Structural Estimation of Price Adjustment Costs in the European Car Market

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Abstract

Exchange rate pass-through literature identifies an important delay in price responses, especially in differentiated products. Using the methodology of Bajari, Benkard and Levin (2007), I estimate the structural price adjustment cost consistent with this fact in the European car market. My approach differs from previous work in that I do not rely on first order conditions of Bertrand competition. My main result is that relatively small adjustment costs rationalize the observed inertia in car prices. Intuitively, forward looking price setters face an autocorrelated economic environment (like the nominal exchange rates, GDP and wages) such that just a small cost of repricing justify the persistent prices in the European car market. Additionally, my estimates stress a market-specific heterogeneity in price stickiness suggesting a new dimension of pricing to market behavior.

Keywords: exchange rate pass-through, discrete choice model, structural estimation, menu costs.

JEL Classification: F10, F31, L11, L16

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1 Introduction

One of the most studied issues in international economics is the exchange rate pass-through, which is the effect of fluctuations in exchange rates on export/import prices.\footnote{I refer to “zero pass-through” if prices are totally insensitive to changes in exchange rates. On the other hand, I refer to “full pass-through” if prices change one to one due to changes in exchange rates.} Since exporters/importers have costs and revenues in different currencies, any exchange rate movement affects markups directly. Therefore, the key stone of this phenomenon is to understand the optimal pricing policy of international traders. How firms set prices determine the degree and the dynamics of the exchange rate pass-through.

The degree of exchange rate pass-through is crucial to policy makers. In fact, the optimal exchange rate regime and the transmission channels of international shocks are totally related to how exporters/importers react to exchange rate movements. For instance, the common wisdom that a devaluation boosts the export sector (expenditure - switching effect) disappears completely if international traders set prices in their consumers’ currency.

The exchange rate pass-through literature strongly supports two stylized facts: i) an incomplete degree of pass-through, and ii) a persistent delay in the price response. The first fact emphasizes a heterogenous degree of pass-through with an usual complete exchange rate pass-through in commodities, whereas an incomplete pass-through especially in manufactured sectors. The second fact highlights the slow adjustment of prices after movements in the relevant exchange rates. Reduced form estimates usually identify “short-run” and “long-run” pass-through coefficients, stressing a delay in price responses.

These two stylized facts have had a deep impact on the field. The fist fact ruled out models of perfect competition, since the incomplete pass-through contradicts a constant markup. The persistent incomplete pass-through is consistent with “pricing to market” behavior, as coined by Krugman (1987). Pricing to market essentially allows for price discrimination based on the currency, and the market where the transaction takes place. This behavior requires segmented markets and imperfect substitution, such as in differentiated products. The second stylized fact challenges how to address dynamic pricing. Empirical research has focused on time-series and panel data reduced forms to capture co-movements that can shed light on the underlying mechanisms of firm’s behavior.

To have a deeper understanding, a new empirical literature has moved from reduced forms to structural estimation. This econometric approach allow us to identify parameters that have a clear root in the microeconomic foundations of the respective model. Goldeberg (1995), Verboven
(1996), Golberg and Verboven (2001), Nakamura and Zerom (2008) and Goldberg and Hellerstein (2008) have done great advances in estimating structural parameters using the setting of differentiated products. So far, most of the structural estimations in this topic has only considered firms in a repeated static framework. A static setting can not fully address the pass-through delay already mentioned. A remarkable attempt of including dynamic considerations is done by Emi Nakamura and Dawit Zerom (2008), who estimates a fully dynamic model using the optimal price rule given by the static first order conditions of previous literature.

The aim of this paper is to extend the structural estimation of exchange rate pass-through to include price adjustment costs. Basically firms are forward looking in order to set current optimal prices because undoing previous actions will be costly in the future. In fact, expectations about future exchange rate become crucial to determine the price level since the firm is aware of the costs associated with any future price change. The producers need to consider how far is the current scenario from the steady state environment, so to minimize adjustment costs in this autocorrelated, persistent but still convergent world. Previous literature relied on first order conditions in a Bertrand fashion with differentiated products. This approach differs totally, since I estimate the pricing rule or policy function from the data so then I use this to identify the structural parameters that rationalize that rule.

I estimate this dynamic model for the European automobile market, which is a perfect example of differentiated products that are traded in segmented markets by international multiproduct oligopoly. To estimate this dynamic game with private information, I use the recent methodology developed by Bajari, Benkard and Levin (2007, hereafter BBL). This methodology considers agents that face intertemporal constraints and a dynamic environment that lead them to set an optimal pricing policy, accounting for the optimal degree and temporal profile of cost pass-through. This technique estimates the policy function from the actual data and allow me to recover the cost parameters that rationalize that observed behavior. Using those structural cost parameters I can decompose the sources of the incomplete exchange rate pass-through as well as the price adjustment cost that explain the inter-temporal profile that we observe.

The data taken from Brenkers and Verboven (2006) fits nicely in this study for the following reasons: i) The car industry is the perfect example of differentiated products that exhibit incomplete exchange rate pass-through, with an stable oligopoly over the years and quite segmented markets, and ii) During the period 1970-1999, I have the presence of several currencies, whose relative prices had large and persistent changes ensuring a proper

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2The countries included in the sample are Belgium, France, Germany, Italy and United Kingdom. They account for around 80% of the sales in Europe, including 47 international multiproduct firms for the period 1970-1999.
exogenous source of variation to study the exchange rate pass-through. My estimates support pricing to market behavior under the presence of heterogeneity in demand and supply parameters. Consumers have different degree of substitution among international producers, supporting different pricing policies by producers. Based on my estimates, I discard full pass-through because around one third of the costs are denominated in consumers' currency (destination market wages). Additionally, there is no need of huge adjustment costs to rationalize the actual large degree of inertia in prices. In this very autocorrelated and persistent world, just a small adjustment cost may generate autocorrelated and persistent prices. My estimates show that less than 10% of total cost can generate the observed large price stickiness. Moreover, the estimated adjustment cost of repricing seem to be market-specific adding a new dimension of pricing to market not explored before.

Section 2 presents the entire dynamic game considered in the European car market for supply and the demand system to close the model. Section 3 presents the data on European car markets. Section 4 presents the results of estimating the model with some exercises of impulse-response functions. Finally section 5 presents the general conclusions.

2 The Model

This section presents the dynamic game of pricing among international firms with multiple currencies in the presence of price adjustment costs. The first subsection presents the game in terms of Bajari, Benkard and Levin (2007), setting the problem of the producers, their control and state variables, and their information sets. The second subsection presents the demand system for differentiated products, which is the static discrete choice model as in Berry, Levinsohn and Pakes (1995).

2.1 A Dynamic Game of Price Adjustment Costs

This section presents the dynamic game of pricing with adjustment cost in several currencies as in the European car market. I set the problem and define the control and state variables, as well as the information sets. The players of this game are the car manufacturers aggregated in $F$ nationalities, so they are indexed by $f \in \{1, \ldots, F\}$. All the players trade in $M$ segmented markets indexed by $m \in \{1, \ldots, M\}$. Since this is a multiproduct industry, each firm $f$ sells a subset $F_{fm}$ of the $J_m$ car models available in each market $m \in \{1, \ldots, M\}$.

I do not consider neither entry/exit of firms nor entry/exit of models, so I do not have a subscript $t$ in the product sets. I mainly focus on price adjustment costs, whereas entry/exit issue requires a very different
theoretical setting\(^3\). I discuss this issue again in section 3 to see their empirical relevance.

The action or control variable of player \( f \) is the set of nominal prices \( p_{jt}^m \) for all her models \( j \) in market \( m \) at time \( t \) \((j \in \mathcal{F}_m)\), hence the actions are the set \( \{ p_{jt}^m \}_{j \in \mathcal{F}_m} \).

The vector of actions of all \( F \) players at time \( t \) in market \( m \) is given by the price vector \( p_t^m = (\{ p_{it}^m \}_{i \in \mathcal{F}_m}, \cdots, \{ p_{it}^m \}_{i \in \mathcal{F}_m}) \).

The players choose their optimal price simultaneously in all markets at the beginning of each period.

I assume that the relevant economic environment is totally summarized in a set of state variables \( s_t \). The considered state variables are the nominal exchange rates, the characteristics of all the products (own and competitors’ models), the nominal wages, and the nominal GDP per capita. I explain the underlying economic reasons to consider this particular set in the respective terms of the profit function below.

I assume that cost parameters \( \nu_f \) are firm specific. This set of parameters are constant over time and observable for competitors. This feature allows us to have different policy functions to account for “pricing to market” behavior.

So far the state variables are public information. I include an extra state variable for each player that is private information. There is a model-time specific characteristic \( \xi_{jt} \) that is unobservable for the competitors when setting prices. This random shock has mean zero and explain any deviations of a deterministic model. The vector of all shocks for firm \( f \) is denoted \( \xi_t^m = (\{ \xi_{it}^m \}_{i \in \mathcal{F}_m}, \cdots, \{ \xi_{it}^m \}_{i \in \mathcal{F}_m}) \).

Given a current state \( s_t \), firm \( f \)’s expected future profit is given by:

\[
E \left[ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi_{ft}(p_\tau, s_\tau, \xi_\tau, \nu_f) \right]_{s_t} \tag{1}
\]

where

\[
\pi_{ft} = R_{ft} - C_{ft} - AC_{f,t}
\tag{2}
\]

The profit function \( \pi_{ft} \) includes the current revenues \( R_{ft} \) and the current cost of production \( C_{ft} \). The key new ingredient is the adjustment costs \( AC_{f,t} \) or penalty associated with price changes, so undoing past decisions will be costly. Notice that the expectation is over the firm \( f \) competitors’ actions in the current period, as well as future values of the state variables, and actions. I discuss these three terms in detail below.

\(^3\)To address the entry/exit of firms I would need a benchmark to deal with mergers, exit of incumbents, and entry and location of the new firms. Similarly, to deal with entry/exit of cars I need a model to select those cars to withdraw and the multidimensional characteristics of the new entering models.
Let us go over the revenues of international producer $f$, $R_{ft}$. Since the firm $f$ produces for domestic and foreign markets, they have revenues in foreign and domestic currencies. Expressed in $f$’s currency, I add all the revenues across markets:

$$R_{ft} = \sum_m \sum_{j \in F_{fm}} e_{fmt} \cdot p_{jt} \cdot q_{jt} \cdot (p_{t}^{m}, X_{jt}^{m}, Y_{m}^{t}, \xi_{jt}^{m})$$  \hspace{1cm} (3)$$

where $e_{fmt}$ is the ratio of currencies to convert revenues in destination currency $m$ to firm $f$’s currency (expressed as $f$/m$)$. This justifies the inclusion of the nominal exchange rates as relevant state variables for the producer.\footnote{The set includes the currencies of the producer countries (\{e_1, ..., e_F\}) as well as the destination markets (\{e_1, ..., e_M\}), although the intersection is almost complete. The extensive list of currencies considered are: Belgian Franc, French Franc, German Mark, Italian Lira, British Pound, Japanese Yen and American Dollar.}

The next term $p_{jt}$ is the nominal wholesale price of model $j \in F_{fm}$ expressed in the currency of the selling market $m$. $q_{jt}$ is the total number of units of model $j$ sold at time $t$ in market $m$. Notice that the demand depends on the entire vector of prices $p_{t}^{m}$ and characteristics, $X_{jt}^{m}$, of the models in that respective market/time since the consumer compare all the models before buying. Moreover, the demand function depends on real prices (not nominal prices), so I used the nominal GDP per capita in the destination market, $Y_{m}^{t}$, as denominator. This implies that the nominal GDP per capita must be also included as another state variable. I discuss this demand function for differentiated products in section 2.3.

The second term in the profit function is the direct production cost $C_{ft}$. I assume that producers only own plants in their origin country, hence the costs of production are expressed in domestic currency only.

$$C_{ft} = \sum_m \sum_{j \in F_{fm}} C_{jt}^{m}(X_{jt}^{m}, W_{ft}, W_{mt}, q_{jt}^{m}, \xi_{jt}^{m}; \nu_{f})$$  \hspace{1cm} (4)$$

Basically the production cost of each model $j \in F_{fm}$ depends on the characteristics $X_{jt}^{m}$ of that model, the nominal wages of the manufacturing sector in the source country $f$ and the destination market $m$ ($W_{ft}$ and $W_{mt}$ respectively) and the number of manufactured units $q_{jt}^{m}$. Recall that the demand $q_{jt}^{m}(p_{t}^{m}, X_{jt}^{m}, Y_{m}^{t})$ depends on all competitor’s prices and characteristics as well as the consumer’s income. Thus, the production cost term justifies the inclusion of the nominal wages as state variable. I assume that the evolution of nominal labor cost is observable through the nominal wage time series and it is same within each country.

I assume that capital price is firm specific since it is closely related to the idiosyncratic firm’s risk. Capital price is important for investment decisions (such as to build a manufacturing plant), but pricing decisions are based on marginal cost that I assume are mainly driven by labor cost. I
can not identify sunk cost of production such as investments, research and
development of new cars. Capital effects can be seen as nuisance parameter
all over the cost parameters of the firm \( f, \nu_f \), but it can not be recovered
separately.

Finally, I turn to the price adjustment cost term with structural pa-
rameters \( \Psi_{fm} \subset \nu_f \). I usually do observe smooth changes in the data,
then a fixed cost of price adjustment seems not to be the best approach.
Instead, I have penalty term that is proportional to the magnitude of the
price change. Thus, I estimate two specifications in order to identify the
adjustment cost:

\[
AC_{f,t,1} = \sum_m \sum_{j \in F_{fm}} \Psi_{fm} \cdot e_{fmt} \cdot |p_{jt}^m - p_{jt-1}^m| \tag{5}
\]

and I also estimate:

\[
AC_{f,t,2} = \sum_m \sum_{j \in F_{fm}} \Psi_{fm} \cdot |\log(p_{jt}^m) - \log(p_{jt-1}^m)| \tag{6}
\]

This term is crucial to turn this setting into a dynamic problem since it
is the one that links two consecutive periods. Without this term, the model
is reduced to an infinitely repeated static game, in which the producer do
not care about future consequences of current actions, since undoing is
free.\(^5\) Lagged price will be considered also a state variable, since past
prices will be the source of the dynamics.

I assume that there is no penalty to set the first price, thus the term
that only appears at first time pricing, say \( p_{-1} \) is equal to \( p_0 \) for all models
and for any \( p_0 \) the first \( \Psi \)-term is zero. I think this as equivalent to assume
a zero entry cost.\(^6\) Recall that in the model there is no decision about
entry\(\backslash\)exit of firms\(\backslash\)models, hence a fixed entry cost (zero or positive) only
appears once.

