Misfits in the car industry:
Offshore assembly decisions at the variety level[*]

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Abstract

This paper estimates the role of country-variety comparative advantage in the decision to offshore assembly of more than 2000 models of 197 car brands headquartered in 23 countries. While offshoring in the car industry has risen from 2000 to 2016, the top five offshoring brands account for half the car assembly relocated to low-wage countries. We show that the decision to offshore a particular car model depends on two types of cost (dis)advantage of the home country relative to foreign locations. The first type, the assembly costs common to all models, is estimated via a structural triadic gravity equation. The second effect, model-level comparative advantage, is an interaction between proxies for the model's skill and capital intensity and headquarter country's abundance in these factors.

1   Introduction

Concern over the effects of offshoring on workers motivates a large body of empirical research. A prominent recent example is Pierce and Schott (2016), who attribute a large part of the decline in US manufacturing employment to the reallocation of production to China by US firms. They point out that the biggest increase in Chinese exports to the US following WTO accession was for foreign affiliates. Furthermore, WTO accession boosted the number

of related-party import transaction in US imports. Hummels et al. (2018) survey the empirical literature about offshoring effects, and report substantial impacts of offshoring on rich countries' labor markets, regarding both employment and wage inequality.

Which products are most vulnerable to the offshoring threat? While Blinder (2006) contends that "virtually all [manufacturing] jobs were potentially moveable offshore'," Hanson (2015) finds that in reality even within manufacturing, offshoring is confined to a handful of sectors. In this paper we zoom in on one of those sectors, the car industry, to examine the country and variety-level characteristics that make offshoring more likely. One unsurprising factor promoting offshoring is sectoral cost competitiveness of the potential offshoring country. A second key factor is variety-level *misfit* between product factor intensities and country factor abundances. We investigate these hypotheses, exploiting exceptionally detailed data from the car industry.

Car makers have a long history of assembly in foreign countries: Ford of Canada began manufacturing operations in 1904. For the most part, the car industry, like other industries, has moved production abroad to obtain better access to foreign customers.[1] Recently, there has been a rise in use of foreign assembly to serve markets other than just the host country. In 2010, with unions complaining that Renault had moved three quarters of its car production outside of France, then president Sarkozy summoned Renault's CEO, Carlos Ghosn, to the Elysée Palace "to explain the carmaker's strategy." He was reportedly told to retain production of the Clio for the French market in France, rather than move it to the Renault plant in Turkey. Six years later 64 percent of the new generation Clios sold in France were produced in Turkey with the remainder in France. In March 2014 Porsche announced that it would move production of the Cayenne SUV from Germany to Slovakia. This would mark the first time that Porsches would be assembled in a poorer country than Germany.

Stories such as these suggest a major change in the pattern of auto assembly is under way. To what extent will auto production go the way of clothing and consumer electronics and migrate to less developed countries? This paper quantitatively investigates the state of offshoring in the passenger car industry. We propose two ways to measure the amount of offshoring of assembly and show that it is not growing as much as the anecdotes above suggest. Furthermore, offshoring for the home market is highly heterogeneous: the top five offshoring brands account for half of the cars made abroad and sold in the brands' home market.

To explain the large observed variation in offshoring, we examine the country- and model-level determinants of the decision to assemble a particular model in a lower wage country.

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[1]Irarrazabal et al. (2013) report that 62% of the goods made by US affiliates are sold in the domestic market.

Our aim is to understand why offshoring takes place and in particular which firms find it attractive. The results we obtain support a simple comparative advantage model of offshoring. Firms based in countries that have relatively high assembly costs are more likely to offshore in general and the most likely models to be offshored are the less expensive cars of brands based in high income countries. We interpret price as a proxy for the skill and capital intensity of the model and per capita income as a proxy for abundance in the corresponding factors of production.

Why is offshoring in the car industry of particular interest? First of all, the car industry is large and considered important by government policy makers. Passenger cars are the largest expenditure category among goods.[2] Industry associations in the European Union (EU) and United States (US) report very large employment shares for the broadly defined automotive sector. Including parts and other related activities, it accounts for 5.8% of the total employed population of the EU and nearly 5% of US employment. Car makers were deemed sufficiently important to receive $US 81 bn under both the Bush and Obama administrations. In January 2017, Donald Trump threatened General Motors with border taxes if it continued to make Chevrolet Cruzes intended for the US market in Mexico.

A second compelling reason to study offshoring in the car industry is the existence of extraordinarily rich data. IHS Markit, an automotive consultancy, provides a nearly exhaustive account where cars are made and then sold. Comparable data do not appear to be available on a worldwide basis for any other sector of the economy. Most government-provided data sets are restricted to parent firms or affiliates based in a single reporting country. IHS tracks the factories where over 2000 models are assembled by nearly all manufacturers and brands. The data, running from 2000 to 2016, shows annual flows at the level of individual models identifying location of assembly and country of sale (the data are based in part on new car registrations). Because we can map the origins of each brand back to a headquarters country (which we designate as the brand's "home"), we capture the three essential locations that form part of our criteria for offshoring: where each brand makes the cars it sells in its brand home and other markets. Some important dimensions of the data include the following:

- 2444 local nameplates for 2026 "global nameplates" (models) identified by the makers.

- For each model we also know the start and end year of each "program" (version of the model).

- The data also distinguishes the size and function of the model.

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[2] They account for 4% of personal consumption expenditures in the United States.

- For about 1000 models and 28 countries (contained in a second module offered by IHS Markit), we have destination-specific sales price information.

- 197 brands from 23 different brand homes.

- 76 different markets (countries that record brand/origin).

- 52 different assembly countries (almost all world production).

Using the auto data set, we conduct three main empirical exercises. The first step quantifies the magnitude and direction of offshoring to this date. By offshoring we mean the relocation of production intended for a given market to new assembly sites. Our narrow definition of offshoring focuses on the *home* market of the brand. The narrow definition of offshoring thus removes all relocation of production to get closer to foreign customers.[3] Our broad definition considers all assembly outside the brand's home country to be offshoring. In both cases, we define the home country to be the place where the headquarters of the brand is located. In cases such as Volvo where headquarters functions are mixed between countries (Sweden and China), the home country is defined based on where the brand was founded (Sweden). By direction, we distinguish "downward" offshoring to lower income countries from "flat" and "upward" offshoring to other countries at similar or higher income levels. Our threshold for flat is for the producing country per-capita income to be no more that 20% above or below the per capita income of the brand home.

After establishing that offshoring to serve the home market remains small and is mainly carried out by a small number of brands, we investigate the determinants of the decision to offshore all or part of the production of a car model. Drawing elements from Dornbusch et al. (1980) and Feenstra and Hanson (1997) we develop a simple model of the variety-level decision to offshore. The model is deliberately parsimonious, abstracting from dynamic aspects such as switching costs and the hysteresis they would induce. Our purpose is to formalize in a straightforward way the idea that products which are misfits in the brand's home market are more like to be offshored. Our notion of "misfit" is a skill-intensive car model that is produced in a country where skilled workers are relatively scarce and hence relatively highly paid.

In addition to variety-level comparative advantage, a second driver of the decision to offshore is the general cost advantage of the home country in car assembly. To obtain the country-specific "assembly advantage" term, we first estimate a specification of multinational production (MP) flows derived from Arkolakis et al. (2018). This specification has origin-year

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[3]This motive for production abroad is also referred to as "tariff-jumping" though tariffs are often not the main trade cost.

and brand-destination-year fixed effects as well as measures of frictions between assembly country and market as well as headquarter and assembly country. Our paper is the first to estimate the triadic gravity regression for multinational production using data with the appropriate dimensions. In the model, the origin-year fixed effects are proportional to the ratio of worker productivity to their wages.

Our final exercise is to estimate a fractional logit on the share of production that is off-shored at the model level. One previous study has also sought to identify the characteristics of vehicles that makes them more susceptible to offshoring: McCalman and Spearot (2013) examined the Post-NAFTA expansion of capacity to produce light trucks in Mexico. They found that US firms "offshored varieties that were older and less complex to produce." We compare our worldwide car results to their North American trucking results.

The remainder of the paper consists of five sections. Section 2 documents the changes that occurred in worldwide production of cars over the 2000–2016 period. Section 3 then specifies our definitions of offshoring, and quantifies its extent and patterns over time and space. Our modeling of the offshoring decision and estimating equation are described in section 4. The measurement of the different covariates involved in the offshoring regression is contained in section 5, and section 6 provides our estimates of the decision to produce their models in a country where costs are lower than at home.

## 2 Emerging economies in the auto assembly sector

In this section we chart the changes in the location of passenger car production that have occurred from 2000 to 2016. We look at three specific cases of "emerging market" economies that assemble growing shares of the world's cars.

We begin by noting that total car production in the OECD in 2016 is 41.78 million units, only 9% higher than in 2000. It increased somewhat in the lead-up to the 2008 crisis, then fell sharply, before stabilizing at the old level in 2013 and has been growing slowly since then. On the other hand, non-OECD production has risen every year since 2000, cumulating a more than six-fold increase from 2000 to 2016.

Figures 1 and 2 zoom in on the changing nature of production in three economic areas that have experienced impressive growth in their shares of world production: China, Eastern Europe (Poland, the Czech Republic, Slovakia, Hungary, Slovenia, Romania, and Bulgaria), and Mexico.

The case of China, shown in Figure 1 is the most straightforward to describe. There, production growth has matched demand growth almost exactly one for one until purchases outstripped production in 2010 and China became a small net importer. Foreign brands

Figure 1: The Growth of China
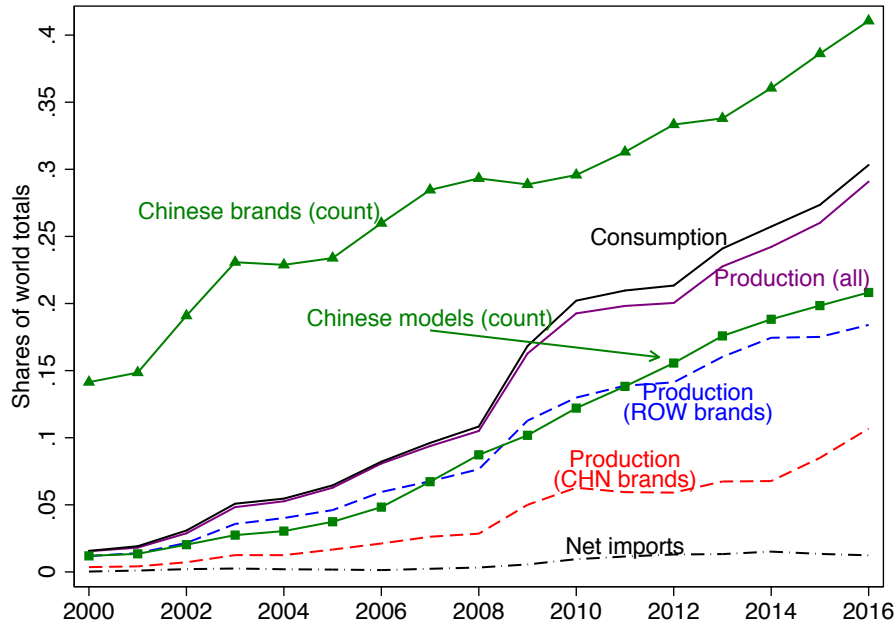
have gradually moved ahead of Chinese brands. Initially China had a very large number of very small brands. In 2000 its share or world brands was 9.2 times higher than its share of world production. Over the following 16 years the Chinese brands expanded the scale of production. By 2016 the brand to production share ratio fell to 1.4. Chinese brands remain on the small side and based on the experience of the traditional producers, we may expect a "shake-out" to occur in the future.

China may one day replicate in car assembly its success in areas like electronics assembly where it is already the "workshop of the world." However there is no sign of this in the data yet. One limitation China faces is that it has few free trade agreements with major markets. Our regression analysis in section 5.1 finds that trade agreements and tariff rates have large effects.

