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Publication Date

2010

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Essays on Structural Estimation in the European Car Market

by

Carlos Esteban Noton Norambuena

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Economics

in the

GRADUATE DIVISION
of the
UNIVERSITY OF CALIFORNIA, BERKELEY

Committee in charge:
Professor Maurice Obstfeld, Chair
Professor Daniel L. McFadden
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Spring 2010

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Abstract

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Doctor of Philosophy in Economics

University of California, Berkeley

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This dissertation consists of two essays of structural estimation in the European car market, where the first chapter focuses on the demand side and the second chapter focuses on the supply side.

In the first chapter, I incorporate home bias in a structural demand, consistent with the strong dominant position of domestic car manufacturers in Europe. I use the Berry, Levinsohn, and Pakes (1995) methodology which considers heterogeneous consumers, controls for price endogeneity, and does not impose decision nests. My estimates suggest that home bias is a key determinant of the market shares differences and is well captured by a fixed effect. Contrary to previous finding, domestic producers do not face a less sensitive demand in their domestic markets than foreign competitors, which is a crucial distinction for pricing behavior.

In the second chapter, I estimate the underlying cost structure of the car manufacturers to rationalize two key features: incomplete degree of exchange rate pass-through and gradual price adjustments. Using the methodology developed by Bajari, Benkard, and Levin (2007) to estimate dynamic games, I identify structural cost parameters including destination-currency cost components and price adjustment costs. The main results are: i) the destination-currency cost component should be about 20 – 30% of total costs in order to rationalize the observed incomplete degree of exchange rate pass-through; ii) relatively small price adjustment costs can rationalize the observed inertia in car prices; iii) there are heterogeneous price adjustment costs at producer-market level suggesting a new dimension of pricing to market behavior; and iv) in this particular dynamic environment, there is a positive relationship between price elasticities and markups.

To Charo

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Acknowledgments

I thank Maury Obstfeld, Dan McFadden and Sofia Villas-Boas for guidance, support and generosity. Also Lanier Benkard, who after his visiting to Berkeley in 2006, kept helping me with incredible generosity, especially in the nitty-gritty of his methodology. Also Yuriy Gorodnichenko, Pierre Olivier Gourinchas, Emi Nakamura, Denis Nekipelov, and Kenneth E. Train contributed with very insightful comments. This is also extended to many graduate students at Berkeley, who generously contributed with their time.

Finally, a special acknowledgment should be granted to my wife Charo, who supported me all these years. I truly believed that without her no achievements could be done. To my parents and my sister for their long distance support from Chile. And to all my friends, who contributed with their smiles to make my life better.

Chapter 1

Home Bias and Market Power in the European Car Market

1.1 Introduction

Domestic car producers have an extremely dominant position in the European car market. Table 1.1 presents average market shares in 5 European markets for 30 years (1970-1999).

Table 1.1: **Average market shares by brand's nationality**

Brand's Nationality	Belgium	France	Germany	Italy	UK
Americans	9.7	6.1	10.8	5.8	25.4
French	28.2	69.9	10.6	15.9	15.5
Germans	19.9	8.1	44.6	9.8	8.2
Italians	6.9	6.2	5.2	59.0	3.8
British	13.4	5.6	18.9	5.5	33.0
Japanese	17.3	2.3	7.8	1.1	9.7
Others	4.6	1.9	2.0	2.8	4.2

There are several potential explanations for this outcome with some hypothesis relying on the supply side¹ and others on the demand side.² In this chapter, I look for the right modelling in demand side estimations. In particular, I want to identify the type of advantage (if any) domestic producers have at the demand level in order to rationalize these large market share differences.

Basically, I estimate a structural demand that properly accounts for potential effects of this home bias preference. I have two main research questions: i) Does this home bias act as a demand shifter in favor of domestic producers? , and ii) Does this home bias generate a different price sensitiveness for domestic producers in their respective markets?

To answer these questions, I use the estimates to test whether the home bias is well captured by a positive demand shifter and whether home bias implies a less sensitive demand for domestic producers. This distinction is important because their very different implications

¹For instance, we could have the multi-market collusion hypothesis as in Bernheim and Whinston (1990); heterogeneous hidden cost differences, heterogeneous regulations, etc.

²For example, we could have brand loyalty as in Train and Winston (2007), historical inertia in consumers, better supporting network for domestic cars with cheaper replacement parts and repair services, etc.

for producer's optimal pricing. Optimal pricing in this market can shed light in various issues, like pricing to market³ or exchange rate pass-through⁴ which have important implications for trade policy and optimal exchange rate regime.⁵

To include home bias in the structural estimation, I use the framework of Berry, Levinsohn, and Pakes (1995) to estimate the demand for new cars in Europe. This framework does not impose any sequential decision, takes into account the car's characteristics (observed and unobserved), considers heterogeneous consumers and account for potential endogeneity of prices. This new evidence suggests that home bias is well captured by a large fixed effect, which explains most of the market share differences. Contrary to previous literature, I found no price-elasticity advantage for European car producers in their domestic markets.

The chapter is organized as follows: section 1.2 presents the framework and estimation methodology, section 1.3 presents the data for demand estimation. Section 1.4 presents the results and exercises, while section 1.5 presents the final remarks of the chapter.

1.2 Demand for Differentiated Products

This section presents the model of demand for differentiated products which was developed by Berry, Levinsohn, and Pakes (1995), henceforth BLP.

Section 1.2.1 presents the general framework, while section 1.2.2 presents the actual estimation procedure. Section 1.2.3 presents how this methodology can disentangle these particular research questions.

1.2.1 Theoretical Framework

This section presents the general framework to estimate a demand system for differentiated products. I focus on the mixed logit model, also called random coefficients model, among the wide range of discrete choice models started by the seminal work of McFadden (1974).

Let us introduce some notation: x_{jt} is a k -dimensional (row) vector of observable characteristics of product $j = \{1, \dots, J\}$ in market $t = \{1, \dots, T\}$, y_i is the income of consumer $i = \{1, \dots, R\}$, p_{jt} is the price of product j in market t , ξ_{jt} is the unobserved (by the econometrician) scalar product characteristic, and ε_{ijt} is a mean-zero stochastic term. Hence, the utility function is given by:

$$U_{ijt} = x_{jt}\beta_i + \alpha_i(y_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt} \quad (1.1)$$

where β_i is a k -dimensional (column) vector of individual-specific taste coefficients, and α_i is consumer i 's marginal utility from income. Notice that α_i does not depend on good j .

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

$$\begin{bmatrix} \beta_i \\ \alpha_i \end{bmatrix} = \begin{bmatrix} \beta \\ \alpha \end{bmatrix} + \Sigma v_i \quad \text{where} \quad v_i \sim \mathcal{N}(0, I_d)$$

where v_i captures unobservable consumer heterogeneity.

(α, β) are the linear parameters of the model, Σ are the non linear parameters and $\theta = (\alpha, \beta, \Sigma)$ is the vector containing all the parameters of the model.

³Practice of charging different prices in different markets.

⁴The degree of exchange rate pass-through is how much of the nominal exchange rate fluctuations are expressed into the final prices.

⁵See Corsetti and Pesenti (2004).

Define:

$$\delta_{jt}(\alpha, \beta) \equiv x_{jt}\beta - \alpha p_{jt} + \xi_{jt} \quad (1.2)$$

$$\mu_{ijt}(\Sigma) \equiv [x_{jt}, p_{jt}] \Sigma v_i \quad (1.3)$$

So the utility can be re-written as:

$$U_{ijt} = \alpha_i y_i + \delta_{jt}(\alpha, \beta) + \mu_{ijt}(\Sigma) + \varepsilon_{ijt} \quad (1.4)$$

Notice that $\alpha_i y_i$ plays no role in the consumer's ranking. Since it is the same for all goods and enters in a linear way, it cancels out in all the utility comparisons. δ_{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 (including an unobservable term ξ_{jt}). $\mu_{ijt}(\Sigma)$ is a heteroscedastic disturbance and ε_{ijt} is a homoscedastic disturbance.

First, I need to compute the individual choices in order to compute the market shares for each product. Let us define the set A_{jt} , which has all the individuals who choose brand j in market t :

$$A_{jt}(x_{\cdot,t}, p_{\cdot,t}, \xi_{\cdot,t}, \theta) = \{(v_i, \varepsilon_{i0t}, \dots, \varepsilon_{iJt}) / U_{ijt} \geq U_{ilt}, \forall l = \{0, \dots, J\}\} \quad (1.5)$$

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} . Using the independence assumptions, it yields:

$$s_{jt}(x_{\cdot,t}, p_{\cdot,t}, \xi_{\cdot,t}, \theta) = \int_{A_{jt}} dF_\varepsilon(\varepsilon) d\Phi_v(v) \quad (1.6)$$

If the random terms ε have the extreme value distribution, then the individual probability is given by the following closed form:

$$s_{ijt} = \frac{\exp(x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_h \exp(x_{ht}\beta_i - \alpha_i p_{ht} + \xi_{ht})} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_h \exp(\delta_{ht} + \mu_{iht})} \quad (1.7)$$

By adding over all the consumers, I have the market shares:

$$s_{jt}(x_{\cdot,t}, p_{\cdot,t}, \xi_{\cdot,t}, \theta) = \int_{A_{jt}} \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_h \exp(\delta_{ht} + \mu_{iht})} d\Phi_v(v) \quad (1.8)$$

The integral over v has no closed form so I compute it through simulations. Basically, I take R draws to simulate individuals' shocks, in order to construct the consumer's decision in each market. Aggregating the R simulated consumers I obtained the predicted market shares for each product at market level.

The car characteristics $\xi_{\cdot,t}$ is the only unobservable variable left. Vector $\xi_{\cdot,t}$ plays the role of the random disturbance which rules out a deterministic result allowing an imperfect fit with actual market shares.

Let us stack the predicted market shares in vector $s(\theta)$ and the actual market shares in vector S for each market pair. The natural estimator $\hat{\theta}$ is given by:

$$\hat{\theta} = \arg \min_{\theta} \| s(x_{\cdot,t}, p_{\cdot,t}, \xi_{\cdot,t}, \theta) - S \| \quad (1.9)$$

1.2.2 BLP Estimation

This section presents the actual estimation of the BLP parameters. Solving the problem of equation 1.9 is very hard, since ξ 's are not observable and most variables enter in a very non-linear fashion.

Berry (1994) and BLP (1995) developed an iterative process, in which the problem is linearized in ξ . Then the minimization is straightforward through a GMM procedure based on suitable instruments.

BLP suggested a set of instruments that I followed closely. These instruments are based on the characteristics of the competitors and within the same producer.

Suppose β is vector of the k linear parameters and Σ is the cholesky decomposition of the variance covariance matrix of β . Notice that since β has dimension k , the variance-covariance matrix $V = \Sigma\Sigma'$ has dimension $(k+1)k/2$. Usually most covariances are set to zero for simplicity.

This procedure is a three step procedure to estimate parameters $\theta = [\beta, \Sigma]$:

- I) Find vector $\delta(\Sigma)$ given initial Σ_0 .
- II) Use $\delta(\Sigma)$ to estimate $\beta(\delta(\Sigma)) = \beta(\Sigma)$.
- III) Compute GMM objective function $G(\Sigma, \delta, \beta) = G(\Sigma)$. Find $\hat{\Sigma}$ that minimizes $G(\Sigma)$.

In order to find the ‘‘mean utility’’ vector $\delta(\Sigma)$, I need to compute the predicted market shares s_j for a given matrix Σ_0 . I draw shocks v for the k random coefficients for each of the R consumers:

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

So the i^{th} row of \tilde{v} is a $1 \times k$ vector of multivariate normal distribution with variance-covariance $V = \Sigma\Sigma'$.⁶

Choose an arbitrary initial value for δ , say δ_0 . I compute the implied vector predicted market shares s , simulating the consumers decision and computing the integral as follows:

$$s_j(\Sigma, \delta) = \frac{1}{R} \sum_{i=1}^R \left[\frac{\exp(\delta_j + X_{j, \cdot} \tilde{v}'_{i, \cdot})}{1 + \sum_{h=1}^{H_j} \exp(\delta_h + X_{h, \cdot} \tilde{v}'_{i, \cdot})} \right] \quad (1.10)$$

where $X_{N, k}$ is the matrix of the k characteristics for all the N products.

Strictly speaking to find the value of δ , I need to solve the N by N non linear system to match predicted and actual shares:

$$s(\delta, \Sigma) = S \quad (1.11)$$

Instead, Berry, Levinsohn, and Pakes (1995) suggested a recursive procedure that converges to δ , given Σ . Given a initial value of δ_0 , the recursive formula to find the next round δ is given by:

$$\delta^{h+1} = \delta^h + \log(S) - \log(s(\Sigma, \delta^h))$$

⁶Recall that in general:

$$\nu \sim N(0, I_d) \Rightarrow \Sigma\nu \sim N(0, \Sigma\Sigma')$$

Given an arbitrary small tolerance parameter, this procedure converges to the unique fixed point $\delta(\Sigma)$ that matches predicted and actual market shares.

To estimate the vector $\beta(\Sigma)$, I just need to run a simple instrumental variable regression as follows:

$$\delta(\Sigma) = X\beta + \xi \quad (1.12)$$

with the moment condition that $\mathbb{E}(Z'\xi) = 0$ for suitable instruments $Z_{N \times J}$ with $J > k$. The usual IV estimation lead us to:

$$\widehat{\beta}(\Sigma) = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'\delta(\Sigma) \quad (1.13)$$

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

Given Σ , compute the residuals ξ as follows:

$$\xi(\Sigma) = \delta(\Sigma) - X\widehat{\beta}(\Sigma)$$

Hence, $\widehat{\Sigma}$ is:

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

where Θ is the set of feasible cholesky decompositions of a positive definite matrix.

1.2.3 Demand and Home Bias

This subsection presents the implications of including a home bias preference in the BLP framework. I show how a home bias fixed effect in the utility function can change the price elasticities for domestic goods.

Let us consider the domestic/foreign distinction as another relevant car characteristic for the consumer, who derives utility from a domestic car. The “domestic producer” dummy captures the effect of a wide range of causes like “nationalism”, historical inertia, network effects, replacement availability, etc. In this chapter, I account for the home bias effect, but I can not dig into the deep root of this behavior since this data can not identify the source of this preference.

Also, these estimates are conditional on the characteristics and models available for each market. From the consumer’s perspective the choice set is exogenous, so I estimate consumer’s behavior conditional on the choice set.

Recall that x_{jt} is the vector of observable characteristics (size, motor power, fuel efficiency, dummies for market, year, brand, firm, segment, and location of plants); p_{jt} is the price of product j in market t , measured as nominal price over nominal GDP per capita as in Goldberg and Verboven (2001). Particularly important, define the home bias dummy, $home_{jt}$, which is one if the car j is sold in the same country as the associated brand’s nationality and zero otherwise. Hence, the utility can be expressed as:

$$U_{ijt} = \gamma_i home_{jt} + \beta_i x_{jt} + \alpha_i (y_i - p_{jt}) + \xi_{jt} + \varepsilon_{ijt} \quad (1.14)$$

the parameter γ_i is the random coefficient that captures the idiosyncratic individual taste for domestic cars. Notice that the expected home dummy coefficient, $\gamma = E(\gamma_i)$, captures the expected effect that is common across people and domestic cars. This linear setting captures the home bias preference as a “demand shifter”.

From a theoretical point of view, the price coefficient, α_i , is the marginal utility of income for each individual i . Hence, the term α_i may change across consumers but not across

products for a given consumer. Consequently, the price parameter should not depend on the characteristic of the product. Nevertheless, I could have effects of home bias on the own price elasticities.

In the model, the price elasticity of the market share of product j with respect to its own price is given by:

$$\eta_{jt} \equiv \frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = -\frac{p_{jt}}{s_{jt}} \int |\alpha_i| s_{ijt} (1 - s_{ijt}) d\Phi_v(v) \quad (1.15)$$

Notice that the home bias fixed effect γ enters through the individual shares s_{ijt} :

$$s_{ijt} = \frac{\exp(\gamma_i \text{home}_{jt} + \beta_i x_{jt} - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_h \exp(\gamma_i \text{home}_{ht} + \beta_i x_{ht} - \alpha_i p_{ht} + \xi_{ht})} \quad (1.16)$$

Therefore, I can check whether domestic producers face a more inelastic demand or not (relatively to foreign producers) through the elasticities of the model. In fact, I do not have product-specific marginal utilities and still can have elasticity advantages of domestic over foreign producers.

The change in the price elasticity due to a home bias does not have a straightforward sign. To make this point clear, let us start with the easier logit case. The logit elasticities are given by:

$$\eta_{jt} \equiv \frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = -\frac{p_{jt}}{s_{jt}} |\alpha| s_{jt} (1 - s_{jt}) = -|\alpha| p_{jt} (1 - s_{jt}) \quad (1.17)$$

Suppose j is a domestic product (so $\text{home}_{jt} = 1$). In the simplest logit, the elasticity gets closer to zero as the market share gets larger. In the logit model, the home bias fixed effect ($\gamma > 0$) implies a larger market share ($\frac{\partial s_{jt}}{\partial \gamma} > 0$), hence a more insensitive demand (elasticity closer to zero) for domestic producers:

$$\frac{\partial \eta_{jt}}{\partial \gamma} = -|\alpha| p_{jt} \left(-\frac{\partial s_{jt}}{\partial \gamma} \right) > 0 \quad (1.18)$$

In the case of heterogeneous consumers, this conclusion is not always the case. Doing some algebra yields:

$$\begin{aligned} \frac{\partial \eta_{jt}}{\partial \gamma} &= \frac{\partial}{\partial \gamma} \left[-\frac{p_{jt}}{s_{jt}} \int |\alpha_i| s_{ijt} (1 - s_{ijt}) d\Phi_v(v) \right] \\ &= -\frac{p_{jt}}{s_{jt}^2} \left[s_{jt} \int |\alpha_i| \frac{\partial s_{ijt} (1 - s_{ijt})}{\partial \gamma} d\Phi_v(v) - \left(\frac{\partial s_{jt}}{\partial \gamma} \right) \int |\alpha_i| s_{ijt} (1 - s_{ijt}) d\Phi_v(v) \right] \\ &= -\frac{p_{jt}}{s_{jt}^2} \left[\underbrace{s_{jt} \int |\alpha_i| (1 - 2s_{ijt}) \frac{\partial s_{ijt}}{\partial \gamma} d\Phi_v(v)}_{+} - \underbrace{\left(\int \frac{\partial s_{ijt}}{\partial \gamma} d\Phi_v(v) \right) \int |\alpha_i| s_{ijt} (1 - s_{ijt}) d\Phi_v(v)}_{+} \right] \end{aligned}$$

In this particular case I have home bias preferences ($\frac{\partial s_{ijt}}{\partial \gamma} > 0, \forall i$) and products with small market shares ($s_{ijt} < 0.5$). Hence, there is no obvious sign and the empirical results are required to shed light on this effect.

1.3 Data for Demand Estimation

This section describes and discuss the data in the demand estimation. The dataset was collected by Brenkers and Verboven (2006) and is an updated version of the one used by Goldberg and Verboven (2001).⁷

The yearly dataset consists of prices, sales and physical characteristics of (mostly) all car models sold in five European markets from 1970 until 1999. The 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, and Toyota Corolla.

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 dataset also includes the the brand, the firm, place of production, information about the market segment of the car (compact, subcompact, standard, intermediate and luxury) and the specific model. Each firm can have several brands (for example BMW produces brands BMW and since 1994 also the brand Rover-Triumph). Firm's nationality is given by ownership so mergers can change it. Instead, brands have a fixed nationality that is given by the historic perception of the consumers (Rover-Triumph is perceived as British regardless the ownership of the firm).

The dataset is augmented with macro-economic variables including population, exchange rates, nominal and real GDP.

1.3.1 Nationalities from Consumer's Perspective

This subsection presents the definition of car's nationality, which is fundamental to define "domestic" producers so to account for any home bias in the demand side of the model. I consider the historic brand association for the demand side. Consequently, from the consumers' point of view, mergers do not change the perceived nationality of the brands.

Table 1.3 shows the models available per market of each brand's nationality and table 1.2 shows in detail the nationalities based on the brand criterium.

1.3.2 Domestic and Foreign Car Characteristics

This section briefly presents and compares car characteristics between domestic and foreign manufacturers across the relevant European markets.

The price data is post-tax list prices, i.e., the final prices suggested by manufacturers to retailers. For each market-time pair I expressed prices as the ratio of nominal price over nominal GDP per capita in domestic currency to deal with different inflation rates and different incomes between countries as in Goldberg and Verboven (2001).

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.⁸

⁷The data is available in the authors' webpage.

⁸Also, I require to reduce the dimensionality of the problem since k characteristics imply $k(k+1)/2$ unknown parameters in the full variance-covariance matrix.

Table 1.2: **Brand's nationalities**

Country	Brand Name	Country	Brand Name
Czech R.	Škoda	Japan	Daihatsu
France	Citroën		Honda
	Peugeot		Mazda
	Renault		Mitsubishi
	Talbot		Nissan-Datsun
	Talbot-Hillman-Chrysler		Subaru
	Talbot-Matra		Suzuki
Talbot-Simca	Toyota		
Netherlands	DAF	US	Ford
Germany	Audi BMW MCC Mercedes Princess Volkswagen	Korea	Daewoo Hyundai Kia
		Spain	Seat
		Sweden	Saab
			Volvo
Italy	AlfaRomeo Autobianchi Fiat Innocenti Lancia	UK	Opel-Vauxhall
			Rover
		Rover-Triumph	
		Yugoslavia	Yugo

Table 1.3: **Available models by brand's nationality**

Nationality of brand	Belgium	France	Germany	Italy	UK	Total
American	130	126	126	123	126	631
French	566	561	509	509	502	2647
German	338	325	347	317	293	1620
Italian	408	379	340	478	242	1847
British	329	274	224	229	364	1420
Japanese	629	377	533	136	523	2198
Others	273	223	204	235	251	1186
Total	2,673	2,265	2,283	2,027	2,301	11,549

Table 1.4: **Shares of cars by brand's nationality**

	% of Sold Cars	% of Models
USA	11.57	5.46
France	28.02	22.92
Germany	18.12	14.03
Italy	16.23	15.99
UK	15.29	12.30
Japan	7.66	19.03
Korea	0.39	2.43
Sweden	1.53	4.80
Spain	0.80	2.14
Yugoslavia	0.03	0.24
Netherlands	0.20	0.24
Czech Republic	0.16	0.42

The summarized characteristics are size, inverse of motor power and fuel efficiency. Size is the product of length (Le), height (He) and width (Wi), ($Size = He \times Le \times Wi$). Inverse of Motor Power is the scalar that summarizes the motor characteristics ($IP = [Hp \times Cy \times Sp]^{-1}$), 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).