As a real world evidence Gopinath and Rigobon (2008) report estimates
for stickiness at-the-dock prices in the US. They found the astonishing
duration of 14.5 months for cars. The theoretical literature has developed
some frameworks to rationalize these price adjustment costs.\(^7\)

As in Goldberg and Hellerstein (2008), “...the specific causes of this
cost is beyond the scope of this paper, however I define costs of repricing
in the broadest possible way. It may include the small costs of re-pricing
(“menu-costs”) as well as the more substantive costs associated with the

\(^5\)As in Golberg and Verboven (2001).

\(^6\)Assuming \( p_{-1} = p \) different from zero, lead us to an one-time punishment term \( \Psi |p_0 - p_{-1}| \)
that could be interpreted as a positive fixed entry cost.

\(^7\)I mention the classic papers in menu costs (Barro (1972), Rotemberg (1982), Mankiw
(1985)) and staggering contracts (Taylor (1980, 2000)). In a different setting, Krugman (1987)
included reputation cost in a two stage purchase.
managements time and effort in figuring out the new optimal price, the additional costs of advertising and more generally communicating the price change to the consumers”. An important improvement of this paper is that only in this fully dynamic framework I can account for the option value of avoiding price changes in the face of ongoing uncertainty.

We already know that prices are persistent at micro level in differentiated products like cars. However, it is only through a dynamic structural benchmark that I can properly estimate the magnitude of the parameters $\Psi_{fm}$. Previous dynamic reduced forms can not identify these parameters since the effect might be mixed with other sources of stickiness. Previous structural estimations strongly relies on the static first order conditions of a multiproduct firms competing a la Bertrand. Most of them are repeated static frameworks and only Nakamura and Zerom (2008) explores the dynamic setting but still using the first order conditions as the pricing rule. My fully dynamic model obtain the structural parameters without that assumption. I discuss this advantage in detail in the next section but basically the policy function does not follow theoretical restrictions since it is statistical tool to capture the observed behavior.

2.2 Estimating the Dynamic Game: BBL approach

This subsection presents the main methodology to estimate this dynamic game, which was developed by Bajari, Benkard, and Levin (2007, hereafter BBL). I present the general functional forms so in the empirical section I focus in the estimated specifications.

First, I need to model the transition between states. Let the state vector at date $t + 1$, denoted $s_{t+1}$, is drawn from a known probability distribution $P(s_{t+1}|p_t, s_t)$. I assume that current car’s prices do not affect future state variables as exchange rates, car’s characteristics, GDP per capita or nominal wages. Therefore my state variables $s_{t+1}$ are exogenous. Furthermore, I assume that the process is a first order Markov process. Formally, the transition probabilities for tomorrow’s states $s_{t+1}$ are given by:

$$P(s_{t+1}|p_t, s_t) = P(s_{t+1}|s_t) \tag{7}$$

Second to analyze equilibrium behavior, I focus on pure strategy Markov perfect equilibria (MPE). In a MPE, each firm’s behavior depends only on the current state $s_t$ although the function might be firm specific. The definition of Markov Perfect equilibrium requires that players only care about the current states and not “how the state was reached”, so I rule out the possibility of “state path dependance”. I should think the price decision as any other “investment decision” that only depends on the current situation and the last decision.\footnote{Previous BBL applications were done for entry/exit decision and the logic is the same:}
Formally in this setting, a Markov strategy for firm $f$ is a function $\sigma_f : S \to P_f$, where $S$ is the set of relevant state variables and $P_f$ is the action space for firm $f$. A profile of Markov strategies is a vector, $\sigma = (\sigma_1, ... , \sigma_F)$, where $\sigma : S \to P = (P_1, ... P_F)$. If the behavior is given by a Markov strategy profile $\sigma$, the firm $f$’s expected profit $V_f(s, \sigma)$ given a state $s$ can be written recursively:\footnote{Assume that $V_f$ is bounded for any Markov strategy profile $\sigma$.}

$$V_f(s, \sigma_f) = \mathbb{E} \left[ \pi_f(\sigma_f(s), s) + \beta_f \int V_f(s', \sigma) dP(s' | \sigma, s) | s \right] \quad (8)$$

The profile $\sigma$ is a Markov perfect equilibrium if, given the opponent profile $\sigma_{-f}$, each firm $f$ prefers its strategy $\sigma_f$ to all alternative Markov strategies $\sigma'_{f}$,

$$V_f(s, \sigma) = V_f(s, \sigma_f, \sigma_{-f}) \geq V_f(s, \sigma'_{f}, \sigma_{-f}) \quad (9)$$

This inequality requires that for each firm $f$ and initial state $s$, $\sigma_f$ outperforms each alternative Markov strategy $\sigma'_{f}$ so there is no profitable deviations.

The BBL algorithm has two stages. The goal of the first stage is to estimate the state transition probabilities $P(s_{t+1} | s_t)$ and the equilibrium policy functions $\sigma_f(s)$. The second stage uses the equilibrium conditions described above to estimate the structural parameters of the model denoted $\nu$.\footnote{For econometric purposes, I treat the player specific discount factor $\beta_f$ as known. I use the average inflation over 30 years to account for differences in the inflation rates between countries.} Suppose the profit functions for firm $f$ is a known function indexed by a finite parameter vector $\nu_f$ so the structural parameters of the model are given by the profit functions $\pi_1(p, s; \nu_1), ..., \pi_F(p, s; \nu_F)$. Assuming the data is generated by a MPE of the model, the goal is to recover the true value of $\nu = (\nu_1, ... , \nu_F)$, denoted $\nu_0$.

The first step of BBL approach is to estimate the policy functions, $\sigma_f : S \times \nu_f \to p_f$ for $f = \{1, ... , F\}$, and state transition probabilities, $P : S \to \Delta(S)$. The purpose of estimating the equilibrium policy functions is that they allow us to construct estimates of the equilibrium value functions, which can be used in turn to estimate the structural parameters of the model. Forward simulation are used to estimate firms’ value functions for given strategy profiles (including the equilibrium profile) given an estimate of the transition probabilities $P$.

Given any policy function $\sigma$ and transition probability $P$, a simple single simulated path of play can be obtained as follows:

1. Set an initial cost parameters $\nu = \{\nu_1, ... , \nu_F\}$ and initial state $s_0 = s$. Investment may depend on what happened last period, but not how we reached the current stage.
2. Draw a sequence of states over $T$ periods using the estimated transition probabilities $\mathbb{P}(.|s_t)$, hence I generate the sequence $\{s_1, s_2, ..., s_T\}$.

3. Compute the actions for every player $f$ through the estimated policy function, thus: $p_t = \sigma_f(s_t)$, hence I generate the respective sequence $\{p_1, p_2, ..., p_T\}$.

4. Given the known functional form of profit function $\pi_{ft}$ and the discount factor $\beta_f$, I compute the resulting profits $\hat{\pi}_{ft}(p_t, s_t; \nu_f)$, for all players $f \in \{1, ..., F\}$ at every simulated time period $t$.

5. Compute the present discounted value for each player:

$$\hat{V}_f(\nu_f, \sigma, \mathbb{P}) = \sum_{h=1}^{\infty} \beta_f^{T-t} \hat{\pi}_{ft}(\nu_f, \sigma, \mathbb{P})$$

6. Repeat steps 1-5 for a large number, $NR$, of alternative paths each of $T$ periods.

Averaging firm $f$’s discounted sum of profits over many simulated paths of play yields an estimate of expected value of the players’ payoff:

$$\hat{E}(V(\nu_f, \sigma_f, \mathbb{P})) = \frac{1}{NR} \sum_{h=1}^{NR} \hat{V}_h^f(\nu_f, \sigma_f, \mathbb{P})$$

Notice that the data is used to estimate the pair $(\sigma, \mathbb{P})$ in the first stage only. After that, the entire forward simulation depends on those estimates and does not require actual data.

Such an estimate can be obtained for any $(\sigma, \nu_f)$ pair, including $(\hat{\sigma}, \nu_f)$, where $\hat{\sigma}$ is the policy profile that results from first stage estimation. Because the first stage estimation $\hat{\sigma}$ is based on the observed data, I infer that it represents the optimal policy function given the equilibrium beliefs.

It follows that $\hat{V}_f(s, \hat{\sigma}, \nu_f)$ is an estimate of firm $f$’s payoff from playing $\hat{\sigma}_f$ in response to opponent behavior $\hat{\sigma}_{-f}$, and $\hat{V}_f(s, \sigma_f, \hat{\sigma}_{-f}, \nu_f)$ is an estimate of its payoff from playing $\sigma_f$ in response to $\hat{\sigma}_{-f}$, in both cases conditional on all players parameters $\nu$. Combining such estimates with the equilibrium conditions of the model permits the estimation of the underlying structural parameters.

Based on MPE definition, optimality requires no profitable deviations, i.e.:

$$V_f(s|\sigma_f, \sigma_{-f}, \nu_f) \geq V_f(s|\sigma'_f, \sigma_{-f}, \nu_f)$$

Let $x \in X$ index the equilibrium conditions, so that each $x$ denotes a particular $(f, s, \sigma'_f)$ combination. In a slight abuse of notation, define:

$$g(x, \nu, \alpha) = V_f(s|\sigma_f, \sigma_{-f}, \nu, \alpha) - V_f(s|\sigma'_f, \sigma_{-f}, \nu, \alpha)$$

The dependence of $V_f(s, \sigma, \nu, \alpha)$ on $\alpha$ reflects the fact that functions $\sigma$ and $\mathbb{P}$ are parameterized by first stage parameters $\alpha$. The inequality defined by $x$ is satisfied at $\nu, \alpha$ if $g(x, \nu, \alpha) \geq 0$. 


Define the function

\[ Q(\theta, \alpha) \equiv \int \left( \min \left\{ g(x, \nu, \alpha) \right\}, 0 \right)^2 dH(x) \]  

(13)

where \( H \) is a distribution over the set \( X \) of inequalities. The true parameter vector, \( \nu_0 \), satisfies:

\[ Q(\nu_0, \alpha_0) = 0 = \min_{\nu \in \Theta} Q(\nu, \alpha) \]  

(14)

Given a sequence of inequalities \( \{X_k\}_{k=1}^{n_I} \), I use an alternative policy

\[ \tilde{\sigma}_f(s, \nu_f) = \sigma_f(s, \nu_f, \hat{\alpha}) + u \]  

(15)

where \( u \) is white noise. By definition of \( \sigma_f \), this alternative policy function \( \tilde{\sigma}_f \) is suboptimal. For each chosen inequality the forward simulation procedure can construct analogues of each of the \( V_f \) terms, say \( V_f^{\tilde{}} \). Formally;

\[ \tilde{g}(x, \nu, \hat{\alpha}_n) = V_f(s, \sigma_f, \sigma_{-f}, \nu, \hat{\alpha}_n) - V_f(s, \tilde{\sigma}_f, \sigma_{-f}, \nu, \hat{\alpha}_n) = V_f - \tilde{V}_f \]  

(16)

whenever \( \tilde{g} \) is negative it means that \( \tilde{\sigma}_f \) was a profitable deviation for firm \( f \).

Finally the second stage estimator is:

\[ \hat{\nu} = \arg \min_{\nu \in \Theta} \frac{1}{n_I} \sum_{k=1}^{n_I} \left( \min \left\{ \tilde{g}(x_k, \nu, \hat{\alpha}) \right\}, 0 \right)^2 \]  

(17)

I explain the details about functional forms estimated in the empirical section.

2.3 Estimating the Demand: BLP Approach

This section presents the general framework to estimate demand for differentiated products as in BLP (1995). The mixed logit (also called random coefficients model) is the starting point of this approach taking advantage of a more realistic substitution patterns than logits models and allowing estimation with market level data. As in previous sections, a market is defined as a combination of a buying country \( m \) at time \( t \), although for simplicity I just use the subscript \( t \) in this subsection.

Following the usual approach (Nevo 2000), the utility has a deterministic and random components given by:

\[ U_{ijt} = X'_{jt} \alpha_{1i} + \alpha_{2i} (y_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt} \]  

(18)

where \( X_{jt} \) is a K-dimensional vector of observable characteristics of product \( j = \{1, ..., J\} \) in market \( t = \{1, ..., T\} \), \( y_i \) is the income of consumer \( i = \)
\{1, \ldots, R\}, \ p_{jt} \ is \ the \ price \ of \ product \ j \ in \ market \ t, \ \xi_{jt} \ is \ an \ unobserved \ (by 
the \ econometrician) \ scalar \ product \ characteristic, \ and \ \epsilon_{ijt} \ is \ a \ mean-zero \ stochastic \ term. \ Finally, \ \alpha_{1i} \ is \ a \ K-dimensional \ vector \ of \ individual-specific 
taste \ coefficients, \ and \ \alpha_{2i} \ is \ consumer \ i's \ marginal \ utility \ from \ income. 
Notice \ that \ the \ marginal \ utility \ parameter \ vary \ across \ consumers \ but \ not 
across \ products \ for \ given \ a \ individual. \ I \ specify \ the \ list \ of \ considered 
characteristics \ in \ the \ empirical \ section \ 4.

Formally, \ the \ distribution \ of \ the \ idiosyncratic \ parameters \ is \ given \ by:

\[
\begin{pmatrix}
\alpha_{1i} \\
\alpha_{2i}
\end{pmatrix} = \begin{pmatrix}
\alpha_1 \\
\alpha_2
\end{pmatrix} + \Sigma v_i = \alpha + \Sigma v_i \quad \text{where} \quad v_i \sim N(0, I_{K+1})
\]

where \(v_i\) \ captures \ the \ unobservable \ consumer \ heterogeneity \ and \ \(I\) \ is \ a \ \(K+1\) \ by \(K+1\) \ identity \ matrix. \ Since \ I \ assume \ a \ standard \ multivariate \ normal 
distribution, \ the \ matrix \ \Sigma \ is \ my \ unknown \ parameter \ for \ the \ variance-
covariance \ matrix \ \Sigma \Sigma'..

Let \(\theta = (\alpha, \Sigma)\) \ be \ a \ vector \ containing \ all \ the \ parameters \ of \ the \ demand 
where \(\alpha\) \ is \ the \ linear \ parameter \ vector \ and \ \Sigma \ is \ the \ non \ linear \ parameter 
matrix.