Contrasting with the Chinese case, Figure 2 shows that Eastern Europe and Mexico have experienced sluggish growth in domestic demand, while hosting a share of world production that grows steadily over time starting in 2004. In both cases, net exports grow substantially over the period as a result. This pattern is particularly pronounced for Eastern European countries who joined the European Union. Since 2004 exports of foreign brands (mainly from Western Europe) have boomed.

Two cases provide a good illustration of the migration of assembly to Eastern and Central Europe. Starting in the 1970s, an assembly factory in Tychy assembled a Polish version of the

Figure 2: The Growth of the Periphery

(a) Central & Eastern Europe (CEEC)   (b) Mexico
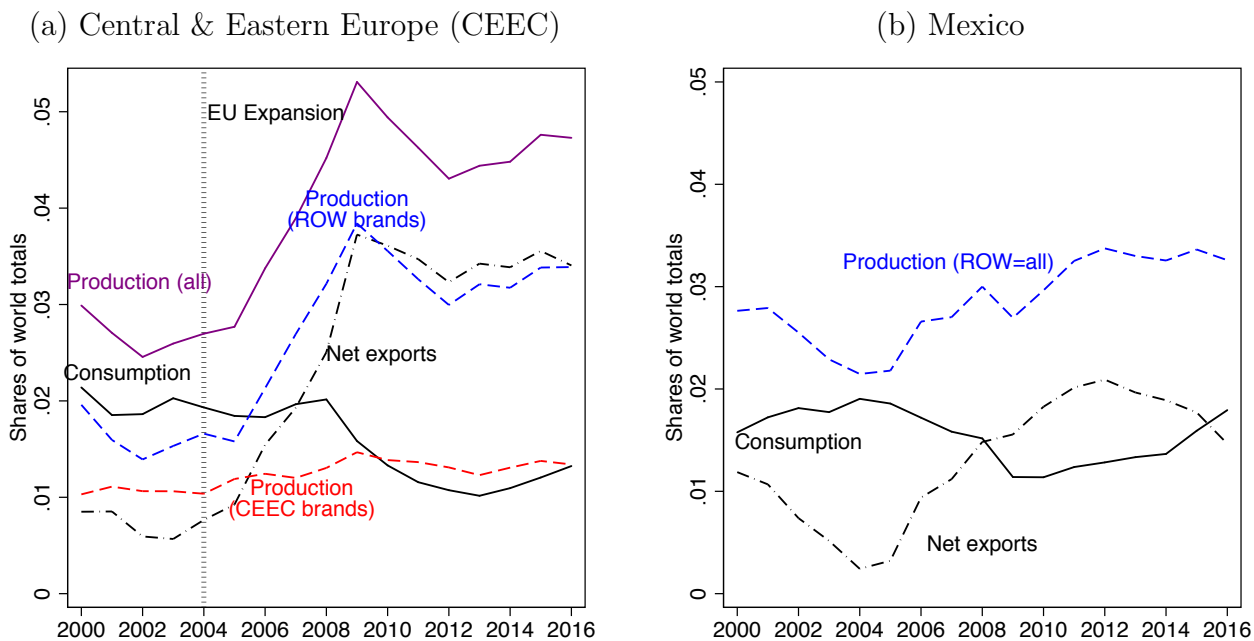
Fiat 126. Fiat purchased the plant in 1992 when it was privatized. Recently, Fiat allocated to the Tychy factory the new and highly successful 500 model. Tychy assembled almost as many cars as Fiat's five biggest plants in Italy with one third the workers each earning one third the pay.[4] Tychy operates 24 hour per day, six days per week, whereas Fiat's Italian plants operated at 40% capacity utilization in 2012.

Renault's Revoz plant in Novo Mesto, Slovenia provides a somewhat similar story. It began as a joint venture in the 1980s. The plan was to focus on selling cheap Renaults in the Yugoslav market. That plan had to be altered when Yugoslavia fell apart. Slovenia emerged instead as an offshoring and exporting platform.

Mexico (which has no local brand), also benefits from a regional trade agreement. NAFTA was signed in 1993, but its tariff reductions were phased in over the next decade. We unfortunately lack data before 2000 so we miss most of the period where the NAFTA tariff cuts were being phased in. The reasons behind the 2004 turnaround and subsequent boom in Mexico's net exports shown in Figure 2(b) are unclear.

The picture that emerges from figure 2 is one of two major historical production bases (North America and Western Europe) offshoring part of their car assembly to their respective low-cost "peripheries" (Mexico for the US brands and Eastern Europe for the European

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[4]Facts taken from Rattner article in *Financial Times*, October 4, 2012.

brands). We now try to quantify the offshoring movement in a more global and systematic way.

3   Measuring offshoring

The data set we have allows us to track the production of individual products. We can distinguish horizontal (market-seeking) activities from offshoring because we know the location of assembly and also where the cars are sold for each model. Another great advantage of our data is to be able to follow a specific variety over time, and therefore keep track of changes in the location of production with potential transfer to low cost countries.

To measure offshoring we must first define it. Feenstra (2004) defines offshoring as the "transfer of production overseas, whether it is done within or outside the firm." We focus on single task or activity, the assembly of passenger cars. Our data has no information on the sources of components so this will not be a paper about "slicing the value chain" except in the sense of separating final assembly from design and distribution. The question begged by Feenstra's definition is when should we consider overseas production to be *transferred*? It seems like the essential condition should be that *but for* this increase in offshore production, there would have been no corresponding reduction in home-country production.

We work with two definitions of offshoring. Our first definition is that *a car is considered offshored if it is consumed in the home country but assembled in a different country.* This approach excludes offshore production that is aimed at serving the host country's market, with the general presumption that much or all of those sales would not be served by the brand if it did not produce locally. Such production therefore has small or no impact on domestic workers. This version of offshoring focuses on the home country, which is the only market firms are guaranteed to be able to serve without facing tariff or non-tariff barriers. "Narrow" offshoring refers to cars assembled overseas but sold in the home market.[5] This seems to correspond to what political leaders have in mind when talking about offshoring. We reproduce a quote by French president's Chief of Staff, made public at a time when the French government was negotiating with Renault's CEO Carlos Ghosn about the potential re-location of a new model's (Clio 4) assembly in Turkey:

> "Ghosn said very clearly that the Clio 4s corresponding to the French market will
> be made in France... You can't ask Renault to make cars for Turkey in France,

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[5]Ramondo and Rodríguez-Clare (2013) refer to this as "pure vertical MP" but the "vertical" terminology would be confusing in this context since we only consider one stage of production (assembly). Also, offshoring has become the standard term in policy discussions.

which would mean not selling any more cars in Turkey." (Claude Guéant, Sarkozy Chief of Staff, January, 18, 2010)

The narrow definition of offshoring is the appropriate one if most overseas production for foreign markets would have to be produced in those markets. Thus it would not substitute for domestic employment.

An alternative definition, takes a quite opposite view, emphasizing substitution between domestic and foreign employment, regardless of the final market. From a worker perspective, Renault Clios made in Turkey are Clios not made in France—no matter who ultimately buys them. Consequently, our "broad" definition of offshoring is production outside the brand home divided by the brand's production in all locations.[6] The right definition depends on the cross-substitution possibilities, which are difficult to assess *ex ante*. Therefore, our approach is to "bracket" the actual extent of offshoring with these two admittedly extreme definitions.

Narrow offshoring selects a home where the brand was historically produced and divides imports by total consumption. Broad offshoring looks at the total production outside of the brand home base. This "brand home" country is therefore an essential concept in our definitions of offshoring. We choose to define "home" as the country where the brand is headquartered or where it was founded.

The case of the Renault Twingo illustrates some of the important issues involved in defining offshoring. Table 1 displays sales of that model in the HQ country and in the only 4 markets that are served by one of the Latin American plants. For almost all markets, this model was sourced entirely from the Flins factory near Paris until 2007. The exceptions were assembly in Colombia and Uruguay for local sales ("horizontal MP" in the taxonomy of Ramondo and Rodríguez-Clare (2013)). In 2007, with the launch of a new version (II), Twingo production in France was terminated and all (new) Twingo production was concentrated in Slovenia to be exported to most destinations (including France).[7] Again, the exception was a small amount of production for the version I in Colombia, mainly for the local market, but with a few cars shipped to neighboring Ecuador and Venezuela ("export platform MP"). All Twingo cars sold in France since 2008 were produced in Novo Mesto, Slovenia. Under the narrow definition, this car switch from 0 to 100% offshored in 2008. Under the broad definition, the pivotal year involved a change from a small positive number (the local sales in Latin America) to 100%. The offshoring rate remained 100% under both definitions with the third generation of Twingo started in 2014, and entirely concentrated in the Slovenian plant (selling in 29 countries).

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[6]This includes vertical, horizontal and export platform MP. We thank Peter Neary for suggesting us that we should consider export platform production in our definitions of offshoring.

[7]The Flins factory continued to produce the Clio but production at the factory in 2016 was only a quarter

Table 1: The Twingo example

Market:	FRA			COL		URY	VEN	ECU
Plant:	Flins	Novo Mesto		Medellin	Novo Mesto	Montevideo	Medellin	Medellin
Version:	I	II	III	I	II	I	I	I
2000	76622			1749		578		
2001	78891			1927		476		
2002	67588			3508				
2003	53146			4503				
2004	47699			5168				
2005	45594			7456				
2006	38133			9937			2666	53
2007	8525	43618		10069			3377	34
2008		65333		6660			960	
2009		107456		7756			137	25
2010		92183		5565				
2011		68236		6780			23	
2012		39697		3273				
2013		39032			277			
2014		15824	26195		134			
2015			45425		2			
2016			40796					

Note: The figures reported are total sales. Over the whole period, this model is sold by Renault in 46 different markets and produced in 4 different plants: Flins in France, Novo Mesto in Slovenia, Medellin in Colombia, and Montevideo in Uruguay (which stopped production in 2002). All other countries where that car is continuously sold (Germany, Italy, etc.) exhibit the same sourcing pattern as for cars sold in France.

Figure 3: Offshoring by income level of source country, narrow (solid) and broad (dashed) definitions
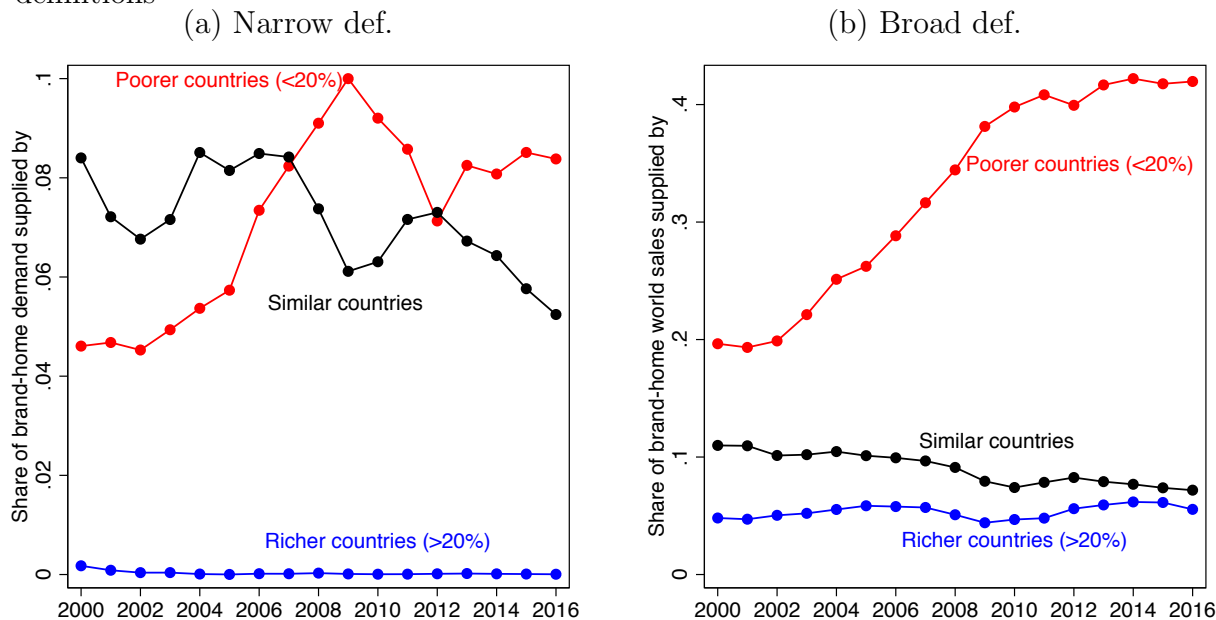

(a) Narrow def.