As shown in table 1.1, the market shares of the domestic producers are astonishing large. A natural question is whether the domestic car characteristics are different from foreign cars. Goldberg and Verboven (2001) present compelling evidence that (observed) characteristics can not explain alone the dramatic market share differences. To illustrate this point table 1.5 presents comparisons of size, motor power index, fuel efficiency and price.⁹ Roughly speaking, domestic cars are quite similar to foreign cars based on these observed characteristics, which is consistent with the domestic cars being the foreign car models abroad.

Table 1.5: **Domestic and foreign car characteristics**

Characteristic	Origin	Belgium	France	Germany	Italy	UK
Size	Domestic		9.60	10.34	8.94	9.66
	Foreign	9.65	9.64	9.57	9.80	9.74
Motor Power Inv.	Domestic		1.97	1.03	1.87	1.06
	Foreign	1.36	1.16	1.37	1.31	1.23
Fuel Efficiency	Domestic		7.85	8.75	8.10	8.53
	Foreign	8.22	8.21	8.15	8.07	8.17
Price	Domestic		0.69	0.80	0.98	1.08
	Foreign	0.72	0.77	0.63	0.99	1.04

1.4 Results

This section presents the demand estimates using the European car data. I first present the utility function estimates to discuss the home bias fixed effect captured by γ . Secondly, I

⁹The price is the ratio of nominal price over nominal GDP per capita.

simulate some counterfactual market shares under no home bias to have an order of magnitude of the phenomenon. Finally, I construct the elasticities consistent with the estimates and see whether there is a “elasticity advantage” or not for domestic producers.

1.4.1 Utility Function Estimates

This section presents the full body of estimates using the European car data under different assumptions and specifications.

Regarding the consumer simulations, I considered 50 individuals per market. Regarding the optimization stage, the best performance was achieved by the gradient free method based on the Nelder-Mead algorithm (also known as Simplex). This method has a slow rate of convergence but it is robust to discontinuities.

I used several starting points to find global minimizers. There are two important initial values: δ_0 and Σ_0 . Since the random coefficient model is a mixture of logits, the logit’s mean utility is the natural initial value for δ_0 . Also, I explored combinations of starting values for each diagonal element $\sigma_{k,k} = \{0.25, 0.75\}$ in Σ_0 . I scaled the data such that all the IV estimates (using the BLP instruments but considering homogeneous consumers) have an absolute value smaller than 2. While the results were not sensitive to the initial values of Σ_0 , they were sensitive to δ_0 . However, using values different from δ_0 implied convergence to higher values of the objective function.

BLP (1995) suggested instruments to control for endogeneity of prices because of the potential correlation between unobserved characteristics and price. I followed closely the instruments suggested by them. Hence, 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. The results support that the instruments are extremely strong in this application, with a nice predictive power over the instrumented variable.

Table 1.6 presents the OLS, IV and BLP estimates imposing the same parameters to every market (pool estimation). The relationship between these three estimations and the formula for the standard errors in each case is explained in appendix A. All specifications considered dummies by market (5), segment (5), year (30), brand (39), firm (31) and location (14) but due to space reasons I do not report the dummy coefficients.

Table 1.6: **BLP pool estimates**

		Logit	s.d.	IV	s.d.	BLP	s.d.
$-\widehat{\alpha}$	Price	-1.51	(0.05)	-1.54	(0.24)	-2.22	(1.00)
$\widehat{\gamma}$	Home	1.79	(0.03)	1.79	(0.03)	1.79	(0.58)
$\widehat{\beta}$	Inv-Pow	-0.98	(0.09)	-0.98	(0.11)	-1.60	(0.63)
	Size	0.54	(0.16)	0.56	(0.22)	0.69	(0.51)
	Liters per Km	-1.47	(0.11)	-1.45	(0.18)	-1.45	(1.00)
$\widehat{\sigma}$	Price					0.63	(1.20)
	Home					0.00	(2.63)
	Inv-Pow					0.75	(0.59)
	Size					0.00	(4.44)
	Liters per Km					-0.22	(3.50)

Table 1.7 presents the results when allowing the price and home coefficients to be market specific whereas keeping the other coefficients common across markets.

Table 1.7: **BLP estimates with price and home bias country specific coefficients**

	Estimates	Logit	s.d.	IV	s.d.	BLP	s.d.
$-\widehat{\alpha}$	Price-Bel	-1.85	(0.08)	-1.39	(0.38)	-1.81	(1.67)
	Price-Fra	-1.98	(0.09)	-3.63	(0.87)	-4.06	(2.22)
	Price-Ger	-1.99	(0.11)	-3.10	(0.84)	-3.20	(1.50)
	Price-Ita	-1.56	(0.06)	-1.37	(0.31)	-2.01	(1.71)
	Price-UK	-1.52	(0.06)	-0.70	(0.39)	-1.22	(2.13)
$\widehat{\gamma}$	Home-Fra	1.92	(0.06)	1.75	(0.09)	1.63	(4.71)
	Home-Ger	1.17	(0.07)	1.39	(0.18)	1.19	(5.47)
	Home-Ita	2.51	(0.06)	2.53	(0.07)	2.40	(5.17)
	Home-UK	1.33	(0.07)	1.27	(0.10)	1.12	(6.13)
$\widehat{\beta}$	Inv-Pow	-1.03	(0.09)	-1.05	(0.11)	-1.12	(0.29)
	Size	0.68	(0.16)	0.72	(0.25)	0.63	(2.96)
	Liters per Km	-1.36	(0.11)	-1.32	(0.21)	-1.42	(0.35)
$\widehat{\sigma}$	Price					0.61	(2.08)
	Home					0.59	(10.03)
	Inv-Pow					0.00	(5.81)
	Size					0.42	(4.69)
	Liters per Km					0.00	(9.66)

Table 1.8 presents different specifications for the unobserved heterogeneity patterns through having different set of random coefficients.

Table 1.8: **BLP estimates different specifications**

BLP	Estimates	Coef	s.d.	Coef	s.d.	Coef	s.d.
$-\widehat{\alpha}$	Price-Bel	-1.81	(1.67)	-2.04	(0.64)	-1.87	(0.60)
	Price-Fra	-4.06	(2.22)	-4.43	(1.12)	-4.09	(1.13)
	Price-Ger	-3.20	(1.50)	-3.00	(0.94)	-3.25	(0.93)
	Price-Ita	-2.01	(1.71)	-2.37	(0.60)	-2.03	(0.77)
	Price-UK	-1.22	(2.13)	-1.39	(0.74)	-1.29	(0.68)
$\widehat{\gamma}$	Home-Fra	1.63	(4.71)	1.75	(0.10)	1.78	(0.66)
	Home-Ger	1.19	(5.47)	1.23	(0.19)	1.35	(0.51)
	Home-Ita	2.40	(5.17)	2.52	(0.07)	2.55	(0.56)
	Home-UK	1.12	(6.13)	1.27	(0.10)	1.29	(0.40)
$\widehat{\beta}$	Inv-Pow	-1.12	(0.29)	-1.28	(0.26)	-1.11	(0.11)
	Size	0.63	(2.96)	0.92	(0.66)	0.77	(0.25)
	Liters per Km	-1.42	(0.35)	-3.69	(3.74)	-1.41	(0.24)
$\widehat{\sigma}$	σ_{Price}	0.61	(2.08)	0.65	(0.41)	0.68	(0.41)
	σ_{Home}	0.59	(10.03)			0.16	(14.87)
	σ_{InvPow}	0.00	(5.81)	0.00	(2.39)		
	σ_{Size}	0.42	(4.69)	0.00	(5.24)		
	$\sigma_{FuelEff}$	0.00	(9.66)	0.19	(2.42)		
GMM	Obj function	286.13		286.35		286.46	

Finally, table 1.9 presents the final specification that includes statistically significant coefficients only. These are the estimates to be used in the rest of this work.

Table 1.9: **Final BLP estimates**

BLP	Estimates	Coef	s.d.	t-test
$-\widehat{\alpha}$	Price-Bel	-1.86	(0.55)	-3.40
	Price-Fra	-4.09	(0.97)	-4.22
	Price-Ger	-3.25	(0.85)	-3.82
	Price-Ita	-2.03	(0.62)	-3.26
	Price-UK	-1.28	(0.63)	-2.05
$\widehat{\gamma}$	Home-Fra	1.75	(0.09)	19.07
	Home-Ger	1.33	(0.18)	7.40
	Home-Ita	2.53	(0.06)	39.01
	Home-UK	1.28	(0.10)	13.23
$\widehat{\beta}$	Inv-Pow	-1.11	(0.11)	-9.70
	Size	0.77	(0.25)	3.10
	Liters per Km	-1.41	(0.23)	-6.09
$\widehat{\sigma}$	σ_{Price}	0.68	(0.35)	1.93
GMM	Obj. function	286.46		

Notice that the random unobserved heterogeneity only is significant in the price coefficient, once country specific price and home bias coefficients are considered.

1.4.2 Counterfactual Market Share Simulations

This section presents exercises of simulated market shares using the BLP estimates under counterfactual scenarios. This exercise can give us an order of magnitude of the estimated effects.

Recall that predicted market shares match the actual shares by construction.¹⁰ Table 1.10 presents the predicted shares which are the same as those in table 1.1.

Table 1.10: **Actual and predicted market shares across Europe**

Brand's Nationality	Belgium	France	Germany	Italy	UK
American	9.7	6.1	10.8	5.8	25.4
French	28.2	69.9	10.6	15.9	15.5
Germans	19.9	8.1	44.6	9.8	8.2
Italians	6.9	6.2	5.2	59.0	3.8
British	13.4	5.6	18.9	5.5	33.0
Japanese	17.3	2.3	7.8	1.1	9.7
Others	4.6	1.9	2.0	2.8	4.2

Now I turn to compute the predicted market shares under different counterfactual set of parameters. I use equation 1.19 to construct the market shares under different assumptions.¹¹

$$s_{jt} = \frac{1}{R} \sum_{i=1}^R \left[\frac{\exp(\gamma_i \text{home}_{jt} + \beta_i x_{jt} - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_h \exp(\gamma_i \text{home}_{ht} + \beta_i x_{ht} - \alpha_i p_{ht} + \xi_{ht})} \right] \quad (1.19)$$

¹⁰Considering the second digit of significance, the shares are the same.

¹¹This evaluation affects the outside good market share too.

In order to know the order of magnitude of the unobserved characteristics, table 1.11 presents the predicted market shares assuming no unobserved characteristics ($\xi_{jt} = 0, \forall j, t$). Notice that I can expect some correlation between the price p_{jt} and the unobserved characteristic ξ_{jt} (formally $cov(\xi_{jt}, p_{jt}) \neq 0$), therefore under no unobserved characteristic, it is likely to have different prices as well. Nevertheless, the size of this effect seems to be rather small.

Table 1.11: **Predicted market shares with no unobserved characteristic ($\xi = 0$)**

Brand's Nationality	Belgium	France	Germany	Italy	UK
American	15.8	7.5	10.8	8.1	11.7
French	24.1	70.1	16.0	12.2	17.2
Germans	21.4	6.3	50.6	9.6	16.0
Italians	8.4	4.3	5.5	60.3	4.5
British	12.7	5.7	6.7	5.5	38.1
Japanese	12.1	3.9	7.8	1.8	8.1
Others	5.4	2.3	2.7	2.5	4.2

On the other hand, home bias has quite large effects. Table 1.12 reports the predicted market shares, assuming no home bias in all markets ($\gamma = 0$) while the other characteristics remain fixed (including the unobservable ξ). Analyzing the changes, table 1.13 presents the

Table 1.12: **Predicted market shares with no home bias ($\gamma = 0$)**

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

percentage difference between actual and predicted shares under no home preferences. Of course there are no changes in Belgium where there are no domestic producers.

Table 1.13: **% Changes in market shares due to no home bias ($\gamma = 0$)**

Brand's Nationality	Belgium	France	Germany	Italy	UK
American	0.0	7.8	5.3	6.2	7.9
French	0.0	-39.3	5.2	20.7	4.9
Germans	0.0	10.5	-27.0	11.2	2.4
Italians	0.0	8.7	2.6	-47.7	1.2
British	0.0	7.2	9.2	6.1	-20.6
Japanese	0.0	2.9	3.8	0.8	2.9
Others	0.0	2.2	1.0	2.6	1.2

To analyze the order of magnitude of the home bias I comment the changes market by market. In France, the French cars suffer a huge reduction of 39% with an even increase in the competitors' share (Germans increase by 10.5% and Italians by 8.7%). Still the French producers

keep the leadership in France. In Germany, the absence of home bias implies a decrease of the domestic share by 27%. The winners are basically the British cars with an increase of market share of 9.2%, becoming the new leaders. In Italy, the domestic share reduction is a large 47.7% with the French becoming the new leaders due to an increase of 20.7%. Finally, in the UK, the British loose 20.6% of the market and Americans take the leadership with an 7.9% increase until reaching one third of the market.

1.4.3 Price Elasticities

This section presents the estimated own price elasticities $\hat{\eta}$ using the BLP estimates. Doing so, I can check whether domestic producers have any price-elasticity advantage in their domestic market. Using equation 1.20, I compute the own price elasticity for all the 11,549 models.

$$\hat{\eta}_{jt} = -\frac{p_{jt}}{s_{jt}} \frac{1}{R} \sum_{i=1}^R |\alpha_i| s_{ijt} (1 - s_{ijt}) \quad (1.20)$$

The results are in the expected ranges. Table 1.14 presents the average price elasticity by destination markets and figure 1.1 presents the histogram of the estimated elasticities.

Table 1.14: **Estimates of price elasticities by market**

	Belgium	France	Germany	Italy	UK
$\frac{\partial \log(s_i)}{\partial \log(p_i)}$	-1.09	-2.79	-1.92	-1.53	-0.83

To figure out if domestic manufacturers have any advantage in terms of elasticities, I cluster the elasticities by nationality-market pair, weighting by quantity. Therefore, I compare domestic versus foreign producers' elasticity and see if there is any systematic advantage.

I consider an elasticity advantage if a producer faced systematically a more inelastic demand. Thus, from figure 1.2 to 1.6, the closer to the top the better, because the producer faces a more inelastic or insensitive demand.

Based on figures above, I found no evidence of any elasticity advantage for domestic manufacturers. Domestic producer's elasticities are always in the range (or below) of the other producers' elasticities. This is a robust fact when replicating the analysis by car segment.¹²

Previous work of Goldberg and Verboven (2001) used a nested logit framework and found the two discussed effects of home bias (demand shifter and also price-elasticity advantage for domestic cars). One of the nests they considered was the decision between a domestic versus a foreign car. Cardell (1997) formally proves that the nested logit model can be written as a special case of the mixed logit framework.¹³

The main advantage of this approach is that BLP does not impose arbitrarily chosen nested decisions. Perhaps, the results of Goldberg and Verboven are driven by the assumed structure, especially the decision nest of choosing between domestic and foreign cars.

¹²The 25 figures available upon request.

¹³An interesting debate about the empirical properties of this two settings can be found in Wojcik (2000) and the reply by Berry and Pakes (2001).

