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Why trucks jump: Offshoring and product characteristics ☆

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ABSTRACT

In this paper, we study the role of vertical product differentiation in the decision to allocate production between domestic and foreign plants. To do so, we examine the first wave of light-truck offshoring to Mexico that occurred due to substantially lower post-NAFTA trade barriers and a coincident increase in US demand for light trucks. In contrast to the typical assumption, but similar to many other industries, the need for additional capacity was accommodated by investment in both the US and Mexico for the same models of light trucks. Using a new dataset that details the extent of offshoring and domestic production within models, we document sharp differences in how capacity was utilized. Specifically, within models, we find that automakers offshored varieties which tend to be older in design vintage, lower scale, and less complex to produce. In contrast, we find that varieties "inshored" to newer capacity in the US exhibit the opposite characteristics. This highlights the important role of vertical differentiation and the associated variation in production complexity for the sorting of production across borders. A product with a large degree of vertical differentiation may provide scope for a firm to maximize profits by "inshoring" the more complex varieties while offshoring the less complex versions.

1. Introduction

It is well-known that multinationals are big, productive, and by definition operate multiple plants within and across multiple locations. However, a fact often lost in the multi-plant nature of multinationals is that many firms produce the same basic product across locations with very different production characteristics. Moreover, these plants serve the same markets.[1] For example, the Fender guitar company produces the "Stratocaster" – a very specific style of electric guitar – in California and Mexico. Whirlpool produces refrigerators in Arkansas (until recently), Iowa, and Mexico. Indeed, this behavior extends beyond manufacturing trade, where some tele-radiology firms headquartered in the US own assets in Sydney, Barcelona, Tel Aviv, and Bangalore to perform radiological services for US hospitals (Levy and Goelman, 2005). What causes a firm to source a very similar product across multiple plants, and once these plants are operational, how do multinationals allocate output across these plants?

A natural industry in which to study these decisions is the US automobile industry. Like the industries described above, it is characterized by large multinationals that source many models of products across a number of plants globally. However, in terms of sheer scale few sectors match the US automotive industry, comprising a large share of overall trade (Hellerstein and Villas-Boas, 2010) and in some cases, driving a large share of trade growth following trade agreements.[2] Furthermore, due to comprehensive registration requirements, excellent data exists to study the production sourcing decisions of these firms, and in particular, the location of final assembly. In this paper, we focus on the offshoring decisions of light-duty trucks within this industry over the period 1990–2000. In particular, we present new facts for large multi-plant firms, and study how these firms allocate the final assembly of light-duty trucks across similarly capable plants based in very different locations.

What does theory suggest should drive the sourcing decisions of multinationals? Theory tends to emphasize production characteristics such as factor intensity as determinants of the location of production. Following this logic, to serve US and Canadian consumers, it may be

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[1] This feature distinguishes these investments from platform FDI which can have a horizontal dimension.

[2] For example, after NAFTA, the US auto industry was responsible for 25% overall trade growth (Hufbauer and Schott, 2005).

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optimal to build complex, high-tech products within the US–Canadian market, where capital and automation are relatively cheap, and low-quality, low-tech, and standardized varieties in Mexico where unskilled production labor is relatively cheap (Vernon, 1966; Feenstra and Hanson, 1997; Antràs, 2005; Keller and Yeaple, 2012).[3] On the other hand, if consumers in Mexico demand the same low-quality products (as in Verhoogen, 2008; Fajgelbaum et al., 2011) that are optimal to produce in Mexico for factor endowment reasons, then it is an empirical question as to whether any sorting of production across borders is due to local demand or relative factor endowments.

To study this issue, we use an extremely detailed dataset of light truck sales in the US and Canada, along with supplementary (though more aggregate) information on sales in Mexico. Studying the final assembly of light-duty trucks, which includes SUVs, pick-ups, and vans, has a number of advantages. First, final assembly represents a common point in the value-chain within and across firms, where a mix of workers and machines assembles large primary inputs, but potentially also adds a wide variety of other options to complete the finished product. Second, it is notable that the pre-NAFTA trade barriers were effectively prohibitive, so their removal provides scope for greatly expanded trade in light trucks. However, this is only part of the story. A rapid expansion of demand for light trucks – demand doubled in the US in the 1990s – provided a need for additional assembly capacity.[4] The combination of the elimination of trade barriers and a dramatic increase in demand makes low wage Mexico an attractive location for investment in light truck assembly capacity. However, similar to the examples cited above, any light truck model that was offshored post-NAFTA to Mexico was also inshored to new facilities in the US. This suggests that locations with very different labor costs are producing the same product from investments that are made at the same time. Is it possible to rationalize this behavior in terms of the theories developed in the existing literature or does this behavior point to new and unexplored factors?

To begin our analysis, we outline how *scale* and *vertical differentiation* motivate the production of a common light truck model across multiple plants. In terms of scale, as the market naturally grows, additional capacity is warranted. However, it may be easier to expand production at a new location rather than increase capacity at an old one, or spread production over multiple locations to minimize the down-side risk of local production disruptions. In both cases, increased scale of a model optimally leads to more plants tooled specifically for that model. In terms of vertical differentiation, a model with many different varieties should be optimally produced by plants with different characteristics. For example, a newer plant in the US may be more technologically advanced, which facilitates production of more sophisticated or non-standard varieties within a model. On the other hand, a plant in Mexico may be more labor intensive, and a facility at which less-sophisticated varieties are produced. Hence, models with a high degree of vertical differentiation could potentially be sourced across a heterogeneous set of plants. This provides scope for plants in both the US and Mexico to produce nominally the same "model", though the extent of vertical differentiation means that the actual characteristics of the vehicles produced are different.[5]

We find evidence for both predictions, and a particularly pronounced role for vertical differentiation, where within firm–year pairs, models with a greater mix of varieties, and higher scale, tend to be produced across more plants. Furthermore, when a model receives additional plants, it is associated with a reduction in the percentage of total varieties that are produced at the typical plant. Hence, greater differentiation is associated with more plants and more plants are associated with increased specialization at each plant. The question then becomes how plants are utilized conditional on being tooled for a specific model. If the role of vertical differentiation operates as suggested above, then we should see a clear segmentation of varieties within a model across plants as a function of their attributes. Indeed we find this to be the case. Specifically, we find that offshored varieties tend to be of older design vintage, less complex and lower scale. This is true both in comparison to established facilities and also new domestic plants. Within the US, we also find that newer plants tend to receive higher scale, more complex, and newer vintage varieties when compared to older plants. Overall, our results are consistent with the notion that vertical differentiation plays a role in sourcing of varieties across locations. Moreover, the patterns that we document for offshoring are in-line with the role of labor intensity in automobile production (low-scale, low complexity) and the role of product cycles (older design vintage) through the relative abundance of unskilled labor.

To test whether these patterns are related to supply motives for offshoring, or are driven by local demand considerations, we merge an auxiliary dataset of sales in Mexico at the model level and test whether these sorting patterns are more pronounced when Mexican demand is relatively low. If these sorting patterns are more pronounced when demand in Mexico is relatively high, then this suggests that local demand in Mexico is "pulling" the offshore production of varieties for the US that would also be produced in Mexico due to relative factor endowments. In contrast, if these sorting patterns are more pronounced when demand in Mexico is relatively low, this suggests that the supply characteristics of producing in Mexico are the main factor, not local demand for less-sophisticated varieties. Indeed, we find the latter is the case for all characteristics, where the pattern of offshoring is more pronounced when demand in Mexico is a very small share of total demand. Hence, we conclude that the supply characteristics of producing in Mexico are driving the patterns of offshoring, not demand characteristics. Furthermore, we also evaluate various measures of input quality, and show that while it appears physical quality and residual prices are lower for offshored varieties, these are not driving the main results described above.

The results in our paper add a new dimension to the understanding of production allocation decisions of large firms, and in particular, multinational firms. Similar to Hanson, Mataloni and Slaughter (2005), our primary analysis evaluates allocation decisions internationally conditional on the state of production facilities at a given point in time. However, we augment this perspective by emphasizing the role of product characteristics, especially vertical differentiation within a product line and the associated variation in production complexity. If a product is defined at a relatively aggregate level (such as a light truck model), then theory may suggest that highly differentiated products should not be produced in less developed locations due to their complexity. However, this ignores the fact that a product with significant within-; product differentiation can potentially have different quality varieties targeted to different plants, both inshore and offshore. At the finest level of detail, we find that highly complex and/or "new" varieties are in fact unlikely to be produced in Mexico, as theory would suggest.[6] While this makes a more basic (and obvious) point about getting the data "right", and is similar to Schott (2004) and Khandelwal (2010) where specialization occurs within products rather than across products, it makes a deeper point about the economics of production allocation decisions within multinationals. That is, while product differentiation can lead to more complexity, it can also provide

[3] Also see Helpman (1984), Grossman and Rossi-Hansberg (2008), and Baldwin and Robert-Nicoud (2010).

[4] For brevity, the US also includes Canada for the remainder of the paper.

[5] This is in spirit similar to Grossman and Rossi-Hansberg (2008), where given sufficient differentiation in tasks, inputs for a given product will be split by location. Otherwise, production will be located either all offshore or all inshore.

[6] This would suggest that models of vertical specialization such as Hummels et al. (2001) may be capturing trade in low-specialization varieties within industries. In terms of the magnification of trade shocks through this channel, if these different varieties have different elasticities, it is no longer clear how generalizable their results are to industries that are not offshored.

opportunities for specialization within the firm. Indeed, we find that US automotive firms exploit these opportunities for specialization within high-differentiation models and across those plants which are specifically tooled for them.