(b) Broad def.

Figure 3 depicts trends in offshoring based on the two different definitions of offshoring and three different offshoring destinations. Panel (a) is based on the narrow definition, while panel (b) is for the broad definition. The direction of offshoring will be considered "up" for imports from countries that have per capita incomes that are 20% higher than the home country. Offshoring "down" corresponds to imports from countries 20% poorer than the home. "Flat" offshoring refers to similar average income levels. We use market exchange rates in each case since we are aiming at comparing wages, rather than standards of living.[8] We average incomes from 2000 to 2016 so as to prevent offshoring in a given country from shifting from being down to flat if, say the income of the country grew substantially during the period.[9] The relative nature of this definition implies that assembly in a well-to-do country like Belgium can be considered offshoring down if, as in the case of Volvo, the brand home is more than 20% higher income.

The picture from figure 3 is that in narrow offshoring remains globally a limited phenomenon, since the part of it that concerns low cost locations peaks at 10% of home demand.

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of its 2000 level.

[8]We considered using data on manufacturing wages in the transport equipment sector but the loss of countries due to missing data did not seem like a good trade-off given that we are dividing countries into coarse categories.

[9]This prevents sudden jumps in offshoring that are not related to actual changes in production but only to country classification.

However, offshoring "down" is now twice as high (8%) as it was in 2000, contrasting sharply with the declinging trends for both offshoring "up" and of offshoring "flat." The broad offshoring shares are uniformly higher than the corresponding narrow shares, as was to be expected from the inclusion of all kinds of MP (vertical, horizontal and export platform) under that approach.

Figure 4 shows that the patterns we see at the global level for offshoring are not replicated evenly across the main brand homes. The figure applies the same vertical range (0–50%) to each country's level of narrow offshoring so as to facilitate comparisons. The top row shows the two large countries whose increase in offshoring from lower income countries was most pronounced, France and Italy. The United States and Germany exhibit quite different patterns. While the low cost locations are also attracting production of US and German brands, the rate of progress is much more modest. The extraordinary level of "flat" offshoring of US brands is distinctive and almost entirely attributable to the long history of market integration with Canada. The UK and Japan, are at the other extreme from France and Italy, with extremely little narrow offshoring. While this is perhaps not so surprising for UK brands, consisting mainly of luxury and sports cars, it is quite striking for Japanese mass-oriented car producers.
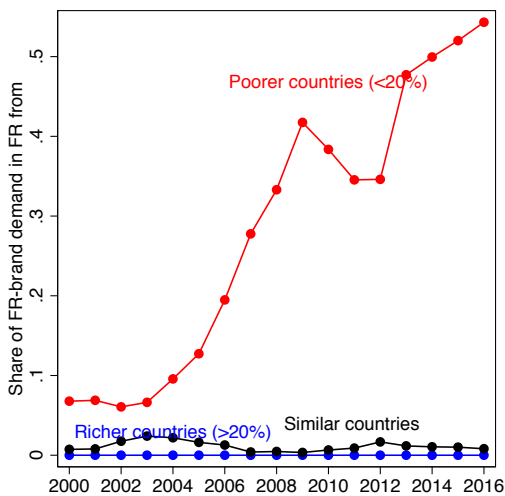
The broad definition of offshoring does not change the picture dramatically for France and Italy (figure 5). Both countries have seen a very impressive rise in the share of production in poorer countries for cars aimed at serving both the domestic and foreign consumers. The picture for the USA is more radically changed suggesting that when serving third markets, US brands tend to use more low-cost production facilities (often local) than when serving the domestic market. Offshoring of US cars in Canada seems to be mainly intended to serve the US market. The UK remains an exception with very low levels of broad offshoring. However, the share of Japan-brand cars produced in poorer countries has risen from 10% to 40%.

Figure 6 shows that even within a brand home like France, the country that shows the most marked trend towards offshoring, there has been remarkable heterogeneity across the brands in terms of their expansion of narrow offshoring. All three brands have dramatically increased sourcing from poorer countries. However, Renault's rise from near 0 to 60% off-shoring in just 6 years (2003–2009) is the most spectacular boom in narrow offshoring we have seen. The Novo Mesto, Slovenia and Bursa, Turkey plants were the primary beneficiaries of this massive reallocation of assembly activity.

Figure 7 shows that the brand heterogeneity exhibited in France is part of a broader phenomena in which just five top brands account for 50% of the world's offshoring. This figure holds for the narrow definition of offshoring in 2016. While these five brands are all large, their global share of sales in 2016 is just 22%. Concentration of offshoring was even

Figure 4: Offshoring (narrow) in six major brand homes

(a) France

(b) Italy
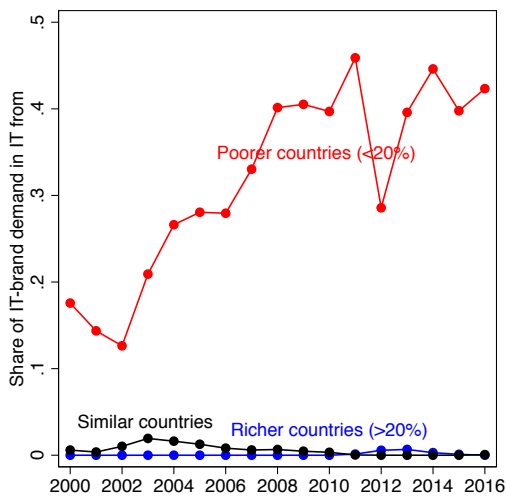
(c) USA

(c) Germany

(c) UK

(c) Japan

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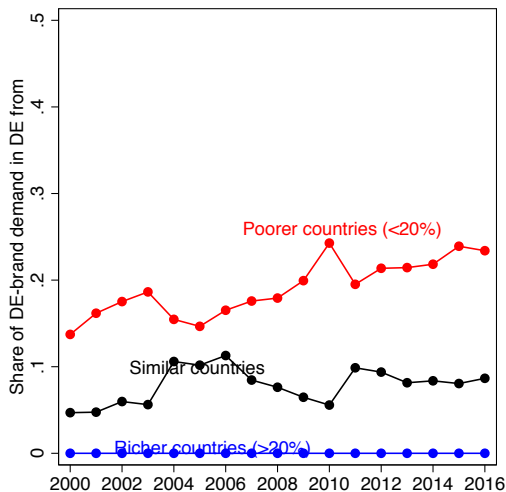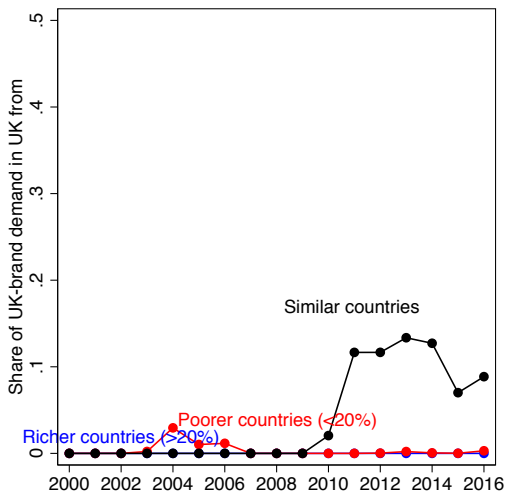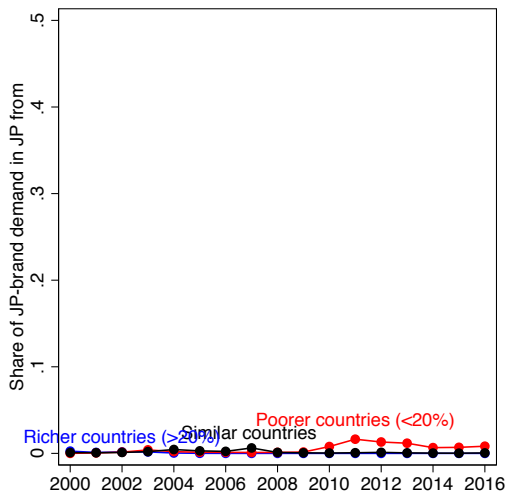
Figure 5: Offshoring (broad) in six major brand homes
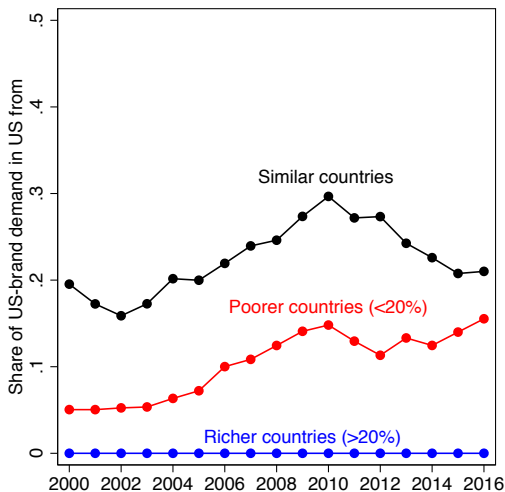
(a) France

Poorer countries (<20%)

Similar countries

Richer countries (>20%)

Share of FR-brand WLD sales from

(b) Italy

Poorer countries (<20%)

Similar countries

Richer countries (>20%)

Share of IT-brand WLD sales from

(c) USA

Poorer countries (<20%)

Similar countries

Richer countries (>20%)

Share of US-brand WLD sales from

(c) Germany

Poorer countries (<20%)

Similar countries

Richer countries (>20%)

Share of DE-brand WLD sales from

(c) UK

Similar countries

Poorer countries (<20%)

Richer countries (>20%)

Share of UK-brand WLD sales from

(c) Japan

Poorer countries (<20%)

Similar countries

Richer countries (>20%)