Figure 1.1: Histogram of price elasticities

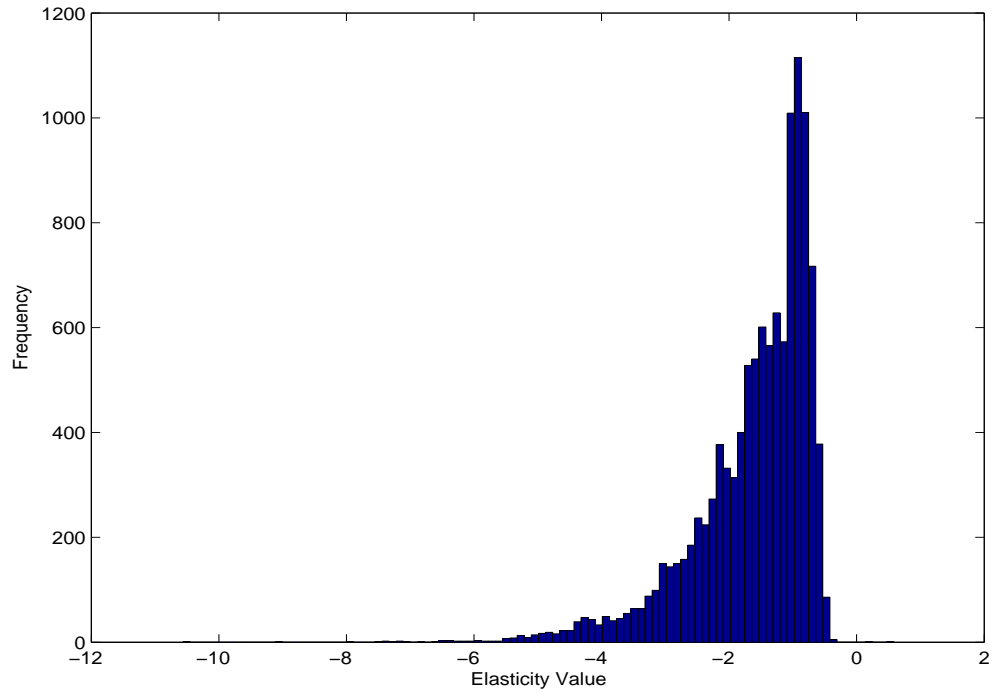


Figure 1.2: Price elasticities in Belgium by nationality

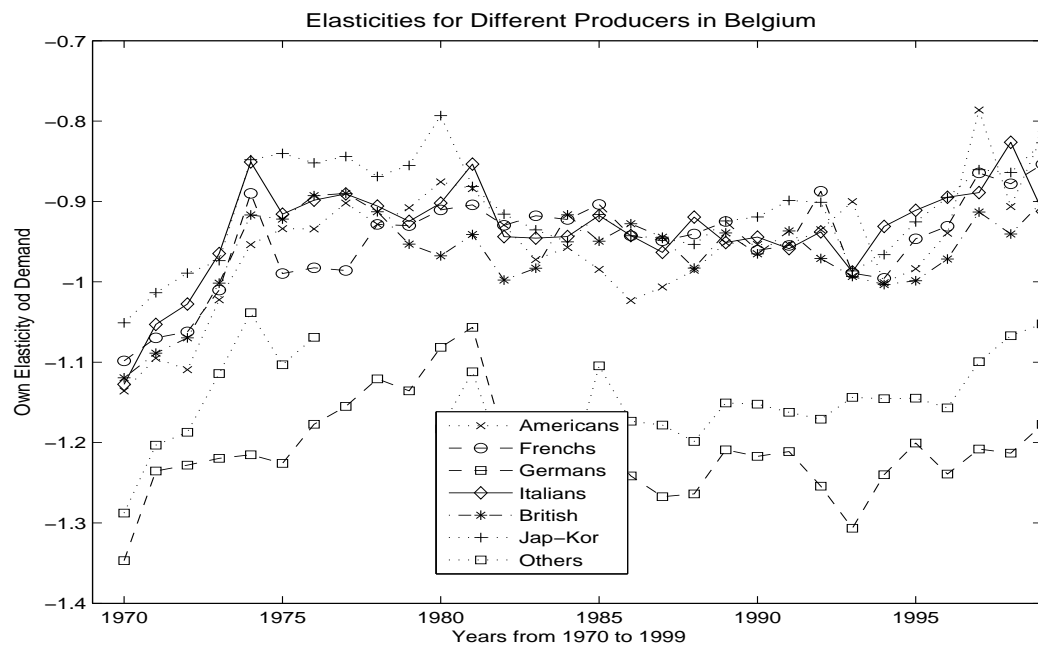


Figure 1.3: Price elasticities in France by nationality

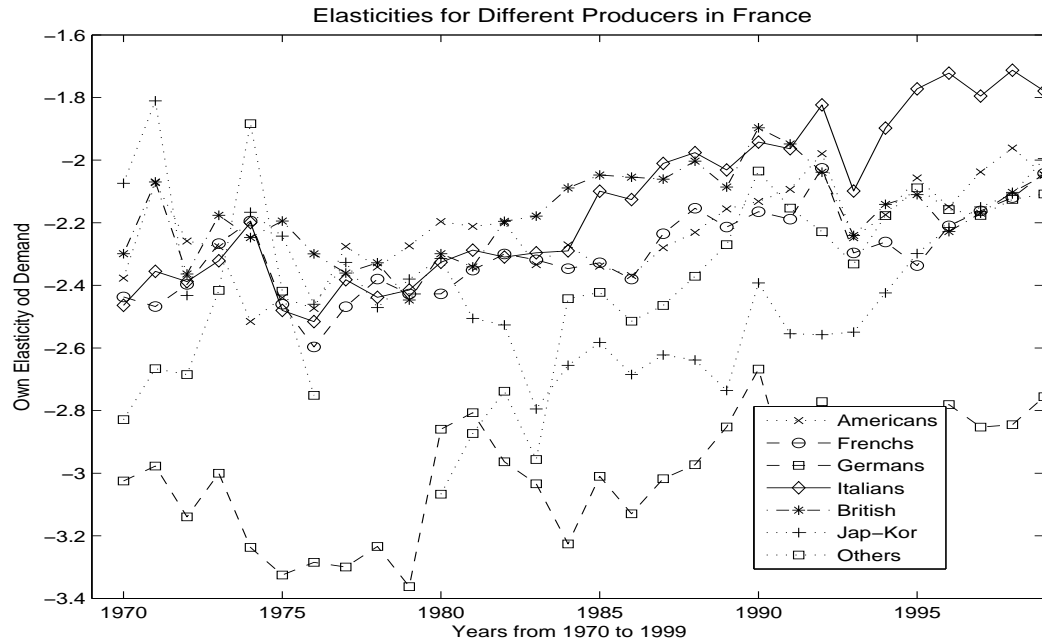


Figure 1.4: Price elasticities in Germany by nationality

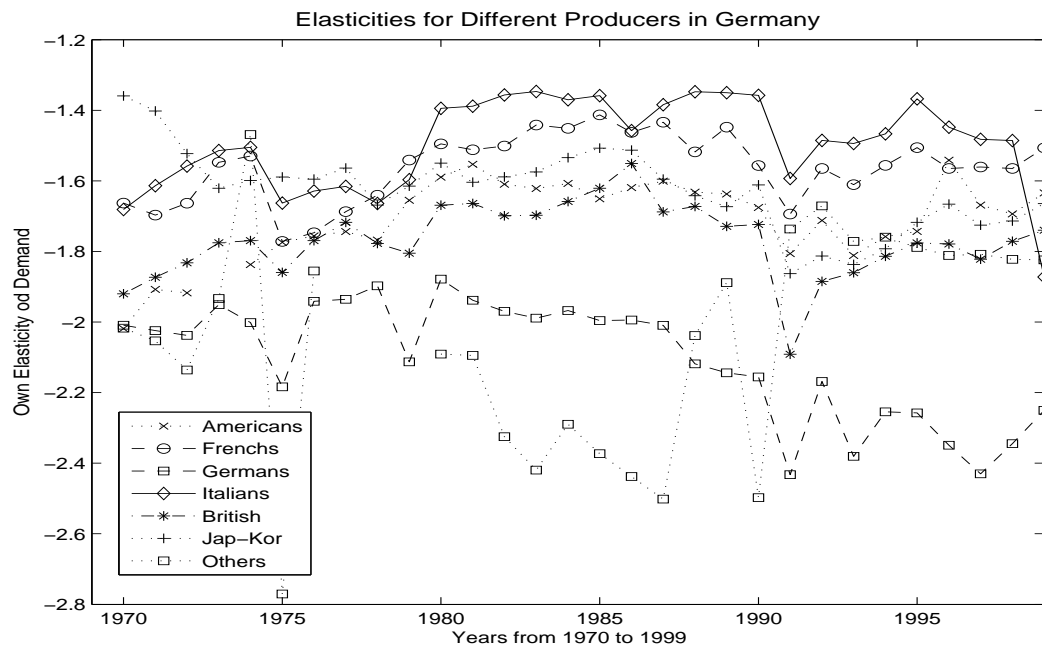


Figure 1.5: Price elasticities in Italy by nationality

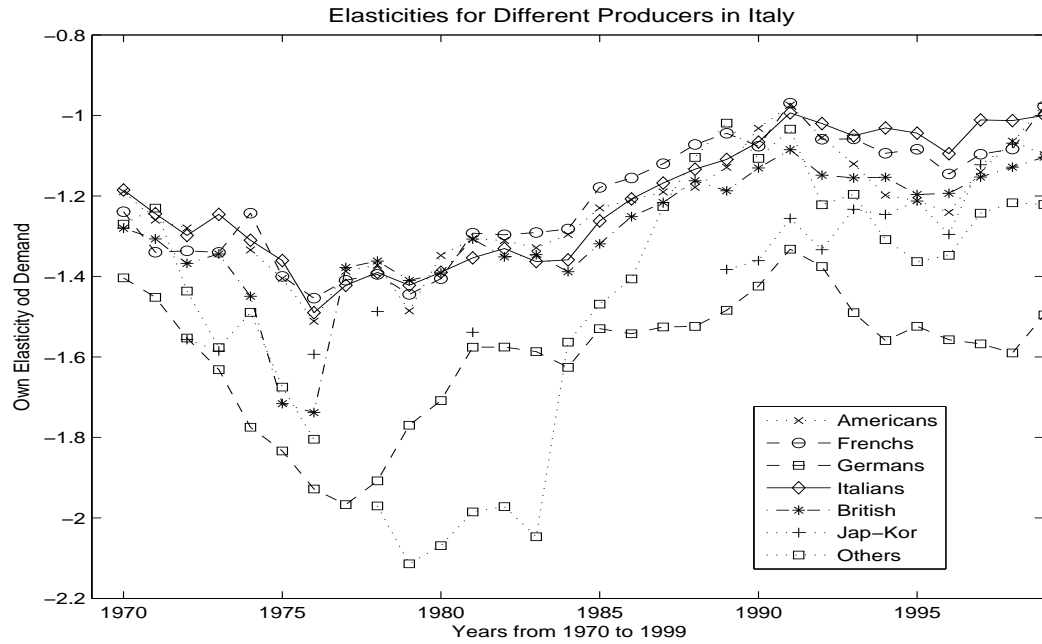
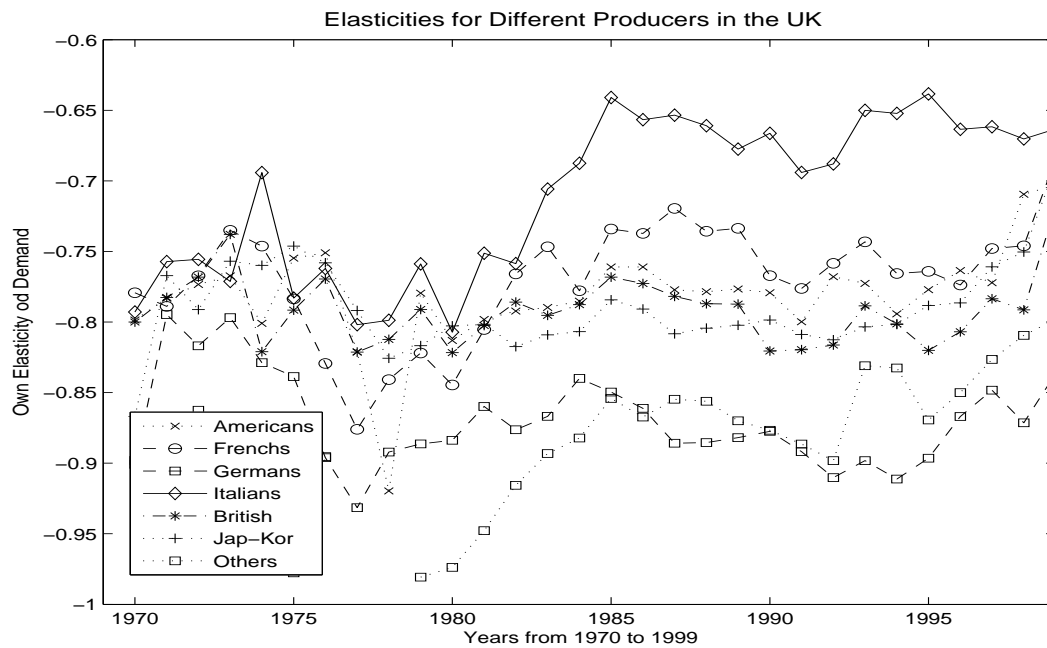


Figure 1.6: Price elasticities in United Kingdom by nationality



1.5 Conclusion

Motivated by the large market shares of domestic cars we observed in Europe, I estimate a structural demand that includes this home bias preference. Mainly, I focus on two questions: i) Does this home bias act as a demand shifter in favor of domestic producers? , and ii) Does this home bias generate a different price sensitiveness for domestic producers in their respective markets?

Using the demand framework developed by Berry, Levinsohn, and Pakes (1995), I estimate the demand for new cars in Europe, considering heterogeneous consumers, controlling for price endogeneity, and not imposing any decision nest.

This evidence suggests that home bias is well captured by a fixed effect. The size of this home bias fixed effect is strikingly large and generates most of the leadership in terms of domestic market share.

Contrary to previous finding European car producers have no particular price-elasticity advantage in their domestic markets.

The correct demand estimates are important inputs for future structural estimation of the supply side, since pricing behavior heavily relies on the marginal effects.

Chapter 2

Structural Estimation of Price Adjustment Costs in the European Car Market

2.1 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.¹ Since exporters/importers have costs and revenues in different currencies, any exchange rate movement or delay in repricing affects markups directly. Therefore, a proper understanding of this phenomenon requires to focus on 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 and timing 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 for manufactured goods: i) an incomplete degree of pass-through, and ii) a persistent delay in the price response. The first fact emphasizes a heterogeneous degree of pass-through away from the extreme full and zero pass-through. The second fact highlights the slow adjustment of prices after movements in the relevant exchange rates. In fact, 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 first 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 since delays in response may deviate prices from their static optimum. Most 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.

¹I 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.

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. Goldberg (1995), Verboven (1996), Goldberg and Verboven (2001) and Goldberg and Hellerstein (2007) have estimated 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 (forthcoming), who solve a fully dynamic model for the coffee industry. However, they are only able to estimate the dynamic model under quite restrictive assumptions regarding the form of marginal costs. My framework allows me greater flexibility in estimating the model.

The aim of this chapter is to extend the structural estimation of dynamic models 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 economic environment 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 and persistent world. Most static previous literature relied on first order conditions in a Bertrand fashion with differentiated products. This approach differs from that, since I estimate the structural parameters that rationalize the pricing rule or policy function taken from the data assuming less structure than previous literature.

I estimate this dynamic model for the European automobile market. Consistent with the evidence in this market, the model considers differentiated cars that are traded in segmented markets by international multiproduct oligopoly. The model explicitly considers a fully structural demand for differentiated products with heterogeneous consumers that may differ between destination markets. On the supply side the model considers international multiproduct firms who set prices simultaneously conditional on the characteristics of the car and the relevant economic environment. The estimation strategy does not require to assume a particular game. Instead, it relies on a reduced form of the optimal pricing rule that is consistent with a Markov Perfect equilibrium for a given set of state variables. The considered states are common knowledge (like exchange rates) and a subset that are private information (unobserved car's characteristics).

To estimate this dynamic game with private information, I use the recent methodology developed by Bajari, Benkard, and Levin (2007), hereafter BBL. Basically, BBL suggest a two stage estimation. In this particular case, the first stage estimates two functions: i) a function to predict the evolution of the relevant economic environment (transition probabilities of state variables), and ii) a function to predict the optimal pricing for each player under a given state of the world (policy function). The second stage is a search for the structural parameters that rationalize the estimated first stage functions. Mainly, BBL do forward simulations for a large number of alternative scenarios and compute the respective set of prices. For each of the simulated path BBL compute each player's discounted sum of profits using the estimated policy function. BBL repeat the procedure using an altered policy function, which should be sub-optimal under the true parameters. Consequently, the estimates are the structural parameters that minimize any profitable deviation making the observed rule optimal. 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 price profile we observe.

The data taken from Brenkers and Verboven (2006)² fits nicely in this study for the

²The countries included in the sample are Belgium, France, Germany, Italy and United Kingdom. They account

following reasons: i) The car industry is the perfect example of differentiated products that exhibits 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 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. The demand side details are presented in chapter 1. On the supply side I allow for policy functions that are producer-destination specifics, hence consistent with pricing to market behavior. Based on my estimates, I discard full pass-through because around one third of the costs are denominated in consumers' currency (destination currency wages along the same lines as Goldberg and Verboven (2001)). Surprisingly, 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. This empirical evidence supports the theoretical idea that small frictions can generate large price stickiness. My estimates show that less than 10% of total cost can generate the observed large price stickiness. Furthermore, my adjustment cost estimates of repricing seem to be producer-market specific. This finding has not been documented before at the best of my knowledge. This feature adds a new dimension of pricing to market heterogeneity not explored before.

Section 2.2 presents the entire dynamic game considered in the supply side of the European car market. Section 2.3 presents the data on European car markets. Section 2.4 presents the results of estimating the model with some exercises of impulse-response functions. Finally section 2.5 presents the general conclusions of the chapter.

2.2 The Model

This section presents the dynamic game of international firms who set prices in multiple currencies facing price adjustment costs. The first subsection 2.2.1 presents the game in terms of Bajari, Benkard, and Levin (2007), stating the objective function of producers, their control and state variables, and their information sets. The second subsection 2.2.2 presents the general BBL framework and the estimation procedure.

2.2.1 A Dynamic Game with Price Adjustment Costs

This section presents the dynamic game of pricing with adjustment cost in several currencies as in the European car market before the Euro adoption. 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 $f \in \{1, \dots, F\}$. All the players trade in M segmented markets indexed by $m \in \{1, \dots, M\}$. Since this is a multiproduct industry, each firm f sells a subset \mathcal{F}_{fm} of the J_m car models available in each destination market $m \in \{1, \dots, M\}$. Notice that this aggregation does not imply any statement regarding the degree of competition in this markets. It only implies that the firms follow the same policy for any degree of competition.

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

for around 80% of the sales in Europe, including 47 international multiproduct firms for the period 1970-1999.

issue requires a very different theoretical setting³. I discuss this issue again in section 2.3 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 ($j \in \mathcal{F}_{fm}$), hence the actions are the set $\{p_{jt}^m\}_{j \in \mathcal{F}_{fm}}$.

The vector of actions of all F players at time t in market m is given by the price vector $\mathbf{p}_t^m = (\{p_{it}^m\}_{i \in \mathcal{F}_{1m}}, \dots, \{p_{it}^m\}_{i \in \mathcal{F}_{Fm}})$.

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 \mathbf{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 ν_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.

Most state variables are public information. I include an extra state variable for each car model that is private information. There is a model-time specific characteristic ξ_{jt} that is unobservable for the competitors when setting prices. This random shock has mean zero and explain deviations from deterministic predictions. The vector of shocks is denoted $\xi_t^m = (\{\xi_{it}^m\}_{i \in \mathcal{F}_{1m}}, \dots, \{\xi_{it}^m\}_{i \in \mathcal{F}_{Fm}})$.

Given a current state s_t , firm f 's expected future profit is given by:

$$\mathbb{E} \left[\sum_{\tau=t}^{\infty} \beta_f^{\tau-t} \pi(\mathbf{p}_\tau, \mathbf{s}_\tau, \xi_\tau, \nu_f) | s_t \right] \quad (2.1)$$

where

$$\pi_{ft} = R_{ft} - C_{ft} - AC_{f,t} \quad (2.2)$$

The profit function π_{ft} includes the current revenues R_{ft} and production cost C_{ft} . The key new ingredient is the adjustment costs $AC_{f,t}$ or penalty associated with price changes, so undoing past decisions is 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.

First, I present 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. All the revenues across markets expressed in f 's currency is given by:

$$R_{ft} = \sum_m \sum_{j \in \mathcal{F}_{fm}} e_{fmt} \cdot p_{jt}^m \cdot q_{jt}^m(\mathbf{p}_t^m, \mathbf{X}_t^m, Y_t^m, \xi_t^m) \quad (2.3)$$

where e_{fmt} is the ratio of currencies to convert revenues from destination currency m into firm f 's currency (expressed as $f\$/m\%$). This justifies the inclusion of the nominal exchange rates as relevant state variables for the producer.⁴ The next term p_{jt}^m is the nominal price of model

³To 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.

⁴The extensive list of producer and destination currencies are: Belgian Franc, French Franc, German Mark, Italian Lira, British Pound, Japanese Yen and American Dollar.

$j \in \mathcal{F}_{fm}$ expressed in the currency of the selling market m .⁵ q_{jt}^m 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 \mathbf{p}_t^m and characteristics, \mathbf{X}_t^m , of the models in that respective market-time pair since consumers rank 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_t^m , as denominator. This implies that the nominal GDP per capita must be also included as another state variable. The demand function for differentiated products is fully described in chapter 1.

The second term in the profit function is the production cost C_{ft} . I assume that producers only own plants in their origin country⁶, hence the costs of production are expressed in domestic currency only.

$$C_{ft} = \sum_m \sum_{j \in \mathcal{F}_{fm}} C_{jt}^m(X_{jt}^m, W_{ft}, W_{mt}, q_{jt}^m, \xi_{jt}^m; \nu_f) \quad (2.4)$$

Basically the production cost of each model $j \in \mathcal{F}_{fm}$ 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 . 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 , ν_f , but it can not be recovered separately.

Finally, I turn to the price adjustment cost term AC with structural parameters $\Psi_{fm} \subset \nu_f$. I want a functional specification to match the observed price behavior where the main path is gradual price changes over years despite large macroeconomic fluctuations. I choose a penalty term that is proportional to the magnitude of the price change that can deliver a better fit to the data.⁷ I estimate two specifications in order to study the order of magnitude of the price adjustment cost:

$$AC_{f,t,1} = \sum_m \sum_{j \in \mathcal{F}_{fm}} \Psi_{fm} \cdot e_{fmt} \cdot |p_{jt}^m - p_{jt-1}^m| \quad (2.5)$$

and I also estimate:

$$AC_{f,t,2} = \sum_m \sum_{j \in \mathcal{F}_{fm}} \Psi_{fm} \cdot |\log(p_{jt}^m) - \log(p_{jt-1}^m)| \quad (2.6)$$

This term is essential 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 does not care about future consequences of current actions,

⁵We take the taxes out for revenues purposes, and we take them into account for demand purposes.

⁶I have data on models produced outside the headquarter's country. Unfortunately, there are too few observations to be reliable in the empirical estimation.

⁷A model with fixed cost of price adjustment would imply a step-function that is not consistent with prices always changing but smoothly.

since undoing is free.⁸ Lagged price is considered also a state variable, since price adjustment costs are the source of 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 Ψ -term is zero. I think this as equivalent to assume a zero entry cost.⁹ Recall that in the model there is no decision about entry\exit of firms\models, hence a fixed entry cost (zero or positive) only appears once.

As a real world evidence to support the inclusion of this term, Gopinath and Rigobon (2008) report estimates of price stickiness at-the-dock prices in the US. They found the astonishing duration of 14.5 months for cars. Theoretical literature has developed several frameworks to rationalize the concept of price adjustment cost.¹⁰

As in Goldberg and Hellerstein (2007), "...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 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 contribution of this paper is that in this fully dynamic framework I can account for the sticky pricing behavior in the face of ongoing uncertainty, which can be associated with an exogenous strategic dynamic pricing that is observationally equivalent to this price adjustment costs.

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 costs represented by parameters Ψ_{fm} . Previous dynamic reduced forms can not identify these parameters since the effect might be mixed with other sources of stickiness. Most of the previous structural estimations relies on the static first order conditions of a multiproduct firms competing a la Bertrand. Only Nakamura and Zerom (forthcoming) solve a fully dynamic model for the coffee industry. However, they are only able to estimate the dynamic model under quite restrictive assumptions regarding the form of marginal costs. My framework allows me greater flexibility since I do not need to solve the dynamic game to estimate the structural parameters.

2.2.2 Estimating the Dynamic Game: BBL Approach

This subsection presents the main methodology of this chapter, 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 particular specifications.

The BBL algorithm has two stages. The first stage estimates two functions: i) how the relevant economic environment evolves (transition probabilities denoted $\mathbb{P}(s_{t+1}|s_t)$) which in general can depend on the action too, and ii) the way players decides in each state of the world (policy functions denoted $\sigma_f(s)$). The second stage uses the equilibrium conditions to estimate structural parameters that rationalize the first stage estimates.

Suppose the state vector at date $t + 1$ (\mathbf{s}_{t+1}) is drawn from a known probability distribution $\mathbb{P}(\mathbf{s}_{t+1}|\mathbf{p}_t, \mathbf{s}_t)$, which we want to estimate. I assume that current car prices do not

⁸As in Goldberg and Verboven (2001).

⁹Assuming $p_{-1} = p$ 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.

¹⁰I 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.

affect future state variables like exchange rates, car's characteristics, GDP per capita or nominal wages. Therefore the state variables \mathbf{s}_{t+1} are exogenous. Furthermore, I assume that the process is a first order Markov process.

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 \mathbf{s}_t although the function might be firm specific. The definition of Markov Perfect equilibrium requires that players only care about the current state of the world and not "how the state was reached", so I rule out the possibility of "state path dependance". We should think the price decision as any other "investment decision" that only depends on the current environment and the last decision.¹¹

Formally in this setting, a Markov strategy for firm f is a function $\sigma_f : S \rightarrow P_f$, 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, $\sigma = (\sigma_1, \dots, \sigma_F)$, where $\sigma : S \rightarrow P = (P_1, \dots, P_F)$. If the behavior is given by a Markov strategy profile σ , the firm f 's expected profit $V_f(s, \sigma)$ given a state \mathbf{s} can be written recursively:¹²

$$V_f(s, \sigma_f) = \mathbb{E} \left[\pi_f(\sigma_f(s), s) + \beta_f \int V_f(s', \sigma) d\mathbb{P}(s' | \sigma, s) | s \right] \quad (2.7)$$

The profile σ is a Markov perfect equilibrium if, given the opponent profile σ_{-f} , each firm f prefers its strategy σ_f to all alternative Markov strategies σ'_f ,

$$V_f(s, \sigma) = V_f(s, \sigma_f, \sigma_{-f}) \geq V_f(s, \sigma'_f, \sigma_{-f}) \quad (2.8)$$

This inequality requires that for each firm f and initial state s , σ_f outperforms each alternative Markov strategy σ'_f so there is no profitable deviations.

Suppose the profit function for firm f , π_f , is a known function¹³ indexed by a finite cost parameter vector ν_f so the structural parameters of the model are given by the profit functions $\pi_1(p, s; \nu_1), \dots, \pi_F(p, s; \nu_F)$. Assuming the data is generated by a unique MPE of the model, the goal is to recover the true value of $\nu = (\nu_1, \dots, \nu_F)$, denoted ν_0 .