Finally, our results also suggest a more nuanced but nevertheless important role for the standard theories of offshoring and the closely associated product cycle model. While the big three had an opportunity to offshore a significant fraction of their light truck production to take advantage of lower labor costs, they pursued a more limited offshoring strategy. The critical limiting factor is production complexity. Broadly, this suggests that the "giant sucking sound" of jobs lost to locations with the lowest labor costs may in fact be mitigated by this type of complexity and the targeting of particular product varieties to specific locations.

2. NAFTA, light-duty trucks, and industry structure

The importance of auto trade among NAFTA countries is undeniable. For instance in 2003 it accounted for 20% of all trade between the NAFTA partners. Moreover, between 1993 and 2003 NAFTA motor vehicle trade almost doubled, accounting for 18% of the growth in NAFTA trade over this period (see Hufbauer and Schott, 2005). The light truck segment stands out as one area where growth was especially rapid. A major reason for this growth is that the policies in place prior to NAFTA essentially eliminated trade in light trucks between the US and Mexico, where along with a number of non-tariff barriers, light truck imports to the US incurred a 25% MFN tariff.[7] The removal of trade barriers due to NAFTA created the potential for significant production to be relocated to Mexico in the light-truck sector — an opportunity that was exploited immediately. From a standing start at the implementation of NAFTA, the big three were able to invest in facilities south of the border to the extent that up to 7% of all pick-ups and SUVs sold in the US in 2000 were produced in Mexico. Within the specific vehicle platforms that were offshored (defined below), up to 50% of total US sales originated from production offshore by the year 2000.

The growth in light-truck trade from Mexico was in stark contrast to that in passenger cars. Part of this was policy driven, where the MFN tariff on passenger cars has long been 2.5%–1/10th of that for trucks. Indeed, prior to NAFTA and unlike light-duty trucks, US automakers had already built production facilities in Mexico to serve the US market. Moreover, no new passenger vehicle facilities were installed south of the border immediately following the implementation of NAFTA.

Another key factor driving investment was the pronounced shift in consumer demand toward light trucks in the US and Canada over the period 1990–2000.[8] In 1990 the big three sold approximately 3 million light trucks domestically which they produced at 23 US plants (average plant scale: 132,944). By 2000 these same firms were producing over 6 million light trucks at 36 North American plants (average plant scale: 168,291). While the reduction in trade costs made Mexico a viable option, it was only one location that was used to meet this increased demand. In particular, four Mexican facilities were producing for the US market by 2000, while a further nine US plants started producing light trucks between 1994 and 2000. Moreover the increase in demand was so pronounced that over this period of expansion almost every North American light-truck plant was essentially producing at full capacity.

So, by 2000 the typical US firm is producing 2 million light trucks in 12 plants. How does it allocate production across these plants? Some constraints are imposed by the market segment previously produced in the plant — for instance significant investment is required to change production from a minivan to a SUV (or even from a compact SUV to a full-size SUV).[9] Furthermore the scale of the various market segments often results in the same types of vehicles being produced across multiple plants. Hence, the question is what particular models or varieties of light-truck were offshored to Mexico, both relative to old plants in the US, and new light-truck plants in the US? Did the firms simply use the Mexican production as a source of flexible capacity (thereby replicating US capacity)? Or, did these firms systematically offshore different varieties of truck to Mexico?

3. Data

The data for this project primarily comes from two industry sources, which are merged into a large dataset of vehicle characteristics, plant of production, and sales information for model years 1990–2000. The source for production information is a custom dataset constructed by *R.L. Polk* (Polk) based on the population of vehicle registrations (sales) in the US and Canada. Specifically we acquired sales information for every observed permutation of vehicle characteristics and plant of production, both types of information available in the vehicle identification number (VIN). We complement this data with manufacturer suggested retail prices as listed at the *beginning* of the model year and important vehicle characteristics such as vehicle weight and maximum cargo weight. This information is obtained from the *Wards Automotive* dataset of vehicle characteristics (Wards). The Wards data provides all information that is in the Polk dataset with the exception of sales and location of production, along with more refined data on characteristics, prices, interior trim levels, and transmission options. Later, we will integrate two smaller datasets to provide supplementary information on sales in Mexico, and labor-hours required for production in the US.

A critical part of our analysis is choosing an appropriate level of detail to define varieties. Previous analyses define varieties by their basic make–model pair (e.g. GMC Sierra), and if applicable, country of origin. Facilitated by our dataset, we can define light trucks at additional levels of detail that will provide insight into the nuanced nature of offshoring decisions.

3.1. Definitions of light truck market segments

Aside from the firm and basic vehicle classes, the broadest level of aggregation is a *platform*. A platform embodies the basic vehicle type within a firm from which different models can be manufactured. From platforms, we define a *model* as some arrangement of a platform that may differ by within-firm brand and weight-class: for example the Chrysler full-size pick-up platform ("BR" Platform at the end of the sample) has three models, the Ram 1500, Ram 2500 and the Ram 3500. Note that this is essentially the level at which the existing literature evaluates trade in autos. Given that there is no standardized classification of platforms across manufacturers, and that platform names may change over time, we organize stated platforms and their associated models into like definitions of platforms across manufacturers. The basic definition follows certain manufactures that define platforms as "the application of … architectural standards to a related family of vehicles (e.g. full-sized SUVs)".[10]

[7] For an extended discussion of substitution and input requirements, see Chapter 4 of *Assessing NAFTA: A Tri-National Analysis*, Fraser Institute, 1993. In terms of a non-tariff barrier to trade within US fuel economy rules, we direct the reader to our companion paper (McCalman and Spearot, 2012) for a detailed analysis of this program.

[8] In 1990 the ratio of passenger vehicle sales to light truck sales was 2 to 1. By 2000 it was 1 to 1.

[9] We document examples of these costs in Section 3.2.

[10] See Winter and Zola (2001). This particular definition is attributed to GM, and some manufacturers use a broader definition (especially for cars). However, inspection of each light-truck platform name within each firm matches well with this definition. A full concordance is presented in Appendix A (in Table 12).

The next level of detail is a *product-line*, which is defined as platform interacted with weight-class and engine-type (engine size (liters), number of cylinders, and whether the engine runs on diesel fuel). As we describe later, this definition is chosen as the natural nest within which offshoring should be analyzed. The finest level of detail (for which sales information is available) is *variety*, which is based on the variation in options that are available within a product-line. These options/features include drive-type (4×4), cab style (regular, extended or crew), whether or not there are heavy duty or long-bed (pickup) options, and within-firm brand if relevant (e.g. GMC vs. Chevy, Ford vs. Mercury, or Dodge vs. Chrysler vs. Plymouth vs. Jeep). At this level of detail, we also introduce the concept of a *configuration*, which is a variant of each variety based on features beyond what Polk provides. These may be interior trim levels, the type of heavy-duty or long-bed options, transmission options (number of gears, automatic), and work truck features. In Appendices A and B, we provide an example of these configurations from the Wards database.

To identify the configurations of each variety in each year, we use the entries in the Wards database that match with each variety in the Polk database. The number of platforms, models, product-lines, and varieties in the dataset are presented in Table 1. We have also provided the average number of configurations per variety. Clearly, the level of detail in our dataset is substantially greater than the current frontier in terms of examining trade or FDI[11]. Hence, the level of detail in our sample will not only allow for an analysis of which models were offshored (the current literature), but also which segments within each model based on their product characteristics were offshored. This is a critical point if we are to provide a comprehensive view of how vertical differentiation acts as a conduit for allocation of varieties to different plants.

3.2. Light-truck investment in the US and Mexico: Offshoring and inshoring

The definition of offshoring for our sample is straightforward. Specifically, since light-truck imports by the domestic automakers were extremely small prior to NAFTA, we define offshored models as those that utilized capacity in Mexico to serve the US market after 1994. This occurred via two brand new plants, one significantly retooled, and one existing.[12] The definition of inshoring is more subtle. Along with some new capacity, one of the interesting features of the 1990s is that idled car plants were refurbished and retooled to satisfy the increasing demand for light trucks in the US. Hence, we define inshoring as a model–plant pair that is not present in the light-truck market prior to 1994 that adds a model that also continues to be produced at an older plant (hence capacity does not just switch from one plant to the next).

These investments for upgrades, product switching across truck and car platforms, and new facilities, are far from trivial. While data on specific capital investments is not systematically available for our sample period, Harbour (1990) details the costs of various upgrades and new facilities for Chrysler and Ford during the 1986–1989 period.[13] New facilities for both firms cost upward of 1 billion (1986) dollars. Various types of modernization are also quite costly. For example, new tooling at Ford Wixom assembly required a $500 million dollar capital expense. Product switching is similarly costly, where switching production at Warren Assembly ("Dodge City") from the Dodge Ram Charger full-size SUV to the Dodge Dakota compact pick-up required a $490 million capital expense. Similar costs are incurred at other plants for similar investments across both cars and trucks.

[11] For research on autos conducted at the model level, see Berry et al. (1995), Goldberg (1995), Blonigen and Soderbery (2010) and Sly and Soderbery (2012).

[12] This information is compiled from various years of the *Harbour Report*.

[13] GM data is not provided.

Table 1
Sample detail.

Platforms	23
Models	76
Product-lines	279
Varieties	845
Avg. configurations per variety	4.08

Notes: This table presents the number of platforms, models, product-lines, and varieties available in the dataset. The table also presents the average number of configurations per variety.