Define

\[
\delta_{jt}(\alpha) \equiv X'_{jt} \alpha_1 - \alpha_2 p_{jt} + \xi_{jt}
\]

\[
\mu_{ijt}(\Sigma) \equiv [X'_{jt}, p_{jt}]\Sigma v_i
\]

So \ the \ utility \ can \ be \ re-written \ as:

\[
U_{ijt} = \alpha_2 y_i + \delta_{jt}(\alpha) + \mu_{ijt}(\Sigma) + \epsilon_{ijt}
\]

First, \ the \ term \ \(\alpha_2 y_i\) \ plays \ no \ role \ in \ the \ consumer’s \ ranking, \ since \ it \ is 
the \ same \ for \ all \ goods. \ Second, \ \(\delta_{jt}\) \ is \ called \ the \ “mean \ utility”, \ which \ is 
the \ component \ of \ utility \ from \ consumer’s \ choice \ of \ product \ \(j\) \ that \ is \ the 
same \ across \ all \ consumers \ (it \ includes \ an \ unobservable \ term \ \xi_{jt}). \ Third \ \(\mu_{ijt}(\Sigma)\) \ is \ a \ heteroscedastic \ disturbance \ and, \ fourth \ \(\epsilon_{ijt}\) \ is \ a \ homoscedastic 
disturbance.

This \ approach \ consider \ an \ outside \ good \ \(j = 0\), \ that \ represents \ “not \ to 
buy \ a \ new \ car” \ and \ it \ is \ normalized \ to \ zero, \ i.e., \ \(U_{i0t} = 0, \forall (i, t)\).

Let \ us \ define \ the \ set \ \(A_{jt}\), \ which \ has \ all \ the \ individuals \ who \ choose 
model \ \(j\) \ at \ market \ \(t\):

\[
A_{jt}(x, t, p_{jt}, \xi_{jt}, \theta) = \{(v_i, \epsilon_{i0t}, \ldots, \epsilon_{iJt}) | U_{ijt} \geq U_{ilt}, \forall l = \{0, \ldots, J\}\}
\]

Because \ income \ enters \ in \ a \ linear \ fashion, \ it \ cancels \ out \ in \ all \ the \ utility 
comparisons. \ Assuming \ ties \ occur \ with \ zero \ probability, \ the \ market \ share 
\(s_{jt}\) \ of \ the \ \(j^{th}\) \ product \ is \ just \ an \ integral \ over \ the \ mass \ of \ consumers \ in \ the 
region \ \(A_{jt}\), \ that \ depends \ on \ random \ variables \ \(v_i\) \ and \ \(\epsilon = (\epsilon_{i0t}, \ldots, \epsilon_{iJt})\).
Consequently, the total demand is just the market share times the population of market $t$, denoted $pop_t$. Formally:

$$q_{jt} = pop_t \cdot s_{jt}(x, t, p, \xi, \theta) = pop_t \cdot \int_{A_{jt}} dF_{\varepsilon}(\varepsilon) d\Phi(v_i)$$

where the joint distribution of shocks $\varepsilon$ and $v$ are the product of the density functions due to the independence assumption.

The next step is to compute the individual probability of buying a particular good $j$, hence the total market share of this good is the integral over all the consumers of that probability given by:

$$s_{jt}(x, t, p, \xi, \theta) = \int_{A_{jt}} dF_{\varepsilon}(\varepsilon) d\Phi(v_i)$$

If the $\varepsilon$s have the usual extreme value distribution, then I have a closed form for the individual probability:

$$s_{ijt} = \frac{\exp(X'_{jt} \alpha_i - \alpha_2 p_{jt} + \xi_{jt})}{1 + \sum_h \exp(X'_{ht} \alpha_i - \alpha_2 p_{ht} + \xi_{ht})} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_h \exp(\delta_{ht} + \mu_{iht})} \quad (22)$$

And the market share integrates over all consumers:

$$s_{jt}(x, t, p, \xi, \theta) = \int_{A_{jt}} \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_h \exp(\delta_{ht} + \mu_{iht})} d\Phi(v_i) \quad (23)$$

The integral over the individual shocks $v_i$ is computed through simulation as I explain in the appendix B. I simulate $R$ individuals and I compute their decisions for each market, obtaining the predicted market shares for each product at market level.

The unobservable characteristics $\xi_{i,t}$ are the only unobservable variable that can explain an imperfect fit with the actual shares.

Stacking the predicted shares in vector $s(.)$. On the other hand let $\textbf{Sh}$ be the actual observed share vector for each market. Naturally, the estimator $\hat{\theta}$ is:

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \| s(X, t, p, \xi, \theta) - \textbf{Sh} \| \quad (24)$$

BLP (1995) suggested instruments to control for the endogeneity of prices because of a potential correlation between unobserved characteristics and prices. Roughly speaking this approach takes two steps: first identify the $\delta_{jt}$ terms for each product in each market matching the market shares, and second, use those $\delta$s to identify $\beta$ vector through a standard instrumental variables regression. Appendix B describes in detail the particular generalized method of moments (GMM) estimation that I used.

---

11Recall that a market is defined as a combination of country $m$ and time $t$.
3 Data

This section describes and discuss the data. The dataset was collected by Brenkers and Verboven (2006) and is an updated version of the one used by Goldberg and Verboven (2001).\footnote{The data is available in the authors’ webpage.}

The yearly data set consists of prices, sales and physical characteristics of (essentially) all car models sold in five European markets from 1970 until 1999. The included destination markets are Belgium, France, Germany, Italy and the United Kingdom. The definition of market is a country-year combination. The total number of observations is 11,549 implying that on average about 80 models are sold in every market/year.

There are about 350 different car models during this period, although many of them are successors of old models. Examples are the Fiat Uno, VW Golf, Toyota Corolla, Peugeot 405, and BMW 5-series.

Sales are new car registrations for the model range. Physical characteristics (also from consumer catalogues) include dimensions (weight, length, width, height), engine characteristics (horsepower, displacement) and performance measures (speed, acceleration and fuel efficiency). The data set also includes variables to identify the model, the brand, the firm, the country of origin/production location, and the market segment (“class” or “category”). The data set is augmented with macro-economic variables including population, exchange rates, nominal and real GDP.

3.1 Car Prices and Characteristics.

This section briefly describes the trends of the data across different European markets. The price data are pre-tax and post-tax list prices, i.e., the final prices suggested by manufacturers to retailers. For each market I have the prices expressed as share of GDP per capita, in the domestic currency and in a common currency.

As mentioned above the data includes several characteristics from consumer catalogues such as weight, length, width, height, horsepower, displacement, speed, acceleration and fuel efficiency at different speeds. Because many of them are very collinear I reduced the dimensionality of this state space constructing three variables that summarize the observed characteristics.

The summarized characteristics are:

**Size**: It is the product of length (Le), height (He) and width (Wi) \(\text{Size} = He \times Le \times Wi\).

**Inverse of Motor Power**: I explore several specification to summarize the car’s motor characteristics. By dar the best fit to a linear model was the inverse of motor power given by \(\text{InvPow} = (Hp \times Cy \times Sp)^{-1}\), where
$Hp$ is horse power, $Cy$ is the number of cylinders and $Sp$ is the maximum speed.

**Fuel efficiency**: is the arithmetic average between the fuel efficiency at “city speed”, 90 and 120 kilometers per hour (measured as liters per kilometer).

The trends of all these three characteristics in the five destination markets are in figure 1, 2 and 3 respectively. Size and Motor power have some linear trend and/or clear autocorrelated process. Instead full efficiency seems to be less systematic.

Figure 1: Evolution of car size across Europe.

I also have full information about the segment of the car (compact, subcompact, standard, intermediate and luxury). Also I know the man-
3.2 Nationalities and Market Shares

This section presents the most salient features of the European car market.

The definition of nationality of the product is fundamental. First, I need to define “domestic” producers so to account for any home bias in the demand side of the model. Second, I need to transform all the revenues into the relevant currency for producers in the supply side.

Thus, I consider the historic brand association for the demand side and firm’s headquarters for the supply side. Appendix A shows in detail the nationalities criteria and their market shares. Now I turn over the nationality based on brand history. Table 1 shows the models available per market of each nationality based on firms’ brand (demand perspective).

From consumers perspective and using the criterium for nationalities based on historic reasons, market shares of the domestic producers are astonishing large. Based on the demand side perspective, table 2 presents the market shares for each nationality in the five European markets.

Based on these striking differences the natural question is whether the domestic cars are really different from foreign cars. Since the domestic cars in one market are the foreign cars in the rest of the markets, I should expect similar characteristics. Goldberg and Verboven (2001, 2005) present compelling evidence that (observed) characteristics can not explain alone

13Consequently, from the consumers’ point of view, mergers do not change the perceived nationality of the brands, although for the supply side the revenues belong to a different firm.
Table 1: Available models across Europe by brand nationality

<table>
<thead>
<tr>
<th>Brand’s Nationality</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>130</td>
<td>126</td>
<td>126</td>
<td>123</td>
<td>126</td>
<td>631</td>
</tr>
<tr>
<td>French</td>
<td>566</td>
<td>561</td>
<td>509</td>
<td>509</td>
<td>502</td>
<td>2647</td>
</tr>
<tr>
<td>German</td>
<td>338</td>
<td>325</td>
<td>347</td>
<td>317</td>
<td>293</td>
<td>1620</td>
</tr>
<tr>
<td>Italian</td>
<td>408</td>
<td>379</td>
<td>340</td>
<td>478</td>
<td>242</td>
<td>1847</td>
</tr>
<tr>
<td>British</td>
<td>329</td>
<td>274</td>
<td>224</td>
<td>229</td>
<td>364</td>
<td>1420</td>
</tr>
<tr>
<td>Japanese</td>
<td>629</td>
<td>377</td>
<td>533</td>
<td>136</td>
<td>523</td>
<td>2198</td>
</tr>
<tr>
<td>Others</td>
<td>273</td>
<td>223</td>
<td>204</td>
<td>235</td>
<td>251</td>
<td>1186</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2,673</strong></td>
<td><strong>2,265</strong></td>
<td><strong>2,283</strong></td>
<td><strong>2,027</strong></td>
<td><strong>2,301</strong></td>
<td><strong>11,549</strong></td>
</tr>
</tbody>
</table>

Table 2: Average Market Share across Europe by brand nationality

<table>
<thead>
<tr>
<th>Brand’s Nationality</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>9.7</td>
<td>6.1</td>
<td>10.8</td>
<td>5.8</td>
<td>25.4</td>
</tr>
<tr>
<td>French</td>
<td>28.2</td>
<td><strong>69.9</strong></td>
<td>10.6</td>
<td>15.9</td>
<td>15.5</td>
</tr>
<tr>
<td>Germans</td>
<td>19.9</td>
<td>8.1</td>
<td><strong>44.6</strong></td>
<td>9.8</td>
<td>8.2</td>
</tr>
<tr>
<td>Italians</td>
<td>6.9</td>
<td>6.2</td>
<td>5.2</td>
<td><strong>59.0</strong></td>
<td>3.8</td>
</tr>
<tr>
<td>British</td>
<td>13.4</td>
<td>5.6</td>
<td>18.9</td>
<td>5.5</td>
<td><strong>33.0</strong></td>
</tr>
<tr>
<td>Japanese</td>
<td>17.3</td>
<td>2.3</td>
<td>7.8</td>
<td>1.1</td>
<td>9.7</td>
</tr>
<tr>
<td>Others</td>
<td>4.6</td>
<td>1.9</td>
<td>2.0</td>
<td>2.8</td>
<td>4.2</td>
</tr>
</tbody>
</table>
the dramatic market share differences. To illustrate this point table 3 compares characteristics between foreign and domestic cars, showing that cars seem alike.\textsuperscript{14}

\begin{table}[h]
\centering
\caption{Domestic and Foreign Car characteristics across Europe}
\begin{tabular}{|l|c|c|c|c|c|c|}
\hline
Characteristic & Origin & Belgium & France & Germany & Italy & UK \\
\hline
Size          & Domestic & 9.65 & 9.60 & 10.34 & 8.94 & 9.66 \\
              & Foreign & 9.64 & 9.57 & 9.80 & 9.74 & 9.74 \\
Motor Power Inv. & Domestic & 1.36 & 1.97 & 1.03 & 1.87 & 1.06 \\
              & Foreign & 1.16 & 1.37 & 1.31 & 1.23 & 1.23 \\
Fuel Efficiency & Domestic & 8.22 & 7.85 & 8.75 & 8.10 & 8.53 \\
               & Foreign & 8.21 & 8.15 & 8.07 & 8.17 & 8.17 \\
Price         & Domestic & 0.72 & 0.69 & 0.80 & 0.98 & 1.08 \\
              & Foreign & 0.77 & 0.63 & 0.99 & 1.04 & 1.04 \\
\hline
\end{tabular}
\end{table}

Therefore, any demand estimation should consider some sort of home bias preference to match these market shares. I discuss it again when presenting the demand results in section 4.1.

\subsection*{3.3 Entry/Exit Behavior}

This section discuss the assumption about entry/exit of firms and models. In general this is important in the sense that large movements in exchange rates can change the relevant players or models and consequently might be a composition effect as highlighted by Rodriguez-López (2008).

To address the entry/exit of firms I would need a benchmark to deal with mergers, entry of new firms and exit of incumbents, in each market at every time period. I argue that the average percentage of new firms is low, with small firms being absorbed by bigger players. The percentage of new firms among total firms across the 30 years is less than 7%. Weighting by market shares, the relevance of new firms is even lower. Figure 4 presents the evolution of the number of new firms.

Similarly, to deal with entry/exit of models I need which incumbent model exits from any given market and the characteristics of the new model that enters, which is prohibitive when the characteristics are multidimensional as in this case. I argue that new models are not a big share of the market. Figure 5 shows the ratio between new models and total number of models in each market, and the average percentage of new models across the 30 years is about 5%.

\textsuperscript{14}I report size, a motor power index, fuel efficiency and “comparable price”. The latter is the ratio of nominal price over nominal GDP per capita.
Figure 4: New firms across Europe.

Figure 5: New models across Europe.
For the forward simulation I consider fixed characteristics as well as fixed models in each market. Hence I know that the results that I find are not contaminated by this composition effect. None of the previous structural empirical work had controlled for this fact, so I think this is quite an improvement.

4 Results

This section presents the empirical results of applying the model to the European market of cars. The first subsection presents the demand results. The second presents the results for the supply side of the industry. Some impulse-response are presented to evaluate the economic sense of the policy functions. Finally I present the structural estimates and their implications for the relative size of price adjustment costs in total cost.