The first step of BBL approach is to estimate the policy functions, $\sigma_f : S \times \nu_f \rightarrow p_f$ for $f = \{1, \dots, F\}$, and state transition probabilities, $\mathbb{P} : S \rightarrow \Delta(S)$. 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 \mathbb{P} .

Given any policy function σ and transition probability \mathbb{P} , a simple single simulated path of play can be obtained as follows:

- 1.- Set an initial cost parameters $\nu = \{\nu_1, \dots, \nu_F\}$ and initial state $s_0 = s$.
- 2.- Draw a sequence of states over T periods using the estimated transition probabilities $\mathbb{P}(\cdot | s_t)$, hence I generate the sequence $\{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_T\}$.

¹¹The logic is the same as in other BBL applications for entry/exit or investment decisions: current decisions may depend on what happened last period, but not how the current state is reached.

¹²Assume that V_f is bounded for any Markov strategy profile σ .

¹³For econometric purposes, I treat the player specific discount factor β_f as known. I use the average inflation over 30 years to account for differences in the inflation rates between countries.

- 3.- Compute the actions for every player f through the estimated policy function, thus: $p_t = \sigma_f(\mathbf{s}_t)$, hence I generate the respective sequence $\{\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_T\}$ for every player.
- 4.- Given the known functional form of profit function π_f and the discount factor β_f , I compute the resulting profits $\hat{\pi}_f(\mathbf{p}_t, \mathbf{s}_t; \nu_f)$, for every player $f \in \{1, \dots, F\}$ at every simulated time period t .
- 5.- Compute the present discounted value for each player:

$$\hat{V}_f(\nu_f, \sigma, \mathbb{P}) = \sum_{\tau=0}^T \beta_f^\tau \hat{\pi}_f(\mathbf{p}_\tau, \mathbf{s}_\tau; \nu_f) = \sum_{\tau=0}^T \beta_f^\tau \hat{\pi}_{f\tau}(\nu_f, \sigma, \mathbb{P})$$
- 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:

$$\hat{\mathbb{E}}(V(\nu_f, \sigma_f, \mathbb{P})) = \frac{1}{NR} \sum_{h=1}^{NR} [\hat{V}_f^h(\nu_f, \sigma_f, \mathbb{P})] \quad (2.9)$$

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

Such an estimate can be obtained for any (σ, ν_f) pair, including $(\hat{\sigma}, \nu_f)$, where $\hat{\sigma}$ is the policy profile estimated in the first stage. Because first stage estimation $\hat{\sigma}$ is based on the actual data, it should represent the optimal policy function under the true parameters ν_0 and 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 σ_f in response to $\hat{\sigma}_{-f}$, in both cases conditional on all players parameters ν . 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.:

$$V_f(s|\sigma_f, \sigma_{-f}, \nu_f) \geq V_f(s|\sigma'_f, \sigma_{-f}, \nu_f) \quad \forall \sigma'_f \quad (2.10)$$

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

$$g(x, \nu, \alpha) = V_f(s, \sigma_f, \sigma_{-f}, \nu, \alpha) - V_f(s, \sigma'_f, \sigma_{-f}, \nu, \alpha) \quad (2.11)$$

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

Define the function

$$Q(\theta, \alpha) \equiv \int (\min\{g(x, \nu, \alpha), 0\})^2 dH(x) \quad (2.12)$$

where H is a distribution over the set X of inequalities. The true parameter vector, ν_0 , satisfies:

$$Q(\nu_0, \alpha_0) = 0 = \min_{\nu \in \Theta} Q(\nu, \alpha) \quad (2.13)$$

Given a sequence of inequalities $\{X_k\}_{k=1, \dots, n_f}$, I use an alternative policy

$$\tilde{\sigma}_f(s, \nu_f) = \sigma_f(s, \nu_f, \hat{\alpha}) + u \quad (2.14)$$

where u is white noise. By definition of σ_f , this alternative policy function $\tilde{\sigma}_f$ is suboptimal under the true parameters. For each chosen inequality the forward simulation procedure can construct analogues of each of the V_f terms, say \tilde{V}_f . Formally;

$$\tilde{g}(x, \nu, \hat{\alpha}_n) = V_f(s, \sigma_f, \sigma_{-f}, \nu, \hat{\alpha}_n) - V_f(s, \tilde{\sigma}_f, \sigma_{-f}, \nu, \hat{\alpha}_n) = V_f - \tilde{V}_f \quad (2.15)$$

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

Finally the second stage estimator is:

$$\hat{\nu} = \arg \min_{\nu \in \Theta} \frac{1}{n_I} \sum_{k=1}^{n_I} (\min\{\tilde{g}(x_k, \nu, \hat{\alpha}), 0\})^2 \quad (2.16)$$

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

2.3 Data for Supply Estimation

This section describes and discuss the data that is the same as discussed in section 1.3. The dataset was collected by Brenkers and Verboven (2006) and is an updated version of the one used by Goldberg and Verboven (2001).¹⁴

The yearly dataset consists of prices, sales and physical characteristics of (mostly) 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. The definition of market is a market-year pair. 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 dataset also includes variables to identify the model, the brand, the firm, the country of origin/production location, and the market segment (“class” or “category”). Notice that the dataset keeps track of consecutive data for a given model.

2.3.1 Nationalities from Manufacturer’s Perspective

This section presents the nationalities considered for each firm. The definition of nationality of the product is fundamental, since I need to express the revenues in a single currency for each producer.

I consider firm’s headquarter nationality for the supply side estimations. Table 2.1 presents firm-nationality links based on the historical nationality of the headquarter location. Firms never change the assigned nationality even though a brand could change due to mergers or acquisitions. For example, BMW produces the brand Rover-Triumph since 1994, hence those revenues are expressed in German currency for the BMW profit function. From the consumers’ viewpoint those cars are perceived as British cars regardless the ownership of the brand.

According to this criterium, table 2.2 and 2.3 presents the market shares and the share of total models available in each market for each nationality and each destination market.

¹⁴The data is available in the authors’ webpage.

Table 2.1: **Headquarter's nationalities**

Nationality	Firm	Nationality	Firm
France	Peugeot Renault TalbotMatra TalbotSimcaHillmanSunbe	Italy	AlfaRomeo DeTomaso Fiat Lancia
Germany	BMW Daimler Mercedes VW	Korea	Daewoo Hyundai Kia
		Netherlands	DAF
Japan	FujiHI (aka Subaru) Honda Mazda Mitsubishi Nissan Suzuki Toyota	Spain	Seat
		Sweden	Saab Volvo
		UK	Rover
		US	Ford GeneralMotors
		Yugoslavia	Yugo

Table 2.2: **Available models by headquarter's nationality**

HQ's Nationality	Belgium	France	Germany	Italy	UK	Total
American	321	273	292	258	315	1,459
French	532	528	475	481	480	2,496
Germans	426	413	420	411	376	2,046
Italians	442	412	374	506	264	1,998
British	132	122	54	84	167	559
Japanese	629	377	533	136	523	2,198
Others	281	439	17	28	28	793
Total	2763	2564	2165	1904	2153	11549

Table 2.3: **Shares of cars by headquarter's nationality**

	Share of Sold Cars	Share of Models
USA	22.12 %	12.63 %
France	26.64 %	21.61 %
Germany	19.56 %	17.72 %
Italy	17.61 %	17.30 %
UK	4.37 %	4.84 %
Japan	7.66 %	19.03 %
Korea	0.39 %	2.43 %
Sweden	1.37 %	3.80 %
Spain	0.06 %	0.15 %
Yugoslavia	0.03 %	0.24 %
Netherlands	0.20 %	0.24 %

2.3.2 Car Characteristic Trends

This section briefly describes the trends of the data across different European markets. As pointed out in section 1.3, I reduced the dimensionality of the characteristic space constructing three variables that summarize the observed characteristics, because many of them are very collinear. The summarized characteristics are size, inverse of motor power, and fuel efficiency.

The trends of all these three characteristics in the five destination markets are in figure 2.1, 2.2 and 2.3 respectively. Size and Motor power have some linear trend and/or clear autocorrelated process. Instead full efficiency seems to be less systematic.

Figure 2.1: Evolution of car size across Europe

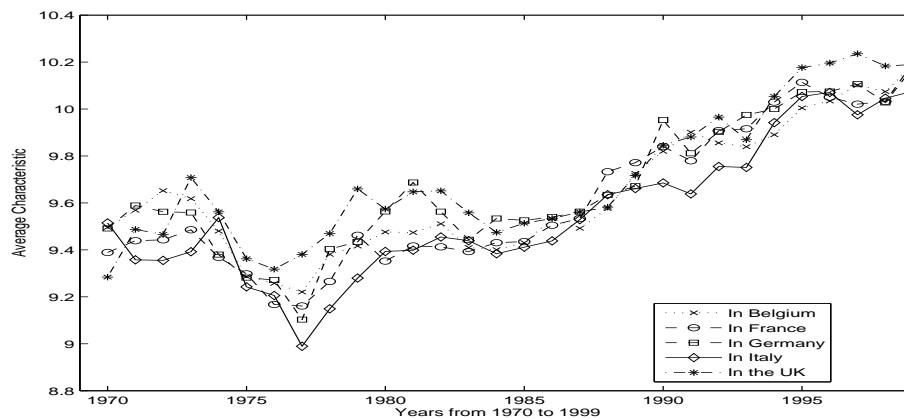
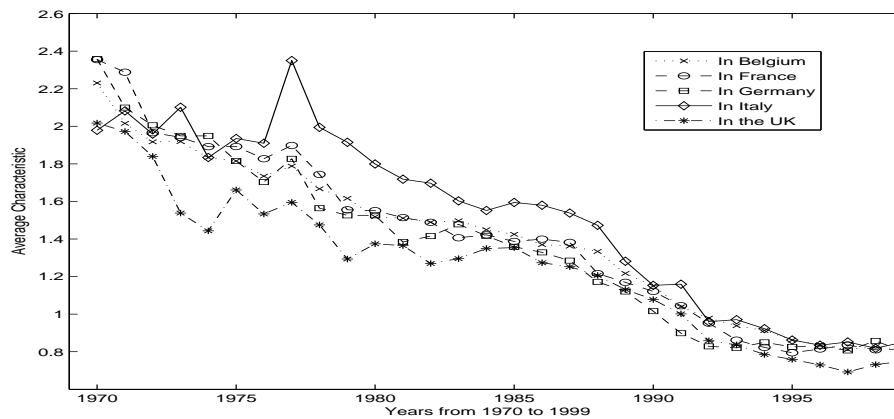


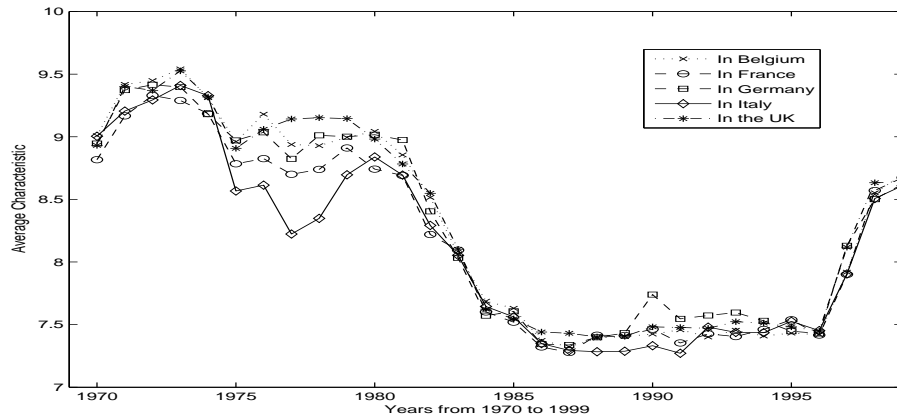
Figure 2.2: Evolution of the inverse of motor power across Europe



2.3.3 Entry/Exit Behavior

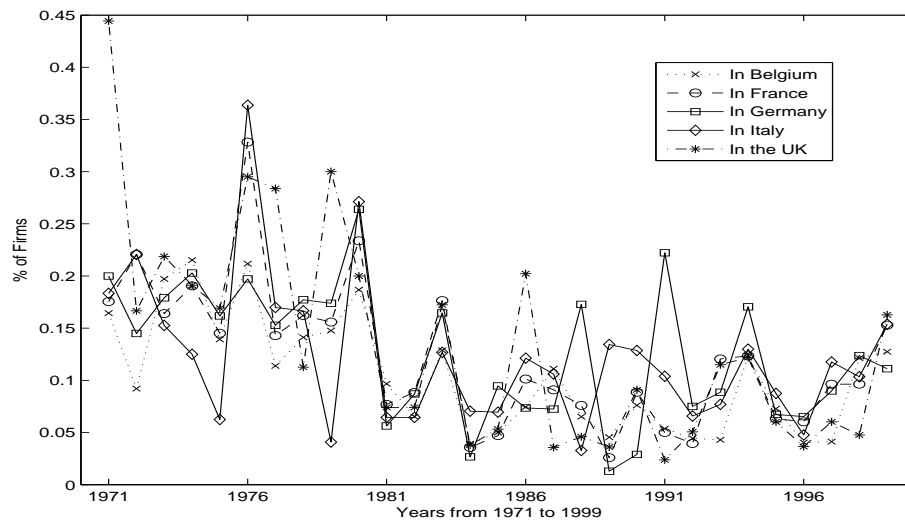
This section discuss the assumption of no entry/exit of firms and models. This might be important in the sense that large movements in exchange rates can change the set of relevant players or models and consequently we can have a composition effect or “survivorship bias” as highlighted by Rodriguez Lopez (2008).

Figure 2.3: Evolution of fuel efficiency across Europe



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 2.4 presents the evolution of the number of new firms.

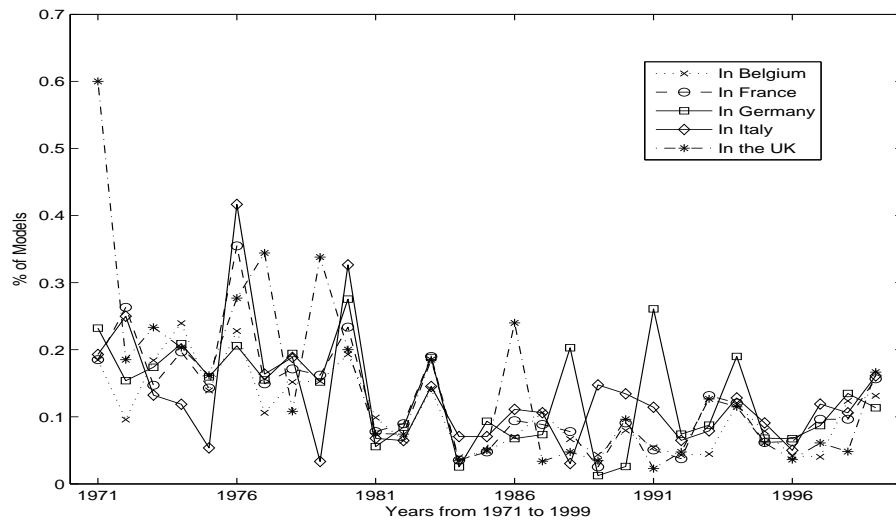
Figure 2.4: New firms across Europe



Similarly, to deal with entry/exit of models I need to predict which incumbent model exits and the characteristics of the new entering model, which is prohibitive when the characteristics are multidimensional as in the auto case. I argue that new models are not a big share of the market. Figure 2.5 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%.

For the forward simulation stage I consider fixed characteristics as well as fixed models in each market for a given year basis. Hence I can ensure that these results are not contaminated by this composition effect. None of the previous structural empirical work in cars had controlled

Figure 2.5: New models across Europe



for this fact.

Recall that this chapter is focus on pricing behavior dynamics given the choice set, so I explore the market's behavior (consumers and producers) for a market configuration in the European car market. Including entry/exit and endogenous location remains as a challenging future research.

2.4 Results

This section presents the empirical results of estimating the model in the European car market. The demand results are discussed in section 1.4 of chapter 1. The subsections 2.4.1 and 2.4.2 present the results for the BBL first stage estimates of transition probabilities and policy functions respectively. Impulse-response exercises are presented in subsection 2.4.3 to evaluate the economic sense of the reduced form policy functions. Finally I present the structural estimates and their implications in subsection 2.4.4.

2.4.1 Transition Probabilities

This subsection presents the transition probabilities estimates that represent the state variable dynamics. The evolution of the state variables, in this case are independent of the endogenous control variable (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.¹⁵ As argued above, I decide to exclude car's characteristics as state variable, so characteristics remain fixed over the forward simulations. The lagged of prices is also a payoff relevant variable due to the nature of the price adjustment costs.

¹⁵This ratio controls for two country-specific dynamics such as inflation rate and consumer's income following the idea of Goldberg and Verboven (2001).

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

Exchange Rates

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

The following time series are the ratio between the local currency and the American dollar. Hence the equation for currency of country $f = \{\text{Belgium, France, Germany, Italy, UK, Japan}\}$ at time t is given by:

$$e_{f,t} = \alpha_f + \rho_f e_{f,t-1} + u_{f,t} \quad (2.17)$$

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

$$\text{cov}(u_{s,t}, u_{r,t}) = \sigma_{s,r} \neq 0 \quad \forall s, r \quad \text{and} \quad \text{cov}(u_{s,t}, u_{r,p}) = 0 \quad \forall t \neq p \quad (2.18)$$

In the BBL estimation I use the ratio between the producer's currency and the selling market currency, so the dollar as denominator does not matter much.

The process of integration towards a common currency shall be mentioned. First, the calendar for the launch of the Euro was set in the Maastricht treaty, 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.¹⁶ There are not big differences among the 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 (1971q1 to 1998q4).

In order to take advantage of the higher frequency data that we have for exchange rates, the estimates are going to use quarterly data although all the forecasts used in the forward simulation stage are yearly.¹⁷

To present the degree of inertia in the series, I compute the number of periods needed to reduce a shock to a 10% of its initial magnitude. Let us call the "absorbing period" \mathcal{T} the number of periods required to have $\rho^{\mathcal{T}} = 0.1$.

As expected, 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 1971q1 until the 2008q2) I can not reject a stationary process ($\hat{\rho}_s < 1$) with a huge persistence.¹⁸

The detailed estimates are presented in table 2.4.

The correlation matrix of the residuals plays an important role, since I need to draw simulations of the random vectors u accounting for the covariance path. During these decades an integration process took place between these European countries that lead to higher correlation between currencies over time. Of course after the launch of the 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 2.5.

¹⁶ i) From 1971q1 to 1989q4; ii) From 1990q1 to 2008q2; iii) From 1981q1 to 1998q4; iv) From 1971q1 to 1998q4; v) From 1971q1 to 2008q2.

¹⁷ Appendix H describes the procedure to use these estimates for yearly forecast.

¹⁸ For a discussion on the lack of power in unit root tests, see Hamilton (1994).

Table 2.4: **Transition probability estimates for nominal exchange rates**

		Quarterly Estimates	Yearly Est.	\mathcal{T}
Belgian	ρ	0.98***	0.93	33
Franc	α	0.06*	0.23	
French	ρ	0.99***	0.96	54
Franc	α	0.02	0.07	
German	ρ	0.98***	0.91	26
Mark	α	0.01	0.04	
Italian	ρ	0.98***	0.92	28
Lira	α	0.15**	0.60	
British	ρ	0.97***	0.89	19
Pound	α	-0.01	-0.05	
Japanese	ρ	0.98***	0.91	24
Yen	α	0.12*	0.44	

* significant at 5% ; ** significant at 1% ; *** significant at 0.1%

Table 2.5: **Correlation matrix of exchange rate shocks**

Yearly	Bel	Fra	Ger	Ita	UK	Jap
Bel	1.00					
Fra	0.93	1.00				
Ger	0.97	0.91	1.00			
Ita	0.81	0.84	0.79	1.00		
UK	0.66	0.65	0.65	0.70	1.00	
Jap	0.62	0.60	0.62	0.45	0.46	1.00

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. Using this set of estimates I can draw alternative paths of nominal exchange rates in the forward simulation stage.

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 a 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:

$$\begin{bmatrix} W_{s,t} \\ Y_{s,t} \end{bmatrix} = \lambda_0 + \lambda'_s \begin{bmatrix} W_{s,t-1} \\ Y_{s,t-1} \end{bmatrix} + \begin{bmatrix} v_{1,s,t} \\ v_{2,s,t} \end{bmatrix} \quad (2.19)$$

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 2.6 are based on yearly data between 1971 and 1999.¹⁹

Table 2.6: **Transition probabilities for nominal wages and GDP per capita**

	GDP			Wage			Correlation Parameter
	GDP_{t-1}	Equation $Wage_{t-1}$	Cons.	GDP_{t-1}	Equation $Wage_{t-1}$	Cons.	
Belgium	0.95***		0.68***	0.07***	0.84***		0.35*
France	0.65***	0.30***	2.93***	-0.25***	1.19***	2.27***	0.59***
Germany	0.95***		0.58***		0.95***	0.19***	
Italy	0.69***	0.28***	2.71***	-0.19***	1.13***	2.04***	0.33*
UK	0.96***		0.45***	0.02***	0.94***		0.42**
Japan	-	-	-		0.90***	1.35***	

Not surprisingly, all the process are extremely autocorrelated. It implies a slow adjustment given a shock. Similarly for most of the countries, the shocks on nominal wages are correlated with the shocks on nominal GDP, captured by the country specific correlation parameter. Germany is the only country where there is no significant wage-GDP correlation.

2.4.2 Policy Functions

This section describes the reduced form policy functions and presents the empirical estimation. The aim of this stage is to retrieve a reduced form of producer's optimal decision function from the observed behavior. I assume agents have taken their optimal decisions based on the observable state variables consistent with Markov perfect equilibrium, 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.

¹⁹ Quarterly data is not available for all the relevant years and countries.

The dependent variable is nominal price in destination currency and the independent variables include car's characteristics, lagged price and macroeconomic variables of the five destinations market (Belgium, France, Germany, Italy and the UK). I aggregate the 31 firms into 6 nationalities (American, French, German, Italian and Japanese) so we should think of 6 different pricing rules in each destination market so this assumes that firms from the same source/destination pair have the same policy function. This is not a statement about the degree of competition or collusion in the European market, since BBL just accounts for the pricing behavior of the firms.