4. Specialization across locations

With this dataset we examine the behavior of multi-plant firms and the specialization across plants within models. As outlined in Van Biesebroeck (2007) firms tool plants for more aggregate units such as platforms or models, but in a flexible manner such that many varieties within the model or platform can be assembled in a fashion consistent with just-in-time manufacturing. Crucially, tooling a plant for a particular platform in most cases prevents other platforms from being built at that plant, and thus restricts the set of varieties that can be built at that plant. Hence, we first look at platforms, and the specialization that occurs within platforms.

A natural null is that a plant is just a plant and that there is no specialization within platforms across plants. More specifically, when scale requires multiple plants the production allocation decision reflects a cost minimizing strategy for expansion (i.e. old plants are hard to expand), or that multiple identical plants are optimal from a diversification perspective. The alternative hypothesis is that there is specialization across plants within platforms and models. To evaluate this hypothesis Table 2 presents the output weighted average of the number of plants per platform, model, and variety. If plants within a platform are the same, and models and varieties were allocated randomly, there should be an equal number of plants per platform, model, and variety. Clearly, this is not the case, where there are more plants per platform than per model, and more plants per model than per variety. This suggests a degree of specialization within platforms across plants.

A more systematic way to evaluate specialization is to look within models over time, and evaluate the share of varieties within a model that are produced at a typical plant. In particular, we estimate the following via OLS:

$$vshare_{m,t} = \alpha \cdot Plants_{m,t} + \alpha_m + \alpha_t + \epsilon_m, t. \quad (1)$$

Here, $vshare_{m,t}$ is the average share of varieties produced at plants tooled for model m in year t, weighted by total output. That is, for each model–plant–year tuple, we calculate the share of distinct model m varieties produced at each plant. Then, we weight using output across plants within models to get $vshare_{m,t}$, the share of varieties produced at a typical plant for model m. Next, $Plants_{m,t}$ is the number of plants that produce model m in year t, α_m is a model fixed effect, and α_t is a year fixed effect. The null hypothesis of replication across plants within a model is that $\alpha = 0$, or that additional plants do not reduce the share of varieties within a model that are produced at the typical plant. In contrast, if more plants lead to more specialization, then $\alpha < 0$, and each plant focuses on a narrower segment of

Table 2
Specialization across plants.

	Sales weighted average
# Plants per platform	2.85
# Plants per model	2.36
# Plants per variety	1.86

Sample: 1990–2000. Sales weights constructed using units sold, not value of units sold.

Table 3
Specialization within models.

	(1)	(2)
# Plants	−0.103***	−0.091***
	(0.018)	(0.014)
Observations	598	598
R^2	0.23	0.33
Year controls	Year	Firm–year

Dep. variable is the average share of varieties produced at plants tooled for model m in year t, weighted by total output. Model fixed effects. Robust standard errors are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

varieties. Clearly, in Table 3, the null is rejected in favor of the alternative in which more plants for a model is associated with to increased specialization across plants for that model. In column one of Table 3, we see that one additional plant for a given model is associated with a 10 percentage point drop in the share of varieties produced at the typical plant. In column two we find a similar estimate when controlling for firm-year fixed effects rather than just year. Clearly, increasing the number of plants leads to decreased scope at the typical plant within models, and replication is strongly rejected.

As a final point focusing on basic specialization, we examine a number of factors associated with the number of plants that are tooled for a model. As discussed in the Introduction, multi-plant models can be explained by a number of factors. In particular, we focus on how *scale* and *vertical differentiation* motivate the production of a common version of a product across multiple plants. While scale is discussed above, we pause for a moment to discuss the economics of how vertical differentiation can motivate production across more plants, and in particular, offshore plants. Specifically, a model with many different types of varieties should be optimally produced by plants with different characteristics. For example, a newer plant in the US may be more technology intensive, which facilitates production of more sophisticated or non-standard varieties within a model. On the other hand, a plant in Mexico may be more labor intensive, and a facility at which less-sophisticated varieties are produced. Hence, models or products with a higher degree of vertical differentiation should ideally be sourced across more and different plants. Indeed, significant vertical differentiation may lead to a segmentation of varieties across inshore and offshore locations.

To test for these associations, we first estimate the following using a fixed-effect Poisson model:

$$E\left[\#Plants_{m,f,t}|X\right] = \exp\left(\alpha_1 \cdot ln(Scale)_{m,f,t} + \alpha_2 \ln(Varieties)_{m,f,t} + \alpha_{f,t}\right). \tag{2}$$

In Eq. (2), we associate the number of plants tooled for model m by firm f in year t as a function of $ln(Scale)_{m,f,t}$, the log sales of model m by firm f in year t for the US, Canada, and Mexico, the log of the number of distinct varieties within m by firm f in year t, $ln(\#\ Varieties)_{m,f,t}$, and firm-year fixed effects, $\alpha_{f,t}$. To measure sales in Mexico, we merge in supplemental data from *Wards Automotive* at the model level. To measure differentiation, we adopt a very simple measure and tally the number of distinct varieties within a model.[14] If vertical differentiation does not lead to additional plants (holding output constant), it must be the case that $\alpha_2 = 0$. However, if increased differentiation within a model in a given year leads to more plants, then $\alpha_2 > 0$.

The results from Eq. (2) are presented in the first two columns of Table 4. In columns one and two, we confirm the hypotheses conjectured above, where within firm-year groups, models with higher output and a larger mix of varieties tend to receive more plants. However, the question still remains on how these two factors associate with capacity in Mexico. To answer this question, we close this section by focusing on the role of scale and differentiation on offshoring of demand in the US to production in Mexico. Specifically, we run the following linear probability model predicting $Mex_{m,f,t}$, a dummy variable identifying sales in the US of model m by firm f in year t that originate from Mexico:

$$\begin{aligned} Mex_{m,f,t} = {} & \alpha_1 \cdot log(Scale)_{m,f,t} + \alpha_2 \ln(Varieties)_{m,f,t} \\ & + \alpha_3 MexSalesShare_{m,f,t} + \alpha_4 log\left(Hours_{m,f}\right) + \alpha_{f,t} + \epsilon_m, f, t. \end{aligned} \tag{3}$$

In Eq. (3), the two new variables are $Hours_m$, which is the output-weighted average labor-hours-per-vehicle at plants producing model m prior to 1996, and the share of total sales in Mexico for model m in year t, $MexSalesShare_{m,f,t}$. Labor-hours-per-vehicle is constructed from plant-level data available in the *Harbour Report*, and is merged by plant–year to our dataset. Though not a perfect measure, it is meant to roughly capture aggregate labor intensity, which is a standard explanation for why models are offshored. As discussed above, data from *Wards Automotive* is merged with our primary dataset to provide a measure of relative demand at the model level in Mexico.

The results of estimating Eq. (3) are presented in columns three through five in Table 4. In column three, we find that there is a positive though insignificant association between scale and offshore capacity. However, we find a strong and highly significant association between the number of varieties within a model and offshore capacity in Mexico for the US market. Since labor hours per vehicle are not available for some trucks (since they begin later in the sample), we run this same regression in column four using the sample for which we have $Hours_m$ reported. Here, the number of varieties still has a positive and significant effect on offshoring. Finally in column five, we add-in log-hours-per-vehicle and the Mexican sales share, where neither has a discernible relationship to production in Mexico.

Overall, Tables 2, 3, and 4 paint a very clear picture about the general allocation of production across plants. While there is evidence to suggest that increased scale of a model leads to more plants, there is

Table 4
Specialization within models.

Variables	(1) # Plants	(2) # Plants	(3) Mex?	(4) Mex?	(5) Mex?
ln(*Scale*)	0.207***	0.143***	0.012	−0.010	−0.021
	(0.018)	(0.015)	(0.012)	(0.018)	(0.036)
ln(*#Varieties*)		0.211***	0.165***	0.182***	0.180***
		(0.021)	(0.047)	(0.054)	(0.052)
Mexican Sales Share					0.056
					(0.209)
ln(*Worker-hours per vehicle*)					−0.095
					(0.174)
Observations	315	315	315	252	252
R^2			0.17	0.16	0.17

Notes: The unit of observation is model–year. Firm-year fixed effects. The sample is 1996–2000, which is the sample such that offshoring occurred (after a single transition year). Using shares of offshoring to Mexico rather than a dummy variable as a dependent variable leads to qualitatively similar results, though the estimates of the coefficient on *ln*(*#Varieties*) are one third the size. Robust standard errors are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

[14] This is similar to the notion of input complexity in Levchenko (2007), where (low) complexity is the concentration of inputs used within a product as measured by a Herfindahl index. Later, we adopt a Euclidean-based metric for vertical differentiation as a function of product attributes. Using such a metric here leads to qualitatively similar results, but we choose the more straightforward measure for exposition.

no evidence to support that this is done randomly. In particular, when conditioning on scale, we find that models with a greater number of varieties are associated with more plants, and also associated with offshore capacity in Mexico directed for the US market. What we don't find, however, is an obvious relationship between labor-hours-per-vehicle or relative demand and production in Mexico, which are both classic explanations for segmentation of production across borders. On some level this is not surprising, since any model that received capacity in Mexico received roughly equivalent additional capacity in the US. Overall these results suggest that vertical differentiation is an important conduit for offshoring.

To this point our analysis of the offshoring decision has employed a relatively aggregate perspective by focusing on the model and the platform. If this were the relevant level of aggregation then theory predicts that production of a model should be either offshored or inshored due to the differences in the characteristics of each location. However, this discrete segmentation doesn't occur. This suggests that within-model characteristics play an important role in the offshoring process and that more disaggregated data is required.