Share of JP-brand WLD sales from

Figure 6: Brand-level differences in offshoring within France

more impressive in the early 2000s, when the top five offshoring brands represented 76% of world (narrow) offshoring (and 26% of world production). These figures suggest that brand heterogeneity must be examined if one is to understand the rise in offshoring. One might question our insistence on brands at this point. Is it not really just *firm* heterogeneity? The 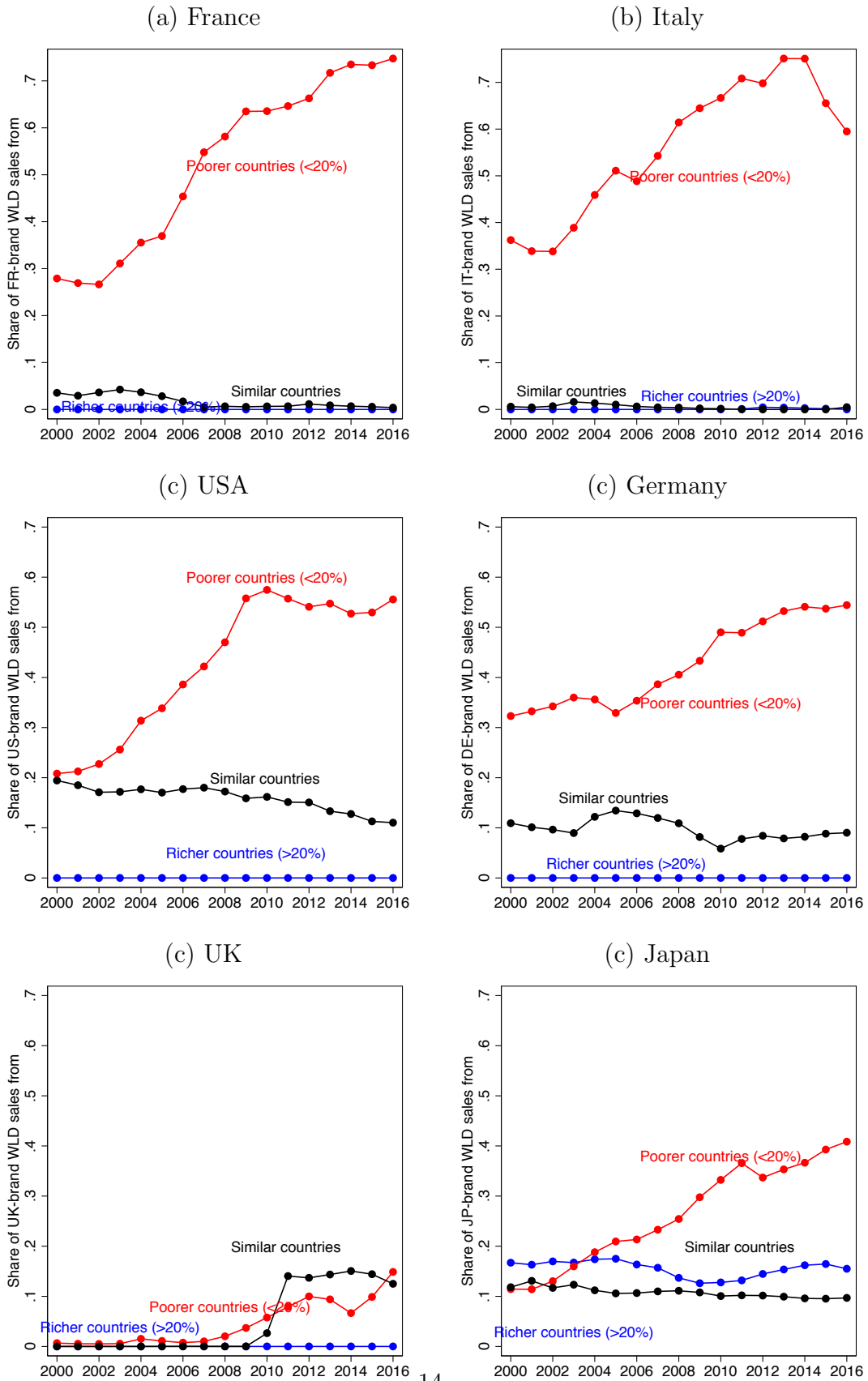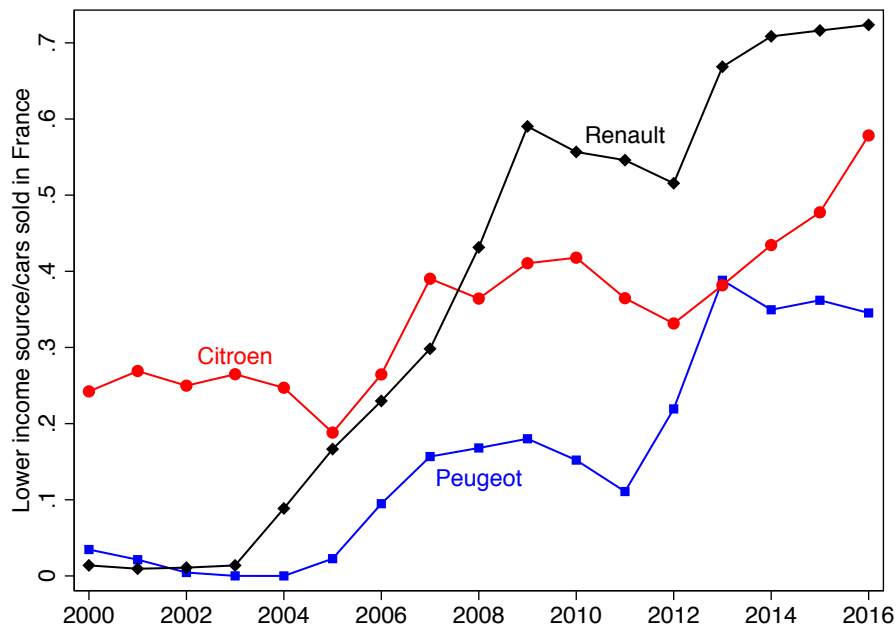case of Fiat is our best reply since both Ferrari and Maserati are owned by Fiat but neither brand offshores production. Similarly, within our data range, of the Volkswagen-owned brands (Audi, Bugatti, Porsche, Seat, Skoda, etc.), only VW itself engages in significant offshoring.

We summarize offshoring trends as follows: Offshored cars from poorer—yet OECD—countries have small market shares at home, but have doubled from four to eight percent. Downward offshoring exceeds offshoring from similar-income sources. Broad definition offshoring is much larger but it includes horizontal (market-seeking) MP that probably does not substitute much for home production. The China story in cars is completely different from iPhones. There is massive heterogeneity in offshoring: Similar countries and firms offshore in vastly different amounts. The "few" (top 5 brands) account for the majority of offshoring.

Figure 7: A few firms account for most offshoring from low-wage countries
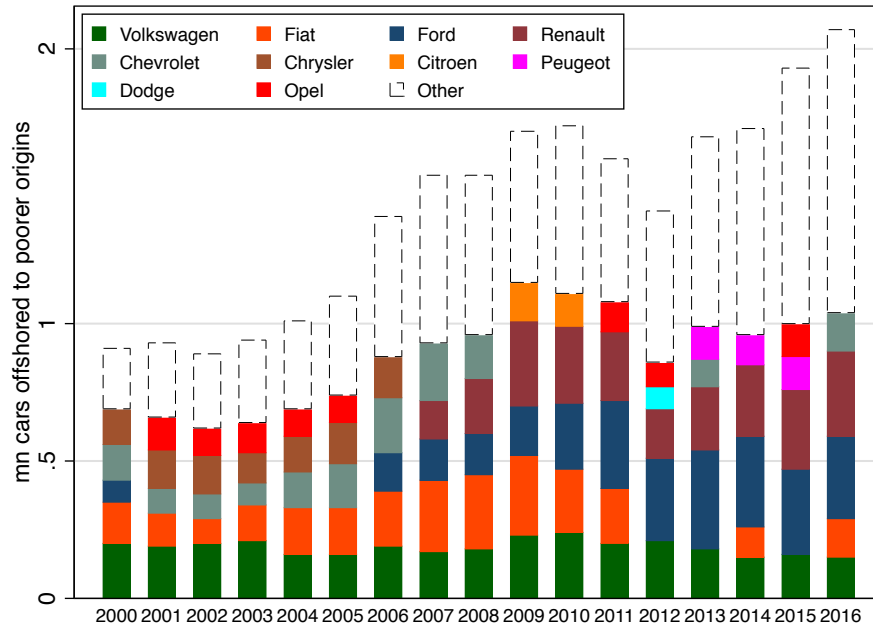
4   Comparative advantage and the offshoring decision

What factors drive offshoring? Why are some models offshored and others not? McCalman and Spearot (2013) study US truck makers offshoring to Mexico. Their results point to low complexity, older vintages, and small scale as variables associated with higher shares of trucks sourced from Mexican factories. With only one outsourcing country in their data set, they obviously could not investigate the role of headquarter country attributes. On the other hand, since our data contains 23 HQ countries and 50 assembly countries, we are able to examine the roles of country and country-model interactions in determining comparative advantage.

To explain why some models are offshored but others are not, we need a theory and measurement of *model-level comparative advantage*. For this exercise, we employ a simple two-country model of a home country that potentially offshores assembly of a car model to a lower income foreign country. When necessary to avoid confusion between the two uses of the term model, we will refer to car models as varieties.

Our model of the offshoring decision takes its inspiration from the seminal papers of Dornbusch et al. (1980), Feenstra and Hanson (1997), and Schott (2004). We hypothesize that model m-level comparative advantage of country i is determined by the *interaction* of i development level and m skill-intensity.

Let costs of domestic production for a model m be given by a nested Cobb-Douglas that takes the following form

$$c(m) = \alpha \left(w_H^{z(m)} w_L^{1-z(m)} \right)^{\beta} p_I^{1-\beta} \exp(\epsilon(m)), \tag{1}$$

where $z(m)$ is the cost share parameter for high-skilled workers, paid w_H, while the low skilled ones are paid w_L. Importantly, those cost shares can vary by model. Costs comprise labor with share β and a basket of intermediate inputs priced p_I and used with a constant share $1 - \beta$. There is also a random term $\epsilon(m)$ that captures the (mis-)match between the precise model m and the domestic country in terms of overall productive efficiency. In log terms,

$$\ln c(m) = \ln \alpha + z(m)\beta \ln w_H + (1 - z(m))\beta \ln w_L + (1 - \beta) \ln p_I + \epsilon(m). \tag{2}$$

Car manufacturers can also resort to a different production location than the domestic market, i.e. offshore to a country where all variables are superscripted with an asterisk, and ship back to home the assembled cars, with cost τ. There is also an additional cost for operating a factory abroad by the manufacturer denoted γ. Both τ and γ take the iceberg form. Costs in the case of offshoring are given by

$$\ln c^*(m) = \ln \alpha^* + z(m)\beta \ln w_H^* + (1 - z(m))\beta \ln w_L^* + (1 - \beta) \ln p_I^* + \ln(\tau\gamma) + \epsilon^*(m). \tag{3}$$

It is convenient to introduce notation ω and κ, such that

$$\omega \equiv \ln \left(\frac{w_H}{w_L} \right) \quad \text{and} \quad \kappa \equiv \ln \alpha + \beta \ln w_L + (1 - \beta) \ln p_I,$$
$$\omega^* \equiv \ln \left(\frac{w_H^*}{w_L^*} \right) \quad \text{and} \quad \kappa^* \equiv \ln \alpha^* + \beta \ln w_L^* + (1 - \beta) \ln p_I^* + \ln(\tau\gamma).$$

The choice to offshore will be driven by cost minimization, such that

$$\begin{aligned}
\text{Prob(offshoring)} &= \text{Prob}\left[\ln c^*(m) < \ln c(m) \right] \\
&= \text{Prob}\left[\kappa^* + z(m)\beta\omega^* + \epsilon^*(m) < \kappa + z(m)\beta\omega + \epsilon(m) \right] \\
&= \text{Prob}\left[\epsilon^*(m) - \epsilon(m) < \kappa - \kappa^* + z(m)\beta(\omega - \omega^*) \right]. \tag{4}
\end{aligned}$$

Assuming that $\epsilon^*(m) - \epsilon(m)$ is distributed logistically (which will be the case if each of those terms is distributed Gumbel) gives immediately a closed form formula for this probability of

offshoring:

$$\text{Prob(offshoring)} = \Lambda\left[\kappa - \kappa^* + \beta z(m)(\omega - \omega^*)\right], \qquad \text{with} \qquad \Lambda(x) = (1 + e^{-x})^{-1}. \quad (5)$$

There are two variables in equation (5) that affect the propensity to offshore. The first, $\kappa - \kappa^*$, is the additional cost needed to assemble cars (to be delivered to the domestic consumer) in the home country of the brand compared to alternative assembly locations. Our regressions will use the fixed effect of country i as a production site from our gravity equation (described in next section), together with estimated frictions γ and τ as proxies for $\kappa - \kappa^*$. The second variable in (5) is an interaction between skill intensity, $z(m)$, and the relative costs of skilled and unskilled labor compared to the rest of world, $\omega - \omega^*$. The latter factor (captured empirically with the level of development of the HQ country) make offshoring more likely for models that intensively use skilled labor. Intuitively, a rich country where the *relative* wage of skilled labor is low will tend to offshore models with low z. We refer to low z models assembled in skill-abundant countries as "misfits." On the contrary, rich countries will keep at home the models for which they have a comparative advantage, i.e. the ones that use skilled labor intensively. Empirically, we expect the combined skill and capital intensity of a model to be well proxied by its relative price. As we describe in the next section, we must purge the prices of each model of market-level determinants (such as sales taxes).