4.1 Demand Estimation

This section presents the estimates of the demand for new cars in Europe, using the general demand framework developed by Berry, Levinsohn and Pakes (1995). This framework considers heterogenous consumers, controls for price endogeneity and does not need a sequential nested decision.

One of the most important features that I have to match is that domestic car producers have an extremely dominant position in the European car market, as I show in data section. Roughly speaking, domestic cars are quite similar to foreign cars based on observed characteristics, but their market shares are huge. Therefore, any demand estimation should consider some sort of “home bias” and unobserved characteristics in order to match these market shares.

Using a nested logit estimation, Goldberg and Verboven (2001) found that domestic producers face two advantages: i) a fixed positive effect on demand and ii) a systematic more inelastic demand. Notice that one of the considered nest is the decision between a domestic and foreign car. The latter nest provided them a elasticity parameter by car’s origin that granted a domestic advantage at price elasticity level besides the fixed effect (after controlling for other characteristics).

BLP technique does not impose any arbitrary decision nest\textsuperscript{15}, hence my price elasticities are robust to those considerations. As I see below, this new evidence suggests that the home bias is totally captured by a fixed effect and there are no particular price-elasticity advantages for domestic producers in their domestic markets.

\textsuperscript{15}Cardell (1997) formally shows that the nested logit can be written as a special case of the mixed logit. An interesting debate about this two settings can be found in Wojcik (2000) and the reply by Berry and Pakes (2001).
The specification of the utility function is given by:

\[ U_{ijt} = \alpha_1 X_{jt} \text{home}_{jt} + \alpha_2 (y_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt} \]  

(25)

where \( X_{jt} \) is the vector of observable characteristics: size, motor power and fuel efficiency. Also includes the set of dummies (segment, market, year, brand, firm, and location of plants); I explicitly consider the home bias preferences through the dummy variable \( \text{home}_{jt} \), which is 1 if the destination market is the same country as the brand nationality. \( p_{jt} \) is the real price of product \( j \) in market \( t \), measured as nominal price over nominal GDP per capita.\(^\text{16}\) Notice that in general there are no restrictions about which coefficients can vary across consumers, so I try in principle several specifications and leave only the statistically significant coefficients.

BLP (1995) suggested instruments to control for endogeneity of prices because of the potential correlation between unobserved characteristics \( \xi_{jt} \) and price \( p_{jt} \). I closely follow the instruments suggested by BLP, so I use the sum of the competitors’ characteristics, the sum of the other own product’s characteristics, the number of competitors and the number of the other own products, and their powers as well. These instruments are very strong in this case, with a nice predictive power over the prices.

Table 4 presents the demand estimates that will be used in the next sections.

<table>
<thead>
<tr>
<th>Linear BLP Parameters ( \alpha )</th>
<th>Coef</th>
<th>s.d.</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price-Belgium</td>
<td>-1.86</td>
<td>( 0.55 )</td>
<td>-3.40</td>
</tr>
<tr>
<td>Price-France</td>
<td>-4.09</td>
<td>( 0.97 )</td>
<td>-4.22</td>
</tr>
<tr>
<td>Price-Germany</td>
<td>-3.25</td>
<td>( 0.85 )</td>
<td>-3.82</td>
</tr>
<tr>
<td>Price-Italy</td>
<td>-2.03</td>
<td>( 0.62 )</td>
<td>-3.26</td>
</tr>
<tr>
<td>Price-UK</td>
<td>-1.28</td>
<td>( 0.63 )</td>
<td>-2.05</td>
</tr>
<tr>
<td>Home-Bias-France</td>
<td>1.75</td>
<td>( 0.09 )</td>
<td>19.07</td>
</tr>
<tr>
<td>Home-Bias-Germany</td>
<td>1.33</td>
<td>( 0.18 )</td>
<td>7.40</td>
</tr>
<tr>
<td>Home-Bias-Italy</td>
<td>2.53</td>
<td>( 0.06 )</td>
<td>39.01</td>
</tr>
<tr>
<td>Home-Bias-UK</td>
<td>1.28</td>
<td>( 0.10 )</td>
<td>13.23</td>
</tr>
<tr>
<td>Inverse Power</td>
<td>-1.11</td>
<td>( 0.11 )</td>
<td>-9.70</td>
</tr>
<tr>
<td>Size</td>
<td>0.77</td>
<td>( 0.25 )</td>
<td>3.10</td>
</tr>
<tr>
<td>Liters per Km</td>
<td>-1.41</td>
<td>( 0.23 )</td>
<td>-6.09</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Non-Linear Parameters ( \sigma )</th>
<th>Coef</th>
<th>s.d.</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std Dev on Price Coeff.</td>
<td>0.68</td>
<td>( 0.35 )</td>
<td>1.93</td>
</tr>
</tbody>
</table>

| GMM Obj. function                  | 286.46 |

\(^\text{16}\)This solves the problem due to differences in inflation and income between markets.
Notice that once country specific price and home bias coefficients were considered, the random unobserved heterogeneity only is significant in the price coefficient ($\sigma_p > 0$).

In this setting the own price elasticity of product $j$ is given by:

$$\eta_{jt} \equiv \frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = \frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt} (1 - s_{ijt}) d\Phi(v_i)$$

Notice that the home bias effect only enters through the individual share $s_{ijt} = s(p_{jt}, x_{jt}, home_{jt}, \xi_{jt}, \alpha_i)$.

Figure 6 presents the distribution of the elasticity estimates.

Recall that by assumption all the producers know the parameters of the demand function when pricing cars in each market. Optimal pricing policy heavily relies on the marginal effects of changes in prices, so it is very relevant whether domestic producers have an elasticity advantage in their domestic market. I namely define an elasticity advantage if a domestic producer faces systematically a more inelastic demand than their foreign competitors.

In order to identify any advantage at price elasticity level, first I cluster the elasticities by market destination so all producers face the same set of consumer’s parameters. In each market, I aggregate by nationality so I can compare the elasticities of domestic and foreign producers.

Recall that price and home bias coefficients are market specific.
The five figures in appendix C strongly suggest that domestic producers do not face a systematic less elastic demand, since domestic’s elasticities are in the range of the other producers’ elasticities. This is a robust fact when replicating the analysis by car segment. Notice that the absolute values of my estimates are smaller than the nested logit estimates of Golberg and Verboven (2001), especially for the UK. This in usual first order conditions approach lead to higher markups, but I do not compute markups in that way. As I discuss in the result section, these smaller price elasticities predict a smaller lost in revenues after an adverse change in the relevant nominal exchange rate.

Another important feature of these estimates is the fact that the fixed effects of home bias are quite large. To illustrate this point, table 5 reports the predicted market shares, assuming no home bias at all in all markets, i.e., replacing zero in the home bias coefficient in all the five markets while keeping all the other characteristics fixed (including the unobservable characteristic $\xi$). The reduction of domestic shares are quite large comparing with table 2 supporting the idea that the large domestic dominance is not due to the (un)observed characteristics only.

<table>
<thead>
<tr>
<th>Brand’s Nationality</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>9.7</td>
<td>13.8</td>
<td>16.1</td>
<td>12.0</td>
<td>33.3</td>
</tr>
<tr>
<td>French</td>
<td>28.2</td>
<td>30.6</td>
<td>15.8</td>
<td>36.7</td>
<td>20.4</td>
</tr>
<tr>
<td>Germans</td>
<td>19.9</td>
<td>18.6</td>
<td>17.6</td>
<td>21.0</td>
<td>10.7</td>
</tr>
<tr>
<td>Italians</td>
<td>6.9</td>
<td>14.9</td>
<td>7.8</td>
<td>11.3</td>
<td>5.1</td>
</tr>
<tr>
<td>British</td>
<td>13.4</td>
<td>12.9</td>
<td>28.1</td>
<td>11.7</td>
<td>12.5</td>
</tr>
<tr>
<td>Japanese</td>
<td>17.3</td>
<td>5.2</td>
<td>11.6</td>
<td>1.9</td>
<td>12.6</td>
</tr>
<tr>
<td>Others</td>
<td>4.6</td>
<td>4.1</td>
<td>3.0</td>
<td>5.4</td>
<td>5.5</td>
</tr>
</tbody>
</table>

Finally, some caveats about these demand estimates. First, I can account and identify these large domestic fixed effect, but I can not tell the underlying reasons why this is the case. The home dummy might capture several phenomena such as “nationalism”, network effects, replacement availability, any kind of asymmetric information about the products, historical arguments or (most likely) a mix of all reasons above.

Also, these estimates are conditional on the characteristics and models available for each market since 1970. These parameters just rationalize the options taken by the consumers, given the choice set they faced. Regulations or any constraints that play against foreign cars change the choice set. Still, this lack of competition should be observed in differences in the

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18 Although I do not report the all 25 figures.
19 Such as the quotas faced by Japanese cars in Italy.
car characteristics between foreign and domestic models at some point. As we can see there is no such a gap. A more serious non-competitive behavior (such as a multi-contact market collusion) can not be addressed only with these demand side estimates.

4.2 Transition Probabilities

This subsection presents the estimation of the transition probabilities. These processes determine the evolution of the state variables, which are independent of the endogenous control variables (prices). The state variables of the model are: exchange rates, nominal wages in the manufacturing sector (or car sector if available) and nominal GDP per capita in the buying markets. Exchange rates are crucial to express the profits and costs in the same currency. Nominal wages are the source of nominal variation in the costs. Recall that the comparable price used in the demand side is given by the ratio between the nominal price and the nominal GDP per capita, both in destination market currency. Potentially, I could also include car’s characteristics but it requires to define the entry-exit decisions of the models.

I assume that all state variables follow a first order Markov process. The following sections present the actual estimates for these state variables.

4.2.1 Exchange Rates

I assume that the nominal exchange rate follow a first order autocorrelated process, $AR(1)$, considering correlated contemporary shocks across countries (as in the seemingly unrelated regressions, SUR). All the estimations consider the log of the nominal exchange rates.

Hence the equation for currency of country $s = \{\text{Belgium, France, Germany, Italy, UK, Japan}\}$ at time $t$ is given by:

$$e_{s,t} = \alpha_s + \rho_s e_{s,t-1} + u_{s,t}$$  \hspace{1cm} (26)

where the shocks $u_{s,t}$ are correlated among countries but not correlated across time.

$$\text{cov}(u_{s,t}, u_{r,t}) = \sigma_{s,r} \neq 0 \ \forall s, r \ \text{and} \ \text{cov}(u_{s,t}, u_{r,p}) = 0 \ \forall t \neq p$$  \hspace{1cm} (27)

The series are the ratio between the local currency and the American dollar. Nevertheless, in the BBL estimation I use the ratio between the producer’s currency and the selling market currency, so the dollar as denominator do not matter.

Several events might be important for this integration process. First, the calendar for the launch of the Euro was set in the Maastricht treaty,\footnote{This ratio captures two dynamic effects: inflation and higher consumer’s income.}
which was signed in February 1992, as a consequence of previous treaties and negotiations in the late 80s (Single European Act (SEA), 1987). The Euro was introduced in 1999, hence after the 4th quarter of 1998 there is no variation between 4 out of 6 of my considered currencies. Hence I estimate five alternative subsamples: 1) from 1971-Q1 to 1989-Q4; 2) from 1990-Q1 to 2008-Q2; 3) from 1981-Q1 to 1998-Q4; 4) from 1971-Q1 to 1998-Q4; 5) From 1971-Q1 to 2008-Q2. There are not big differences between estimates, however I see a slight decline in the inertia over the years. I select the model based on the quarters just before the launch of the Euro as the most appropriate process to consider (1971-Q1 to 1998-Q4).

The estimates are going to be estimated with quarterly data but all the forecasts used in the forward simulation stage are yearly.\(^{21}\) To compare the degree of inertia of the series I compare the “absorbing period” \(T\) which is the number of periods needed to reduce a shock to a 10% of its initial magnitude, i.e, \(\rho^T = 0.1\).

As a result, I find a huge autocorrelation, that might lead to consider a non-stationary series. Although BBL technique does not require to the state variables to be stationary, it turns out that using extended quarterly data (from Q1/1971 until the Q2/2008) I can not reject a stationary process (\(\hat{\rho}_s < 1\)) with a huge persistence.\(^{22}\) Hence, I compute the long run value for the nominal relation between each European currency and the dollar.\(^{23}\) The detailed estimates are presented in table 6.

### Table 6: Transition Probability estimates for Nominal Exchange Rates.

<table>
<thead>
<tr>
<th></th>
<th>Quarterly Estimates</th>
<th>Yearly Est.</th>
<th>Long-run level</th>
<th>(T)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgian</td>
<td>(\rho) 0.98 ***</td>
<td>0.93</td>
<td>31.24</td>
<td>33</td>
</tr>
<tr>
<td>Franc</td>
<td>(\alpha) 0.06 *</td>
<td>0.23</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>French</td>
<td>(\rho) 0.99 ***</td>
<td>0.96</td>
<td>5.61</td>
<td>54</td>
</tr>
<tr>
<td>Franc</td>
<td>(\alpha) 0.02</td>
<td>0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>German</td>
<td>(\rho) 0.98 ***</td>
<td>0.91</td>
<td>1.52</td>
<td>26</td>
</tr>
<tr>
<td>Mark</td>
<td>(\alpha) 0.01</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italian</td>
<td>(\rho) 0.98 ***</td>
<td>0.92</td>
<td>1,726.98</td>
<td>28</td>
</tr>
<tr>
<td>Lira</td>
<td>(\alpha) 0.15 **</td>
<td>0.60</td>
<td></td>
<td></td>
</tr>
<tr>
<td>British</td>
<td>(\rho) 0.97 ***</td>
<td>0.89</td>
<td>0.62</td>
<td>19</td>
</tr>
<tr>
<td>Pound</td>
<td>(\alpha) -0.01</td>
<td>-0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Japanese</td>
<td>(\rho) 0.98 ***</td>
<td>0.91</td>
<td>116.87</td>
<td>24</td>
</tr>
<tr>
<td>Yen</td>
<td>(\alpha) 0.12</td>
<td>0.44</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Legend: *\(p\) value < 0.05 ; **\(p\) value < 0.01 ; ***\(p\) value < 0.001.

---

\(^{21}\)Appendix H describes the procedure to use these estimates for yearly forecast.

\(^{22}\)For a discussion of unit root tests, see Hamilton (1994).