5. Offshoring, inshoring, and variety characteristics

In this section, we explore the composition of offshoring by narrowing the perspective from model–year to varieties within a product-line–year.[15] This sharper focus has the advantage of matching the capabilities of any two plants very closely, and also focuses on the variation that is likely to be the critical elements in the final assembly of a truck. By looking within a product–line year, we are absorbing variation related to the engine. This is helpful on two levels. Engines tend to be sourced from large plants that exploit significant economies of scale and produce the same engine for multiple platforms, and hence, may be subject to time-varying shocks unrelated to the final assembly of the variety. In some cases, these engines are also sourced from outside manufacturers. As we do not have good data on input sourcing from these (and other) plants, we have chosen to absorb this variation for our primary analysis. Second, and arguably more important, is that the engine is a relatively standardized input, which does not necessarily relate to the large number of tasks that final assembly workers must complete to finish a vehicle. In other words, while adding a long-bed or extended cab may add additional features that the worker must install to finish the vehicle, installing an engine with 0.5 additional liters displacement should not.[16] Furthermore, while a large majority product-lines within offshored platforms were produced in Mexico at some point (89.3%), there is much larger variation in the offshoring propensities at the variety level (66.1% of varieties were offshored at some point). Hence, we choose to look within product-lines, which intuition and aggregate summary measures suggest is the meaningful decision point for any segmentation of production. We examine this claim in the robustness section toward the end of the paper.

To begin the analysis, we examine the relationship between product characteristics and which "type" of plant produces which light truck varieties within a product-line. As in Section 3, we classify plants as new or retooled capacity in Mexico (offshoring), new or retooled production in the US (inshoring), or existing production in the US ("no shoring"). For a given variety v from product-line p in year t, it must be the case that the share of production that occurs at each type of plant adds to 1:

$$MexShare_{v,p,t} + InShare_{v,p,t} + NoShare_{v,p,t} = 1. \tag{4}$$

Here, $MexShare_{v,p,t}$ is the share of variety v from product-line p that is sourced from Mexico in year t, and $InShare_{v,p,t}$ and $NoShare_{v,p,t}$ are the equivalent variables for inshoring and no shoring. Via Eq. (4), if the same regressors are used in predicting $MexShare_{v,p,t}$, $InShare_{v,p,t}$, and $NoShare_{v,p,t}$, then the OLS coefficients will add up to zero.[17] Hence, it is the ordering of, and statistical difference between, these coefficients that is of interest in this section. As a benchmark, using a simple replication strategy (production of any variety at a plant is just proportional to total sales) would satisfy the adding-up property since the estimated coefficients on regressors (other than the constant) would be zero.

To explore this null of replication, we focus on three characteristics that vary across varieties within a product-line: variety dissimilarity, variety vintage, and variety scale. These variables can be interpreted in turn as measures of a variety's complexity, age, and capital intensity — three factors that serve to measure different dimensions of vehicle options within a product-line, and three factors that link to mechanisms suggested by trade theory. If a plant is just a plant and replication is a strategy that characterizes production decisions, then the proportion of vehicles with these features will not vary across plants producing that product-line. These features were chosen since they represent economically meaningful dimensions of a light truck and have the potential to influence the allocation across plants that differ by technology vintage and location. An alternative hypothesis is that vintage of technology and plant location do influence the allocation of production across plants. In particular, new technology is likely to attract production of varieties that are more complex to produce, are relatively new, or have scale commensurate with capital or automated production. From a theoretical perspective, the disadvantages of offshore production and a less-educated workforce are likely to be associated with production that has systematically lower complexity, older vintage varieties that are more standardized, and low in scale. We now discuss each characteristic in detail.

5.1. Dimensions within a product-line

To measure the complexity of vehicle assembly, we calculate the dissimilarity of configurations within a variety. The focus on dissimilarity is motivated by the fact that each variety may have different options available that a line worker must distinguish when putting together the most refined aspects of the vehicle. For example, while all vehicles need a steering wheel, not all vehicles need a leather-wrapped steering wheel. For varieties that exhibit variation across configurations within a variety, there is more information for the line worker to process when producing the vehicle. Hence, the more dissimilar the configurations within a variety, the more complex it is to produce.[18] This issue is likely to be more pronounced for offshoring on three levels that are related to

[15] In our data, variation within a model–year is based on elements of vehicle performance and optional-extras/comfort. Issues of performance relate to engine characteristics with variation in cylinders (for example) that could include 6, 8 or 10 cylinder engines. The optional extras relate to the drive train (wheels driven), body styles (cab-type, heavy duty and long bed packages), and in some cases, brand identity that may result in additional unobserved features and price variation. Looking within product-lines focuses our analysis on the latter type of variation.

[16] We take the view that body-styles, drive trains, and brands embody the features associated with the final assembly process. All three of these attributes link with differences in the interior of the vehicle which must be correctly installed by the *final assembly* worker. For example, the presence of a 4 × 4 drive-train requires different features on the console of the vehicle. Obviously, differences in cab-type require different types of seats, restraints, interior trim, and other features that are installed on-site. Difference in within-firm brand may also be important, where for example, Chevy and GMC both make a Suburban, though the latter is generally considered a higher-end model, and may require additional accoutrements that are installed by workers during final assembly. In contrast engine types in broad terms (liters, cylinders, fuel) do not naturally change the interior of the vehicle. Furthermore, assembling the same model with a different engine should not be technically different — engines are never directly built at the site of final assembly, and is also one input that is required with certainty for every vehicle.

[17] Similar decomposition methodologies are used by Hummels and Klenow (2005) and Bernard et al. (2009).

[18] This is consistent with the notion of "parts and option complexity" in MacDuffie et al. (1996) where "… production workers face a more complicated array of different parts – and less predictable combinations of parts – to install.". This is also similar to the measure used by Levchenko (2007), which uses the scope of inputs as a measure of complexity.

trade theory. First, if information transmission regarding the production of different configurations is more costly when production is offshore (as in Keller and Yeaple, 2012), it may be less likely for a firm to offshore its most complex varieties within a product-line. Second, if unskilled labor is used more intensively, it may be less likely for a firm to offshore its most complex varieties within a product-line. Finally, if an antiquated plant layout or poorly designed inventory system leads to excess inventory at work stations, these issues of selecting the proper inputs for a given configuration of a variety will be more pronounced.

To measure dissimilarity within a variety (and thus complexity), we use a standard deviation based on the "Mahalanobis Distance" of Mahalanobis (1936), which is essentially the Euclidean distance between two points in a multi-dimensional space, but correcting for the fact that some dimensions may be correlated. Specifically, define a vector of characteristics for configuration c of variety v from product-line p in year t as $x_{c,v,p,t}$, the mean characteristics across all configurations within v from product-line p in year t as $\mu_{v,p,t}$, and the covariance matrix of characteristics across all configurations from product-line p in year t, $V_{p,t}$, then the Mahalanobis distance from the mean for configuration c within variety v from product-line p in year t, $D_{c,v,p,t}$, is:

$$D_{c,v,p,t} = \sqrt{\left(x_{c,v,p,t} - \mu_{v,p,t}\right) \cdot V_{p,t}^{-1} \cdot \left(x_{c,v,p,t} - \mu_{v,p,t}\right)^T}.$$

Conveniently, $D_{c,v,p,t}$ is scale invariant, which is a nice property given that we will be using this metric across very different platforms, products, and varieties. To measure the average dissimilarity across configurations within a variety, we use a measure similar to the sample standard deviation:

$$D_{v,p,t} = \sqrt{\frac{1}{N_{v,p,t} - 1} \sum_{c \in \Omega_{v,p,t}} D_{c,v,p,t}^2}. \tag{5}$$

In Eq. (5), $N_{v,p,t}$ is the number of configurations within variety v from product-line p in year t, and $\Omega_{v,p,t}$ is the set that contains these configurations. When taking this measure to the data, which we label the "Mahalanobis Dissimilarity", we use the manufacturers' suggested retail price, gross vehicle weight, curb weight, length, width, and height to define configurations of a variety. The variance–covariance matrix, $V_{p,t}$, is also defined over these characteristics within each product-line in each year.[19] If there is only one configuration within each variety, $D_{v,p,t}$ is forced to zero. Finally, in the estimation that we undertake below, we normalize $D_{v,p,t}$ by the sample standard deviation to aid in interpretation. The Mahalanobis measure itself exhibits wide variation within the sample. For example, within the sample of platforms that were offshored, 35.4% of variety-year observations reported no variation in configurations as calculated by the Mahalanobis measure. However, the sample average measure of dissimilarity is 1.2 standard deviations above zero, and the most dissimilar variety is two standard deviations above this average.

Variety vintage, which for each variety v in year t is defined as the current year t minus the first year the variety is observed in the sample. For estimation, we include a dummy variable for varieties that are in their initial year in the data to proxy for the intensity of human capital in production. Indeed, many models of trade based on product cycles predict that new variety introductions are more likely to be sourced from the North – with proximity to engineers and managers – and only offshored to the South after production of a variety is more "standardized" or lower in terms of human capital intensity (Vernon, 1966; Antràs, 2005). Given that we will be using product-line–year fixed effects, we are estimating the propensity of shoring options based on the relative newness within each product-line–year (so the effects are unrelated to overall trends). Within our sample, roughly 10% of observations represent new varieties in that particular year.