5   The proxies for assembly costs and skill intensity

The next two subsections explain how we estimate our proxies for $\kappa - \kappa^*$, the cost disadvantage of the home country in assembly, and $z(m)(\omega - \omega^*)$, the product-level comparative advantage misfit term.

5.1   Triadic gravity estimates of assembly costs

First, we need to estimate cost advantage in assembly of each car-producing nation. To do so, we take an equation from the multinational production model by Arkolakis et al. (2018), hereafter ARRY, to the data. The US-source data they use lacks the variation needed to estimate the two sets of frictions present in this equation. We therefore believe this is the first empirical estimate of what we will call the "triadic gravity" equation. The triad in question is

1. The HQ country, denoted i,

2. The final assembly location, denoted ℓ,

3. The country in which the car is sold, denoted n.

Let $X_{i\ell nt}/X_{nt}$ denote the market share obtained by ℓ-made cars of i-based brands in n and year t. ARRY's equation (7) delivers this share as the product of two factors:

$$\frac{X_{i\ell nt}}{X_{nt}} = \psi_{i\ell nt}\lambda_{int}^{E},$$

where $\psi_{i\ell nt}$ is the probability that country ℓ is the minimum-cost location for a firm from i serving market n in t, and λ_{int}^{E} is the share of n's expenditures spent on firms from i. We can leave λ_{int}^{E} unspecified here because it is captured by a fixed effect in the empirical implementation of the triadic gravity.

The costs associated with delivering a car designed in i and produced in ℓ to consumers in n depend on marginal production costs denoted $c_{\ell t}$, costs $\tau_{\ell nt}$ for shipping products from ℓ to n, and costs $\gamma_{i\ell t}$ for i-based transferring HQ inputs to factories in ℓ.[10] The aggregation of model-specific unit cost functions such as equation (1) has not yet been solved in the literature.[11] To make headway, we will therefore work with an approximation involving a representative variety so that we can still obtain aggregate flow shares of the form derived by Arkolakis et al. (2018) in their Lemma 1. The unit costs in country ℓ for that representative model are

$$c_{\ell t} = \alpha_{\ell t}\left(w_{H\ell t}^{z}w_{L\ell t}^{1-z}\right)^{\beta}p_{It}^{1-\beta}, \tag{6}$$

There are also unobserved productivity shocks, distributed multivariate Pareto with parameters θ and ρ.[12] The probability i-based firms serving n choose ℓ as supplier is

$$\psi_{i\ell nt} = \frac{\left[(c_{\ell t}\tau_{\ell nt}\gamma_{i\ell t})^{-\theta}\right]^{\frac{1}{1-\rho}}}{\sum_{k}\left[(c_{kt}\tau_{knt}\gamma_{ikt})^{-\theta}\right]^{\frac{1}{1-\rho}}}. \tag{7}$$

We can therefore express market shares as a function of two frictions and two sets of fixed effects:

$$\frac{X_{i\ell nt}}{X_{nt}} = \exp\left[\mathrm{FEA}_{\ell t} + \mathrm{FES}_{int} - \frac{\theta}{1-\rho}(\ln\tau_{\ell n} + \ln\gamma_{i\ell t})\right]$$

---

[10]Our model does not consider dynamic issues involving switching costs and uncertainty. These are likely to be important but a first step is to consider the most basic economic mechanisms in a static setting.

[11]The problem is that heterogeneity in $z(m)$ is analogous to random coefficients in a differentiated products demand model. Since heterogeneity cannot be isolated into a multiplicative shock, there is no closed form for the aggregate probability $\psi_{i\ell n}$.

[12]Tintelnot (2017) and Head and Mayer (2019) obtain an observationally equivalent $\psi_{i\ell n}$ by assuming Type 1 Extreme Value productivity shocks.

The assembly (A) and sales (S) fixed effects (FE) have structural interpretations with,

$$\text{FEA}_{\ell t} = -\frac{\theta}{1-\rho}\ln c_{\ell t}$$

$$\text{FES}_{int} = \ln \lambda_{int}^E - (1-\rho)^{-1}\ln\left[\sum_k (c_{kt}\tau_{kn}\gamma_{ikt})^{-\theta}\right].$$

We refer to $\text{FEA}_{\ell t}$ as the *cost advantage* in this industry. The next step is to parameterize the two frictions, $\tau_{\ell n t}$ between factory and buyer, $\gamma_{i\ell t}$ between HQ and factory. Let $\mathbf{D}$ represent the vector of five common friction determinants

- Home, a dummy set to one for $\ell = n$ ("tau" effects) and $i = n$ ("gamma" effects) can be thought of as the reverse of a border effect. We also interact the home dummy with indicators for whether the assembly country is a member of the OECD or, if not, is an LDC.

- Distance measures the great-circle physical separation between the main cities (weighted by population) in the assembly and market or assembly and headquarters countries.

- Contiguity: an indicator for country pairs that share a land border.

- A dummy for regional trade agreements (RTAs) such as NAFTA and the European Union.

- Applied tariffs: $\ln(1+\text{tariff}_{\ell n t})$ where $\text{tariff}_{\ell n t}$ is the tariff rate relevant when exporting cars from ℓ to n and $\ln(1+\text{tariff}_{i\ell})$ with $\text{tariff}_{i\ell t}$ being an average of tariffs paid when importing car parts in ℓ from HQ country i.

Note that the two last frictions are policy variables that vary over time unlike the geography frictions.

Denoting the corresponding vector of marginal costs for trade and production as $\mathbf{g}^T$ and $\mathbf{g}^P$, trade and multinational production frictions are given by

$$\tau_{\ell n t} = \exp(\mathbf{D}'_{\ell n t}\mathbf{g}^T), \qquad \gamma_{i\ell t} = \exp(\mathbf{D}'_{i\ell t}\mathbf{g}^P)$$

The triadic gravity estimating equation is therefore obtained by substituting the frictions terms for τ and γ, yielding

$$\frac{X_{i\ell n t}}{X_{nt}} = \exp\left[\text{FEA}_{\ell t} + \text{FES}_{int} - \frac{\theta}{1-\rho}\mathbf{D}'_{\ell n t}\mathbf{g}^T - \frac{\theta}{1-\rho}\mathbf{D}'_{i\ell t}\mathbf{g}^P\right]$$

20

We use quantity shares $Q_{i\ell nt}/Q_{nt}$, with $Q_{nt} \equiv \sum_i \sum_\ell Q_{i\ell nt}$ in place of unobserved *value* market shares $X_{i\ell n}/X_n$. Acknowledging unobserved/imperfectly measured frictions determinants, the moment condition we want to estimate is

$$\mathbb{E}\left[\frac{Q_{i\ell nt}}{Q_{nt}}\right] = \exp\left[\text{FEA}_{\ell t} + \text{FES}_{int} + \mathbf{D}'_{\ell nt}\widetilde{\mathbf{g}}^T + \mathbf{D}'_{i\ell t}\widetilde{\mathbf{g}}^P\right] \tag{8}$$

where the $\widetilde{\mathbf{g}}$ coefficients multiply $\mathbf{g}$ by $-\theta/(1-\rho)$.

Comparing this to ARRY equation (29), we see that their specification features $i\ell$ fixed effects which absorb $\gamma_{i\ell}$. Because c_ℓ and $\gamma_{i\ell}$ enter multiplicatively in the numerator of (7), a structural $i\ell$ fixed effect is separable into ℓ terms and $\gamma_{i\ell}$ if one is willing to parameterize $\gamma_{i\ell}$. However, ARRY only have data on exports for affiliates from one origin, the USA, courtesy of the BEA (ARRY's empirical application uses cross-sectional data for 1999, hence the omission of index t in this paragraph). This data limitation implies that $\gamma_{i\ell}$ is not identified in the presence of ℓ fixed effects.

A further advantage of our dataset concerns destination markets n. BEA data used by ARRY have just five specified destinations: USA, CAN, JPN, GBR, and a 14-country European Union composite. Our estimation includes 21 HQ countries, 52 producing, and 76 consuming countries.[13] Thus we have the requisite HQ-assembly variation to identify $\gamma_{i\ell}$ and much more variation for estimating the effects of the five determinants of $\tau_{\ell n}$. It should be noted, however that a large fraction (73%) of the final estimating sample has $Q_{i\ell n} = 0$.

Last, our data has a substantial panel nature (we cover the period from 2000 to 2016). This allows part of the identification on frictions to come from the within dimension for the RTA and tariff variables. It also allows for the cost advantage of country ℓ in the assembly of cars to vary over time, accounting for differences in how productivity, wages, land prices, etc. change over time across countries.

Taking triadic gravity to the data requires an error term. If we assumed a multiplicative error term distributed as a homoskedastic log-normal then we could take logs and estimate the MLE via OLS. Santos Silva and Tenreyro (2006) argue that we should prefer estimators that are consistent under weaker assumptions on the error term, such as the Poisson pseudo-MLE (PPML).This estimator has the additional advantage of keeping the zeros in the regression. We estimate this condition using PPML with market shares as the dependent variable. Our estimator is equivalent to the multinomial pseudo-MLE proposed by Eaton et al. (2013).[14]

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[13]There are two countries, Brazil and Uruguay, that the estimation drops because their sole brands (Agrale and Effa, respectively) produce only at home, thus preventing identification of fixed effects for both brand and location.

[14]Head and Mayer (2014) show that the estimator performs well under a fairly wide range of error term

Table 2: Triadic gravity trade and MP frictions estimates. Dependent variable: {HQ i, made-in-ℓ} market shares in n

	trade $\tau_{\ell n}$	MP $\gamma_{i\ell}$
home (OECD)	1.454^a	2.807^a
	$(.367)$	(1.019)
home (LDC)	3.364^a	3.743^a
	$(.517)$	$(.855)$
ln distance	$-.536^a$	$.081$
	$(.11)$	$(.215)$
contiguity	$.339^c$	$.063$
	$(.18)$	$(.399)$
RTA	$.79^a$	$.589$
	$(.255)$	$(.567)$
ln (1+tariff)	-9.285^a	-5.759
	(1.024)	(6.361)

200,735 observations (21 HQ, 52 assemblers, 76 markets, 17 years). PPML with ℓt and int fixed effects. Standard errors clustered at the assembly-country (ℓ) level. Significance levels: c: $p < 0.1$, b: $p < 0.05$, a: $p < 0.01$. The squared correlation between predicted and actual market shares (our measure of fit) is 0.91.

Table 2 provides results of our triadic gravity regression. The display is organized such that the first column shows results related to $\tau_{\ell n}$, while the second shows the ones for $\gamma_{i\ell}$, all variables being included in the same regression that also includes the full set of production(-time) and HQ-destination(-time) fixed effects. The most impressive coefficients relate to the home dummies. They point to very large advantages of producing where the markets are (first column), and for operating an assembly plant in the same country where the brand is headquartered. For both variables, the revealed effects on market share are very large: Sales in a OECD market are 4 times larger ($\exp(1.45) = 4.2$) if the car is assembled locally, and 16 times larger when the production country is also the HQ country. The corresponding home "premia" for LDCs are 29 and 42. An important point is that these large home effects are present even though tariffs are controlled for in the regression. Tariffs on assembled cars have a strong impact on sales. Our elasticity of 9.3 is reasonably close to the estimates from Arkolakis et al. (2018) (Table 1, 8.4 to 11.6 in estimations that aggregate over multiple industries), and Head and Mayer (2019) (Table 3, estimate of 7.7 using brand-level sourcing decisions that condition on each brand's set of production locations). The combination of

structures. To deal with the large number of FEs, we use the **poi2hdfe** estimator provided by Paulo Guimaraes.

typically very large tariff rates on assembled cars with this high elasticity and large LDC home coefficients implies that production has to be local for market shares to be lifted out of the negligible area in poor countries.