\(^{23}\)The formula to compute the long run price is given by \(\bar{e}_s = \frac{\alpha_s}{1-\rho_s}\).
I also am interested in the correlation matrix of the residuals, since I want to draw simulations of the random terms \( u_s \). During these decades I observe an integration process between these European countries that lead to an almost perfect correlation between currencies. Of course after the launch of Euro the correlation is perfect, since the currencies of Belgium, France, Germany and Italy just disappeared. The estimated correlation matrix for the selected period is presented in table 7.

Table 7: Correlation Matrix of Exchange Rate Shocks.

<table>
<thead>
<tr>
<th>Yearly</th>
<th>Bel</th>
<th>Fra</th>
<th>Ger</th>
<th>Ita</th>
<th>UK</th>
<th>Jap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bel</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fra</td>
<td>0.93</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ger</td>
<td>0.97</td>
<td>0.91</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ita</td>
<td>0.81</td>
<td>0.84</td>
<td>0.79</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK</td>
<td>0.66</td>
<td>0.65</td>
<td>0.65</td>
<td>0.70</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Jap</td>
<td>0.62</td>
<td>0.60</td>
<td>0.62</td>
<td>0.45</td>
<td>0.46</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Among the countries that adopt the Euro, the Italian currency has a quite lower correlation than the others. The UK did not adopt the Euro and kept its currency showing an intermediate level of correlation. As expected, the Japanese Yen is the less correlated currency.

4.2.2 Nominal Wages and Nominal GDP per capita

Now I turn to the transition probabilities of the nominal wages, \( W \), and the nominal GDP per capita, \( Y \). I consider both GDP per capita and wages in the manufacturing sector (or car sector if available) to be correlated within each country (Belgium, France, Germany, Italy, and the UK). Furthermore, I assume segmented labor markets and therefore I rule out correlation between countries through the random term \( v_s \).

Using the log of the variables, the estimated model is the following \( VAR(1) \) system:

\[
\begin{bmatrix}
W_{s,t} \\
Y_{s,t}
\end{bmatrix} = \lambda_0 + \lambda_s' \begin{bmatrix}
W_{s,t-1} \\
Y_{s,t-1}
\end{bmatrix} + \begin{bmatrix}
v_{1,s,t} \\
v_{2,s,t}
\end{bmatrix} \tag{28}
\]

where \( E(v_{1,s,t}v_{2,r,p}) \neq 0 \) if and only if \( s = r \) and \( t = p \).

The estimates I present in table 8 are based on yearly data between 1971 and 1999.\(^{24}\)

Not surprisingly, all the process are extremely autocorrelated. It implies a slow adjustment given any unexpected shock. Similarly for most of the

\(^{24}\)Quarterly data is not available for the relevant years and countries.
Table 8: Transition Probability estimates for Nominal Wages and GDP per capita.

<table>
<thead>
<tr>
<th></th>
<th>GDP Equation</th>
<th>Wage Equation</th>
<th>( \rho )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lag GDP</td>
<td>lag Wage</td>
<td>Cons</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.95</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>0.00</td>
<td>0.30</td>
<td>2.93</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Germany</td>
<td>0.95</td>
<td>0.58</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>0.69</td>
<td>0.28</td>
<td>2.71</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>UK</td>
<td>0.96</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

countries, the shocks on nominal wages are correlated with the shocks on nominal GDP, captured by the country specific parameter \( \rho \). Germany is the only country where there is no significant wage-GDP correlation.

4.3 Policy Functions

This section describes the policy functions and presents the estimates. The aim of this stage is to retrieve the optimal decision function from the observed behavior. I assume agents have taken their optimal decisions based on observable state variables, hence I estimate the relationship through a reduced form using actual data.

Remember that the BBL approach uses the transition probabilities to simulate several paths of future scenarios. Given those alternative sequence of state variables, I compute the optimal response using the estimated policy functions in each scenario.

Basically, I want to predict future car prices based only on fixed car’s characteristics and simulated macroeconomic variables. My dependent variable is nominal prices in destination currency and the states variables include car’s characteristics and macroeconomic variables of the five destinations market (Belgium, France, Germany, Italy and the UK). I aggregate the 31 firms into 6 nationalities (Americans, French, German, Italian and Japanese) so we should think of 6 players meeting in 5 different markets.

I have emphasized the strong evidence of “Pricing to Market” behavior,
especially important in differentiated products. To account for “pricing to market” in the European car industry, I allow different policy functions in each market/producer combination, so the Markov perfect equilibrium is not assumed to be the same. Hence each producer’s policy function has different parameters in each different market. I estimate each combination of the 6 firm’s nationalities over the 5 destination markets. There is no free lunch and the cost of having producer/market estimations is the reduction in the sample that limits more flexible functional forms in the estimation.25

From the initial 11,549 observations I must restrict the sample for various reasons. First, I only use those that belong to the 6 nationalities.26 Second, I need information of at least two consecutive periods in order to estimate the lagged price coefficient. Third, I only use those with domestic production. Although most of the models were made in the domestic headquarter country, some firms have production in different locations. I discard the other location’s cars because do not have enough observations to avoid the strong assumption of a common policy function and cost parameters with the headquarter’s production. The exception is given by the American cars that are made in the UK (for the British market) and in Germany (for the rest of the markets). The available number of observations for each estimation is given in table 9.

Table 9: Sample for Policy Function Estimation.

<table>
<thead>
<tr>
<th>Nation/Market</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>211</td>
<td>175</td>
<td>204</td>
<td>165</td>
<td>174</td>
<td>929</td>
</tr>
<tr>
<td>French</td>
<td>463</td>
<td>462</td>
<td>413</td>
<td>418</td>
<td>390</td>
<td>2,146</td>
</tr>
<tr>
<td>Germans</td>
<td>296</td>
<td>286</td>
<td>301</td>
<td>280</td>
<td>252</td>
<td>1,415</td>
</tr>
<tr>
<td>Italians</td>
<td>355</td>
<td>325</td>
<td>279</td>
<td>404</td>
<td>197</td>
<td>1,560</td>
</tr>
<tr>
<td>British</td>
<td>104</td>
<td>94</td>
<td>34</td>
<td>69</td>
<td>140</td>
<td>441</td>
</tr>
<tr>
<td>Japanese</td>
<td>515</td>
<td>272</td>
<td>416</td>
<td>55</td>
<td>405</td>
<td>1,663</td>
</tr>
<tr>
<td>Total</td>
<td>1,944</td>
<td>1,614</td>
<td>1,647</td>
<td>1,391</td>
<td>1,558</td>
<td>8,154</td>
</tr>
</tbody>
</table>

The policy functions (or first stage estimation) should have a flexible functional form in order to capture the unknown relationship between states and control variables. I do not have any structural interpretation for these estimates and only through the second stage estimates I will have structural parameters. Of course the considered explanatory variables must have an underlying economic reason to be part of the relevant state variables for these players in this particular pricing decision.

25 Exploring policy functions that are asymmetric or a S-s function is totally desired but requirements on the number of observations are prohibitive.
26 I leave out the models from the Netherlands, Czechoslovakia, Sweden, Spain, Korea, Russia, Yugoslavia.
I have 30 combinations for the six nationalities in each of the five markets. Denote m the market of destination and denote s the country of production which most of the cases is the same as the head quarter country or nationality f.\textsuperscript{27}

Hence, for a given car model in market m, produced in market s at time t, I have:

$$\log(p_{jt}^m) = \alpha \log(p_{jt-1}^m) + \beta_1 \log(e_{mt}/e_{st}) + \beta_2 \log(e_{mt}/e_{st})^2$$

(29)

$$+ \beta_3 \log(e_{mt}/e_{st}) \cdot \log(X_{jt}^m) + \gamma_0 \log(X_{jt}^m) + \gamma_1 \log(W_{st})$$

$$+ \gamma_2 \log(X_{jt}^m) \cdot \log(W_{st}) + \lambda_1 \log(Y_{jt}^m) + \lambda_2 Dummies + \varepsilon_t$$

where the dependent variable is the log of the nominal price of model j in destination m currency at time t, $p_{jt}^m$, highlighting that I want to explain a nominal phenomenon. The explanatory variables I consider are:

- The ratio of nominal exchange rates terms ($e_{mt}/e_{st}$) that considered polynomials and product with the characteristics $X_{jt}^m$ that are model specific.
- The characteristics $X_{jt}^m$ and the nominal wage $W_{st}$ in the producer country s. These terms are a measure of nominal cost of production.
- The lagged price $p_{jt-1}^m$ which represents the price stickiness in a reduced form. Notice that this estimate can not be interpreted as the adjusting cost parameter directly.
- The nominal GDP per capita,$Y_{jt}^m$ in the destination market m at time t. This captures the income effect of the consumers in each market m. Recall that the real price consider in the demand is the ratio $p_{jt}^m$ over $Y_{jt}^m$.\textsuperscript{28}
- The dummies per firm and market segment (compact, subcompact, standard, intermediate and luxury cars).

In order to give us a sense of the price stickiness that I observe in the policy function, table 10 present the estimated coefficients $\hat{\alpha}$, which are large, significant and origin-destination market specific.

These coefficient are not meant to be interpreted as a meaningful economic parameters.\textsuperscript{29} The degree of fitness is quite good with R-squared above .95 although the statistic significance are quite low in general. This is expected given the high collinearity of many of these variables and the high degree of autocorrelation of the series. One way to evaluate them is through the implications for forecasting.

\textsuperscript{27}Except for American firms, who produced in Germany and the UK.

\textsuperscript{28}This is very collinear with nominal domestic wages at the destination market. This fact does not allow us to include a term that represents domestic components in the cost function.

\textsuperscript{29}The entire set of 13 regressors for each of the five markets for each of the six producers is available upon request.
The forecasts are useful for the structural second stage estimation as long as their economic implications are reasonable. I then rule out pass-through estimates that either predicts overshooting or negative pass-through for exchange rates and wages. Hence I might have zeros pass-through in some very particular cases. To ensure that policy functions imply sensitive economic results, I stress the importance of Impulse Response exercises, since these forward simulation are the key ingredient to identify the deep parameters that rationalize the optimal behavior.

4.4 Checking the Policy Function through Impulse-Response Experiments

This section discuss the results and the criteria to evaluate to estimated policy functions, since the aim of these estimates is to feed the forward simulation in the second stage.

From a pure game theory point of view, the optimal policies estimated here are just statistical representations of the true theoretical policy functions, that only can be found solving the theoretical game. Under this point of view, any real counterfactual exercise only can be done with those theoretical policy functions. However, so far I am able to solve simple games with few players (usually duopolies). Most of the examples are focused in discrete choices and a reduced number of state variables. In my case the choice variable is continuous (pricing) as well as the state variables (exchange rates, wages and GDP). On top of that the game is between 6 players in 5 different markets. There are recent tools to address these challenges such as the homotopy method that deals with all the equilibria. This area of research is the theoretical complement of this empirical work and should be explored in future work. Therefore, my estimated policy functions can not be interpreted as the optimal response to do counterfactual exercises because there is no formal concept of price equilibrium along the temporal profile of responses, but it still represents what players have
I focus on the predictions of each specifications to feed the second stage with economically reasonable forward simulations. One key prediction for the second stage is to obtain reasonable price ratios with respect the the nominal GDP per capita in each market. Recall that that nominal GDP per capital follows its own AR(1) process and therefore any miss-specification will lead the price ratio directly to infinity or zero. This prediction can not be tested directly in the data since usually the car models exit before I could asses the steady-state ratio. I ensured that selected specifications yield sensitive forecast for these ratios.

An important forecast to consider is the response to an unexpected change in some of the nominal state variables. I evaluate the policy functions under different paths of the state variables to asses the differences in prices, demand and revenue for each player. Since I have a fully structural demand for differentiated products, I evaluate the implications of the price changes on demand and revenues. Recall that the elasticity patterns in the demand estimation consider not only the change in relative prices but also the characteristics of each subset of cars, therefore it suits perfectly in this setting.

Using the estimates of each policy function, I simulate two different paths under two different scenarios. The benchmark keeps all the state variables in their long run value, whereas the other initially perturb a given state variable in 10% increase (I focus on exchange rate and wage perturbations). After the initial perturbation, the state variable follows its own AR(1) process until getting closer to their steady-state. I simulate the exercise for 40 periods ahead.

Notice that this evaluation does not consider any cost parameter, hence I can not argue the profitability of these actions.

4.4.1 Exchange Rate Depreciation

This subsection graphically analyzes the impulse-response experiments after a 10% nominal depreciation of each of the nominal currencies.

Although the reaction is symmetric between a depreciation of the destination currency and an appreciation of the origin currency, the temporal profile of the reaction will be different because of the different speed of adjustment of each currency.

Also, the shock affects differently to domestic and foreign producers. For example a depreciation of the French Franc may change the price of all the French cars outside France. The depreciation allows to the French producers to cut prices abroad keeping markups constant. On the other hand,

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30 The existence of steady-state is not necessary for the estimation under BBL technique. However, it simplifies this exercise because otherwise the reaction are determined by the initial conditions. Based on yearly data I do find stationary processes for the state variables.
only Foreign producers are affected in France. The depreciation might force the foreign producers to increase their prices since their revenues are less valuable in producer’s currency. Because French producers have costs in this depreciated currency, they do not change their prices domestically. I denoted these two effects as International effects when domestic producers can sell cheaply abroad and Domestic effects when foreign competitors are more expensive.

As special case I have Belgium where there are no domestic producers, hence all the cars are more expensive in Belgian Franc after a domestic depreciation. Similarly, since I do not consider the Japanese domestic market, a Japanese Yen depreciation implies lower prices all across Europe.

I present the figures for the French franc. The entire set of figures for all the responses after a 10% depreciation of each currency in each separate market is in appendix D and E. Appendix F presents the 90% confidence intervals for each response based on a bootstrapping of 1000 draws of each policy estimation. I refer to these figures whenever I claim that the response are not statistically significant.

Figure 7 presents the reaction of French producers outside France. The evidence remarks the heterogeneity in responses, both in size and temporal profile of the price change. The price change is close to 6% in the UK, while only 1% in Germany. Notice also the delay of six periods to reach the peak of reaction, even though there is a unique initial shock and afterwards each state variable follows its own process. Also notice that I do not observe a full pass-through and after a 10% depreciation, the prices respond partly.

Figure 7: Reactions in Europe after a 10% depreciation of the French Franc.

Figure 8 presents the reaction of foreign producers in France after a depreciation of the French Franc. Since their revenues are smaller in terms
of their cost’s currency, foreign producers increase their price. French producer’s price remain the same since their cost and revenues currencies have been not affected by the depreciation.

The price increases and temporal profile are quite similar among producers (about 6% and similar speed of reduction), except by Japanese cars that increase only 1% and remains almost flat along the simulations.