Finally, consider the role of scale of production. Scale is important for all models of FDI since fixed costs are incurred in the process of investment in a new or retooled plant, which implies that those products which earn the highest revenues are the most likely to warrant such an investment. However, at a more micro level, if certain varieties are candidates for capital investment such as increased automation, the investment itself will not take place unless scale warrants such an investment. Moreover, planning for high scale varieties where fixed investments have been made may also provide a useful hedge when there is pronounced macroeconomic uncertainty.[20] Hence, given that labor costs are relatively low in Mexico, this may yield a natural sorting of production that selects low-scale varieties (labor-intensive) to be produced in Mexico. To examine whether the best selling variety is also the most likely to be offshored, or whether a more subtle sorting occurs, we expand on the definition of new varieties described in the previous paragraph. Specifically, we classify products into three groups — new varieties, old varieties that are above their product-line median production level in the previous year, and old varieties that are below their product-line median in the previous year. Excluding the last group in the estimating equation, we estimate the model with an additional dummy variable that identifies old varieties that are relatively high-selling varieties within their product-line in the previous year.

5.2. Specification

To examine the relationship between shoring options and characteristics, we estimate the following via OLS:

$$Share_{v,p,t}^r = \alpha^r \cdot Characteristics_{v,p,t} + \alpha_{p,t}^r + \epsilon_{v,p,t}^r \tag{6}$$

where $Share_{v,p,t}^r$ is the share of variety v of product-line p in year t that is sourced from plant-type r, α^r is the vector of coefficients that are associated with the regression for plant-type r, and $\alpha_{p,t}^r$ is a product-line–year fixed effect.[21] Since we are using the same characteristics, $\sum_{r \in R} \alpha^r = 0$, where 0 is a vector of zeros of the same dimension as α^r, and R is the set of plant types. The null associated with a hypothesis that production within a product-line at a plant is just proportional to aggregate sales would then result in any element in this vector also being equal to zero. This provides a clear benchmark for the analysis.

5.3. Results

The results from estimating Eq. (6) for all three share variables are presented in columns one through three of Table 5. The first result is that the null of simple replication of production patterns across plants with the same capabilities within a product-line is rejected since the majority of coefficients are estimated to be significantly different from zero. Furthermore the pattern associated with the deviation from zero is also informative and systematic. The plants included in the sample differ in two fundamental dimensions: age and country of production.

First, the estimates in column one indicate that, for the sample of offshored platforms, less complex, older, and lower scale varieties tend to be offshored. In terms of interpretation, note that the sample average of $MexShare_{v,p,t}$ in our sample (for offshored platforms) is 0.30. Hence, the results indicate that a one-standard deviation increase

[19] If $V_{p,t}$ were the identity matrix, $D_{c,v,p,t}$ would be the Euclidian Distance from the variety average configuration, and $D_{v,p,t}$ would be the standard deviation of Euclidian distances across configurations within the variety.

[20] We have experimented with measures of volatility to test for exactly this issue, but the relatively short pre-NAFTA sample and the extensive variety growth throughout the sample do not allow us to construct a robust measure of volatility for each variety.

[21] The choice of fixed effects is crucial in that given the nature of investment in the auto industry, selection issues from tooling a plant for a given model or product-line in a given year will be absorbed by this fixed effect. Further, any time-varying issues related to engine sourcing will be absorbed by this fixed effect.

Table 5
Offshoring, inshoring, and variety characteristics.

Variables	(1) *MexShare*	*diff*	(2) *NoShare*	*diff*	(3) *InShare*	(4) *InShare*
Mahalanobis dissimilarity	−0.094***	***	0.026		0.068***	0.104***
	(0.020)		(0.028)		(0.024)	(0.034)
First year of variety?	−0.505***	***	−0.044	***	0.549***	−0.053
	(0.136)		(0.046)		(0.125)	(0.050)
Above-median scale?	−0.098*		−0.013	**	0.112**	−0.021
	(0.055)		(0.032)		(0.047)	(0.054)
Observations	496		496		496	567
R^2	0.15		0.01		0.23	0.05
Number of product-line–year	109		109		109	111
Platforms	Offshored		Offshored		Offshored	Inshored

Notes: This table presents results from regressing the share of "offshoring", "inshoring", and "no shoring" for each variety v from product-line p in year t on characteristics. Columns (1)–(3) are estimated using the sample of platforms that were both offshored and inshored, and column (4) is estimated on the sample of platforms that were only inshored. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses. Columns labeled *diff* report whether the adjacent coefficients are significantly different from one another.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

in complexity yields a 9 percentage point decrease in the average offshoring share, or roughly 30% evaluated at the offshoring sample mean. This is substantial. The effects of vintage are even stronger, where being in the first year of a variety essentially reduces the predicted offshoring share to zero. Later, we will evaluate the robustness of this effect when bounding the values of the dependent variable more precisely. Finally, being above the median level of scale reduces the probability of being offshored by a similar amount as dissimilarity.

To focus on the effects of technology, we next compare columns two and three, which highlights systematic differences in production patterns of plants in the same location but utilizing technology of different ages. Newer technology is associated with "inshoring" relative to "no shoring". In response to these technology differences we see that inshore plants produce light-trucks in the same product-line that are more complex and more likely to be in their first year of production. This is consistent with new plants being more technology intensive, and with upgrades in that area biased toward skilled workers.[22] Furthermore, newer plants produce the higher scale varieties, which matches the more capital intensive nature of new plants. These results are consistent with surveys documenting that retooled plants also receive technology upgrades related to efficiency and automation.[23] Indeed, the manpower required to produce a wider variety of vehicle types can be accommodated efficiently by a wider use of automation within the plant, which is consistent with our evidence linking new technology to more complex varieties.[24]

To reinforce this pattern of sourcing we estimate the model on the set of platforms that report inshoring but no offshoring; see column four of Table 5. Since there are two sourcing options for these varieties, we only report results for regressing $InShare_{v,t}$ on characteristics. In column four, we find evidence that is consistent with the same effects presented in columns one through three for complexity. That is, those varieties with more dissimilar configurations are more likely to be sourced from new/retooled capacity in the US. However, the other characteristics are insignificant, likely due to the lack of new varieties and overall differentiation within these non-offshored varieties.

Returning to the discussion of offshoring, comparing columns one and three (approximately) fixes the time since new capacity was installed and varies the country of production. This comparison establishes that varieties with a greater level of dissimilarity in configurations are more likely to remain in the domestic market at new or retooled plants. In addition, varieties in their first year of production are more likely to remain in the US and be sourced from new or retooled plants. Moreover, relative to the group of old varieties that are below their within-product-line median of sales, above-median varieties are less likely to be offshored. In contrast, relatively large selling varieties are more likely to be inshored. All these differences between columns one and three are significant. Finally, comparing "no shoring" to "offshoring" in columns one and two, we find that even the older US plants have a significant production bias toward higher scale, more complex and newer varieties.

These results are also supported by discussions in industry sources which characterize the new light truck facilities in Mexico as using significantly less automation than their sister plants in the US.[25] Furthermore, education levels tend to be very low, where for example, the typical line worker at the most modern plant, Silao, is not greater than a grade 9 education (Rothstein, 2004). However, despite these technique and factor input differences, the light truck facilities tend to be seen as clean, safe, and high quality plants that have adopted many modern principles of lean manufacturing. Silao, in particular, is nicknamed "the NUMMI transplant", in reference to a related facility in Freemont, CA (Rothstein, 2004). Overall, while this capacity is indeed new, it is tailored to a different location from the US in which unskilled labor is used more intensively relative to automation. Across all Mexican capacity, we document that these plants tend to produce less-refined varieties.

5.4. Mechanisms

The above results are suggestive of specialization across borders due to the relative unskilled labor intensity at plants in Mexico, and the relative capital and technology intensity at plants in the US. In this section, we evaluate alternate mechanisms that could potentially be driving the above patterns.

5.4.1. Local demand

To begin, we focus on the role that local demand may play in the patterns of offshoring that we present in Table 5. While our data offers a number of advantages in terms of detail, it is constructed by registrations in the US and Canada which do not include sales in Mexico or other third markets. For example, perhaps a variety of truck is a large seller in the Mexican market but not in the US or Canadian markets, and as such, any US or Canadian production is naturally sourced from Mexico. This becomes problematic when these varieties are also likely sourced from Mexico. To investigate this issue, albeit at a relatively aggregate level, we compare our sales information with alternative sources for plant production data. This comparison reveals that sales in Mexico comprised only a small fraction of production in Mexico.[26] Moreover, in Table 4 in Section 4, there was no significant relationship between the presence of capacity in Mexico and the share of sales in the US, Canada, and Mexico that go to Mexico.

[22] For examples of skill and technology upgrading at retooled plants, see Milkman and Pullman (1991).

[23] Harbour (1998) noted the "major conversion" of GM Arlington relative to its previous large sedan production, which included a "new automated body shop" and "new paint system".

[24] See the Harbour (1997) for a discussion of the role of complexity at automotive plants.

[25] See Harbour (1998), Harbour (1999), and Harbour (2000). Also, MacDuffie et al. (1996) document more generally that automotive plants in newly industrialized countries (Brazil, Korea, Mexico, and India) use significantly less automation than plants in industrialized countries.

[26] As a bounding exercise, using Wards global production data, we can look at this in two ways. First, aggregate demand in Mexico for offshored models over 1996–2000 was 12.4% of total production in Mexico. Second, aggregate sales in the US sourced from Mexico over the same period was 83% of production in Mexico. As an alternate source, the Harbour Report (1997) states that aggregate demand in Mexico was roughly 2 weeks worth of demand in the US. Clearly, the US and Canada were the primary sales location for all plants in North America.