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 across markets. Hence each producer's policy function has different parameters in each different destination 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.²⁰

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.²¹ Second, I need information of at least two consecutive periods in order to estimate the lagged price coefficient. Third, I only use those cars produced in domestic locations. 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 2.7.

Table 2.7: **Sample for policy function estimations**

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

The policy functions 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 can have structural parameters.

I choose to have all the states variables related to own production costs. 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, however as a any reduced form estimation it could be arbitrarily extended. I also tried several other specifications including

²⁰Exploring policy functions that are asymmetric or a S-s function is totally desired but requirements on the number of observations are prohibitive.

²¹I leave out the models from the Netherlands, Czechoslovakia, Sweden, Spain, Korea, Russia, and Yugoslavia.

some competitors' variables (average of all competitor's past prices or by segment; competitor's characteristics, competitor's wages and competitor's exchange rates). None of these attempts made sense neither statistically nor economically, so I kept the minimum set of variables directly related to own production costs. Still we can think of strategic behavior being triggered or coordinated by the changes in the state variables, for example the exchange rates.

Let us denote m the market of destination and denote f the country of production which most of the cases is the head quarter nationality.²²

Hence, the log-price of model j in market m , produced in source country f at time t is given by:

$$\begin{aligned} \log(p_{jt}^m) = & \alpha \log(p_{j,t-1}^m) + \beta_1 \log(e_{mt}/e_{ft}) + \beta_2 \log(e_{mt}/e_{ft})^2 \\ & + \beta_3' \log(e_{mt}/e_{ft}) \cdot \log(X_{jt}^m) + \gamma_0 \log(X_{jt}^m) + \gamma_1 \log(W_{ft}) \\ & + \gamma_2' \log(X_{jt}^m) \cdot \log(W_{ft}) + \lambda_1 \log(Y_t^m) + \lambda_2' \text{dummies} + \varepsilon_t \end{aligned} \quad (2.20)$$

The considered independent variables are:

- The ratio of nominal exchange rates terms (e_{mt}/e_{ft}) 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_{ft} in the producer country f . These terms are a measure of nominal cost of production.
- The lagged price $p_{j,t-1}^m$ which represents any inertia and 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_t^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 .²³
- The set of dummies that account per firm and market segment (compact, subcompact, standard, intermediate and luxury cars).

From this reduced form estimations I can see that there is a huge autocorrelation in prices but at the same time it is very heterogeneous for different source-destination pairs. To give a sense of this fact, table 2.8 presents the estimated coefficients $\hat{\alpha}$, which are always significant and vary a lot for each origin-destination pair.

These coefficient are not meant to be interpreted as a economic meaningful parameters.²⁴ 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.

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

²²American firms are the exception since they produced in Germany and the UK.

²³Consumer's income Y_{jt}^m is very collinear with nominal domestic wages at the destination market, so W_{ft} is not included.

²⁴The entire set of 13 regressors for each of the five markets for each of the six producers is available upon request.

Table 2.8: **Estimates of lagged price coefficient**

	Belgium	France	Germany	Italy	UK	Producer Av.
American	0.53	0.64	0.65	0.42	0.42	0.53
French	0.85	0.80	0.75	0.71	0.67	0.76
Germans	0.70	0.74	0.86	0.71	0.70	0.74
Italians	0.63	0.70	0.71	0.77	0.57	0.67
British	0.56	0.67			0.30	0.51
Japanese	0.75	0.50	0.64		0.77	0.67
Market Av.	0.67	0.67	0.72	0.65	0.57	0.66

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.

2.4.3 Impulse-Response Experiments

This section discusses and evaluate the estimated policy functions. Recall that the aim of these estimates is to have a good predictive power with sensitive economic implications to feed the forward simulation second stage.

One key prediction for the second stage is to obtain reasonable price-nominal GDP ratio in each market. Recall that that nominal GDP per capital follows its own AR(1) process and therefore any miss-specification might lead the price ratio to infinity or zero. I selected those specifications that yield sensitive forecast for these ratios.

Also an important forecast to consider is the response to a shock in the nominal state variables. I evaluate the policy functions under different paths of the state variables to asses the changes in price, demand and revenue for each player.

Let me state the limitations up front. The estimated reduced form policy functions are statistical representations of the true theoretical policy functions, which can only be found solving the game. Hence, the following impulse-response exercises assume that shocks in the state variables do not change the policy rule. I'm not able to perform counterfactual exercises for scenarios that should imply changes in the pricing behavior function.

Using the policy function estimates, I simulate two different paths under two different scenarios. The baseline case keeps all the state variables in their long run value. A second path has a initial perturbation of 10% increase. (exchange rate and wage perturbations). After the initial perturbation²⁵, the state variable follows its own AR(1) process.²⁶ I simulate the exercise for 40 periods ahead.

Notice that these predictions are based on the best reduced form estimations taken from the data, so these predictions are only the best statistical responses and does not impose any assumptions of a specific game, degree of competition or any other type of imposed optimality.

Exchange Rate Depreciation

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

²⁵The shocks are uncorrelated to clarify the presentation, during the forward simulation stage I draw the shocks using the estimated correlations in the transition probabilities.

²⁶The 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.

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 is different because of the different speed of adjustment of each currency and the non-linear terms of the regression.

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. On the other hand, 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. In general, we could include a domestic effect of domestic depreciation in a strategic way. Empirically, it did not work. Therefore we imposed a zero effect on all the domestic policy functions.

As special case Belgium has 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.

As an example, I present the figures for the French franc case. The entire set of figures for all the responses after a 10% depreciation of each currency in each separate market is in appendix B and C. Appendix D 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 2.6 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 gradually.

Figure 2.6: Price path in Europe after a 10% depreciation of the French Franc

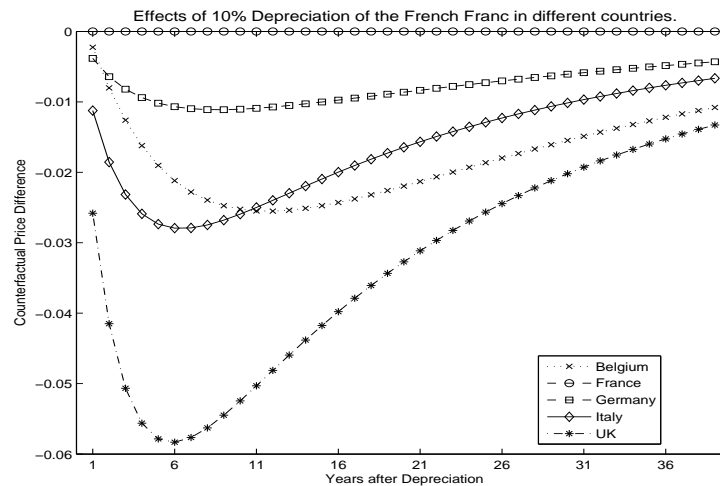
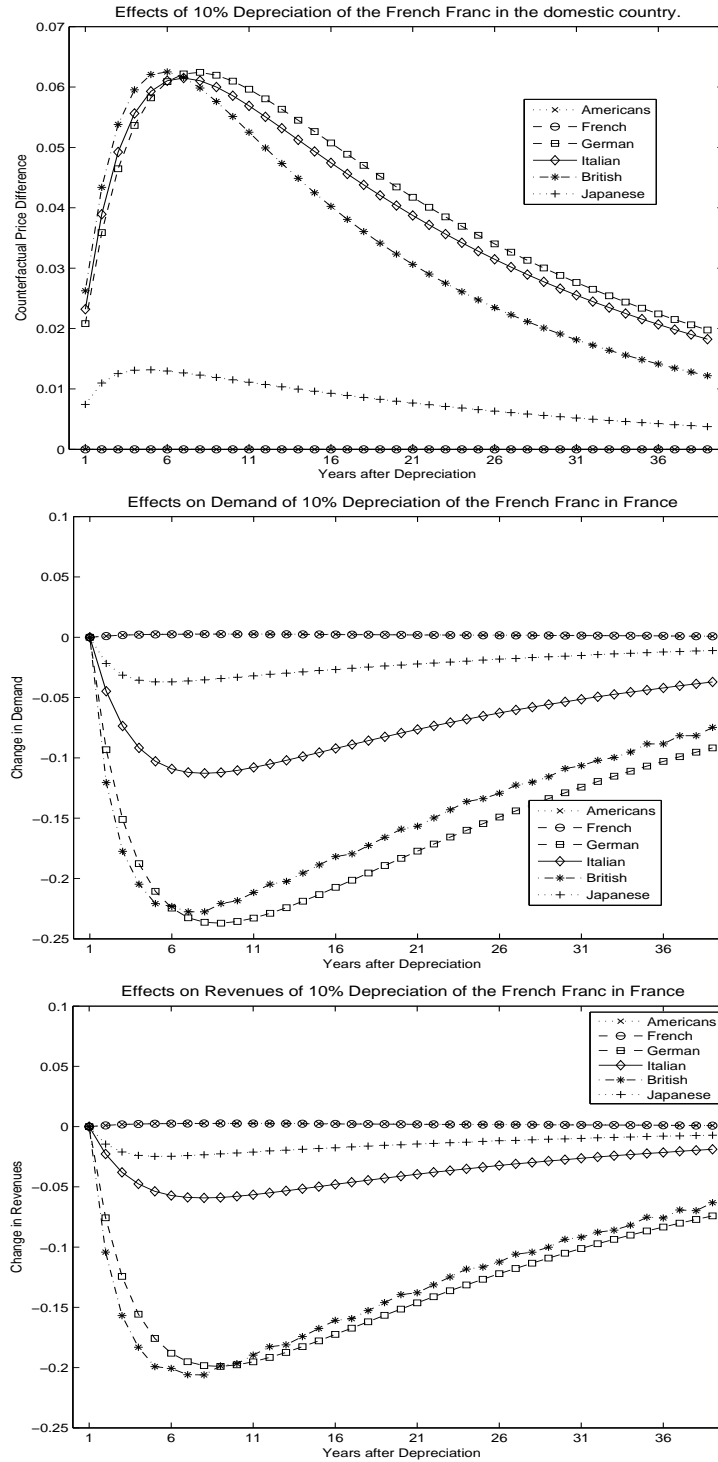


Figure 2.7 presents the reaction of foreign producers in France after a depreciation of the French Franc. Since their revenues are smaller in terms of their cost's currency, foreign producers increase their price. French producer's prices remain the same since their cost and revenues currencies have been not affected by the depreciation and empirically we reject a strategic behavior.

Figure 2.7: Price path in France after a 10% depreciation of the French Franc

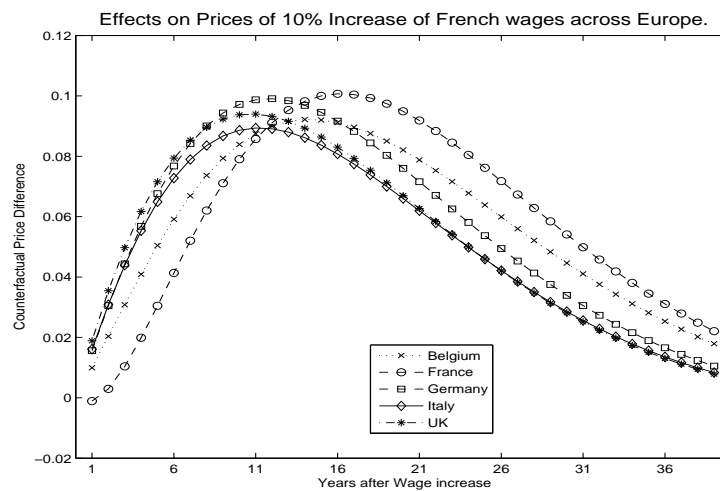


The price movements are quite similar among European producers (about 6% and similar speed of reduction), except by Japanese cars that increase only 1% and remains almost flat along the simulations.

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 domestic cost of production²⁷ and generates a price increase in every destination market. Figure 2.8 presents the percentage responses in price increases and appendix E presents the figures for the rest of European wages.

Figure 2.8: **Price path after a 10% increase in French wages across Europe**



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 this cost pass-through exercise.

Recall that all the policy functions and transition probabilities were taken directly from the data and did not impose any optimality condition. The BBL second stage assumes that producers were optimizers and estimate the cost parameters that support this behavior as the optimal, i.e., search over the structural parameters that rationalize the estimated behavior.

Demand Reactions of Impulse-Response Exercises

This subsection presents the demand reactions for the price reactions in each of the Impulse-response exercises. Since I have a fully structural demand, I evaluate the implications of the price change on demand and consequently in revenues.

Recall that the elasticity patterns in the demand estimation consider not only the change in relative prices but also the characteristics of each car. 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 2.7. The reactions in demand after the price increase stress a heterogeneous pattern of substitution among French

²⁷Except for American cars which are made in Germany and the UK.

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 with absolute values between 2 and 3. 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%. Notice using previous elasticities close to 5, the predicted losses would be close to 40 – 50%.

2.4.4 Structural Cost Parameters

This section presents the estimated structural cost parameters in the European car market. Recall that BBL's second stage searches over the cost parameters to rationalize the behavior found in the data (captured through the first stage estimates). Using these parameters I identify the order of magnitude of both components: the destination wage and the adjustment cost component.

I assume the following cost function for firm f and product $j \in \mathcal{F}_{jm}$ sold in market m :

$$\begin{aligned}
 C_{jt}^m = & \underbrace{\nu_0 \cdot q_{jt}^m + \nu_j \cdot [q_{jt}^m]^2}_{\text{Car's Characteristics}} + \underbrace{\nu_{w1} \cdot W_{ft} \cdot q_{jt}^m + \nu_{w2} \cdot W_{ft} \cdot [q_{jt}^m]^2}_{\text{Production Wage Cost}} \\
 & + \underbrace{\nu_{w3} \cdot e_{fmt} \cdot W_{mt} \cdot q_{jt}^m + \nu_{w4} \cdot e_{fmt} \cdot W_{mt} \cdot [q_{jt}^m]^2}_{\text{Destination Wage Cost}} \\
 & + \underbrace{\Psi_m \cdot e_{fmt} \cdot |p_{jt}^m - p_{jt-1}^m|}_{\text{Price Adjustment Cost}}
 \end{aligned} \tag{2.21}$$

where parameter vector ν represents the production cost parameters and parameter vector Ψ represents the price adjustment costs. The latter the structural parameters are indexed by m since they are destination market specific. q_{jt}^m is the quantity of product j sold in market m , and W_{gt} , $g \in \{m, f\}$ is the nominal wage in destination country m or source/producer's country f . 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 global minimum.

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 the nominal labor cost, which distinguish between wages where the product was made and wages where the car was sold (if different from the producing country along the idea of local-cost component set in destination-currency as in Burstein, Neves, and Rebelo (2003)). 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}^m , so it does not affect the marginal cost of production. 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 in the entry-exit section, I 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.²⁸ This fact keeps our estimates not contaminated by macroeconomic conditions changing endogenously the choice set (composition effect).

For the 1985 models I simulate 1,000 different paths of state variables, each path involving 40 periods of time. Table 2.9 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

²⁸I have the estimates for other years and are they very similar.

and they eventually disappear in the 90's, making impossible to have reliable cost estimation for British producers.

Table 2.9: **Models considered in forward simulations**

	Belgium	France	Germany	Italy	UK	Total
American	9	8	9	7	6	39
French	19	18	16	18	16	87
Germans	10	10	10	10	8	48
Italians	13	16	7	19	5	60
British	4	5	0	5	6	20
Japanese	29	15	20	0	20	84
Total	84	72	62	59	61	338

Some important remark of the cost estimates. First, I can not identify fixed costs of the firm, such as an investment in a new plant or the development of a new technology or model. 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.

Cost Share by Components

This section presents the order of magnitude of each cost component that is consistent with the observed price autocorrelation and actual exchange rate pass-through in the European car market. 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 G, which are qualitatively the same.²⁹

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

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

Table 2.10 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.

Based on the tables, I conclude the following insights. First, the destination market wage component in table 2.10 may explain the incomplete degree of exchange rate pass-through. Roughly speaking the destination wage components contribute to one third of the costs and that share rationalize the incomplete exchange rate pass-through. Goldberg and Verboven (2001) find

²⁹In 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 2.10: **Cost components (%) over total cost in 1985**

Exports	Local Cost	Destination Cost	Adjustment Cost
American	83.17	16.68	0.15
French	77.91	20.11	1.98
German	62.10	37.58	0.31
Italian	35.33	59.17	5.50
Japanese	60.12	28.91	10.97
Sold Domestically	Local Cost		Adjustment Cost
American	100.00		0.00
French	97.42		2.58
German	100.00		0.00
Italian	88.59		11.41

Table 2.11: **Adjustment cost share by destination market**

	Belgium	France	Germany	Italy	UK
American	0.0	0.4	0.0	0.0	0.0
French	0.0	2.2	0.0	7.4	0.1
German	0.1	0.0	0.0	0.8	0.1
Italian	12.9	1.9	0.0	10.2	2.1
Japanese	0.0	1.4	3.8	-	37.2

Table 2.12: **Ratio of adjustment cost parameters: Ψ_{fm}/Ψ_{ff}**

	Belgium	France	Germany	Italy	UK
American	0.07	93.38	1.00	0.22	11.04
French	0.00	1.00	0.00	1.78	0.08
German	3.57	0.00	1.00	1.31	1.49
Italian	0.37	0.02	0.02	1.00	0.23
Japanese	0.00	0.25	1.00	-	14.28

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 too high to be plausible. Intermediate inputs substitution may play a role, unfortunately lack of model level data does not allow us to explore further.

Second, the adjustment cost component seems small and sometimes not economically significant. My estimates in table 2.10 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 calculations 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.³⁰ Nakamura and Zerom (forthcoming) 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 (2007) estimates are less than 1% of revenues in the beer industry. Notice that most papers have weekly data based on scanner data whereas this chapter presents yearly data.

Third, there is a clear heterogeneity in the estimates of tables 2.11 and 2.12. Adjustment cost seemed to be market specific for each producer nationality. Comparing the ratio of coefficients and the relative importance of the cost share. We find a pattern that is origin-destination market specific. To justify such practice we can think of some bilateral country relationships like relative inflation, exchange rate volatility or any other characteristic that is pair-country-specific. Definitely, some interpretations as the cost of some exogenous pricing policies can take place. Strategic long run behavior can be behind this different timing decisions in the European car market. None of the previous literature in this topic has explored this dimension. An interesting research question would be to explore the covariates that explain this cost share, however our 25 estimates are too few to do serious testing.

Table 2.13: **Implied markups in 1985**

	Mean	Std Dev
American	71%	35%
French	83%	31%
German	61%	47%
Italian	74%	37%
Japanese	67%	42%

Fourth, table 2.13 presents the implied markups for year 1985, i.e., the markups that rationalize the behavior described by the policy functions.³¹ Going back to the figures of the policy function impulse-response exercises, we observed that revenues could drop by 20% because of a not unfrequent 10% depreciation, therefore it is not surprisingly that to rationalize that behavior the markups should be large enough. A firm with smaller markups would not survive to the usual exchange rate shocks. In general I compute quite higher markups than the previous usual static approach, but also with a huge dispersion (with some noticeable outliers). Recall that estimated markups rationalize the market behavior where we had: a very volatile macroeconomic environment, little entry/exit of firms (the main players are roughly the same). This ingredients can only be consistent with large markups to survive the negative shocks. In this sense the “bad years” are the most informative ones regarding the real marginal cost.

³⁰Assuming an adjustment cost of 10% of total cost and a markup of 70%.

³¹I do not consider the few models with markups greater than 100% and the British estimates which were based on 5 models).

An interesting feature we found in this setting is the unusual relationship between markups and price elasticity. Since marginal cost estimation looks for consistency with market behavior this does not need to follow the usual Lerner index logic of static settings. Recall our market has a very volatile environment (say exchange rates), then frequent price changes are expected. If on top of this volatility we have a sensitive demand, then firms need a larger markup to survive the frequent bad shocks. Hence, a larger demand elasticity would imply larger markup to sustain the larger decrease in revenues in this setting with few entry/exit of firms. Notice that this is the opposite monotonic relationship that we have in the standard static setting. In this regard, I need fewer assumptions than the standard static approach, since the policy functions are estimated and does not rely on first order conditions.

Important, this chapter can not identify fixed cost, which might be really important in this industry, for example investment in new plants, development of new models or technology. Therefore, without those fixed costs I can not say much about the entire industry profitability.

2.5 Conclusions

The aim of this chapter is to extend the structural estimation in the European car market to study cost parameters that rationalize i) the observed degree of exchange rate pass-through and ii) the timing in the price adjustment dynamics. I consider an international multi-product oligopoly model in which the forward looking firms set optimal prices taking into account the cost of repricing.

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). The main results give us the order of magnitude of price adjustment costs and their origin destination market heterogeneity.

The demand estimates of chapter 1 highlight the consumer heterogeneity that enhances pricing to market behavior. Consumers have different degree of substitution among international producers, and producers have market specific pricing policies.

I also found heterogeneous behavior and cost parameters on the supply side. Among the results, 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.

Finally, I found a positive relationship between price elasticities and markups in this particular dynamic environment. This relationship in dynamic framework breaks the monotonic relationship in static models given by first order conditions. New research is needed to explore the theoretical relationship between elasticities and markup in dynamic settings.

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Appendix A

Logit, IV and BLP

This appendix presents the relationships between the logit model, the logit model with instrumental variables (IV) and the mixed logit model a la BLP. I can express the first two models as particular cases of BLP model.

Following the notation of subsection 1.2.1, the full BLP model can be written as:

$$\delta(\Sigma) = X\beta + \xi \quad (\text{A.1})$$

where parameters Σ and β are unknown.