Using my point estimates of the demand system, I compute the consequences in the traded quantity as well. Notice that the depreciation of one currency changes all players demand. Even though some price may remain constant, the change of any competitor’s price may imply a change on demand. I present the percentage responses in the second panel of figure 8. The reactions in demand after the price increase stress a heterogenous pattern of substitution among French consumers. Domestic cars almost do not change, even though they are relatively cheaper after the depreciation, highlighting that many consumers prefers the outside good. Losses in demand are close to 20%, based on the estimated elasticities between 2 and 3. Notice that the losses would be even larger using previous estimates in the industry that are close to 5. The net result in revenues is just the sum of these two percentage responses. In short, a 10% depreciation in the French Franc leads to a reduction in revenues of about 20%, based on my estimated reduced forms. So far, the policy functions, transition probabilities and demand estimates were taken directly from the data.

The figures above account for the option value of doing nothing. However, this strategy only would be supported in the data if the coefficients for exchange rate are zero. That was not the case for most of the all policy functions estimated. Perhaps a Markov switching regime model could account for zero pass-through around some small changes but positive after a larger depreciation, however the number of observations do not allow us to explore this type of price reactions.

### 4.4.2 Wage Increase Experiment

This subsection presents the price reactions of a 10% increase in producers’ nominal wages, using the estimated policy functions and transition probabilities. This wage increase only affects the costs of producer at the time\(^31\) and it implies a price increase in the domestic market and abroad. Figure 9 presents the percentage responses in price increases and appendix G presents the figures for the rest of European wages.

In general there are no big differences in the magnitudes of the price increases, but in the temporal profile I observe some countries with a longer delay in the cost pass-through.

Finally, these exercises were done using reduced forms of pricing equations and transition probabilities. So no optimality conditions were im-

\(^{31}\) Except for American cars that are made in Germany and the UK.
Figure 8: Reactions in France after a 10% depreciation of the French Franc.
posed. The second stage assumed that producers were rational and estimate the cost parameters as the ones that make this behavior optimal.

4.5 Structural Cost Parameters

This section presents the implications of the structural estimates of cost parameters. This stage look for the cost parameters that rationalize the behavior found in the data (captured through the policy functions). Using these parameters I identify the size of the destination wage component and the size of the adjustment cost component over the total cost.

I assume the following cost function for firm $f$ and product $j \in F_{jm}$:

$$C_{jt}^m = \underbrace{\nu_0 \cdot q_{jt}^m + \nu_j \cdot [q_{jt}^m]^2}_{\text{Car’s Characteristics}} + \underbrace{\nu_{w1} \cdot W_{ft} \cdot q_{jt}^m + \nu_{w2} \cdot W_{ft} \cdot [q_{jt}^m]^2}_{\text{Producing Wage Cost}}$$

$$+ \underbrace{\nu_{w3} \cdot e_{fmt} \cdot W_{mt} \cdot q_{jt}^m + \nu_{w4} \cdot e_{fmt} \cdot W_{mt} \cdot [q_{jt}^m]^2}_{\text{Destination Wage Cost}} + \Psi_m \cdot e_{fmt} \cdot |p_{jt}^m - p_{jt-1}^m|$$

where the $\nu$s are the structural parameters of production cost while the $\Psi$s are the structural parameters of price adjustment cost in country $m$ since they are destination market specific. $q_{jt}^m$ is the quantity of product $j$ sold in market $m$, $W_{gt}$, $g \in \{m, f\}$ is the nominal wage in destination country $m$ or source/producer’s country $s$, $e_{fmt}$ is the nominal exchange rate between country $f$ and $m$. The quadratic terms ensures point estimates since the minimization procedure can achieved a minimum.
I identify each cost component to do the analysis. The first component is a fixed effect per model, so it represents the production cost related to the characteristics of each car, which remain fixed during the forward simulations.

The second and third components are the nominal labor cost, which distinguish between wages where the product was made and wages where the car was sold (if different from producing country). Those are the main nominal component in the marginal cost.

The last component represents the price adjustment cost, which is independent of the quantity $q_{jt}$. I also consider an alternative cost function given by $\Psi_{fm} \cdot |\log(p_{jt}^m) - \log(p_{jt-1}^m)|$. The estimation looks for the price adjustment cost that is consistent with the actual price stickiness.

As discussed above, I want to ensure the same competitors over time. To do so I keep the firms and models that were traded in 1985, which is in the middle point of my sample. For these models I simulate 1,000 different paths of state variables, each path involving 40 periods of time.

Table 11 presents the car models I consider in the forward simulations with no entry or exit of models. As we can see there are few British cars in the sample and they eventually disappear in the 90’s. As I discuss in the result section this is a huge potential problem for cost estimation for British producers.

<table>
<thead>
<tr>
<th></th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>9</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>6</td>
<td>39</td>
</tr>
<tr>
<td>French</td>
<td>19</td>
<td>18</td>
<td>16</td>
<td>18</td>
<td>16</td>
<td>87</td>
</tr>
<tr>
<td>Germans</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>8</td>
<td>48</td>
</tr>
<tr>
<td>Italians</td>
<td>13</td>
<td>16</td>
<td>7</td>
<td>19</td>
<td>5</td>
<td>60</td>
</tr>
<tr>
<td>British</td>
<td>4</td>
<td>5</td>
<td>0</td>
<td>5</td>
<td>6</td>
<td>20</td>
</tr>
<tr>
<td>Japanese</td>
<td>29</td>
<td>15</td>
<td>20</td>
<td>0</td>
<td>20</td>
<td>84</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>84</strong></td>
<td><strong>72</strong></td>
<td><strong>62</strong></td>
<td><strong>59</strong></td>
<td><strong>61</strong></td>
<td><strong>338</strong></td>
</tr>
</tbody>
</table>

Some important remark of the cost estimates. First, I can not identify any fixed cost of the firm, such as an investment in a new plant. The estimation procedure cancel out these terms leaving the variable cost estimates unaltered. Second, I account for the differences among countries at demand and supply level. The demand consider consumer heterogeneity and the optimal policies are market-firms’ specific, hence the equilibrium beliefs and cost parameters are market-firms’ specific as well.

\[^{32}\text{I have the estimates for other years and are they very similar.}\]
4.5.1 Cost Share by Components.

This section presents the cost parameters implications in order to explain the degree of incomplete exchange rate pass-through and the adjustment cost consistent with the observed price stickiness. For simplicity, I present the share of each component over total cost in order to provide an order of magnitude of my estimates. The same charts for the alternative specification are presented in the appendix I, which are qualitatively the same.\(^{33}\)

The shares of each component is given by the following decomposition:

\[
\begin{align*}
\text{Share of Local Production Cost} &= \frac{\nu_0 \cdot q_{jt}^m + \nu_j \cdot [q_{jt}^m]^2 + \nu_{w1} \cdot W_{ft} \cdot q_{jt}^m + \nu_{w2} \cdot W_{ft} \cdot [q_{jt}^m]^2}{C_{jt}^m} \\
\text{Share of Destination Wage Cost} &= \frac{\nu_{w3} \cdot e_{fmt} \cdot W_{mt} \cdot q_{jt}^m + \nu_{w4} \cdot e_{fmt} \cdot W_{mt} \cdot [q_{jt}^m]^2}{C_{jt}^m} \\
\text{Share of Price Adjustment Cost} &= \frac{\Psi_m \cdot e_{fmt} \cdot |p_{jt}^m - p_{jt-1}^m|}{C_{jt}^m}
\end{align*}
\]

Table 4.5.1 presents the share of each component for each producer’s nationality. Naturally, the destination market component appears in the exported cars only. The adjustment cost component is virtually zero for the domestically sold cars of the American and German producers.

<table>
<thead>
<tr>
<th>Exports</th>
<th>Local Cost</th>
<th>Destination Cost</th>
<th>Adjustment Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>83.17</td>
<td>16.68</td>
<td>0.15</td>
</tr>
<tr>
<td>French</td>
<td>77.91</td>
<td>20.11</td>
<td>1.98</td>
</tr>
<tr>
<td>German</td>
<td>62.10</td>
<td>37.58</td>
<td>0.31</td>
</tr>
<tr>
<td>Italian</td>
<td>35.33</td>
<td>59.17</td>
<td>5.50</td>
</tr>
<tr>
<td>Japanese</td>
<td>60.12</td>
<td>28.91</td>
<td>10.97</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sold Domestically</th>
<th>Local Cost</th>
<th>Adjustment Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>French</td>
<td>97.42</td>
<td>2.58</td>
</tr>
<tr>
<td>German</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Italian</td>
<td>88.59</td>
<td>11.41</td>
</tr>
</tbody>
</table>

Table 12: Different Components (%) over Total Cost in 1985.

Based on the evidence of the tables I conclude the following insights.

First, the destination market wage component in table 4.5.1 may explain

\(^{33}\)In general I found plausible results for most producers, except for British producers. Only five cars per market were not enough to identify the cost parameters, which yields negative markups for all models (with some noticeable outliers). Thus I do not report the unreliable British results. Perhaps the small elasticities in the demand estimation can also be the source of the failure of the estimation for this producers.
Table 13: **Adjustment Cost Share by Destination Market.**

<table>
<thead>
<tr>
<th></th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>0.0</td>
<td>0.4</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>French</td>
<td>0.0</td>
<td>2.2</td>
<td>0.0</td>
<td>7.4</td>
<td>0.1</td>
</tr>
<tr>
<td>German</td>
<td>0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.8</td>
<td>0.1</td>
</tr>
<tr>
<td>Italian</td>
<td>12.9</td>
<td>1.9</td>
<td>0.0</td>
<td>10.2</td>
<td>2.1</td>
</tr>
<tr>
<td>Japanese</td>
<td>0.0</td>
<td>1.4</td>
<td>3.8</td>
<td>-</td>
<td>37.2</td>
</tr>
</tbody>
</table>

Table 14: **Ratio of Adjustment Cost Parameters:** $\Psi_{fm}/\Psi_{ff}$.

<table>
<thead>
<tr>
<th></th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>0.07</td>
<td>93.38</td>
<td>1.00</td>
<td>0.22</td>
<td>11.04</td>
</tr>
<tr>
<td>French</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>1.78</td>
<td>0.08</td>
</tr>
<tr>
<td>German</td>
<td>3.57</td>
<td>0.00</td>
<td>1.00</td>
<td>1.31</td>
<td>1.49</td>
</tr>
<tr>
<td>Italian</td>
<td>0.37</td>
<td>0.02</td>
<td>0.02</td>
<td>1.00</td>
<td>0.23</td>
</tr>
<tr>
<td>Japanese</td>
<td>0.00</td>
<td>0.25</td>
<td>1.00</td>
<td>-</td>
<td>14.28</td>
</tr>
</tbody>
</table>

the incomplete degree of exchange rate pass-through. Roughly speaking they contribute to one third of the costs and therefore I should not expect to have full pass-through. Goldberg and Verboven (2001) find destination cost about 40% for the European car market, hence my estimates are along the same lines for most producers. Still the foreign component for Italian producers seems to high to be plausible.

Second, the adjustment cost component seems small and sometimes not economically significant. My estimates in table remark that these terms are larger for Italians and Japanese producers, whereas almost nonexistent for German producers. The adjustment cost component seems more important in exports but recall that most of the cars are sold domestically, so these cars have a bigger denominator.

To compare this conclusion with the related literature, my price adjustment cost represents at most 3% of total revenues, roughly speaking. Nakamura and Zerom (2008) found that adjustment cost represents 0.23% of total revenues in the coffee industry, using a different dynamic approach. Using a static framework, Goldberg and Hellerstein (2008) estimates are less than 1% of revenues in the beer industry.

Third, there is a clear heterogeneity in the estimates of tables 13 and 14. Adjustment cost seemed to be market specific for each producer nationality. Comparing the ratio of coefficients and the relative importance of the cost share. Something that is destination-origin specific might matter.

\[34\] Assuming an adjustment cost of 10% of total cost and a markup of 70%.
To justify such practice I could have some conjectures based on bilateral country relationships like the average of relative inflation, exchange rate volatility or any other characteristic that is pair-country-specific. None of the previous literature in this topic has explored this dimension.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>71%</td>
<td>35%</td>
</tr>
<tr>
<td>French</td>
<td>83%</td>
<td>31%</td>
</tr>
<tr>
<td>German</td>
<td>61%</td>
<td>47%</td>
</tr>
<tr>
<td>Italian</td>
<td>74%</td>
<td>37%</td>
</tr>
<tr>
<td>Japanese</td>
<td>67%</td>
<td>42%</td>
</tr>
</tbody>
</table>

Fourth, table 15 presents the implied markups for year 1985, i.e., the markups that rationalize the behavior described by the policy functions. I do not consider the models with markups greater than 100%. Although these are just a few observations in general it is not the case of the non reported British cars (with a relatively large amount of outliers among few models). I conclude based on the rest of the European evidence that seems consistent.

In general I compute quite higher markups than the previous usual static approach, but also with a huge dispersion (with some noticeable outliers). Notice that I need fewer assumptions than the standard static approach, since the policy function is a reduced form based on observed behavior and does not rely on first order conditions of Bertrand competition for differentiated products. Recall that I can not identify fixed cost, so the total profits must be smaller and I can not say much about the entire industry profitability.

5 Conclusions

The aim of this paper is to extend the structural estimation of exchange rate pass-through to include price adjustment costs. Consequently, forward looking firms set optimal prices taking into account that repricing is costly. In fact, the producers must consider the expected path between the current scenario and the steady state accounting for the respective adjustment speed.

I estimate a fully structural model of demand and supply for differentiated products following the methodology for dynamic games developed by Bajari, Benkard and Levin (2007). My demand estimates highlight the consumer heterogeneity that enhances pricing to market behavior. Con-
sumers have different degree of substitution among international producers, and producers have market specific pricing policies.

On the supply side, I explain incomplete pass-through by a sizable third of the total costs which are denominated in destination currency (destination wage component). Additionally, there is no need of huge adjustment costs to rationalize the large degree of inertia in prices. Intuitively, an economic environment in which wages, GDP and exchange rates are very autocorrelated with persistent shocks, just small adjustment costs can rationalize the actual autocorrelated and persistent car prices. My estimates show that less than 10% of total cost can generate the large observed price stickiness. Surprisingly, my estimates of adjustment cost seem to be market-specific adding a new dimension of heterogeneity to the pricing to market behavior, which has not been explored before.

6 References


APPENDIX SECTIONS

A Nationalities.