However, as there are many varieties within offshored product-lines, it is possible that even a small number of varieties that are sold in Mexico may be "pulling" the offshore production of varieties for the US that would also be produced in Mexico due to relative factor endowments. To test whether this is the case, we adopt an interactions based specification to predict the relationship between characteristics and offshoring shares *when sales in Mexico are relatively unimportant*. Specifically, we obtain data from *Wards* at the model–year level that reports sales in Mexico, the US, and Canada over the period 1996–2000. We then calculate $MexSalesShare_{p,t}$, which is the share of total sales that occurs in Mexico of the model associated with product-line p in year t. This variable ranges between 0 and 10% in any given year, though for the offshored models, it is less than 5% on average over the period 1996–2000. Hence, our goal is to project the relationship between characteristics and offshoring when the share of sales in Mexico is constrained to be zero. To do this, we interact $MexSalesShare_{p,t}$ within our offshoring regression as follows:

$$Share^{off}_{v,p,t} = \alpha^{off} \cdot Characteristics_{v,p,t} + \alpha^{off}_{mex} \cdot Characteristics_{v,p,t} \cdot MexSalesShare_{p,t} + \alpha^{off}_{v,p,t} + \epsilon^{off}_{v,p,t}.$$

Note that the level effects of $MexSalesShare_{p,t}$ are absorbed by the product line-year fixed effects, $\alpha_{v,p,t}$. The coefficients of interest within this specification are now within the vector α^{off}, which is the average relationship between characteristics and offshoring *when the share of sales in Mexico is zero*. If local demand is indeed driving our results, we should expect to see a less-pronounced sorting of offshoring to Mexico when the relative importance of sales in Mexico is low. On the other-hand, if local demand is going in the other direction (for example, if only very high income consumers in Mexico purchase new trucks, and do so in a similar fashion to US consumers), then the patterns of offshoring should be enhanced when Mexican sales share is low.[27] Indeed, we find the latter is the case for all characteristics, where in Table 6 the predicted pattern of offshoring as described above is *more* pronounced when demand in Mexico is a very small share of total demand. Hence, we conclude that if anything, the supply characteristics of producing in Mexico are the driving factor in the patterns of offshoring, not local demand.

5.4.2. Technology vintage

The baseline results in Table 5 lump all Mexican production together, motivated by the fact that both new, refurbished, and existing plants use essentially no automation. However, some plants in Mexico are brand new, so in terms of projecting the future allocation of varieties across locations using state-of-the-art technology within each location, it may be more sensible to evaluate the sorting of varieties across locations by technology vintage more strictly. To do this, we refine our definition of plants in Mexico to distinguish between existing plants and brand new plants, where the shares of production at each plant type at the variety level are now defined as $OldMexShare_{v,p,t}$ and $NewMexShare_{v,p,t}$, respectively. Then, we regress each share on our baseline characteristics as we do above, but evaluating the statistical difference in coefficients within existing plants, and then within new plants. The results, presented in Table 7, show that when focusing the comparison more squarely on differences in labor and skill intensity by adopting more precise definitions of plant vintage, we find that the effect of characteristics on offshoring still holds, where the more dissimilar, newer, and higher scale varieties tend to be produced at new plants in the US relative to new plants in Mexico, and that the same sorting holds when comparing old plants in the US and old plants in Mexico. Hence, while new plants in Mexico appear to be fairly similar to old plants in the US, when fixing technology vintage more precisely, we find that product characteristics still yield a natural sorting of varieties that is consistent with large differences in labor intensity and skill across locations.

Table 6
Offshoring and variety characteristics — local demand.

Variables	(1) *MexShare*	(2) *MexShare*
Mahalanobis dissimilarity	−0.094***	−0.099**
	(0.020)	(0.045)
Mahalanobis dissimilarity × Mex. Sales Share		−0.066
		(0.910)
First year of variety?	−0.505***	−0.926***
	(0.136)	(0.198)
First year of variety? × Mex. Sales Share		8.338***
		(1.929)
Above-median scale?	−0.098*	−0.113*
	(0.055)	(0.057)
Above-median scale? × Mex. Sales Share		0.293
		(0.760)
Observations	496	496
R^2	0.15	0.17
Number of product-line–year	109	109
Platforms	Offshored	Offshored

Notes: This table presents results from regressing the share of offshoring for each variety v from product-line p in year t on characteristics, and an interaction with the Mexican Sales Share. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

5.4.3. Input quality

The next mechanism we discuss is input quality, an issue that has received attention in a number of recent papers on trade with less-developed countries.[28] While many of the US and Canadian input suppliers relocated to Mexico during the late 90s, it still begs the question whether those varieties produced in Mexico were focused on lower input quality. Indeed, it is also possible that lower quality inputs tend to be used in those varieties that are less complex, older, or lower scale.

There are a number of ways that one can attempt to measure quality — using physical measures or measures related to the value of the product in market equilibrium. We begin with the former by measuring input quality using the variety's carrying capacity, which is a measure of *physical* quality. Specifically, the maximum cargo weight to vehicle weight ratio is defined as the maximum possible weight of passengers and cargo divided by the curb weight of the vehicle, where curb weight is defined as the operating weight of the vehicle (including petrol and required fluids to operate). Indeed, vehicles with a higher maximum cargo weight to vehicle weight ratio have structural characteristics that require additional welding, higher strength components, or other unobserved attributes that lead to a greater capacity per pound of material used in the vehicle. For example, aluminum is lighter than steel, but sufficient for the frame of a vehicle, and is generally considered a higher quality input.[29] Overall, we interpret greater carrying capacity as a measure of the input quality of a variety within a product-line. Of note, since these weights are relevant for taxes and fuel economy regulations, overstating is highly unlikely. Furthermore, consumers have shown a willingness to value carrying capacity as an important indicator of light-truck quality more generally.[30] The results when adding carrying capacity as a regressor are presented in Table 8. Here, we find a fairly mild relationship between $\frac{Cargo\ Capacity}{CurbWeight}$ and shoring patterns. However, it is notable that while insignificant, it appears that offshoring tends

[27] Recent work by Faber (2013) makes a similar point.

[28] For example, see Amiti and Konings (2007) and Goldberg et al. (2010).

[29] Of course, the price of aluminum may increase the price of the final product, which is addressed in the next regression.

[30] For instance, the 1998–99 Dakota was marketed as a compact pickup truck that "hauls like a heavyweight". When it was subsequently revealed that the carrying capacity was overstated and led to structural failure of the vehicle, a class action lawsuit was filed based on the misrepresentation of a key vehicle characteristic.

Table 7
Offshoring and variety characteristics — new and old capacities across locations.

Variables	Existing truck plants			"New" truck plants		
	(1) *OldMexShare*	*diff*	(2) *NoShare*	(3) *NewMexShare*	*diff*	(4) *InShare*
Mahalanobis dissimilarity	−0.093**	***	0.026	−0.001	*	0.068***
	(0.043)		(0.028)	(0.047)		(0.024)
First year of variety?	−0.369***	***	−0.044	−0.136*	***	0.549***
	(0.096)		(0.046)	(0.080)		(0.125)
Above-median scale?	−0.109*		−0.013	0.010	*	0.112**
	(0.056)		(0.032)	(0.027)		(0.047)
Observations	496		496	496		496
R^2	0.13		0.01	0.02		0.23

Notes: This table presents results from regressing the share of variety *v* from product-line *p* in year *t* at different plant types on characteristics, where plants are now defined by relative vintage and location. Columns (1) and (2) estimate the relationship between characteristics and production at existing plants in Mexico (including retooled) and existing plants in the US, respectively. Columns (3) and (4) estimate the relationship between characteristics and production at new plants in Mexico and newly retooled plants in the US, respectively. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses. Columns labeled *diff* report whether the adjacent coefficients are significantly different from one another.
*** p < 0.01.
** p < 0.05.
* p < 0.1.

Table 8
Offshoring, inshoring, and variety characteristics — physical input quality.

Variables	(1) *MexShare*	*diff*	(2) *NoShare*	*diff*	(3) *InShare*	(4) *InShare*
$\frac{Cargo\ Capacity}{CurbWeight}$	−0.530		0.487		0.042	0.240*
	(0.352)		(0.341)		(0.159)	(0.131)
Mahalanobis dissimilarity	−0.108***	***	0.038		0.069***	0.088**
	(0.023)		(0.029)		(0.024)	(0.033)
First year of variety?	−0.540***	***	−0.012	***	0.552***	−0.023
	(0.125)		(0.029)		(0.124)	(0.057)
Above-median scale?	−0.120**	*	0.006	*	0.114**	−0.002
	(0.057)		(0.026)		(0.050)	(0.056)
Observations	496		496		496	567
R^2	0.16		0.05		0.24	0.07
Number of product-line–year	109		109		109	111
Platforms	Offshored		Offshored		Offshored	Inshored

Notes: This table presents results from regressing the share of "offshoring", "inshoring", and "no shoring" for each variety *v* from product-line *p* in year *t* on characteristics. Columns (1)–(3) are estimated using the sample of platforms that were both offshored and inshored, and column (4) is estimated on the sample of platforms that were only inshored. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses. Columns labeled *diff* report whether the adjacent coefficients are significantly different from one another.
*** p < 0.01.
** p < 0.05.
* p < 0.1.

to receive the lowest input quality varieties, and without having a large effect on the other characteristics that we study. Hence, physical input quality is not driving the results as related to complexity, newness, or scale, and if anything, physical input quality seems to be negatively associated with offshoring of varieties to Mexico.