The simplest logit model considers a representative consumer and exogenous prices. If there is no heterogeneity, the variance matrix of the random coefficients is given by $\Sigma = 0_{k \times k}$ and the mean utility δ is given by the ratio of market share vector S and outside good market share S_0 :

$$\delta_0 = \delta(\Sigma = 0_{k \times k}) = \log \left(\frac{S}{S_0} \right) \quad (\text{A.2})$$

Therefore in terms of BLP, the logit estimates $\hat{\beta}_L$ with variance $V(\hat{\beta}_L)$ can be written as:

$$\hat{\beta}_L = (X'X)^{-1}X'\delta_0 \quad (\text{A.3})$$

$$V(\hat{\beta}_L) = \sigma_L^2(X'X)^{-1} \quad (\text{A.4})$$

The logit model is just a particular case of ordinary least squares, hence $\hat{\sigma}_L^2 = (\delta_0 - X\hat{\beta}_L)'(\delta_0 - X\hat{\beta}_L)/(N - k)$ and therefore we have the standard asymptotic results.

The logit model with instrumental variables uses the two stage least estimation considering instruments Z , addressing the potential endogeneity between prices and random terms ξ , but still considering homogeneous consumers ($\Sigma = 0_{k \times k}$). The IV estimates $\hat{\beta}_{IV}$ with variance $V(\hat{\beta}_{IV})$ can be written as:

$$\hat{\beta}_{IV} = (\hat{X}'\hat{X})^{-1}\hat{X}'\delta_0 \quad (\text{A.5})$$

$$V(\hat{\beta}_{IV}) = \sigma_{IV}^2(X'Z(Z'Z)^{-1}Z'X)^{-1} \quad (\text{A.6})$$

where $\hat{X} = (Z'Z)^{-1}Z'X$ and $\hat{\sigma}_{IV}^2 = (\delta_0 - X\hat{\beta}_{IV})'(\delta_0 - X\hat{\beta}_{IV})/(N - k)$.

The third specification is the full BLP model which considers heterogeneous consumers with random coefficients for characteristic and also controls the price endogeneity.

The full BLP model is estimated using the Generalized Method of Moments (GMM). Let be θ the ‘‘column vector’’ of unknown parameters of matrix Σ . The GMM estimator $\hat{\theta}_{GMM}$

is given by:

$$\hat{\theta}_{GMM} = \arg \min_{\theta \in \Theta} \xi(\theta)' Z(Z'Z)^{-1} Z' \xi(\theta) = \arg \min_{\theta \in \Theta} g(z, \theta)' W g(z, \theta) \quad (\text{A.7})$$

where $g(z, \theta) = Z' \xi(\theta)$. Define the expected gradient $G = E[\nabla_{\theta} g(z, \theta_0)]$ and $\Omega = E(g(\theta_0)g(\theta_0)')$.

Under mild regularity conditions, the asymptotic normal distribution¹ is given by:

$$\sqrt{N}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, (G' \Omega^{-1} G)^{-1}) \quad (\text{A.8})$$

where the variance of GMM estimates is given by $V(\theta_{GMM}) = (G' \Omega^{-1} G)^{-1}$, since the weighting matrix W is $\Omega^{-1} = [E(Z' \xi \xi' Z)]^{-1} = (Z' Z)^{-1}$. The term $G = E[\nabla_{\theta} g(z, \theta_0)]$ was estimated using the sample counterpart $\hat{G} = \frac{1}{N} \sum_{n=1}^N z_i' D \delta_i$, where $D \delta$ is the explicit derivative as in appendix of Nevo (2000). Similarly, $\Omega = E(Z' \xi \xi' Z)$ was estimated using $\hat{\Omega} = \frac{1}{N} \sum_{n=1}^N \xi_i^2 z_i' z_i$.

¹See Newey and McFadden (1994) for further details.

Appendix B

International Effects of Exchange Rate Depreciation

This appendix presents the impulse response exercises for a 10% depreciation of each of the considered European currencies as explained in section 2.4.3. Each figure presents the percentage difference between the perturbed and the steady state paths for predicted prices. This prices are computed through the estimated policy functions, which uses the exchange rate series predicted by an initial 10% shock increase and 39 subsequent periods predicted by the respective estimated transition probability.

This section presents the effects on every foreign Euro market for a given domestic depreciation. Basically, a domestic depreciation allows domestic producers to sell cheaper abroad.

Recall that in the year 1985 i) there are no British cars in neither Germany nor Italy, ii) there are no Japanese cars in Italy.

Figure B.1: **Price path in Europe after a 10% depreciation of the Belgian Franc**

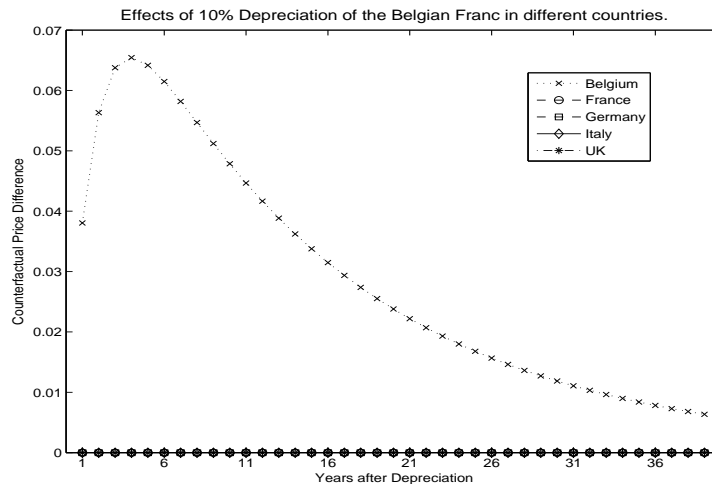


Figure B.2: Price path in Europe after a 10% depreciation of the French Franc

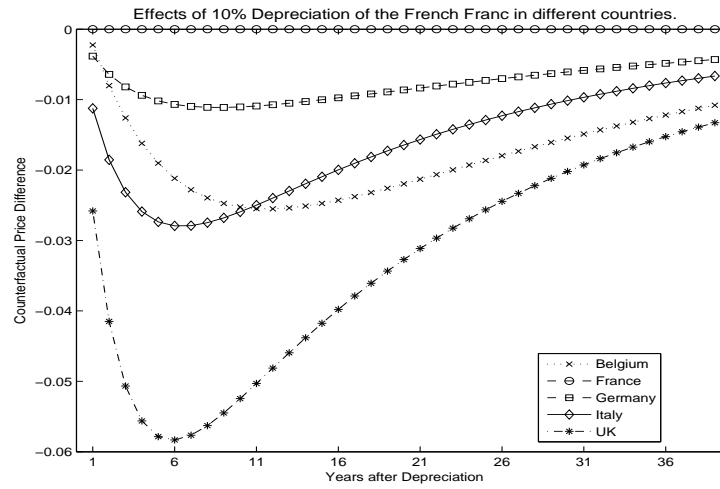


Figure B.3: Price path in Europe after a 10% depreciation of the German Mark

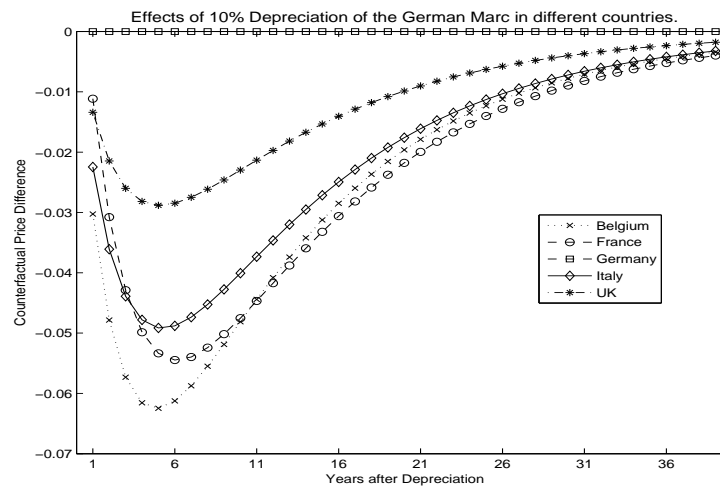


Figure B.4: Price path in Europe after a 10% depreciation of the Italian Lira

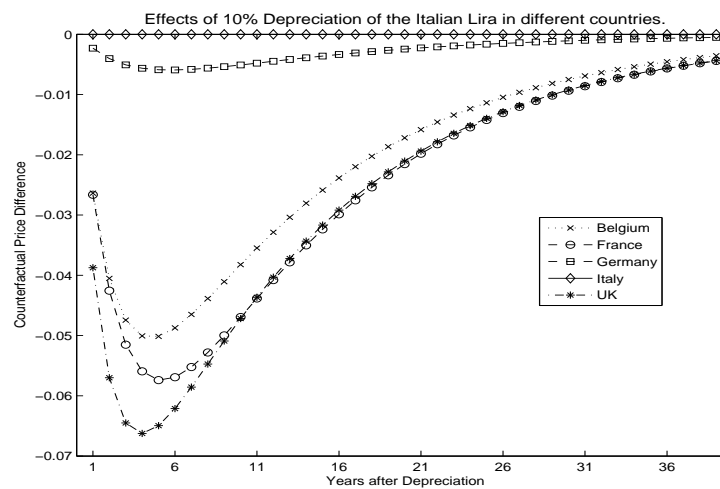


Figure B.5: Price path in Europe after a 10% depreciation of the British Pound

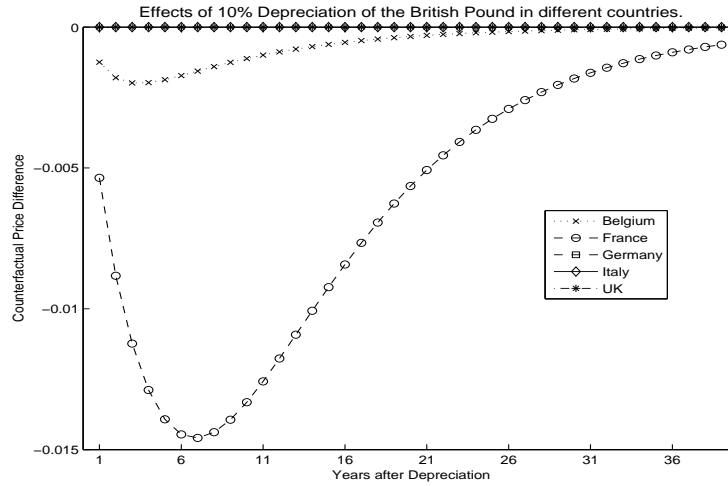
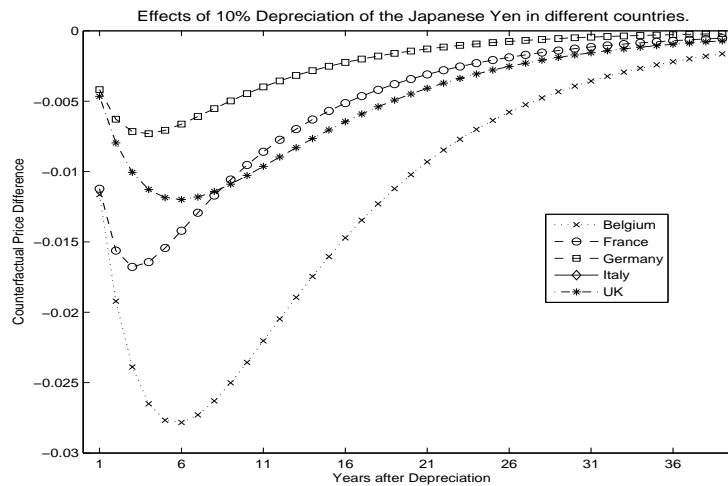


Figure B.6: Price path in Europe after a 10% depreciation of the Japanese Yen



Appendix C

Domestic Effects of Exchange Rate Depreciation

This appendix presents the impulse response exercises for a 10% depreciation of each of the considered European currencies as explained in section 2.4.3. Each figure presents the percentage difference between the perturbed and the steady state paths for predicted prices. These prices are computed through the estimated policy functions, which uses the exchange rate series predicted by an initial 10% shock increase and 39 subsequent periods predicted by the respective estimated transition probability.

This section presents the effects in domestic markets 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 by consumers' substitution. These exercises are extended to compute the path of demand and revenues for each producer in the market.

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 C.1: Reactions in Belgium after a 10% depreciation of the Belgian Franc