This appendix section presents the two criteria to classify the nationality of each car model. First I use the brand’s history to assign a nationality, regardless the change in property (acquisition or merger with other firms). The demand side estimation use this criterium as the most likely perception for European consumers.

Table 16 shows in detail the nationality considered for each brand. Table 17 and 18 present the market shares and the share of total models available under this criterium.

Table 16: Nationality based on brand’s history.

<table>
<thead>
<tr>
<th>Country</th>
<th>Brand Name</th>
<th>Country</th>
<th>Brand Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Czech R.</td>
<td>Skoda</td>
<td>Japan</td>
<td>Daihatsu</td>
</tr>
<tr>
<td>France</td>
<td>Citroën</td>
<td>Honda</td>
<td>Mazda</td>
</tr>
<tr>
<td></td>
<td>Peugeot</td>
<td>Mitsubishi</td>
<td>Nissan-Datsun</td>
</tr>
<tr>
<td></td>
<td>Renault</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Talbot-Hillman-Chrysler</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Talbot-Matra</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Talbot-Simca</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Netherlands</td>
<td>DAF</td>
<td>US</td>
<td>Ford</td>
</tr>
<tr>
<td>Germany</td>
<td>Audi</td>
<td>Korea</td>
<td>Daewoo</td>
</tr>
<tr>
<td></td>
<td>BMW</td>
<td>Hyundai</td>
<td>Kia</td>
</tr>
<tr>
<td></td>
<td>MCC</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mercedes</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Princess</td>
<td>Spain</td>
<td>Seat</td>
</tr>
<tr>
<td></td>
<td>Volkswagen</td>
<td>Sweden</td>
<td>Saab</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Volvo</td>
</tr>
<tr>
<td>Italy</td>
<td>Alfa Romeo</td>
<td>UK</td>
<td>Opel-Vauxhall</td>
</tr>
<tr>
<td></td>
<td>Autobianchi</td>
<td></td>
<td>Rover</td>
</tr>
<tr>
<td></td>
<td>Fiat</td>
<td></td>
<td>Rover-Triumph</td>
</tr>
<tr>
<td></td>
<td>Innocenti</td>
<td></td>
<td>Triumph</td>
</tr>
<tr>
<td></td>
<td>Lancia</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yugoslavia</td>
<td>Yugo</td>
</tr>
</tbody>
</table>

The supply side consider another definition of nationality to construct the profit function, since I need to express firm’s revenues in firm’s headquarter currency. Table 19 presents the assignation between firms and nationalities based on historical nationality of the headquarters location.
Table 17: Available models across Europe by brand’s nationality

<table>
<thead>
<tr>
<th>Brand’s Nationality</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>130</td>
<td>126</td>
<td>126</td>
<td>123</td>
<td>126</td>
<td>631</td>
</tr>
<tr>
<td>French</td>
<td>566</td>
<td>561</td>
<td>509</td>
<td>509</td>
<td>502</td>
<td>2647</td>
</tr>
<tr>
<td>German</td>
<td>338</td>
<td>325</td>
<td>347</td>
<td>317</td>
<td>293</td>
<td>1620</td>
</tr>
<tr>
<td>Italian</td>
<td>408</td>
<td>379</td>
<td>340</td>
<td>478</td>
<td>242</td>
<td>1847</td>
</tr>
<tr>
<td>British</td>
<td>329</td>
<td>274</td>
<td>224</td>
<td>229</td>
<td>364</td>
<td>1420</td>
</tr>
<tr>
<td>Japanese</td>
<td>629</td>
<td>377</td>
<td>533</td>
<td>136</td>
<td>523</td>
<td>2198</td>
</tr>
<tr>
<td>Others</td>
<td>273</td>
<td>223</td>
<td>204</td>
<td>235</td>
<td>251</td>
<td>1186</td>
</tr>
<tr>
<td>Total</td>
<td>2,673</td>
<td>2,265</td>
<td>2,283</td>
<td>2,027</td>
<td>2,301</td>
<td>11,549</td>
</tr>
</tbody>
</table>

Table 18: Shares of cars by brand’s nationality.

<table>
<thead>
<tr>
<th></th>
<th>% of Sold Cars</th>
<th>% of Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>11.57</td>
<td>5.46</td>
</tr>
<tr>
<td>France</td>
<td>28.02</td>
<td>22.92</td>
</tr>
<tr>
<td>Germany</td>
<td>18.12</td>
<td>14.03</td>
</tr>
<tr>
<td>Italy</td>
<td>16.23</td>
<td>15.99</td>
</tr>
<tr>
<td>UK</td>
<td>15.29</td>
<td>12.30</td>
</tr>
<tr>
<td>Japan</td>
<td>7.66</td>
<td>19.03</td>
</tr>
<tr>
<td>Korea</td>
<td>0.39</td>
<td>2.43</td>
</tr>
<tr>
<td>Sweden</td>
<td>1.53</td>
<td>4.80</td>
</tr>
<tr>
<td>Spain</td>
<td>0.80</td>
<td>2.14</td>
</tr>
<tr>
<td>Yugoslavia</td>
<td>0.03</td>
<td>0.24</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.20</td>
<td>0.24</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>0.16</td>
<td>0.42</td>
</tr>
</tbody>
</table>
A firm never changes the assigned nationality even though a brand could change due to mergers or acquisitions. Along the same lines, table 20 and 21 presents the market shares and the share of total models available in each market for each nationality and each destination market.

Table 19: **Nationality based on firms’ headquarter.**

<table>
<thead>
<tr>
<th>Nationality</th>
<th>Firm</th>
<th>Nationality</th>
<th>Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>Peugeot, Renault, TalbotMatra, TalbotSimcaHillmanSunbe</td>
<td>Italy</td>
<td>AlfaRomeo, DeTomaso, Fiat, Lancia</td>
</tr>
<tr>
<td>Germany</td>
<td>BMW, Daimler, Mercedes, VW</td>
<td>Korea</td>
<td>Daewoo, Hyundai, Kia</td>
</tr>
<tr>
<td>Japan</td>
<td>FujiHI (aka Subaru), Honda, Mazda, Mitsubishi, Nissan, Suzuki, Toyota</td>
<td>Spain</td>
<td>Seat</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
<td>Sweden</td>
<td>Saab, Volvo</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
<td>UK</td>
<td>Rover</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
<td>US</td>
<td>Ford, GeneralMotors</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
<td>Yugoslavia</td>
<td>Yugo</td>
</tr>
</tbody>
</table>

Table 20: **Models available across Europe by firms’ headquarter.**

<table>
<thead>
<tr>
<th>HQ’s Nationality</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>321</td>
<td>273</td>
<td>292</td>
<td>258</td>
<td>315</td>
<td>1,459</td>
</tr>
<tr>
<td>French</td>
<td>532</td>
<td>528</td>
<td>475</td>
<td>481</td>
<td>480</td>
<td>2,496</td>
</tr>
<tr>
<td>Germans</td>
<td>426</td>
<td>413</td>
<td>420</td>
<td>411</td>
<td>376</td>
<td>2,046</td>
</tr>
<tr>
<td>Italians</td>
<td>442</td>
<td>412</td>
<td>374</td>
<td>506</td>
<td>264</td>
<td>1,998</td>
</tr>
<tr>
<td>British</td>
<td>132</td>
<td>122</td>
<td>54</td>
<td>84</td>
<td>167</td>
<td>559</td>
</tr>
<tr>
<td>Japanese</td>
<td>629</td>
<td>377</td>
<td>533</td>
<td>136</td>
<td>523</td>
<td>2,198</td>
</tr>
<tr>
<td>Others</td>
<td>281</td>
<td>439</td>
<td>17</td>
<td>28</td>
<td>28</td>
<td>793</td>
</tr>
<tr>
<td>Total</td>
<td>2763</td>
<td>2564</td>
<td>2165</td>
<td>1904</td>
<td>2153</td>
<td>11549</td>
</tr>
</tbody>
</table>
Table 21: Shares of cars by firms’ headquarter.

<table>
<thead>
<tr>
<th>Country</th>
<th>Share of Sold Cars</th>
<th>Share of Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>22.12 %</td>
<td>12.63 %</td>
</tr>
<tr>
<td>France</td>
<td>26.64 %</td>
<td>21.61 %</td>
</tr>
<tr>
<td>Germany</td>
<td>19.56 %</td>
<td>17.72 %</td>
</tr>
<tr>
<td>Italy</td>
<td>17.61 %</td>
<td>17.30 %</td>
</tr>
<tr>
<td>UK</td>
<td>4.37 %</td>
<td>4.84 %</td>
</tr>
<tr>
<td>Japan</td>
<td>7.66 %</td>
<td>19.03 %</td>
</tr>
<tr>
<td>Korea</td>
<td>0.39 %</td>
<td>2.43 %</td>
</tr>
<tr>
<td>Sweden</td>
<td>1.37 %</td>
<td>3.80 %</td>
</tr>
<tr>
<td>Spain</td>
<td>0.06 %</td>
<td>0.15 %</td>
</tr>
<tr>
<td>Yugoslavia</td>
<td>0.03 %</td>
<td>0.24 %</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.20 %</td>
<td>0.24 %</td>
</tr>
</tbody>
</table>

B Computing BLP

This appendix section presents the details on the demand estimation. Berry, Levinsohn and Pakes (1995, hereafter BLP) developed the procedure to estimate a random coefficient model as a demand system for differentiated products with aggregate data. The optimization problem is:

$$\hat{\theta} = \arg \min_{\theta} \| s(x,t,p,t,\xi,t,\theta) - Sh \|$$

where $s(\cdot)$ is the predicted shares of the model and $Sh$ are the observed shares in the data. The minimization problem is far from trivial since $\xi$’s are not observable and all variables enter in a non-linear fashion.

Berry (1994) and BLP (1995) developed an iterative process, in which the problem is linearized in $\xi$. Then the minimization is straightforward through a GMM procedure based on suitable instruments. Also BLP have suggested a set of instruments that may apply in general cases. These instruments are based on the number and characteristics of the competitors.

Using previous notation, want to estimate a parameter $\theta = [\Sigma, \beta]$. $\beta$ are linear parameters and $\Sigma$ is the cholesky decomposition of a variance covariance matrix of the parameters $\beta$.

If parameter $\beta$ has dimension $K$, its $K$ by $K$ var-cov matrix $V = \Sigma\Sigma'$ would have at most $(K + 1)K/2$ unknowns. Usually most covariances are set to zero for simplicity.

This procedure is summarized as a three step procedure:

I ) First given some $\Sigma$, I find a vector $\delta(\Sigma)$. It uses a non linear procedure that involves computation of simulated integrals.

II ) Secondly, using $\delta(\Sigma)$ I estimate $\beta(\delta(\Sigma)) = \beta(\Sigma)$ in a linear way.
Finally, I have a GMM objective function $G$. Since the GMM objective function $G$ can be expressed as $G(\Sigma, \delta, \beta) = G(\Sigma)$, it is a function of $\Sigma$ only. The final stage is to find $\hat{\Sigma}$ that minimizes $G(\Sigma)$.

The basic data consist in: $\mathbf{Sh}_{N \times 1}$ vector of actual markets shares, $X_{N \times K}$ vector of the $K$ characteristics of each product. Let $Z_{N \times J}$ be a vector of the $J$ instruments for each product ($J > K$). $\mathbf{v}_{R \times K}$ is a fixed vector of random draws of a multivariate standard normal. Each row $i$ is a random draw of dimension $K$ that represent a simulated consumer:

$$v_i \sim \mathcal{N}(0, \mathbf{I}_K)$$

where $\mathbf{I}_K$ is an identity matrix of dimension $K$.

**Constructing $\delta(\Sigma)$**: I need to find the “mean utility” vector $\delta(\Sigma)$. Given matrix $\Sigma_{K \times K}$ and fix random draws $v$, I multiply $v$ to construct $\tilde{v}$ for all simulated consumers:

$$\tilde{v}_{R \times K} = v_{R \times K} \ast \Sigma'_{K \times K}$$

Hence, $\tilde{v}_i$ (the $i^{th}$ row of $\tilde{v}$) is a $1 \times K$ vector of multivariate normal distribution with variance-covariance $V = \Sigma \Sigma'$.

Next, I choose an arbitrary initial value of $\delta$, say $\delta_0$. I construct the consistent vector $s$ of predicted shares, simulating the integral. It yields:

$$s_j(\tilde{v}(\Sigma), X_{N \times K}, \delta) = \frac{1}{R} \sum_{i=1}^{R} \left[ \frac{\exp(\delta_j + X_{j,i} \tilde{v}_{i,j})}{1 + \sum_{h=1}^{H} \exp(\delta_h + X_{h,i} \tilde{v}_{i,h})} \right]$$

(31)

To find the right value of $\delta$, I need to solve the $N$ by $N$ non linear system between predicted and actual shares:

$$s(\delta, \Sigma) = \mathbf{Sh}$$

(32)

Instead, Berry (1994) suggested the recursive procedure that converges to an unique $\delta$, given $\Sigma$. Given any initial value of $\delta^0$, the $\delta$ of round $h + 1$ will be:

$$\delta^{h+1} = \delta^h + \log(\mathbf{Sh}) - \log(s(\delta^h))$$

where each of the vectors have dimension $N$ by 1. Uniquely, I find $\delta(\Sigma)$ that matches the best my predicted and actual shares.

Recall that in general:

$$\nu \sim \mathcal{N}(0, \mathbf{I}(K)) \Rightarrow \Sigma \nu \sim \mathcal{N}(0, \Sigma \Sigma')$$

47
Estimating $\beta(\Sigma)$: This step is just a simple instrumental variables estimation (IV). For a given $\Sigma$ (the non-linear parameters) I compute $\beta$ (the linear parameters) using the linear regression:

$$\delta(\Sigma) = X\beta + \varepsilon$$  \hspace{1cm} (33)

with the moment condition that $E(Z'\varepsilon) = 0$. The usual IV procedure lead us to:

$$\hat{\beta}(\Sigma) = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'\delta(\Sigma)$$  \hspace{1cm} (34)

where the weighting matrix used was $W_T = (Z'Z)^{-1}$.

Searching for $\hat{\Sigma}$: Given $\Sigma$ and the previous steps, I construct the residual $\varepsilon_{N\times 1} = \varepsilon(\Sigma)$, as follows:

$$\varepsilon(\Sigma) = \delta(\Sigma) - X\hat{\beta}(\Sigma)$$

Hence finally, $\hat{\Sigma}$ is given by:

$$\hat{\Sigma} = \arg \min_{\Sigma \in \Theta} \varepsilon(\Sigma)'Z(Z'Z)^{-1}Z'\varepsilon(\Sigma)$$

where $\Theta$ is the set of feasible cholesky decompositions of a positive definite matrix.