As an alternate measure of quality, we consider the role that prices play in offshoring decisions. In Tables 5 and 8, we documented differences within product-lines between all three types of plants. However, a question still remains regarding how much these differences in characteristics are attributable to simple differences in price — perhaps due to input quality. To examine the relationship between shoring options, characteristics, and prices, we first estimate the following:

$$Share^r_{v,p,t} = \alpha^r \cdot Characteristics_{v,p,t} + \beta^r \ln\left(price_{v,p,t}\right) + \alpha^r_{p,t} + \epsilon^r_{v,p,t}. \quad (7)$$

In Eq. (7), we will use the base price across configurations within a variety, $price_{v,p,t}$. While care must be taken in drawing inference when using contemporaneous prices, note that this price is set at the very beginning of the model year, and hence, does not vary subsequent to shoring decisions.

In the second, we will use both the predicted and residual prices, respectively, from a first-stage hedonic regression of the base price of each variety on the characteristics within a product-line,

$$Share^r_{v,p,t} = \alpha^r \cdot Characteristics_{v,p,t} + \beta^r_{pred} ln\left(\widehat{price}_{v,p,t}\right) + \beta^r_{res}\hat{\eta}_{v,p,t} + \alpha^r_{p,t} + \epsilon^r_{v,p,t} \quad (8)$$

where $ln\left(\widehat{price}_{v,p,t}\right)$ and $\hat{\eta}_{v,p,t}$ are the predictions and residuals from a hedonic regression of the log price on product-line–year fixed effects, all attributes that define varieties within a product line, along with log of length, width, height, and curb-weight.[31]

Using this two-price technique, the price terms will reflect variation in the base price of each variety that is specifically related to observable features (predicted price), and unobserved features that may affect the price conditional on characteristics (residual price). The results from both approaches are presented in Table 9. In columns one through four we use the base price for each variety, where we find that new inshore capacity tends to receive a higher price variety relative to existing capacity, and offshore capacity. Moreover, there appears to be little difference between offshored capacity and existing capacity. However, the differences related to other characteristics are more sharp when conditioning on the price of each variety, where new capacity tends to receive newer, more complex, higher scale and higher carrying capacity varieties, and offshore capacity receives the opposite.

In columns five through eight, we examine prices more thoroughly by decomposing the price into a predicted and a residual component. Using the predicted hedonic component is similar to the measure of quality used in Feenstra (1988), and relates to the observable attributes of the vehicle. However, an additional dimension through which the price may affect allocation is through the residual price, which may reflect such things as unobserved input quality, or perhaps consumer perceptions of offshore products. Focusing on columns five through seven of Table 9, we see that the differences between inshoring and noshoring are driven by the predicted component of prices, and in contrast, the difference between inshoring and offshoring is driven by the residual variation in the price. However, all other characteristics are estimated with the same sign, ordering, and significance as before. Hence, we conclude that there are no indications that our baseline results are driven by input quality, whether through the price, perceived quality, or physical quality via carrying capacity. However, the results

[31] Specifically, we regress the following using the full sample of trucks:

$$\ln\left(price_{v,p,t}\right) = \theta Attributes_{v,p,t} + \theta_{p,t} + \eta_{v,p,t}.$$

The results from this hedonic regression are the following:

Heavy duty?	Long bed?	Crew?	Extended?	Four?	ln(*Width*)	ln(*Height*)	ln(*Length*)	ln(*Curb weight*)	*R*-squared
−0.005	0.032***	0.095***	0.097***	0.107***	−0.096*	0.001	−0.043	0.307***	0.64
(0.006)	(0.007)	(0.008)	(0.005)	(0.004)	(0.057)	(0.01)	(0.03)	(0.045)	

Table 9
Offshoring, inshoring, and variety characteristics — price and residual prices.

Variables	(1) *MexShare*	(2) *NoShare*	(3) *InShare*	(4) *InShare*	(5) *MexShare*	(6) *NoShare*	(7) *InShare*	(8) *InShare*
$\frac{\text{Cargo Capacity}}{\text{CurbWeight}}$	−0.866	0.295	0.571	0.215	−0.420	−0.093	0.512	0.227
	(0.549)	(0.314)	(0.432)	(0.137)	(0.659)	(0.296)	(0.528)	(0.157)
Mahalanobis dissimilarity	−0.109***	0.037	0.072***	0.081**	−0.115***	0.042	0.073***	0.080**
	(0.024)	(0.029)	(0.022)	(0.035)	(0.023)	(0.026)	(0.023)	(0.039)
First year of variety?	−0.532***	−0.008	0.540***	−0.020	−0.527***	−0.012	0.539***	−0.020
	(0.122)	(0.028)	(0.119)	(0.058)	(0.122)	(0.028)	(0.118)	(0.058)
Above-median scale?	−0.119**	0.007	0.113**	−0.001	−0.136**	0.021	0.115**	−0.002
	(0.056)	(0.026)	(0.049)	(0.055)	(0.053)	(0.025)	(0.048)	(0.055)
ln(*Base MSRP price*)	−0.399	−0.227	0.627*	−0.146				
	(0.407)	(0.179)	(0.359)	(0.171)				
Predicted *ln*(*Base MSRP price*)					0.159	−0.713***	0.554	−0.112
					(0.601)	(0.220)	(0.479)	(0.202)
Residual *ln*(*Base MSRP price*)					−1.098***	0.381	0.718**	−0.184
					(0.380)	(0.241)	(0.289)	(0.285)
Observations	496	496	496	567	496	496	496	567
R^2	0.17	0.05	0.26	0.08	0.19	0.09	0.26	0.08
Number of product-line–year	109	109	109	111	109	109	109	111
Platforms	Offshored	Offshored	Offshored	Inshored	Offshored	Offshored	Offshored	Inshored

Notes: This table presents results from regressing the share of "offshoring", "inshoring", and "no shoring" for each variety *v* from product-line *p* in year *t* on characteristics. Columns (1)–(3) and (5)–(7) are estimated using the sample of platforms that were both offshored and inshored, and columns (4) and (8) are estimated on the sample of platforms that were only inshored. Predicted *ln*(*Base MSRP price*) and Residual *ln*(*Base MSRP price*) are constructed using the regression reported in Footnote 30. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

are informative in that it seems that residual variation in the price is associated with offshore production.

5.4.4. Input sourcing

As discussed above, input trade has been an area of high interest due to trade liberalization making available a greater variety of inputs. Furthermore, inputs are of interest given that they may be produced either in-house or by an outside firm. Indeed, in earlier work, Hellerstein and Villas-Boas (2010) evaluate the response to exchange rate shocks using plant-level foreign content of auto-inputs linked to the models that are produced at these plants. How does input sourcing affect the patterns of offshoring that we document?

Notably, all of the final assembly plants in our analysis are owned by the final product manufacturer (Chrysler, Ford, or GM), and hence, the provision of final assembly services is always done in-house. However, some key inputs are produced by outside manufacturers, where our dataset does provide the manufacturer identity for arguably the most important vehicle component: the engine. In our baseline analysis in Table 5, we absorb average effects of engine sourcing by using product-line–year fixed effects. However, to evaluate a discrete difference in the sorting patterns across borders, we now use an interactions based specification (similar to above) to evaluate the effect of outsourcing the vehicle engine on patterns of offshoring. In particular, defining $Outsource_{p,t}$ as a dummy variable equaling 1 when the engine is not produced by the final assembler, we estimate the following specification for our offshoring shares:

$$Share^{Off}_{v,p,t} = \alpha^{Off}_{inhouse} \cdot Characteristics_{v,p,t} + \alpha^{Off}_{outsource} \cdot Characteristics_{v,p,t} \cdot Outsource_{p,t} + \alpha^{Off}_{p,t} + \epsilon^{Off}_{v,p,t}.$$

The results are presented in Table 10, where we find no significant effect of outsourcing on the sorting of varieties across borders. Including the outsource indicator does reduce the estimates and significance of the above-median scale indicator, likely due to the fact that most outsourced engines are relatively of small diesel varieties. However, when adding the Mexican Sales Share in column three (as used in Table 6), we find an effect of scale that is similar to baseline when we control for outsourcing and local demand conditions in Mexico.

5.5. Robustness

In this subsection, we evaluate the robustness of our main results to specification, alternate definitions of characteristics, and alternate definitions of fixed effects. All results for this robustness section are presented in an online appendix.[32] In Table 13 in Appendix B, we run our baseline offshoring specification (including carrying capacity) adding the regressors one-by-one. It is notable that the relationship between scale and first-year varieties is reasonably strong, where first-year varieties tend to be of lower scale than others. In the one-by-one regressions scale is mildly insignificant without accounting for the degree of newness.

In the second robustness check, we present in Table 14 in Appendix B an alternate definition of product complexity, which is similar to Levchenko (2007) in that different configurations of a variety imply a wider set of input needs. Specifically, we simply count the number of configurations within a variety, and replace the Mahalanobis dissimilarity with this variable. Hence rather than looking at the dissimilarity in configurations within a variety, we count up the configurations without evaluating whether they are different (in terms of observables). Using this alternate measure, all qualitative results remain.