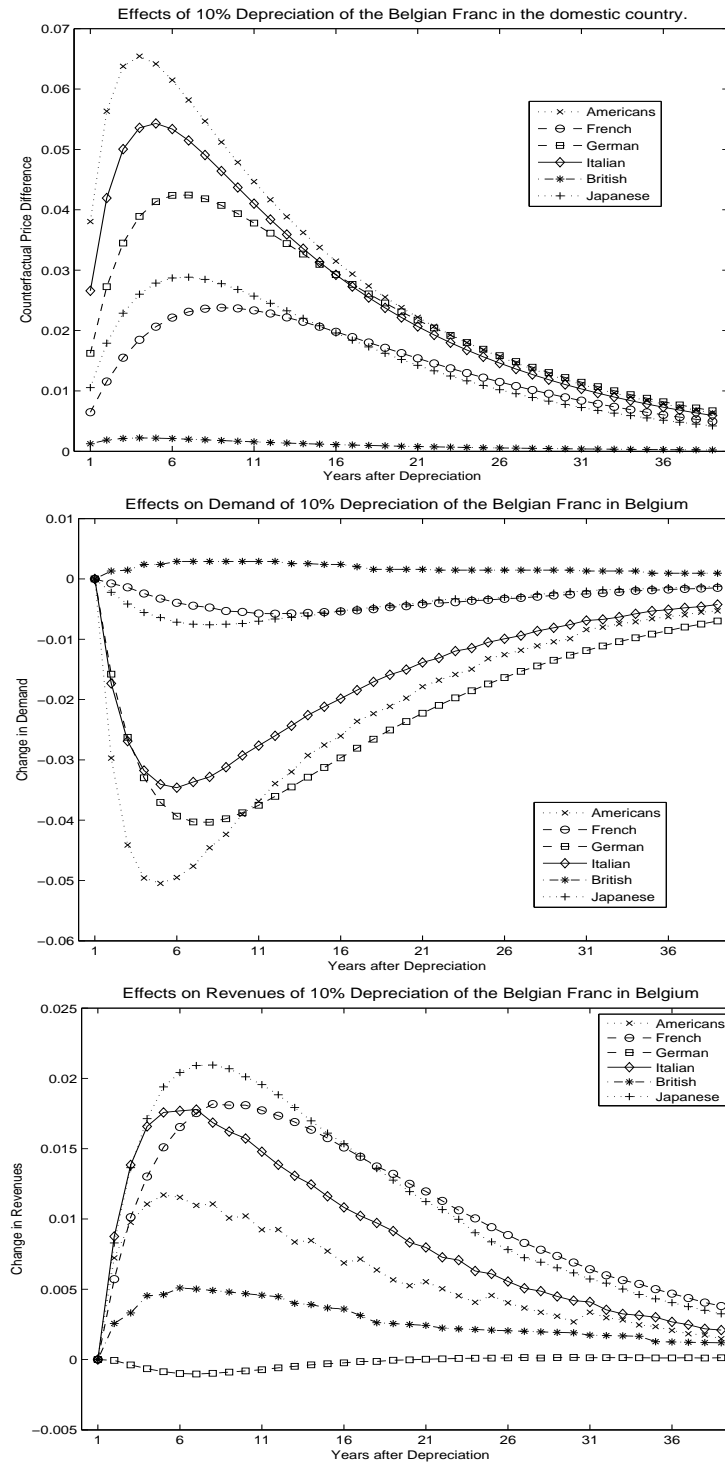


Figure C.2: Reactions in France after a 10% depreciation of the French Franc

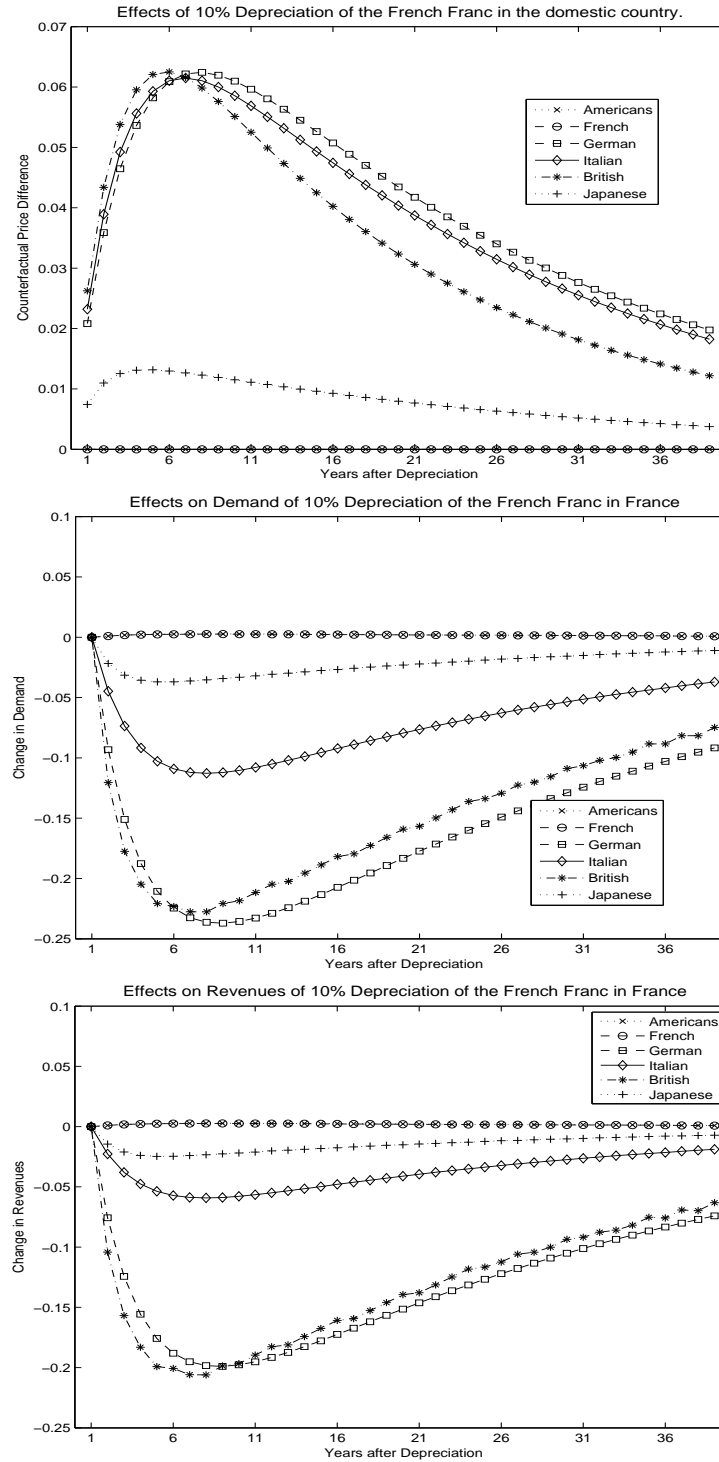


Figure C.3: Reactions in Germany after a 10% depreciation of the German Mark

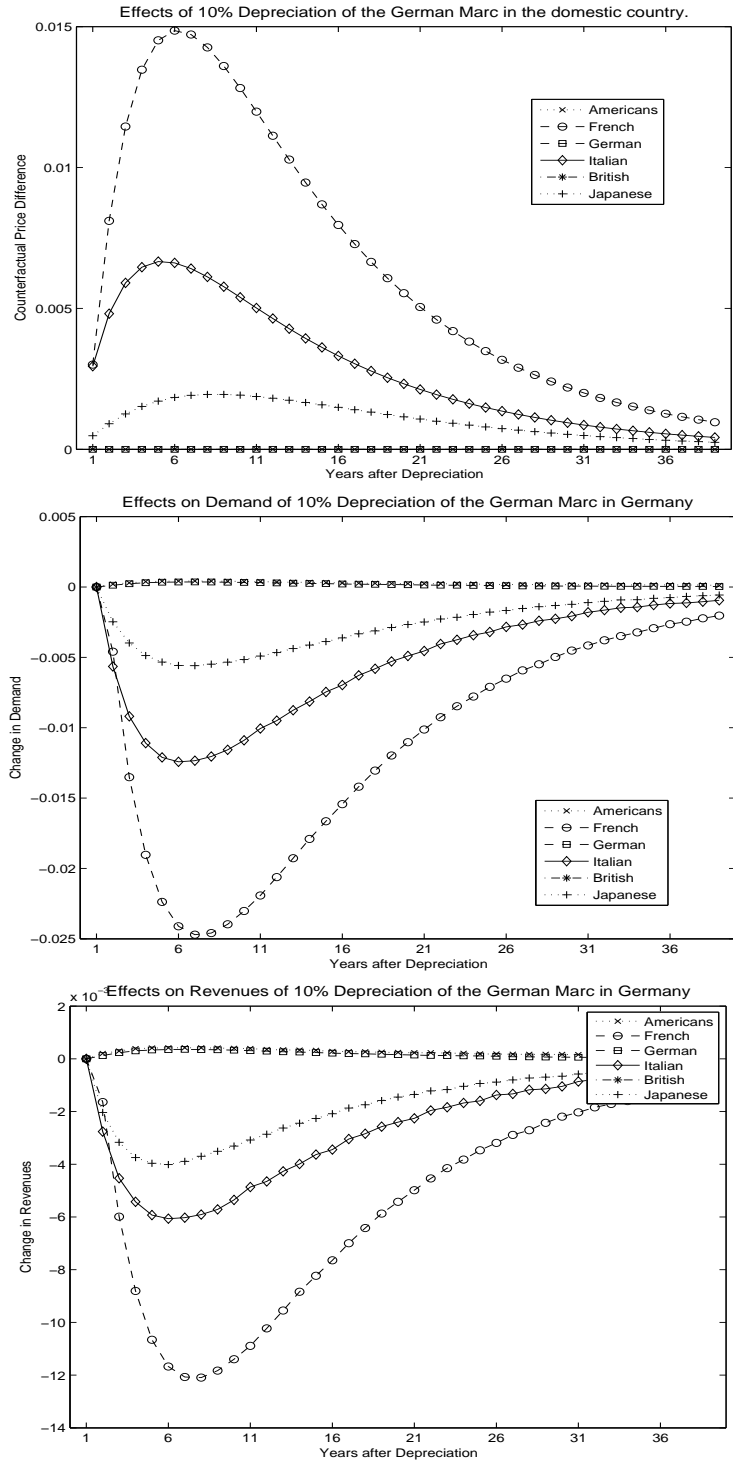


Figure C.4: Reactions in Italy after a 10% depreciation of the Italian Lira

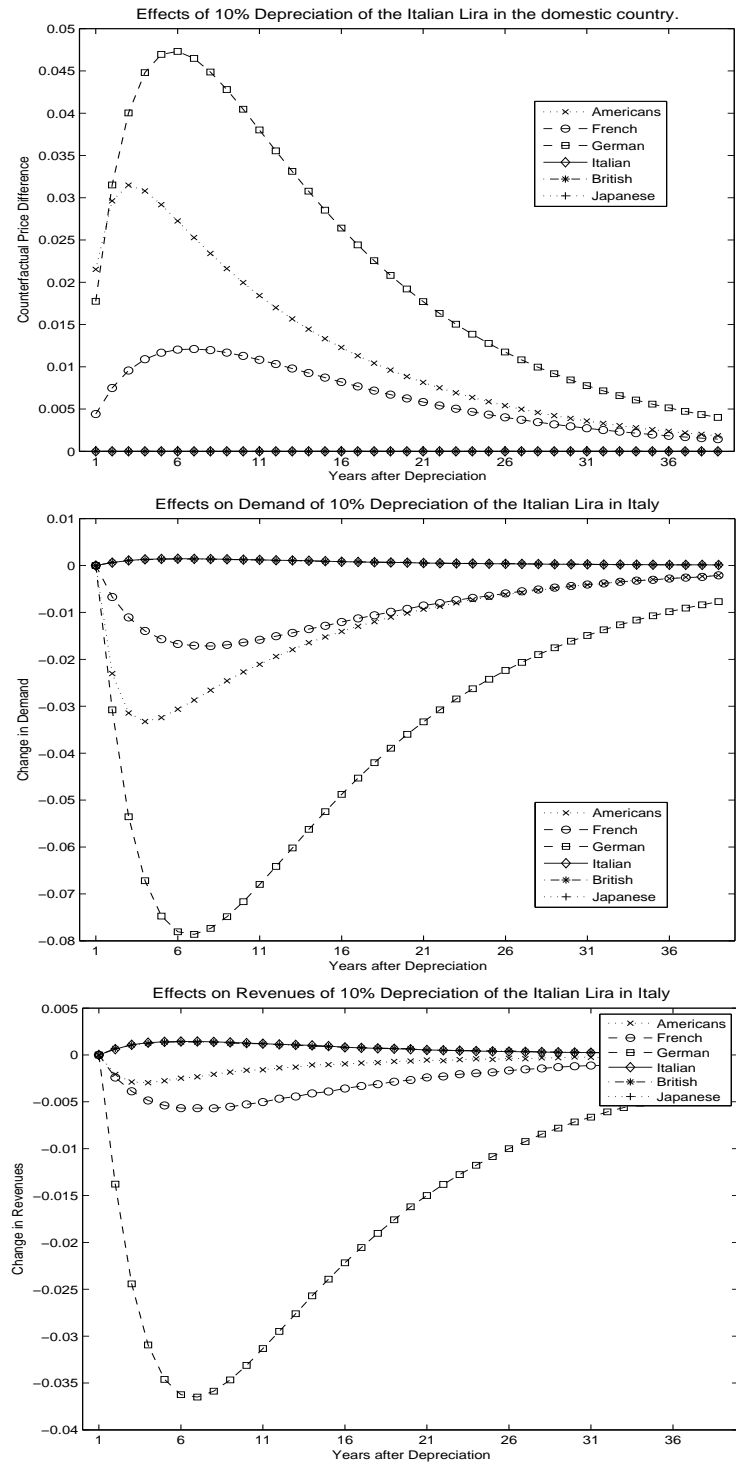
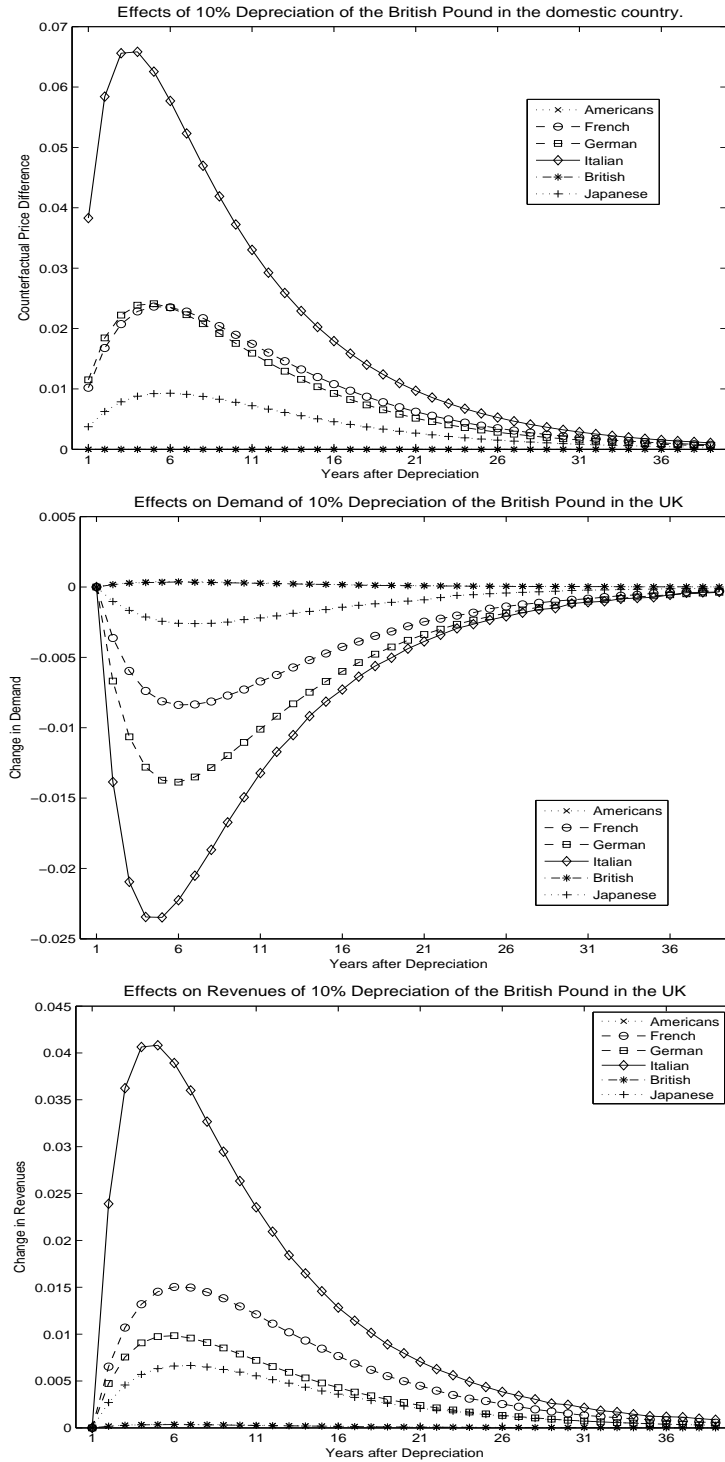


Figure C.5: Reactions in the UK after a 10% depreciation of the British Pound



Appendix D

Confidence Intervals for Policy Functions

This appendix presents the confidence intervals for the impulse-response exercises. We focus on the 10% depreciation of European currencies as explained in section 2.4.3. 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.

Confidence Interval for the International Effect of Domestic Depreciation

Figure D.1: Conf. int. for price path after a 10% depreciation of the Belgian Franc

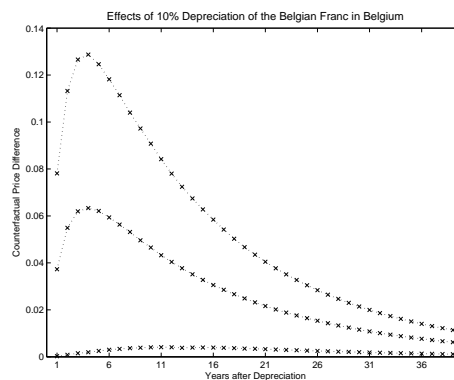


Figure D.2: Conf. int. for price path after a 10% depreciation of the French Franc

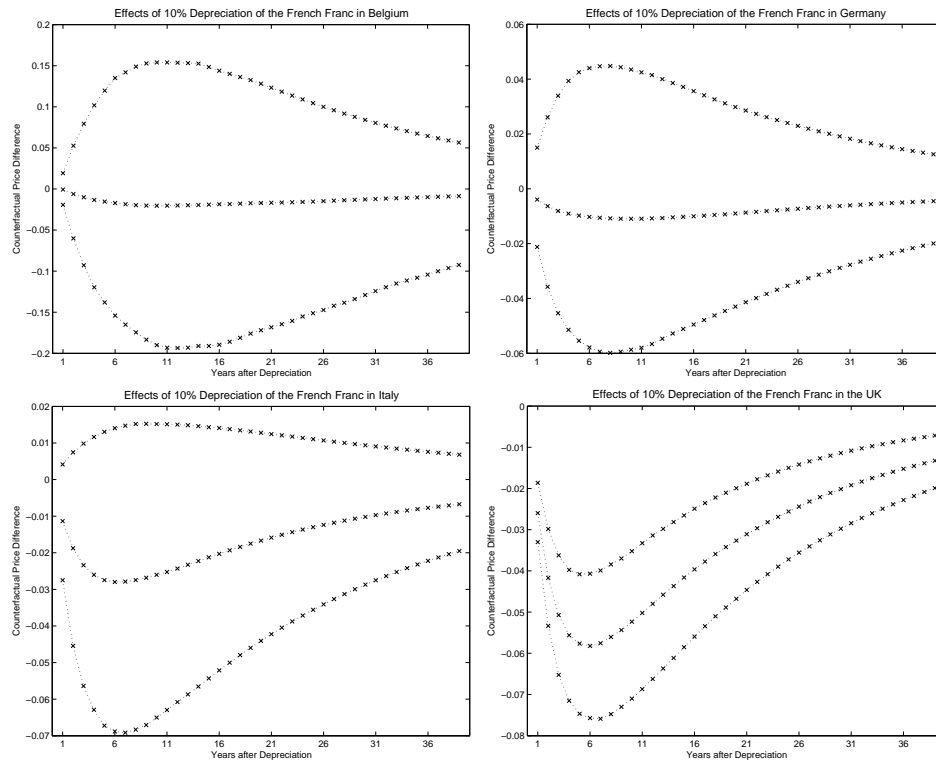


Figure D.3: Conf. int. for price path after a 10% depreciation of the German Mark

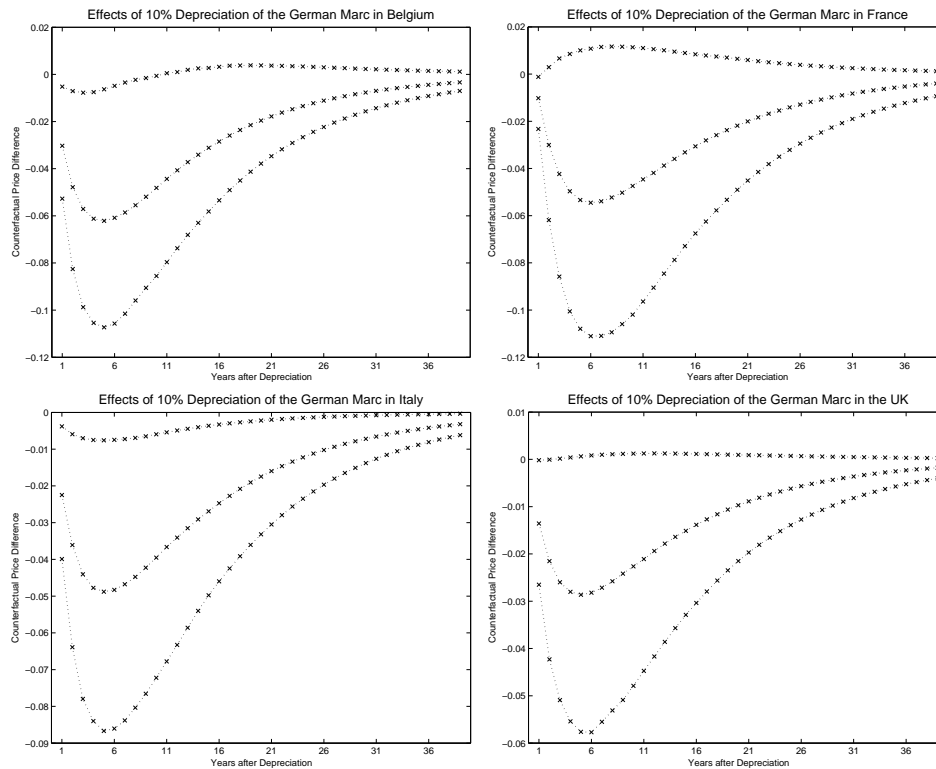


Figure D.4: Conf. int. for price path after a 10% depreciation of the Italian Lira

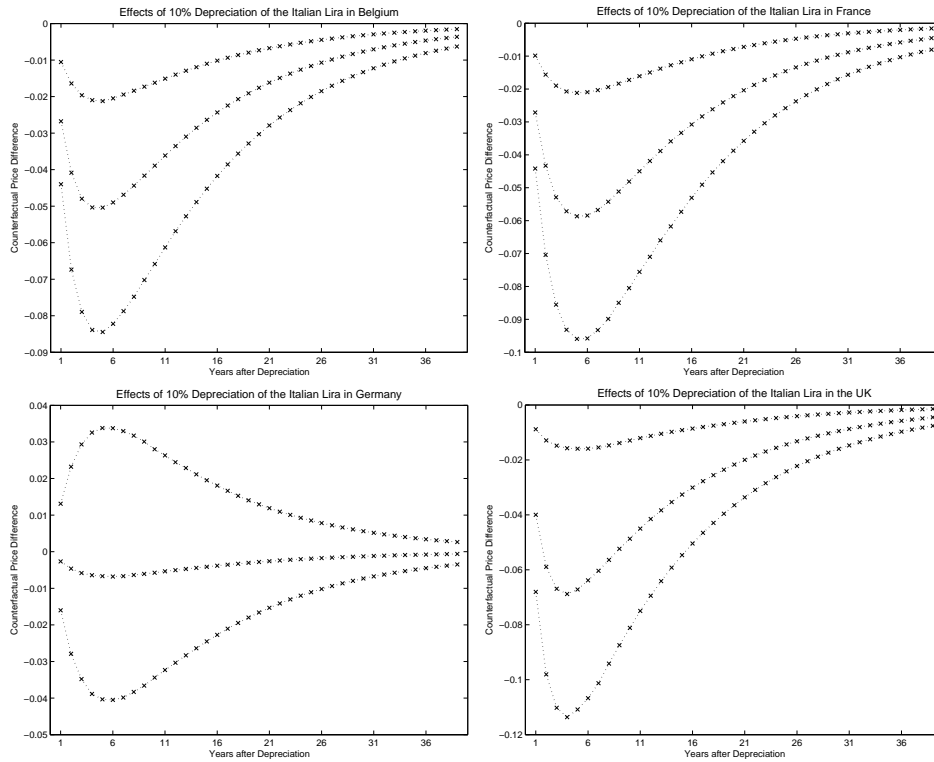


Figure D.5: Conf. int. for price path after a 10% depreciation of the British Pound

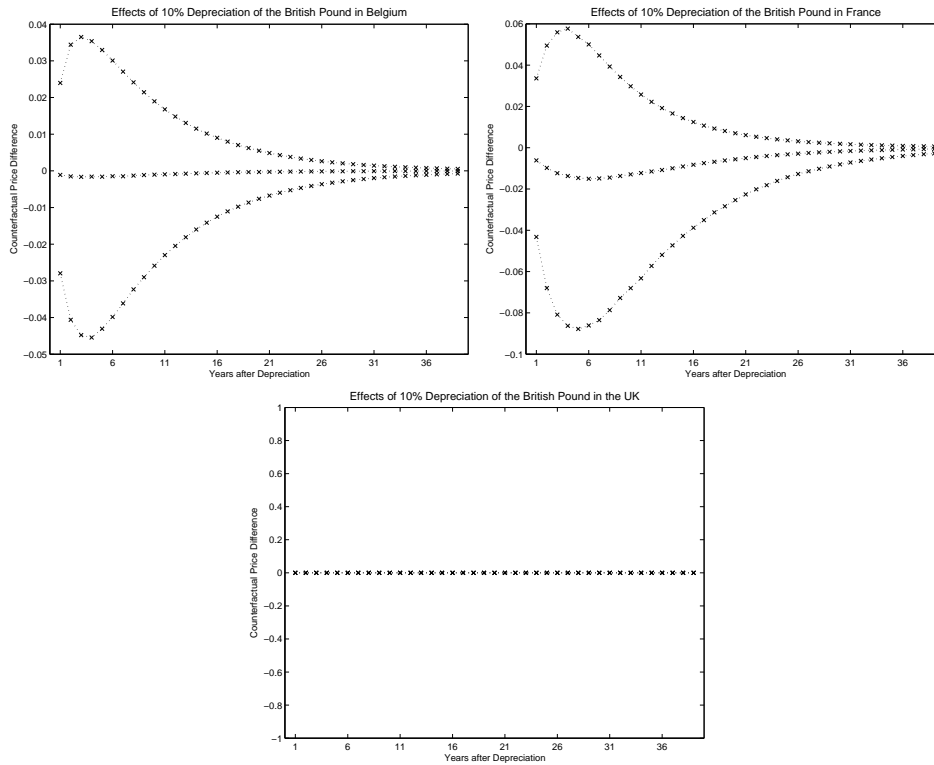
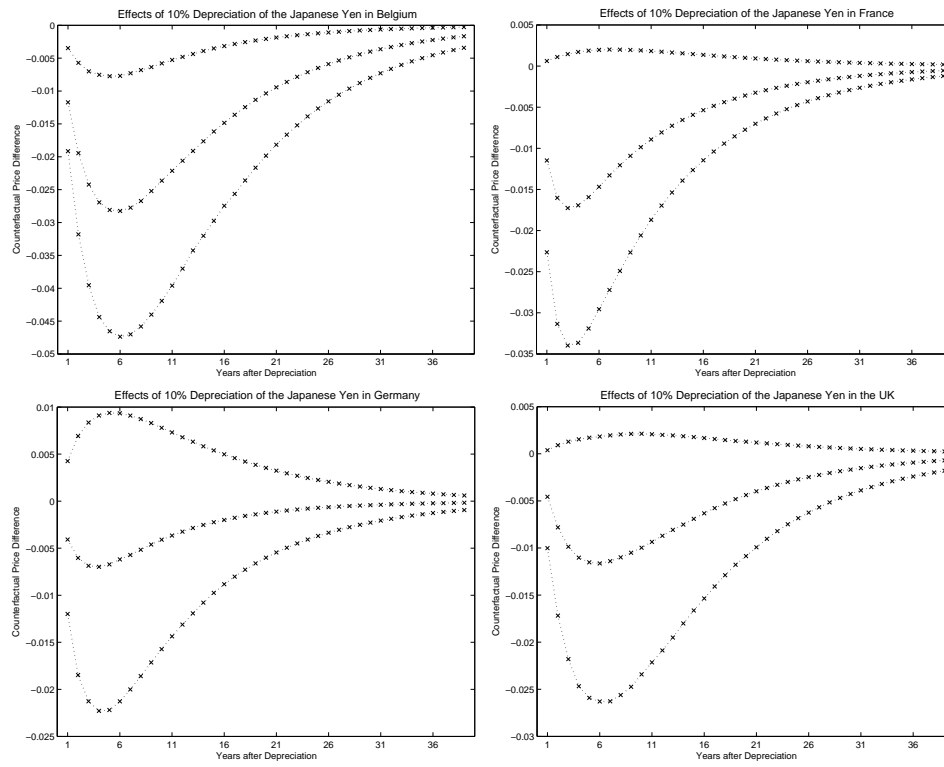


Figure D.6: Conf. int. for price path after a 10% depreciation of the Japanese Yen