The other $\tau_{\ell n}$ frictions have the usual sign and imply overall that even outside national borders, proximity is important for market shares in the car industry. Membership of a regional agreement tends to double market shares ($\exp(0.79) = 2.2$) on average (and this effect is on top of the stimulus to trade from eliminating tariffs). RTA membership also has large positive effects on the headquarter-assembly country dimension, but the coefficient is estimated imprecisely. Distance and contiguity also have noisy estimates in the $i\ell$ dimension but their estimated magnitudes are near zero. In sum, triadic gravity equations yield results similar to conventional gravity estimates in the origin-destination dimension for all the standard determinants, but the only statistically significant determinant of $\gamma_{i\ell}$ is production in the headquarter country (home).

We estimate assembly-country effect, $\text{FEA}_{\ell t}$ separately from the headquarter-country effects contained in the FES_{int} effects. That is we would like to know whether cars made in Germany have high market shares abroad because Germany is a good place to make cars or because German brands are very strong. There is an analogy with worker and firm fixed effects used in employer-employee data sets as well as the "places versus people" issue in economic geography.[15] Identification is impossible without a certain degree of *overlap*. In the case of workers, that means one needs either simultaneous dual-job holders or job-switchers. In labour markets only the latter source of variation is common. Fortunately, both sources of overlap are amply available in the car data. The United States as a production country makes American, German, and Japanese brands along with smaller levels of production of other brands. Meanwhile, Japanese brands are assembled in 31 different countries. This overlap implies that the FEAs estimate the cost advantages of assembly countries after purging the influence of the strong (or weak) brands based in those countries.

Figure 8 reports our results where for each country we average the $\text{FEA}_{\ell t}$ and FES_{int} obtained from the estimation of equation (8). This results in two bars for each country, the blue one giving the advantage of the country as an assembly site, and the red one summarizing the strength of its brands through its position as a headquarters. Italy serves as the reference country in both cases which is why it is set to zero. Bars are sorted from the country implied to have the lowest costs (South Korea) to the one with the highest costs (Egypt).

Korea, Germany, Japan and the United States all rank highly as both as assembly sites and as headquarters of high performance brands. The UK is revealed to be a better pro-

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[15]See Abowd et al. (1999) on the former and Gibbons et al. (2014) on the latter.

Figure 8: The best assembly and HQ countries for cars
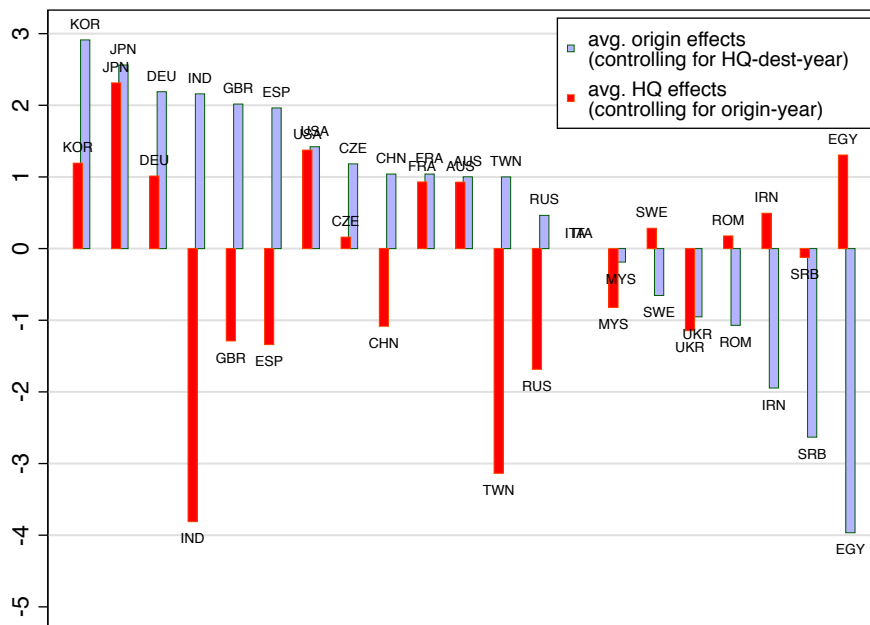
duction place than the US, but the brands originating there are estimated to be weak. This may seem surprising if one thinks of Jaguar, Aston Martin, etc. compared to Chevrolet, Plymouth, etc. However, the regression identifies a strong brand based on its sales volume performance when produced in multiple countries. The UK brands generally obtain low market shares when assembled abroad. The luxury brands from the UK are further penalized by the fact the dependent variable is measured in quantity, rather than value, shares.

Emerging economies such as Malaysia or Russia perform negatively on both metrics. Romania is an interesting case since the regression reveals it to be a quite bad location for assembling cars. In 2016, there were two assembly plants in Romania. One assembled Dacias and re-badged some of them as Renaults (the owner of Dacia). A second plant made Fords. Therefore our regression identifies the FEA for Romania based on the relatively bad performance of Fords and Renaults assembled in Romania compared to other production locations for those brands.

5.2   Model-level measure of skill intensity

To measure the model-specific skill intensity, we rely on information about relative prices. The idea is that high skill intensity requires greater use of workers who command higher wages (engineers, etc.). Our theory implies that with constant markups over marginal costs,

$\mathbb{E} \ln p(m) = \beta \omega z(m) + \text{constant}$. Thus skill intensity rises linearly with log price. This suggests that we want to obtain a market and time-invariant component of prices since we do not think skill-intensity varies in those dimensions. We therefore need to purge prices, $\ln p_m$, of the destination and time shocks. This is especially important because there are *large destination n-level price effects*. For example, a given model is generally much more expensive in Denmark than in other countries. We have 81,727 observations of $\ln p_{mnt}$ for a set of 1777 models and 28 destinations markets. Therefore we run a two-dimension fixed effects regression:

$$\ln p_{mnt} = \text{FEM}_m + \text{FEN}_{nt} + \epsilon_{mnt} \tag{9}$$

With 14 years and 28 countries, there would in principle be 392 destination-years with a full data set. However, the price data is much more sparse. The maximum is 268 with a mean of 46, and a median of nine. The minimum is two.

We define $\ln p_m \equiv \widehat{\text{FEM}}_m - \text{mean}(\widehat{\text{FEM}}_m)$ as the deviation of the model fixed effect from the mean across all models. This normalization is useful because it allows us to interpret the base effects in regression specifications with interactions.

The fixed effects used to estimate $\ln p_m$ are available for 1145 brand-model combinations. For the 1073 remaining distinct brand-models that do not have fixed effects, we use the average within the brand for the segment (14 function-size-price segments identified using Polk). For brands that are not represented in a given segment we use the average for all the models in that segment.

6 Estimates of offshoring probability equation

We use log per capita income, $\ln y_{it}$, as the proxy for the relative abundance of skill and capital in accordance with the model. The coefficient of chief interest in these regressions is the interaction of skill abundance with skill intensity, that is: $\ln y_{it} \times \ln p_m$. Our theory predicts a negative effect for this interaction term so long as the proxies are valid. These proxies receive support from the Schott (2004) finding that high income countries have comparative advantage in high-price varieties within each goods classification.

Combining the proxies for general assembly cost advantage with the interaction term representing model-specific comparative advantage, equation (4) becomes

$$\text{offs}_{m(i)t} = \Lambda(\beta_1 \widehat{\text{FEA}}_{it} + \beta_2 \ln(\hat{\tau}_{it} \hat{\gamma}_{it}) + \beta_3 \ln y_{it} + \beta_4 \ln p_m + \beta_5 (\ln p_m \times \ln y_{it}) + \cdots), \tag{10}$$

where the "$\cdots$" represent additional offshoring determinants that we adopt from the literature. Since the FEA and interaction terms are both increasing in the home's advantages,

the effects of offshoring probabilities are negative, i.e. we expect $\beta_1 < 0$ and $\beta_5 < 0$.

The dependent variable in the narrow-definition offshoring regression specification is the *fraction* of i-brand, model m *sales in i* assembled in a country with *20% lower per capita income* than i. Broad offshoring down is the fraction of i-brand, model m world-wide sales assembled in countries with 20% lower per capita income.[16]

6.1 Linear probability model (LPM) results

The first three terms in equation (10) are country-time specific. This implies that we can use of fixed effects for the headquarter country to capture them. The attraction of this approach is that we no longer need to rely on the estimated proxies from the triadic gravity equation. In this case, it is still possible to estimate the effects of $\ln p_m$, our proxy for the skill intensity of the model, and its interaction with income per capita, our measure of skill abundance. The drawback with this specification is that many of those fixed effects are perfect predictors of whether or not to offshore. Since the coefficients in linear regressions on binary dependent variables are usually very close to the average marginal effects obtained by logit or probit regressions, we run a first set of linear probability model (LPM) regressions.[17]

The first two columns of Table 3 keep offshoring decisions independently of where the model is headquartered, whereas the last two columns limit the sample to OECD countries. In each of those samples, we further distinguish between narrow and broad offshoring. A first result is that high-priced models are less likely to be offshored, especially when the broad definition is applied, in which case a doubling of the price results in a drop of the probability of offshoring to a lower-wage country by about 15 percentage points ($-0.217 \times \ln(2) = -0.15$). This is the effect for an average income country ($\ln y_i = 0$). Our main variable of interest is the interaction between the price of the model and income per capita. For a country with twice the average income in our sample, the impact of doubling a variety's price expand to a 21 percentage point reduction. This supports our hypothesis that rich countries have a comparative advantage in skill-intensive models, which results in a lower propensity to source those from abroad as income rises.

6.2 Fractional logit results

The linear offshoring specification does not take into account that offshoring fractions cannot exceed one or fall below zero. Table 4 shows that in the vast majority of cases the offshoring

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[16]Note that both the numerator and the denominator of broad offshoring are defined more expansively.

[17]This also facilitates comparison with McCalman and Spearot (2013), who estimate a linear specification along these lines.

Table 3: Offshoring regressions—Linear regressions

Sample:	all HQ countries		only OECD HQ	
Definition:	narrow	broad	narrow	broad
ln model price	-0.062^a	-0.217^a	0.020	-0.248^a
	(0.020)	(0.025)	(0.060)	(0.075)
ln model price $\times$ ln y_{it}	-0.055^a	-0.124^a	-0.133^a	-0.142^b
	(0.012)	(0.016)	(0.042)	(0.064)
ln brand sales	0.012^b	0.022^a	0.018^a	0.028^a
	(0.005)	(0.008)	(0.007)	(0.010)
ln model sales	0.002	-0.005	0.002	-0.006
	(0.002)	(0.004)	(0.002)	(0.005)
age of model	-0.000	-0.003	-0.001	-0.006^c
	(0.001)	(0.002)	(0.002)	(0.003)
years left to model	0.005^b	0.009^a	0.007^b	0.012^a
	(0.002)	(0.003)	(0.003)	(0.004)
Observations	12393	18701	9045	14871
R^2	0.263	0.320	0.253	0.287
count of models	1760	2439	1142	1745

Note: Narrow offshoring confines the market to the brand's home. Broad offshoring includes MP in all countries. Brand-clustered standard errors in parentheses. Significance levels: c: $p < 0.1$, b: $p < 0.05$, a: $p < 0.01$. Additional controls not reported here: headquarter-year and segment fixed effects.