Next, we evaluate the differences in results as a function of our fixed effects groups. As argued above, we choose to use variation in body-styles and drive trains within product-lines since this is the variation most associated with the site of final assembly. The alternate choice would be to focus on variation within body-styles. We do exactly this in Table 16 in Appendix B and find no systematic relationship between these characteristics and offshoring or inshoring. As we argued at the beginning of this section, this is intuitive since installing a different engine doesn't add complexity to the installation of nuanced features in the automobile at final assembly. As another robustness check, we again confirm that body-style and drive-train are the primary features to exploit by aggregating fixed effects to the model–year level in Table 15 in Appendix B, showing that the results are quite similar to when looking within product-line–year.

[32] This appendix is available at http://people.ucsc.edu/~aspearot.

Table 10
Offshoring and variety characteristics — input sourcing.

Variables	(1) *MexShare*	(2) *MexShare*	(3) *MexShare*
Mahalanobis dissimilarity	−0.094***	−0.099***	−0.112**
	(0.020)	(0.021)	(0.049)
Mahalanobis × outsourced engine?		0.028	0.035
		(0.052)	(0.054)
Mahalanobis dissimilarity × Mex. Sales Share			0.117
			(0.957)
First year of variety?	−0.505***	−0.431**	−0.855***
	(0.136)	(0.160)	(0.253)
First year of variety? × outsourced engine?		−0.318	−0.180
		(0.271)	(0.296)
First year of variety? × Mex. Sales Share			7.783***
			(2.370)
Above-median scale?	−0.098*	−0.063	−0.093
	(0.055)	(0.053)	(0.056)
Above-median scale? × outsourced engine?		−0.227	−0.231
		(0.167)	(0.166)
Above-median scale? × Mex. Sales Share			0.547
			(0.756)
Observations	496	496	496
R^2	0.15	0.17	0.19
Number of product-line–year	109	109	109
Platforms	Offshored	Offshored	Offshored

Notes: This table presents results from regressing the share of offshoring for each variety *v* from product-line *p* in year *t* on characteristics, and an interaction with a dummy variable identifying outsourced engines and another reporting the Mexican Sales Share. The period for analysis is 1996–2000. Robust standard errors, clustered by product-line, are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Finally, we run a random-effects Tobit model to bound the shares of offshoring, noshoring, and inshoring to be between zero and one. While the random effects assumption is not ideal, it allows us to estimate the model while bounding our dependent variable. The results are presented in Table 17 in Appendix B, where the qualitative results of this section remain.

6. Conclusion

The process of offshoring tasks and products has attracted much attention in both the popular media and also the academic literature. A critical element that underpins all the analyses is that not only can a firm relocate production to a low cost location but that it will do so. Such a process is potentially associated with dramatic changes in the labor markets of both locations, and so is rightly subject to debate. Rather than focus on the implications of offshoring we instead concentrate on the first step: what is offshored. Since the answer to this question hinges on the level of detail available about products, we limit ourselves to a very specific product and a particular instance of offshoring — light trucks post NAFTA. While there may be some concerns about the generalizability of the results from a single market, it is worth noting that more generally auto trade accounts for over one fifth of NAFTA trade, so the study of light trucks allows detailed insight into 50% of a highly globalized and critically important sector.

A notable feature of offshoring in this sector is that the discrete segmentation of tasks and products implied by the theoretical literature is not readily apparent in the data. That is, the big three US auto producers invested in plants with very similar capabilities on both sides of the US–Mexico border. While this feature is at first surprising, it is driven by a general desire to diversify the production of a model across plants and also by the extent of vertical differentiation within light-truck models. Accounting for these issues we examine the variation in production across the age and location of plants. In particular, comparing across new domestic plants and continuing domestic plants, we find that new plants tend to produce newer and higher quality vehicles. This is consistent with the notion that new plants embody newer technology. However, the Mexican capacity also embodies this dimension of newness but it also has the feature that it is in a location that is relatively abundant in unskilled labor. We find that this latter difference drives offshoring patterns, where when comparing with otherwise similar plants in the US, the types of vehicles produced in Mexico are systematically lower in complexity, older in vintage and smaller in scale. All of these features are consistent with the theoretical models of offshoring. This also implies that the issues raised by this literature are likely to be important even when production capabilities are duplicated rather than fragmented across locations.

Appendix A

An example of configurations

One of the novel contributions of the paper is using the Mahalanobis Distance as a metric for measuring the dissimilarity of configurations within a variety. While we do not have sales information for each configuration, we leverage the dissimilarity of configurations as a proxy for the "complexity" in producing a particular variety. Below, we provide an example of these configurations for a variety, the Ford F150 8cyl 5.4 L 4 × 4 longbed for the year 1997.

Table 11
Ford 150 8cyl 5.4 L 4 × 4 longbed configurations.

Trim	Box	Wheelbase	Length	Width	Height	Curb	GVW	Trans	Price
–	6.5	120.2	203.7	79.5	75.3	4235	6000	M5 (A4)	18,380
–	8	138.8	222.3	79.5	75	4339	6000	M5 (A4)	18,575
–	6.5	120.2	203.7	79.5	75.3	4235	6000	M5	18,585
–	8	138.8	222.3	79.5	75	4339	6000	M5	18,900
XL	6.5	120.2	203.7	79.5	75.3	4235	6000	M5 (A4)	19,385
XL	6.5	120.2	203.7	79.5	75.3	4235	6000	M5	19,575
XL	8	138.8	222.3	79.5	75	4339	6000	M5 (A4)	19,585
XL	8	138.8	222.3	79.5	75	4339	6000	M5	19,775
XL flareside	6.5	120.2	207.4	79.5	75.3	4308	6000	M5 (A4)	20,050
XL flareside	6.5	120.2	207.4	79.5	75.3	4308	6000	M5	20,255
XLT	6.5	120.2	203.7	79.5	75.3	4235	6000	M5 (A4)	21,245
XLT	8	138.8	222.3	79.5	75	4339	6000	M5 (A4)	21,445
XLT	6.5	120.2	203.7	79.5	75.3	4235	6000	M5	21,710
XLT flareside	6.5	120.2	207.4	79.5	75.3	4308	6000	M5 (A4)	21,910
XLT	8	138.8	222.3	79.5	75	4339	6000	M5	21,910
XLT flareside	6.5	120.2	207.4	79.5	75.3	4308	6000	M5	22,385

While there isn't much variation in the height of each configuration, there is variation in the length and width depending on the trim level and whether there is a long bed in the configuration (box length, "Box", equals 8). Furthermore, there is variation in prices that can be used to provide an estimate of the heterogeneity across configurations within a variety.

Table 12
Firms, platforms, and models: 1990–2000.

Platform	Model
Chrysler	
Compact pickup (AN)	Dodge Dakota
Compact SUV (XJ)	Jeep Cherokee
	Jeep Wagoneer
Medium SUV (ZJ/WJ)	Jeep Grand Cherokee
Full-size pickup (AD/BE/BR)	Dodge Ram 1500
	Dodge Ram 2500
	Dodge Ram 3500
Full-size van (AB)	Dodge Ramvan 1500
	Dodge Ramvan 2500
	Dodge Ramvan 3500
Full-size SUV (DN)	Dodge Durango
Jeep (YJ/TJ)	Jeep Wrangler
Minivan (AS)	Chrysler Grand Voyager
	Chrysler Town and Country
	Chrysler Voyager
	Dodge Caravan
	Dodge Grand Caravan
	Plymouth Grand Voyager
	Plymouth Voyager
Ford	
Compact pickup (PN105/106)	Ford Ranger
Compact SUV (UN46/UN105)	Ford Explorer
	Mercury Mountaineer
Crossover SUV (CD2)	Ford Escape
Full-size pickup (P)	Ford F-150
	Ford F-250
	Ford F-350
Full-Size SUV (T1)	Ford Bronco
	Ford Excursion
	Ford Expedition
	Lincoln Navigator
Full-size van (VN)	Ford Econoline 150
	Ford Econoline 250
	Ford Econoline 350
Minivan (VN1/V2)	Ford Aerostar
	Ford Windstar
	Mercury Villager
General Motors	
Compact pickup (GMT325)	Chevrolet S10
	GMC Sonoma
	GMC Syclone
Compact SUV (GMT330)	Chevrolet Blazer
	GMC Envoy
	GMC Jimmy
	GMC Typhoon
	Oldsmobile Bravada
Full-size pickup (GMT400/800)	Chevrolet Silverado 1500
	Chevrolet Silverado 2500
	Chevrolet Silverado 3500
	GMC Sierra 1500
	GMC Sierra 2500
	GMC Sierra 3500
Full-size SUV (GMT410-430/GMT820-830)	Chevrolet Suburban 1500
	Chevrolet Suburban 2500
	Chevrolet Tahoe
	GMC Suburban 1500
	GMC Suburban 2500
	GMC Yukon
Full-size van (GMT600)	Chevrolet Express 1500
	CHEVROLET EXPRESS 2500
	Chevrolet Express 3500
	GMC Rally 1500
	GMC Rally 2500
	GMC Rally 3500
	GMC Savana 1500
	GMC Savana 2500
	GMC Savana 3500
Medium van (M van)	Chevrolet Astro
	GMC Safari
Minivan (U van)	Chevrolet Lumina
	Chevrolet Venture
	Oldsmobile Silhouette
	Pontiac Montana
	Pontiac Trans Sport
Jeep (GMT190)	Chevy Tracker
	GEO Tracker

Notes: This table presents a list of platforms and models that are available in our combined dataset. The platform information is self-compiled from industry information regarding firm and vehicle-type. The symbol "/" between platforms represents sequential platform names for different generations, and "–" implies combined sub-platforms.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jinteco.2013.05.004.

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