To compute the standard errors for these estimates, I follow the standard formulae for GMM estimates.$^{36}$

C Elasticity Advantage Assessment.

This appendix section presents evidence to check whether there is any elasticity advantage in the car market in Europe for domestic producers in their domestic market. I consider an elasticity advantage if a producer faces systematically a more inelastic demand.

The following figures present the elasticities faced by producers of different nationalities in each of the five analyzed markets. The closer the elasticities to the top of the figure implies a more inelastic demand.

In general terms I found no evidence of any elasticity advantage for domestic manufacturers since the domestic’s lines are always in the range (or below) of the other producers’ elasticities. This is a robust fact when replicating the analysis by car segment.$^{37}$

$^{36}$See McFadden and Newey (1994) for further details.

$^{37}$Although I do not report the all 25 figures.
Figure 10: Own price elasticities by nationality in Belgium.

Figure 11: Own price elasticities by nationality in France.
Figure 12: Own price elasticities by nationality in Germany.

Figure 13: Own price elasticities by nationality in Italy.
Figure 14: Own price elasticities by nationality in the UK.

D International Effects of Exchange Rate Depreciation.

This appendix presents the impulse response exercises after a 10% depreciation of each of the relevant European currencies as explained in section 4.4. Each figure presents the percentage difference between the paths of steady state values and the variables after an initial shock. Along 40 periods, I present the convergent path predicted by the AR(1) transition probabilities towards the steady state scenario, which of course should close the initial gap.

This section presents the international effects in all the European markets. Basically, a domestic depreciation allows to domestic producers to sell cheaper than foreign competitors abroad. Demand for all producers may be affected since the consumers’ ranking may change abroad.

Recall that in the year 1985 i) there is no British cars in neither Germany nor Italy, ii) there is no Japanese Cars in Italy.
Figure 15: Reactions in Europe after a 10% depreciation of the Belgian Franc.

Figure 16: Reactions in Europe after a 10% depreciation of the French Franc.
Figure 17: Reactions in Europe after a 10% depreciation of the German Mark.

Figure 18: Reactions in Europe after a 10% depreciation of the Italian Lire.
Figure 19: Reactions in Europe after a 10% depreciation of the British Pound.

Figure 20: Reactions in Europe after a 10% depreciation of the Japanese Yen.
E  Domestic Effects of Exchange Rate Depreciation.

This appendix presents the impulse response exercises after a 10% depreciation of each of the relevant European currencies as explained in section 4.4. Each figure presents the percentage difference between the paths of steady state values and the variables after an initial shock. Along 40 periods, I present the convergent path predicted by the AR(1) transition probabilities towards the steady state scenario, which of course should close the initial gap.

This section presents the effects in the domestic market only. A domestic depreciation does not affect domestic producers through cost but makes all the foreign competitors more expensive. Demand for all producers may be affected since the domestic consumers’ ranking may change. This exercises is extended to compute the path of demand and revenues of each producer in the market whose currency has depreciated.

Recall that in the year 1985: i) there were neither American nor British cars made in Germany, ii) there were neither Japanese nor British cars made in Italy and iii) American cars sold in the UK were made also in Great Britain.
Figure 21: Reactions in Belgium after a 10% depreciation of the Belgian Franc.
Figure 22: Reactions in France after a 10% depreciation of the French Franc.
Figure 23: Reactions in Germany after a 10% depreciation of the German Mark.
Figure 24: Reactions in Italy after a 10% depreciation of the Italian Lire.
Figure 25: Reactions in the UK after a 10% depreciation of the British Pound.
F Confidence Intervals for the Policy Function.

This appendix presents the confidence intervals of the impulse response exercises after a 10% depreciation of each of the relevant European currencies as explained in section 4.4. Each figure presents the bootstrapping exercise for each price panel in the appendix section of both: i) the international effects on domestic producers after a domestic depreciation and, ii) the domestic effects on foreign producers after a domestic depreciation.

Recall that i) there are no British cars in Germany and American cars were made in Germany, ii) neither British nor Japanese cars were sold in Italy and iii) American cars were made in the UK.

F.1 Confidence Interval for the International Effect of a Domestic Depreciation.

Figure 26: Confidence Interval for Price reactions in Europe after a 10% depreciation of the Belgian Franc.
Figure 27: Confidence Interval for Price reactions in Europe after a 10% depreciation of the French Franc.
Figure 28: Confidence Interval for Price reactions in Europe after a 10% depreciation of the German Mark.
Figure 29: Confidence Interval for Price reactions in Europe after a 10% depreciation of the Italian Lire.
Figure 30: Confidence Interval for Price reactions in Europe after a 10% depreciation of the British Pound.
Figure 31: Confidence Interval for Price reactions in Europe after a 10% depreciation of the Japanese Yen.
F.2 Confidence Interval for the Domestic Effect of 10% Domestic Depreciation.

Figure 32: Confidence Intervals for Reactions in Belgium after a 10% depreciation of the Belgian Franc.
Figure 33: Reactions in France after a 10% depreciation of the French Franc.
Figure 34: Reactions in Germany after a 10% depreciation of the German Mark.
Figure 35: Reactions in Italy after a 10% depreciation of the Italian Lire.
Figure 36: Reactions in the UK after a 10% depreciation of the British Pound.

Effects of 10% Depreciation of the British Pound in the domestic market by French producers

Effects of 10% Depreciation of the British Pound in the domestic market by German producer

Effects of 10% Depreciation of the British Pound in the domestic market by Italian producers

Effects of 10% Depreciation of the British Pound in the domestic market by Japanese producers
G  Impulse Response Exercise of a 10% Domestic Wages Increase.

This appendix presents the impulse response exercises after a 10% increase of each of the relevant European wages as explained in section 4.4. Each figure presents the percentage difference between the paths of steady state values and the variables after an initial shock. Along 40 periods, I present the convergent path predicted by the AR(1) transition probabilities towards the steady state scenario, which of course should close the initial gap.

This section presents the effects in each of the destination markets. Recall that there is no Belgian producer and I do not analyze the Japanese domestic market.
Figure 37: Reactions across Europe after a 10% increase in French wages.
Figure 38: Reactions across Europe after a 10% increase in German wages.
Figure 39: Reactions across Europe after a 10% increase in Italian wages.
Figure 40: Reactions across Europe after a 10% increase in British wages.
Figure 41: Reactions across Europe after a 10% increase in Japanese wages.
H From Quarterly to Yearly Estimates.

This appendix section describes the procedure under which the quarterly estimates of exchange rates forecast the yearly series for the six currencies used in the paper.

The quarterly process is given by:

\[ e_t = \alpha + \rho e_{t-1} + u_t \quad (35) \]

where \( e_t \) is the vector of \( N \) currencies. \( \rho_{N \times N} \) and \( \alpha_{N \times 1} \) are parameters that generate this AR(1) process. Each currency only depends on its lagged value, thus:

\[
\rho_{N \times N} = \begin{bmatrix}
\rho_1 & 0 & \ldots & 0 \\
0 & \ddots & 0 & 0 \\
\vdots & \ddots & \rho_{N-1} & 0 \\
0 & \ldots & 0 & \rho_N \\
\end{bmatrix}
\]

The \( u_t \) is the random term that allows for correlation among contemporaneous shocks only. Formally, I have:

\[ E(u_t) = 0_{N \times 1} \quad \text{and} \quad E(u_j u_k') = 0_{N \times N} \forall j \neq k \]

The symmetric variance-covariance matrix is given by:

\[ E(u_t u_t') = \Omega_{N \times N} \]

Based on the stationarity conditions, I compute the long run or steady-state value for the \( i \)th currency \( e_t^i \)

\[ E(e_t^i) = \frac{\alpha_i}{1 - \rho_i} \]

Also I express the \( P \) correlation as follows:

\[ E(e_t^i e_t^{i-P}) = E(\alpha_i + \rho_i e_{t-1}^i + u_t e_{t-P}^i) = \ldots = \rho_i^P \]

I want to use these estimates of \( \hat{\rho} \) and \( \hat{\alpha} \) to do forward simulations over the yearly process \( \tilde{e}_t \). Hence, I need to write yearly parameters \( \tilde{\rho} \) and \( \tilde{\alpha} \) in terms of the quarterly parameters \( \rho \) and \( \alpha \).

\[ \tilde{e}_t = \tilde{\alpha} + \tilde{\rho} \tilde{e}_{t-1} + \tilde{u}_t \quad (36) \]

The yearly process is defined as the average of the last four quarters.

\[ \tilde{e}_t = \left[ \frac{e_t + e_{t-1} + e_{t-2} + e_{t-3}}{4} \right] \]
The first order correlation can be written in terms of the quarterly process:

\[ \tilde{\rho}_i = E(\tilde{e}_t \tilde{e}_{t-1}) = E\left( \frac{e_t + e_{t-1} + e_{t-2} + e_{t-3}}{4} \right) \left( \frac{e_{t-4} + e_{t-5} + e_{t-6} + e_{t-7}}{4} \right) = ... \]

\[ \tilde{\rho}_i = \frac{1}{16}(\rho_i + 2\rho_i^2 + 3\rho_i^3 + 4\rho_i^4 + 3\rho_i^5 + 2\rho_i^6 + \rho_i^7) \]  \hspace{1cm} (37)

The steady-state value for the \( i^{th} \) currency \( e_i^t \) of this average can be written as:

\[ E(e_i^t) = E(\tilde{e}_i^t) \Leftrightarrow \frac{\alpha_i}{1 - \rho_i} = \frac{\tilde{\alpha}_i}{1 - \tilde{\rho}_i} \]

and they should match the quarterly steady state, I have the relationship between the constants:

\[ \tilde{\alpha}_i = \frac{\alpha_i(1 - \rho_i)}{1 - \tilde{\rho}_i} \]  \hspace{1cm} (38)

Finally I also need to describe the error parameter for

\[ \tilde{u}_t = \frac{u_t + u_{t-1} + u_{t-2} + u_{t-3}}{4} \]

It is straightforward to show that \( E(\tilde{u}_t) = 0 \) and the covariance matrix is given by:

\[ \tilde{\Omega} = E\left( \left[ \frac{u_t + u_{t-1} + u_{t-2} + u_{t-3}}{4} \right] \left[ \frac{u_t + u_{t-1} + u_{t-2} + u_{t-3}}{4} \right]^\prime \right) = \frac{1}{4} \Omega \]
I Alternative Adjustment Cost Function.

This appendix section presents the results under the alternative specification for the price adjustment cost function given by:

$$AC_{f,t,2} = \sum_m \sum_{j \in F_m} \Psi_{fm} \cdot | \log(p_{jt}^m) - \log(p_{jt-1}^m) |$$

The following tables replicate the results of tables 4.5.1 to 25 using the alternative specification for the adjustment cost function. The main findings still hold, although some rankings or estimates may change about an acceptable neighborhood.

Table 22: Different Components (%) over Total Cost in 1985 using alternative adjustment cost function.

<table>
<thead>
<tr>
<th>Exports</th>
<th>Local Cost</th>
<th>Destination Cost</th>
<th>Adjustment Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>79.81</td>
<td>14.28</td>
<td>5.91</td>
</tr>
<tr>
<td>French</td>
<td>75.51</td>
<td>23.31</td>
<td>1.17</td>
</tr>
<tr>
<td>German</td>
<td>78.75</td>
<td>21.18</td>
<td>0.06</td>
</tr>
<tr>
<td>Italian</td>
<td>20.69</td>
<td>66.38</td>
<td>12.93</td>
</tr>
<tr>
<td>Japanese</td>
<td>59.75</td>
<td>26.99</td>
<td>13.26</td>
</tr>
<tr>
<td>Sold Domestically</td>
<td>Local Cost</td>
<td>-</td>
<td>Adjustment Cost</td>
</tr>
<tr>
<td>Americans</td>
<td>99.97</td>
<td>-</td>
<td>0.03</td>
</tr>
<tr>
<td>French</td>
<td>97.19</td>
<td>-</td>
<td>2.81</td>
</tr>
<tr>
<td>German</td>
<td>100.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Italian</td>
<td>90.37</td>
<td>-</td>
<td>9.63</td>
</tr>
</tbody>
</table>

Table 23: Adjustment Cost Share by Destination Market using alternative adjustment cost function.

<table>
<thead>
<tr>
<th></th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>7.2</td>
<td>0.1</td>
<td>0.0</td>
<td>9.3</td>
<td>0.0</td>
</tr>
<tr>
<td>French</td>
<td>3.4</td>
<td>2.1</td>
<td>0.0</td>
<td>0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>German</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>Italian</td>
<td>18.8</td>
<td>10.6</td>
<td>8.6</td>
<td>9.6</td>
<td>3.5</td>
</tr>
<tr>
<td>Japanese</td>
<td>19.3</td>
<td>0.0</td>
<td>4.1</td>
<td>-</td>
<td>20.2</td>
</tr>
</tbody>
</table>
Table 24: **Ratio of Adjustment Cost Parameters using alternative adjustment cost function**: $\Psi_{fm}/\Psi_{ff}$.

<table>
<thead>
<tr>
<th></th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>44.21</td>
<td>4.98</td>
<td>1.00</td>
<td>75.47</td>
<td>0.05</td>
</tr>
<tr>
<td>French</td>
<td>1.08</td>
<td>1.00</td>
<td>0.04</td>
<td>0.12</td>
<td>0.19</td>
</tr>
<tr>
<td>German</td>
<td>0.26</td>
<td>0.60</td>
<td>1.00</td>
<td>0.93</td>
<td>1.00</td>
</tr>
<tr>
<td>Italian</td>
<td>0.18</td>
<td>0.43</td>
<td>4.27</td>
<td>1.00</td>
<td>0.05</td>
</tr>
<tr>
<td>Japanese</td>
<td>0.44</td>
<td>0.03</td>
<td>1.00</td>
<td>-</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Table 25: **Implied Markups in 1985 using alternative adjustment cost function**.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Americans</td>
<td>71%</td>
<td>40%</td>
</tr>
<tr>
<td>French</td>
<td>81%</td>
<td>36%</td>
</tr>
<tr>
<td>German</td>
<td>51%</td>
<td>46%</td>
</tr>
<tr>
<td>Italian</td>
<td>78%</td>
<td>33%</td>
</tr>
<tr>
<td>Japanese</td>
<td>86%</td>
<td>33%</td>
</tr>
</tbody>
</table>