Table 4: Offshoring fractions: narrow vs broad

Fraction of model-years offshored	Home sales		World sales	
	Count	Percent	Count	Percent
all	1627	8.7	5866	31.37
majority	99	.53	887	4.74
minority	170	.91	1864	9.97
none	10497	56.13	10084	53.92
n/a*	6308	33.73		

* n/a occurs under the narrow definition of offshoring because of model-years not sold in the home market of the model's brand.

fraction is zero or one, i.e. at the boundaries of the permissible range, which suggests we should estimate a binary choice model such as logit (or probit). The logit also allows the marginal effects to depend on the probability of offshoring. Since Table 4 shows that 1.44% (narrow definition) and 15% (broad definition) of offshoring fractions lie between 0 and 1, we use *fractional logit* as our estimation method rather than standard logit, which expects a truly binary dependent variable.

Under this specification, offshoring of model m in year t is a function of two variables obtained from the triadic gravity equation , which replaces the headquarter-year fixed effects: $\widehat{\text{FEA}}_{it}$ and $\ln(\hat{\tau}_{it}\hat{\gamma}_{it})$, with $\hat{\tau}_{it}$ and $\hat{\gamma}_{it}$ being calculated as the average of the predicted bilateral frictions using coefficients from Table 2. As in the linear specification, $\ln p_m$, and its interaction with $\ln y_{it}$ are estimated, and the omission of headquarter-time effects also allows identification of $\ln y_{it}$. Additional explanatory variables are included to capture scale effects (worldwide sales of model and brand) and vintage effects (age of model and years left in program). We also include function-size-price segment dummies and year dummies.

Table 5 provides our estimates of the fractional logit regressions. Columns (1) to (3) consider all models, whereas the last two columns eliminate models associated with 110 non-OECD (mainly Chinese) brands. The first specification is a linear model, which we use as a starting point because it can be compared to the first column of Table 3. We then move to our preferred fractional logit results in column (2). In both the linear and the logit specifications, the assembly cost advantage of the headquarter country strongly reduces the likelihood of offshoring.

The interaction between price and income is negative as expected in both the linear and logit regressions. The linear coefficient, -0.029 is somewhat smaller (in absolute value) than it was in the specification with country-year fixed effects (-0.055). The interpretation of interaction terms is complicated by the non-linearity of the logit model.[18] The best way to

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[18]See Ai and Norton (2003) for a fulsome discussion.

Table 5: Offshoring regressions (fractional logit)

	(1)	(2)	(3)	(4)	(5)
Method:	OLS	Fractional logit			
Sample:	all HQ countries			only OECD HQ	
Definition:	narrow		broad	narrow	broad
HQ comp. adv. $(\widehat{\mathrm{FEA}}_{it})$	-0.036^b	-0.610^a	-0.210	-0.603^a	-0.340^b
	(0.014)	(0.213)	(0.138)	(0.216)	(0.151)
frictions $(\ln \hat{\tau}_{it}\hat{\gamma}_{it})$	-0.018	-2.330^c	-0.347	-2.425^c	-0.293
	(0.025)	(1.209)	(0.220)	(1.299)	(0.425)
$\ln y_{it}$	0.056^b	3.644^a	1.223^a	3.289^a	0.363
	(0.024)	(1.209)	(0.210)	(1.155)	(0.294)
ln model price	-0.012	0.649	-1.347^a	-0.052	-1.983^a
	(0.018)	(1.035)	(0.268)	(1.685)	(0.518)
ln model price $\times \ln y_{it}$	-0.029^b	-1.802^b	-0.865^a	-1.281	-0.507
	(0.014)	(0.807)	(0.262)	(1.203)	(0.520)
ln brand sales	0.007	0.135	0.250^a	0.123	0.242^b
	(0.007)	(0.134)	(0.091)	(0.134)	(0.095)
ln model sales	0.006^b	0.068	-0.035	0.072	-0.031
	(0.003)	(0.057)	(0.029)	(0.058)	(0.031)
age of model	0.001	-0.002	-0.035^c	-0.003	-0.035
	(0.001)	(0.039)	(0.021)	(0.041)	(0.023)
years left to model	0.006^b	0.092^a	0.051^b	0.090^a	0.062^b
	(0.003)	(0.033)	(0.026)	(0.034)	(0.026)
Observations	11796	11796	18076	9039	14864
R^2	0.106	0.243	0.310	0.228	0.288
count of models	1726	1726	2405	1142	1745

Note: Narrow offshoring confines the market to the brand's home. Broad offshoring includes MP in all countries. Brand-clustered standard errors in parentheses. Additional controls not reported here: year, segment. Significance levels: c: $p < 0.1$, b: $p < 0.05$, a: $p < 0.01$.

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understand these effects is through graphical display. The marginal effects (evaluated from the 1st to 99th percentiles) of model price and income are displayed in Figure 9. In panel (a) we see that for low income countries the marginal effect of a higher price is near zero. This is telling us that poor countries are unlikely to offshore *any* models, regardless of their price. This fact is illustrated in Figure 10 where we see the model predicts and the data depicts the absence of offshoring by poor countries.

The marginal effect of a higher price remains near zero until relatively high levels of GDP per capita are achieved. For countries with incomes over that of Spain in 2016, the marginal effect becomes significantly negative. For the highest income HQ countries (USA, Sweden, and Australia in 2016), increasing the price by 10% decreases the likelihood of offshoring by 1.5 percentage points. This should be seen as a substantial effect given that the average probability of offshoring is just seven percent. The histogram of per capita incomes shown below the marginal effects in Panel (a) reveals that most of the models in our sample are produced in countries whose incomes are high enough to yield significantly negative marginal effects of price.

Figure 9: Marginal effects of interacting comp. adv. factors

(a) Model price

(b) GDP per capita
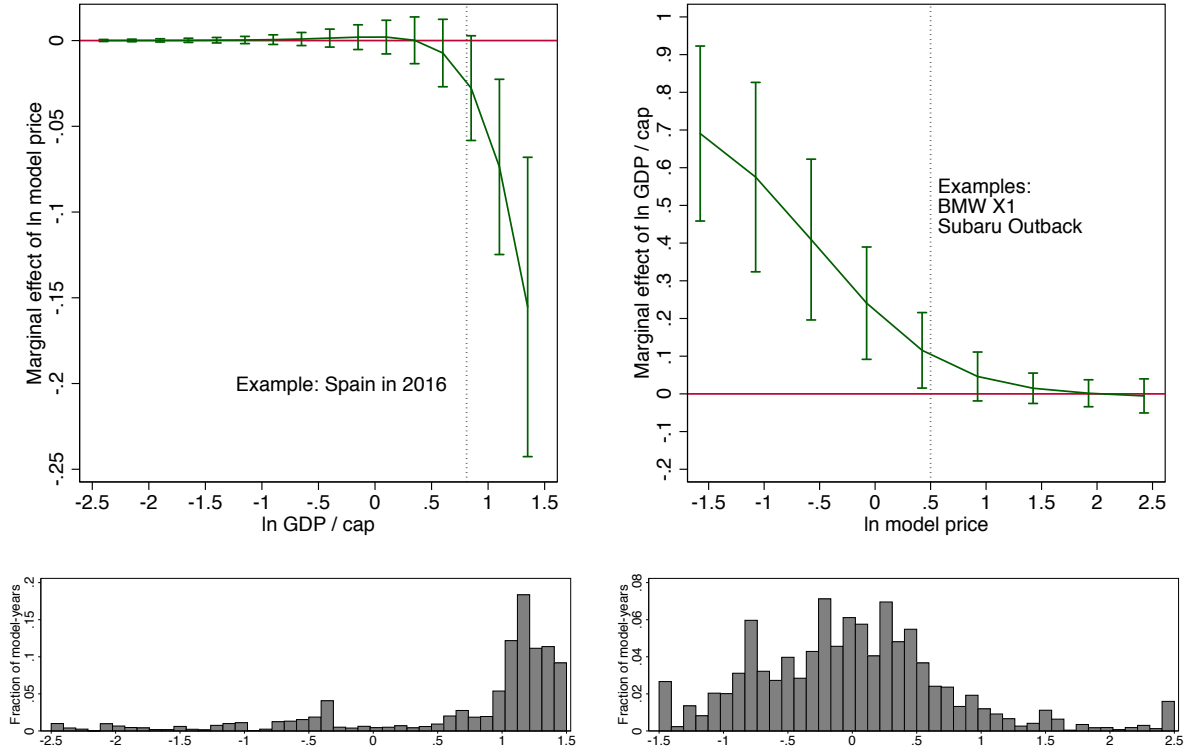
Panel (b) of Figure 9 displays the marginal effects of higher income conditional on model

price. There are large positive effects for inexpensive cars and zero effects for very expensive cars. The switchover point from positive to negative effect occurs at the price level of a BMW X1 or Subaru Outback ($\ln p_m \approx 0.5$). As the histogram below panel (b) indicates, higher income countries are *more* likely to engage in offshoring for the vast majority of the models in our sample.
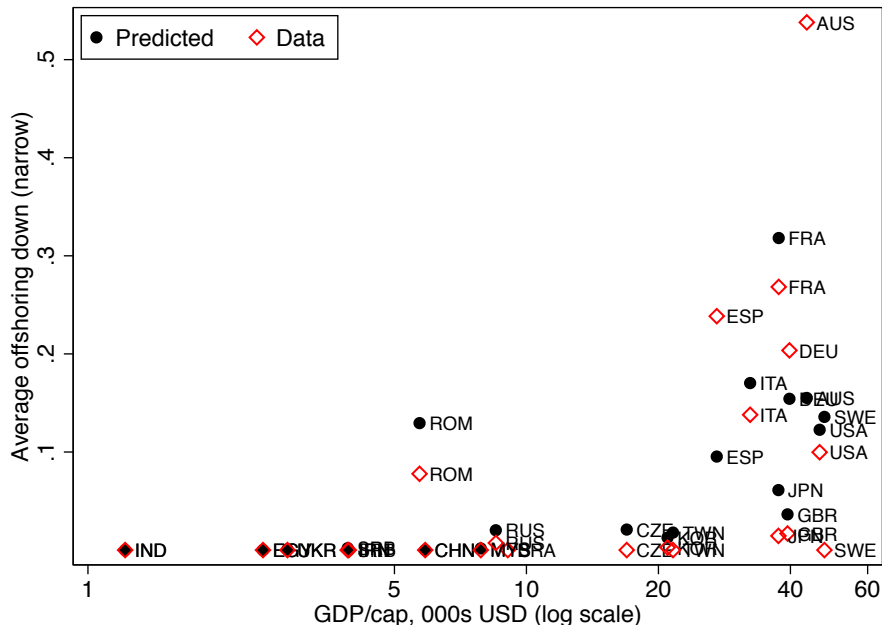
Figure 10: Offshoring is for the rich

Figure 10 shows that the estimated model can predict national rates of offshoring reasonably well. Offshoring in the data by the historical brand headquarters (France, Italy, UK, Germany, Japan, and USA) are all fairly close to their predicted levels. There are two prominent deviations from the predicted offshoring rate that turn out to be based on single brands. Seat (a subsidiary of Volkswagen) is the only Spanish brand. Our regressions predict it should offshore very little and indeed the models from which it derives most sales (Ibiza and Leon) are assembled in Spain. However, Seat offshores four models that it sells in tiny amounts. Australia is an even more glaring case of the regression under-predicting the rate of offshoring. Again there is only a single domestic brand which is owned by a large foreign firm. In this case, General Motors was phasing out the manufacturing activity of Holden over the estimation period. On 20 October 2017, Holden closed its last Australian plant, although the brand continues as an importer of vehicles (that is, offshoring rises to 100% in 2018).

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6.3 Other determinants of offshoring

Our discussion of results in the two previous subsections focuses on the two chief hypotheses about offshoring, general cost advantages in assembly and model-specific comparative advantage. We now discuss the controls that we added to the specification.

Our regressions incorporate dummies for the market "segment" of each model. We classified all models into 14 segments based on three categorical variables provided by IHS:

- Function/usage (SUV, MPV, sport car, etc.) referred to in the data set as "Global Sales Sub-segment"

- Size categories (A–F), measured in length, but relative to the corresponding functional category. In the data this is called the "Global Sales Segment."

