lost its comparative advantage are more likely to be located in the largest cities in 1995. For example, if textile producers tend to be located in larger cities in 1995 compared to other French manufacturers, and the rise of Chinese textile manufacturing has led to a swift decline of French textile manufacturers, then this may potentially play a role in explaining the urban bias of structural change. However, we find that technologically sophisticated manufacturing sectors (i.e., those sectors in which France does not tend to be at a disadvantage) are more likely to be located in large cities in 1995. Further, we find a switch of the firm size-city size relationship from positive to negative even within narrowly defined manufacturing sectors (5-digit). Nevertheless, increased outsourcing of production processes by French manufacturing may lead to such an urban bias if manufacturers that outsource are more likely to be located in large cities in 1995.

How would the change in comparative advantage affect our estimated trade costs, sectoral TFP, and sorting and agglomeration parameters? What would that mean for our main quantitative results? First, note that the aggregate revenue share of manufacturing is:

$$\vartheta_m = \frac{P_m Q_m}{\sum_k P_k Q_k},$$

and the export intensity of a Home exporter is:

$$\frac{\pi_m^x(z,i)}{\pi_m^d(z,i)} = \tau_m^{1-\sigma_m} \frac{P_m^{*\,\sigma_m} Q_m^*}{P_m^{\sigma_m} Q_m},$$

where an asterisk denotes Foreign. Consider a shift of comparative advantage away from French (Home) manufacturing to Foreign-produced goods driven by faster manufacturing TFP growth in Foreign than at Home. Then, there are two effects: (a) Home goods producers will see a decline in Home demand for their goods (import competition); (b) Home goods exporters will see a decline in Foreign demand for their goods. The first effect reduces the manufacturing share of revenue at Home. Since our measure of manufacturing TFP growth targets the actual decline in the manufacturing share of revenue, our measure of TFP growth would overstate manufacturing TFP growth. The second effect reduces export revenues relative to domestic revenues for Home exporters, and thus the ratio $\left(P_m^{*\,\sigma_m} Q_m^*\right)/\left(P_m^{\sigma_m} Q_m\right)$. As such, our measure of variable trade costs would understate the decline in manufacturing trade costs. Given that the services trade balance has been relatively stable, our measure of services trade costs would hardly be affected. Finally, our estimates of the sorting and agglomeration parameters would not be affected since we rely only on the partial equilibrium location choice problem of the firm, and not on general equilibrium quantities.

Given that a larger manufacturing trade deficit would imply overstated estimates of manufacturing TFP growth and understated estimates of manufacturing trade costs relative to services, our model would exaggerate the contributions of sectoral TFP growth and trade costs to urban-biased structural change. Nevertheless, our main quantitative results show that the main drivers of urban-biased structural change are the changes in agglomeration forces.

C Model fit

In Tables 18 and 19 we show the empirical and predicted values of the moments calibrated in our estimation procedure.

Table 18: Model fit (manufacturing)

	Data		**Model**	
Moment	**1995**	**2018**	**1995**	**2018**
Firm size 50-10 ratio	1.14	-	1.17	-
Firm size 75-25 ratio	1.75	-	1.75	-
Firm size 90-50 ratio	2.19	-	2.41	-
Firm size 90-10 ratio	3.33	-	3.58	-
Mean log sales in city bin 2	0.02	0.02	0.05	0.01
Mean log sales in city bin 3	-0.04	-0.05	0.01	-0.02
Mean log sales in city bin 4	0.07	-0.12	0.01	-0.04
Mean log sales in city bin 5	0.07	-0.17	0.02	-0.10
Share of sectoral revenue in city bin 1	0.26	0.31	0.23	0.29
Share of sectoral revenue in city bin 2	0.23	0.24	0.23	0.28
Share of sectoral revenue in city bin 3	0.17	0.19	0.19	0.18
Share of sectoral revenue in city bin 4	0.16	0.15	0.14	0.12
Share of sectoral revenue in city bin 5	0.18	0.11	0.21	0.13

Notes: This table reports the model's fit to the moments used in the structural estimation routine. Mean log sales in each city size bin is defined relative to city size bin 1 (smallest cities). See Section 4 for more information.

Table 19: Model fit (services)

	Data		**Model**	
Moment	**1995**	**2018**	**1995**	**2018**
Firm size 50-10 ratio	1.05	-	1.02	-
Firm size 75-25 ratio	1.31	-	1.35	-
Firm size 90-50 ratio	1.60	-	1.59	-
Firm size 90-10 ratio	2.65	-	2.61	-
Mean log sales in city bin 2	0.07	0.07	0.09	0.08
Mean log sales in city bin 3	0.09	0.08	0.09	0.08
Mean log sales in city bin 4	0.18	0.10	0.17	0.16
Mean log sales in city bin 5	0.47	0.31	0.36	0.34
Share of sectoral revenue in city bin 1	0.14	0.13	0.14	0.13
Share of sectoral revenue in city bin 2	0.15	0.14	0.13	0.12
Share of sectoral revenue in city bin 3	0.16	0.17	0.18	0.17
Share of sectoral revenue in city bin 4	0.17	0.18	0.19	0.19
Share of sectoral revenue in city bin 5	0.38	0.39	0.36	0.39

Notes: This table reports the model's fit to the moments used in the structural estimation routine. Mean log sales in each city size bin is defined relative to city size bin 1 (smallest cities). See Section 4 for more information.

D Online Appendix

D.1 Solution algorithm

Preliminaries:

- Define parameter values.
- Permanently draw firm idiosyncratic productivity 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 $E\big[(\frac{\Phi_j^x(z,i)}{\tau_j})^{\sigma_j - 1}\big]$.
  - Compute 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 equilibrium labor allocation across cities achieved.

D.2 Extension: Land market clearing

In the baseline version of our model, we model 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:

$$\sum_j \left(\int_{z\in\mathcal{Z}_j(i)} p_h(i) h_j(z,i)\; dz \right) + (1-\eta) W(i) L(i) = p_h(i) h^s(i).$$

Using firms' F.O.C.'s 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

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

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:

$$\sum_j \frac{1-\alpha_j}{\alpha_j} L_j(i) + (1-\eta)L(i) = p_h(i)^{\nu+\eta}$$

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

$$p_h(i) = \left((1-\eta) + \sum_j \frac{1-\alpha_j}{\alpha_j} \frac{L_j(i)}{L(i)} \right)^{\frac{1}{\nu+\eta}} L(i)^{\frac{1}{\nu+\eta}}. \tag{19}$$

Note that if all sectors have the same labor and land intensity, then equation (19) 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 (19), firms would additionally take as given the within city sectoral share of employment $L_j(i)/L(i)$. Equation (19) 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 (19) and use it to run counterfactual experiments, we obtain similar estimated sectoral agglomeration externalities and similar quantitative findings.