- Price class: entry/mid-level (1), premium (2), luxury (3). The first two are defined relative to size and function categories; luxury is a stand-alone segment. This variable is called the "Global Sales Price Class."

Table 6: Size of 14 categories (2000–16 totals)

Category	Value ($bn)	Volume (mn)	Price($th)	Brands(#)
midloCar	7794.68	331.47	23.52	94
bigSUV	5873.86	93.28	62.97	96
smallCar	3610.34	226.78	15.92	97
smallSUV	3309.28	98.36	33.64	99
midhiCar	1592.46	46.3	34.39	23
bigMPV	1537.79	40.44	38.03	53
smallMPV	1512.37	65.77	22.99	55
bigmedCar	1379.55	26.61	51.83	26
bighiCar	405.74	3.53	115.03	11
bigloCar	327.84	10.32	31.77	34
midSport	256.18	7.16	35.77	25
bigSport	234.97	2.68	87.56	24
smallSport	83.04	3.18	26.09	23
lux	74.53	.33	228.98	16

We provide some basic information on the 14 segments in Table 6. The table sorts the segments by an estimate of worldwide sales values in that segment. The quantities come from our main data set but the average prices for each segment are estimated based on much more limited data. We see that segments are very different in size. Thus a firm can achieve high market share in the "lux" (luxury) category with much lower volume of sales than in the "midloCar" segment.

Figure 11: Segment-level effects of offshoring rates
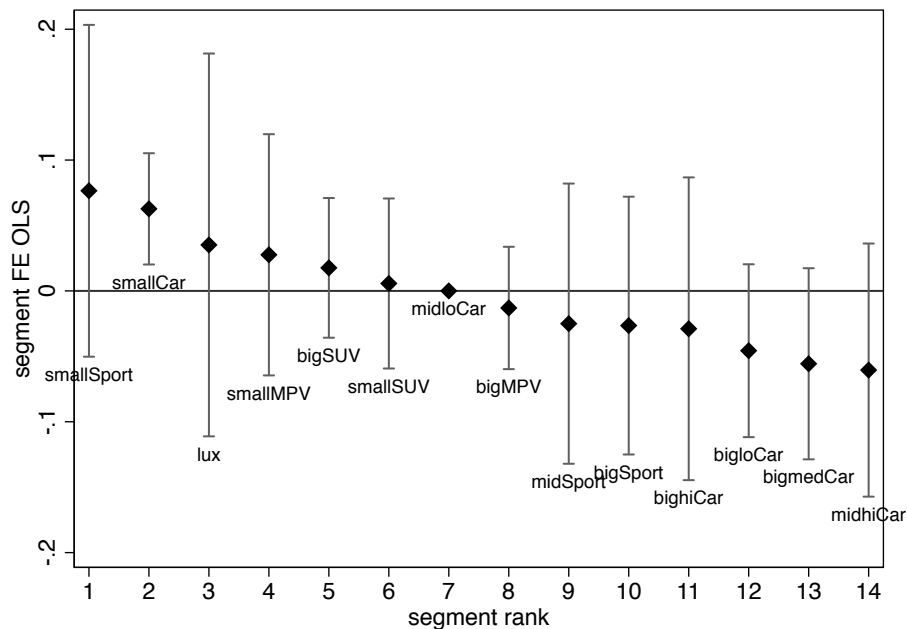
The segment-level fixed effects are displayed in Figure 11, where mid-sized, low price cars (midlocar) are taken as the benchmark.[19] The dominant feature of this figure is that smaller cars are more offshoreable. This effect is above and beyond the fact that smaller cars are cheaper since we have controlled separately for price at the model level. This could be due to lower shipping costs for smaller cars and lower import tariffs (which are generally positively associated with larger engine sizes). Smaller cars may also be less skill-intensive.

We included controls for scale and vintage effects, in part to be able to compare results to those of McCalman and Spearot (2013). They find negative variety-level scale effects on offshoring to Mexico. In particular, trucks produced at above-median scale are *less* likely to be offshored. We cannot think of any microeconomic underpinnings for dichotomizing scale and therefore measure it as log world-wide sales (in units) of the model. Model-level scale has small and statistically insignificant effects. On the other hand, we find brand-level scale is a positive predictor of broad offshoring, a result that is consistent with the mechanism of Helpman et al. (2004).

A second variable for which we can compare results is the "vintage" of a model. Mc-Calman and Spearot (2013) find that varieties are less likely to be offshored in their first year of production. The story attached to this result is older varieties are more standardized and therefore easier to produce far from headquarters. However, recent work by Hanson

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[19]As can be seen in Table 6, midlocar is the by far largest segment by volume.

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(2015) finds a negative relationship between offshoring and routinization that pushes in the opposite direction. He argues that tasks that are routine tend to be easier to automate. When automation is an option, it appears to dominate offshoring. We find that model age has an effect that is small and mainly not statistically different from zero. In the two specifications where variety age is marginally significant, it has a negative effect, more in line with Hanson's result.

Car model designs are referred to in our data as "programs." Since they have different durations we can separate the age of a model from the number of years left in the program. While age has essentially no effect, there are systematically positive and significant effects of "years left" on the offshoring decision. The natural interpretation for such effects is that it is easier to recover the fixed costs of offshoring for models with longer lifespans.

Our price results are quite different from McCalman and Spearot (2013). They find that only price residuals matter and they enter negatively. Our data lacks the features of models that might be used to estimate price residuals. However, we find that prices themselves have negative impacts on offshoring, provided the per-capita income of the home country is high enough.

An important finding of McCalman and Spearot (2013) is that complexity reduces offshoring. They measure complexity using variation in a large vector of features. Our data contains no direct analogue for this measure. However, we conjecture that if we did have variation in features, it would be higher for higher priced and larger cars. Hence our results that higher price varieties and larger cars are less likely to be offshored could arise in part from their greater complexity.

McCalman and Spearot (2013) have data on US and Mexico only so they cannot estimate the role of country-specific "assembly advantage" as we do here. Also they cannot estimate the interaction between country development and model prices. Furthermore, as their data set has sales in Canada and US only, they cannot calculate our "broad" measure of offshoring.

To sum up, we find that controls for variety age and scale have very little effect on the decision to offshore. The variables that do seem to promote offshoring are small size, brand scale, and years left for the model's design. Taken as a whole, however, the controls do not affect in a material way the key results of our paper, namely that richer countries tend to offshore low-end cars. To establish this, we reproduced Figure 9 without any of the additional controls. As can be seen in Figure 12, the structure of the marginal effects remains the same. For per capita incomes over that of Spain, higher priced cars are less likely to be offshored. Moreover, for models less expensive than the Subaru Outback, a rise in income significantly raises the propensity to offshore.

Figure 12: Marginal effects without additional control variables

(a) Model price

(b) GDP per capita
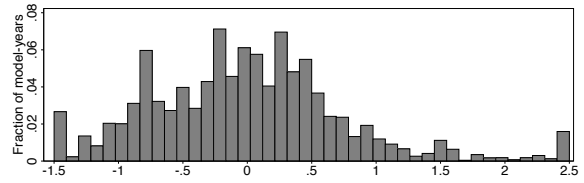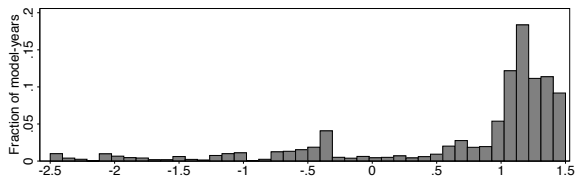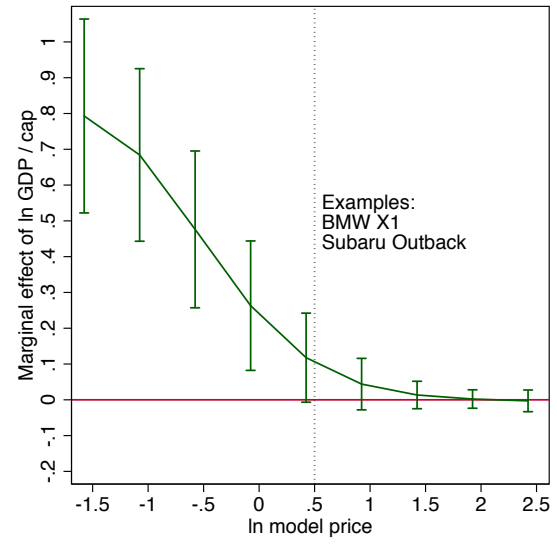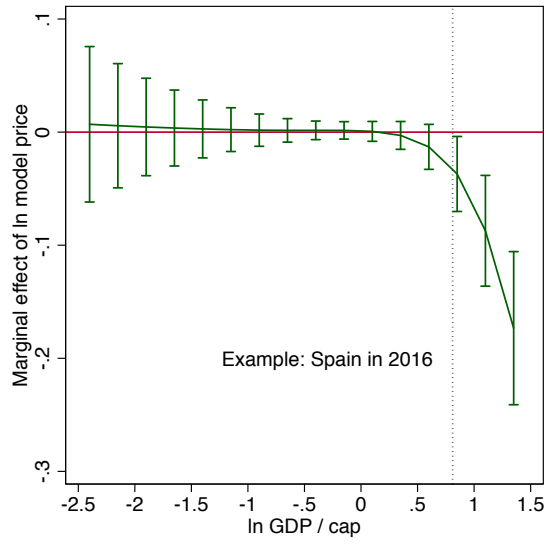
7 Conclusion

Offshoring assembly to lower wage countries is growing in the car industry. Under the broad definition comprising all car assembly in lower income countries, offshoring has risen from 20% (in 2000) to 40% of global production. However, because of tariff and large estimated non-tariff barriers, we find this form of offshoring is mostly motivated by the need to produce locally to serve LDC markets. Under our narrow definition that considers only cars assembled in low wage countries to be sold at home, the amount of offshoring is quite limited, accounting for just eight percent of the home country's market. Furthermore, the lower wage countries in question generally do not include the countries best known as offshoring sites for other industries. Car makers assemble in China mainly for the Chinese market. When making cars for the home or third-country markets, the preferred assembly locations appear to be Mexico (for serving the North American market) and the Eastern European countries that entered the European Union in 2004. The other sense that offshoring is limited is that it is highly concentrated among a few firms. The top five brands in any given year account for about half of narrow offshoring.

Our triadic gravity regressions estimate a substantial *double penalty of offshoring*: γ frictions give a cost disadvantage to factories outside the home country and τ frictions add further costs on the cars when they are imported back into the home market. The only force militating in favour of offshoring by the narrow definition is comparative disadvantage at home. We therefore hypothesize that comparative advantage should play a major role in determining why some models are offshored and others not. We find that estimates of HQ country *cost advantage* in car assembly are strong negative predictors of narrow offshoring but have weaker effect on broad offshoring. This makes sense given that broad offshoring undoubtedly includes much production abroad that is oriented towards market access in the host country.

Looking within countries we find that *low-price* models from *high-income* countries are the most likely to be offshored. A traditional Heckscher-Ohlin interpretation of this result is that price is acting as proxy for skill intensity and per capita income is a proxy for relative skill abundance. Alternatively, it could be that high price is measure of quality, which high income countries have a comparative advantage in supplying. Prices also capture markups, of course. There is a widespread intuition that low markups and competition "force" low-margin varieties to be offshored. However, a cost minimizing firm should still want to produce its high-markup models in the low-cost location. Hence we prefer the interpretation that cross-product variation in offshoring is mainly driven by misfit between variety-level factor intensity and factor abundance in the headquarter country. This view

conforms with the conclusion that Hanson (2015) draws from comparing offshore assembly rates across sectors: "a narrative with strong Heckscher-Ohlin plot lines seems to tell much of the story of changes in global production sharing. It may require much richer industry data to find other determinants at work." The striking result of our paper is that when using the very rich data on global car assembly, we again find a pattern of offshoring that can be well-explained by invoking Heckscher-Ohlin forces.

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