Confidence Interval for the Domestic Effect of Domestic Depreciation

Figure D.7: Conf. int. for price path in Belgium after domestic depreciation

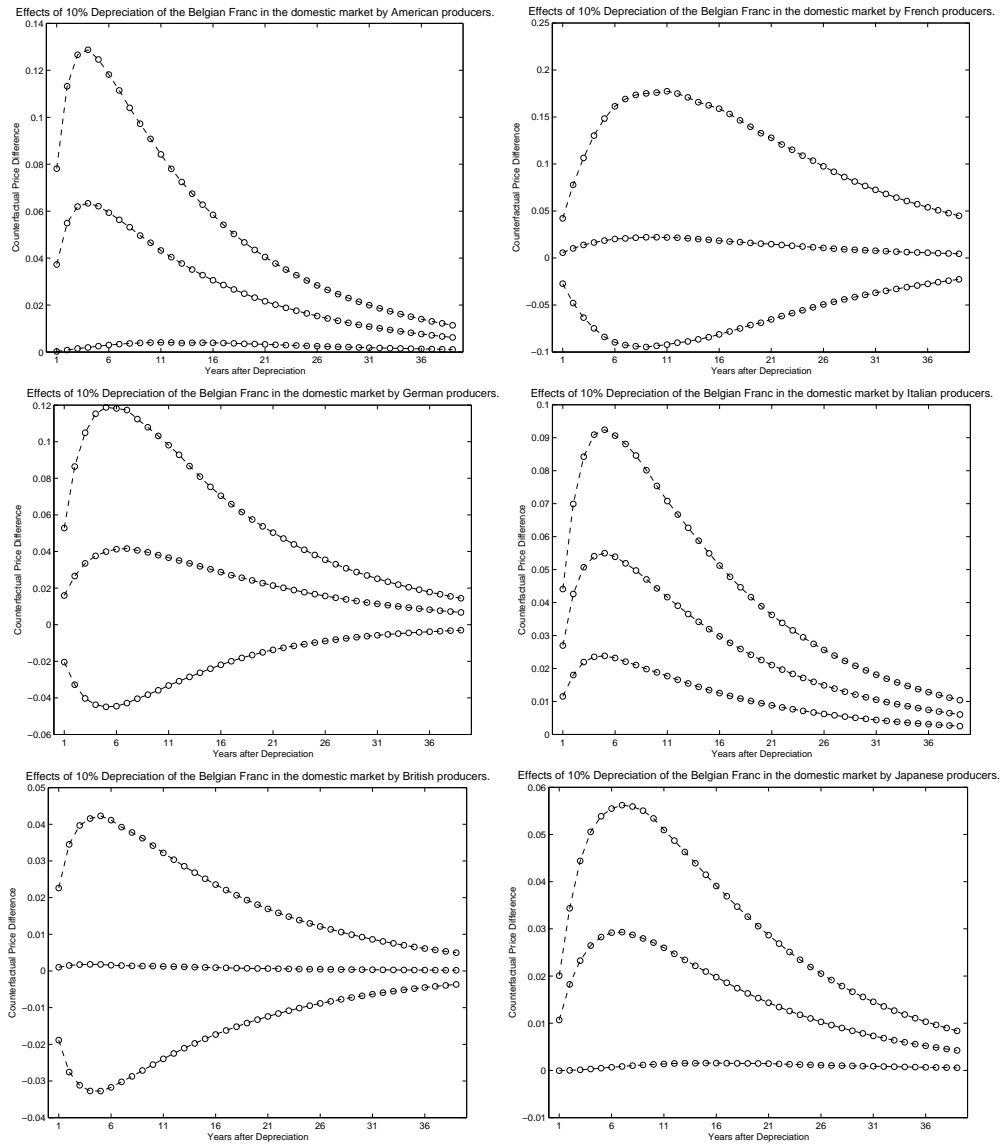


Figure D.8: Conf. int. for price path in France after domestic depreciation

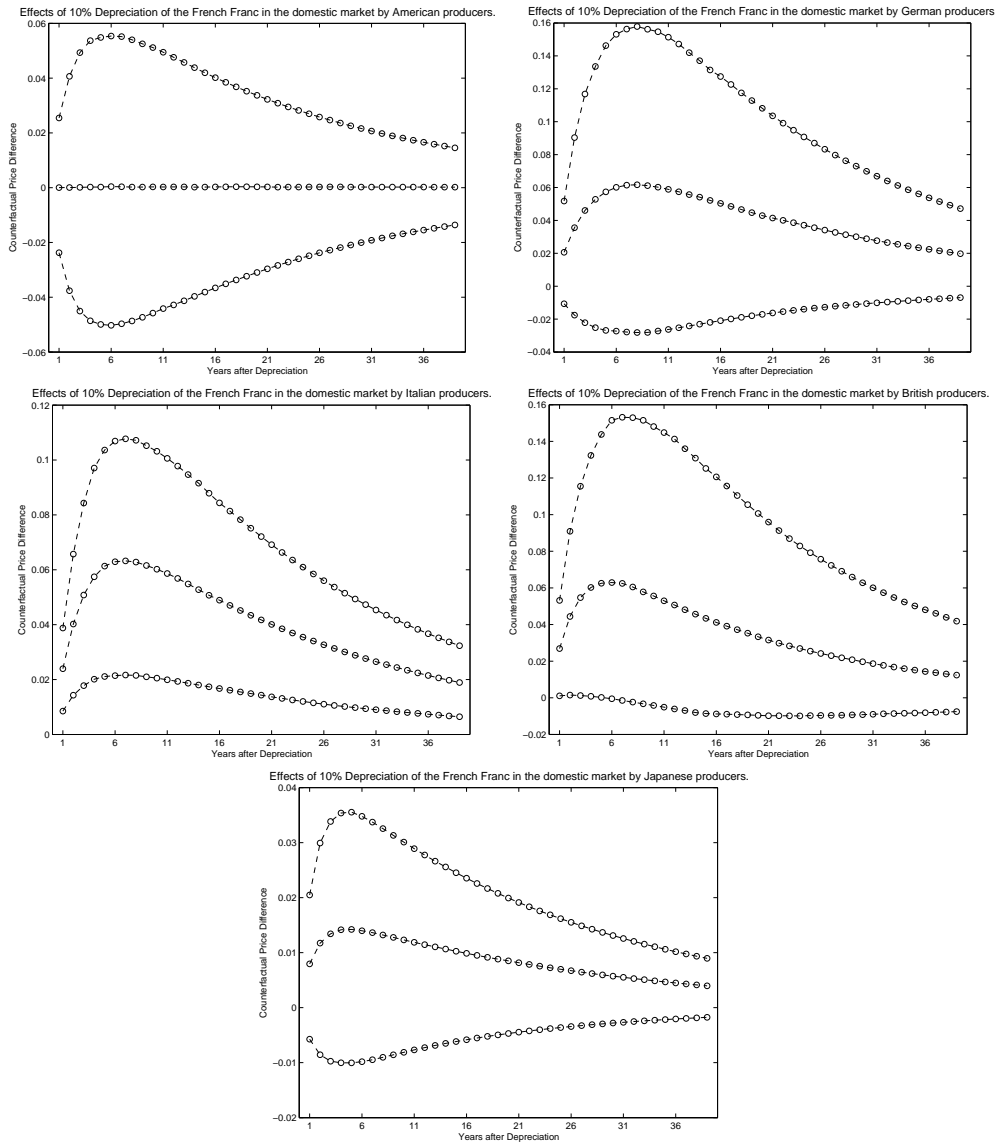


Figure D.9: Conf. int. for price path in Germany after domestic depreciation

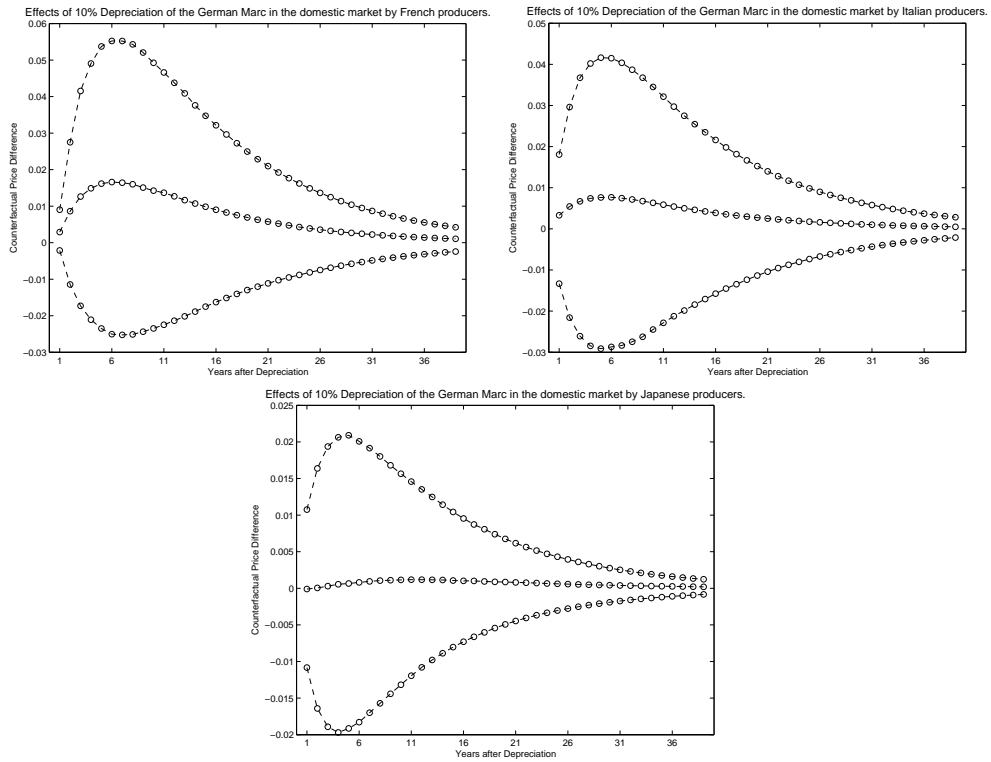


Figure D.10: Conf. int. for price path in Italy after domestic depreciation

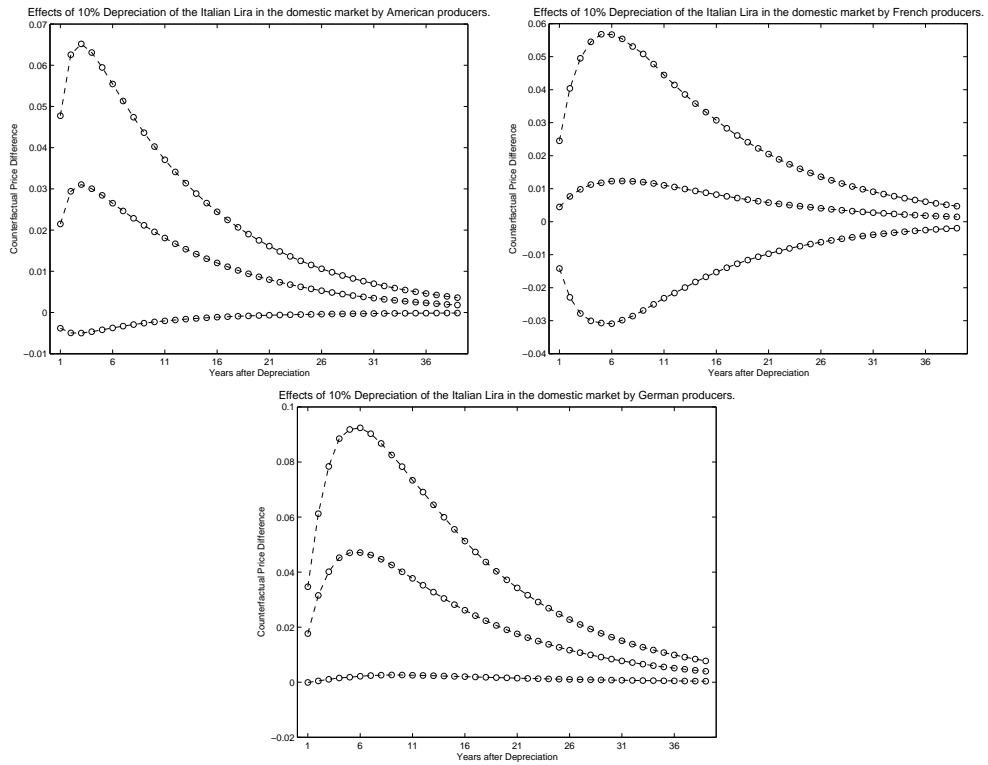
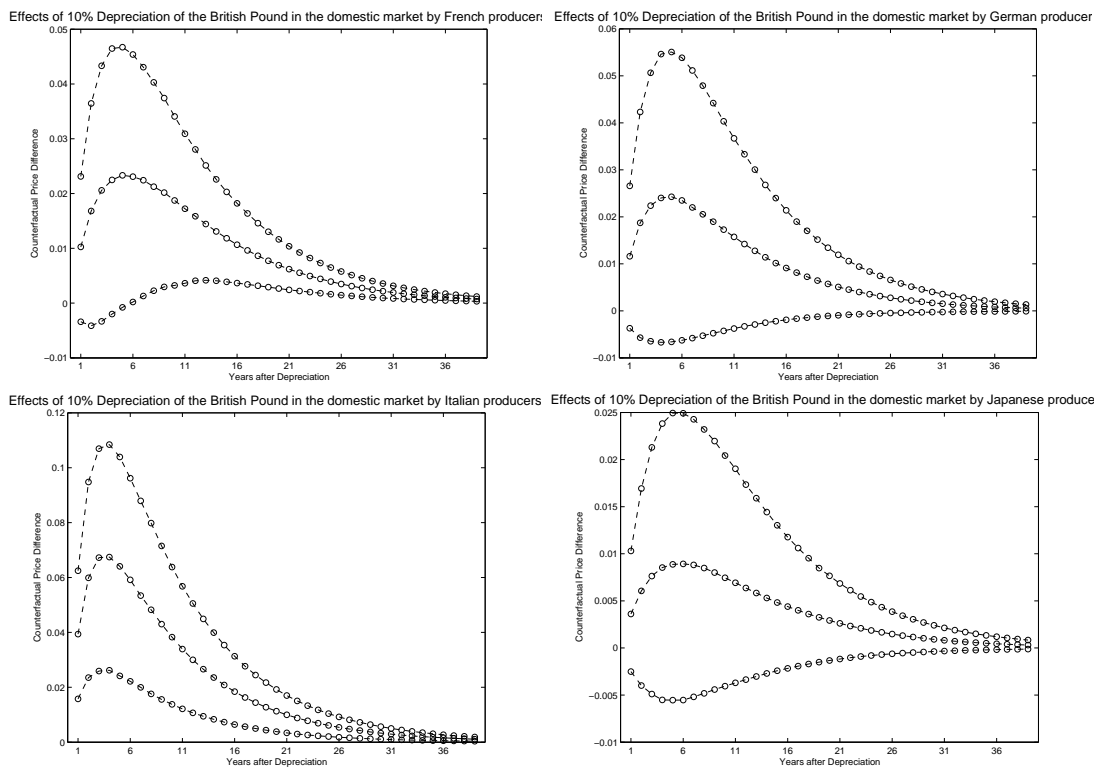


Figure D.11: **Conf. int. for price path in the UK after domestic depreciation**



Appendix E

Price Effects of Domestic Wage Increase

This appendix presents the impulse response exercises for a 10% increase of each of the considered European wages as explained in section 2.4.3. Each figure presents the percentage difference between the perturbed and the steady state paths for predicted prices. These prices are computed through the estimated policy functions, which uses the nominal wages predicted by an initial 10% shock increase and 39 subsequent periods predicted by the respective estimated transition probability.

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 E.1: Price path across Europe after a 10% increase in French wages

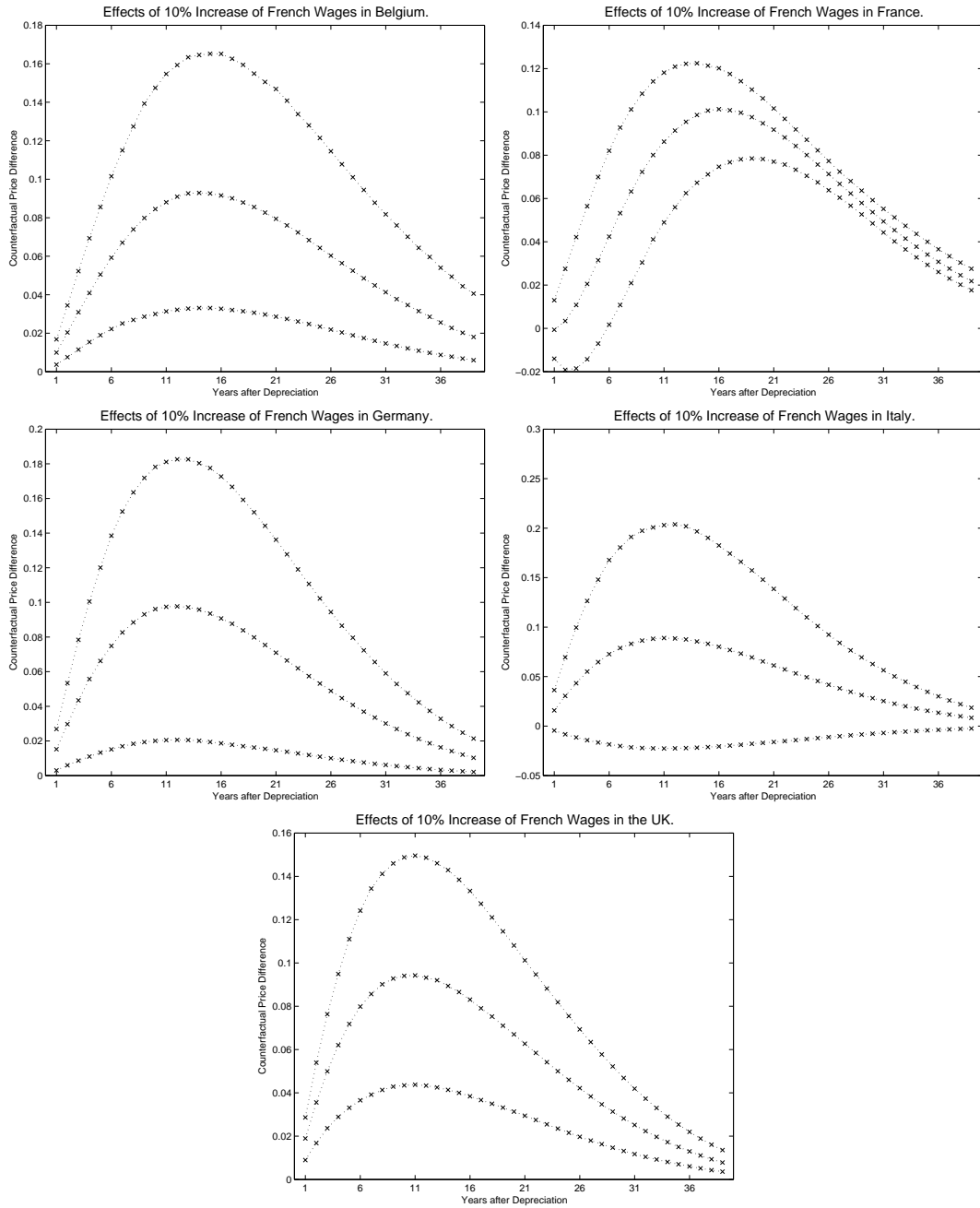


Figure E.2: Price path across Europe after a 10% increase in German wages

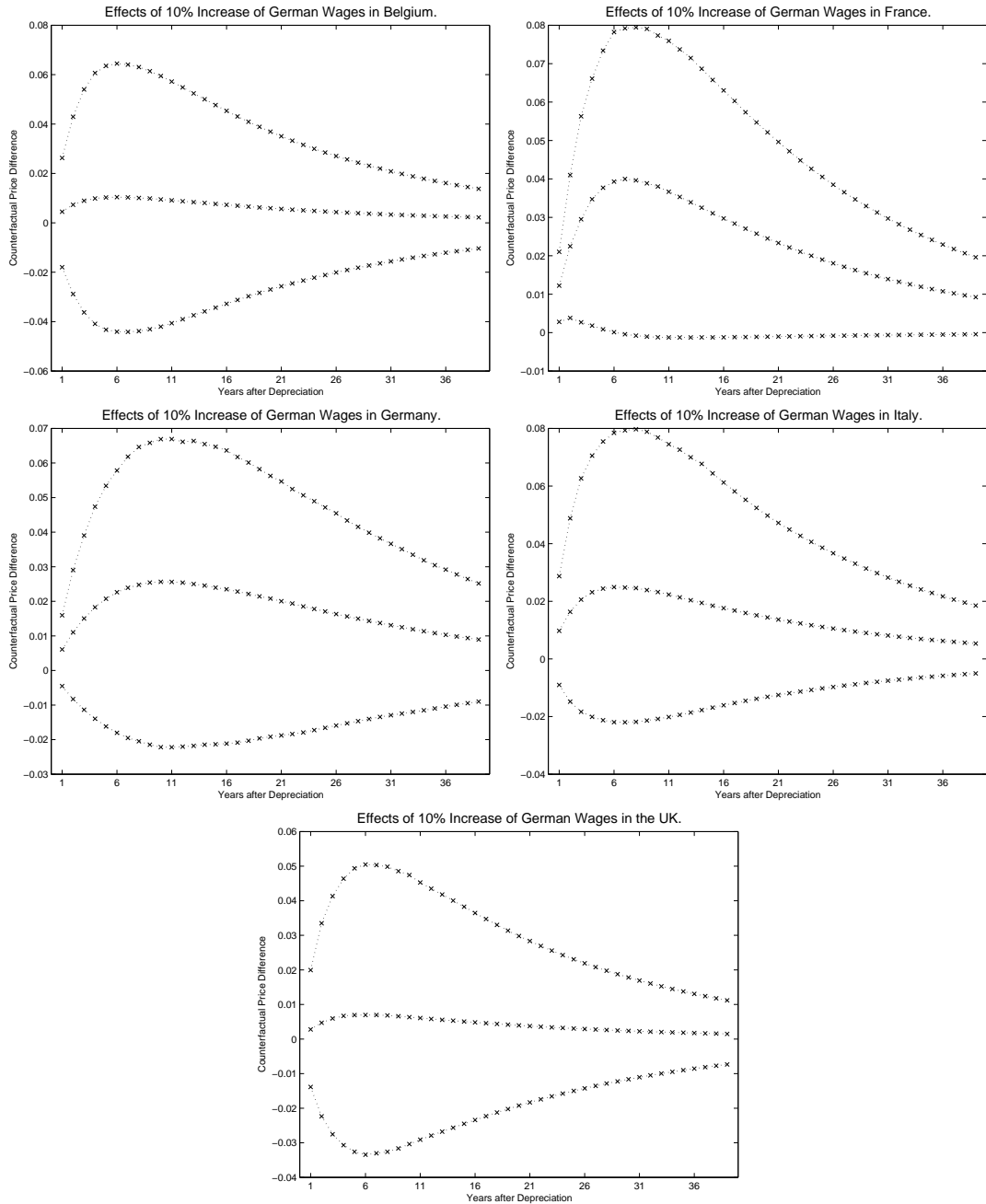


Figure E.3: Price path across Europe after a 10% increase in Italian wages

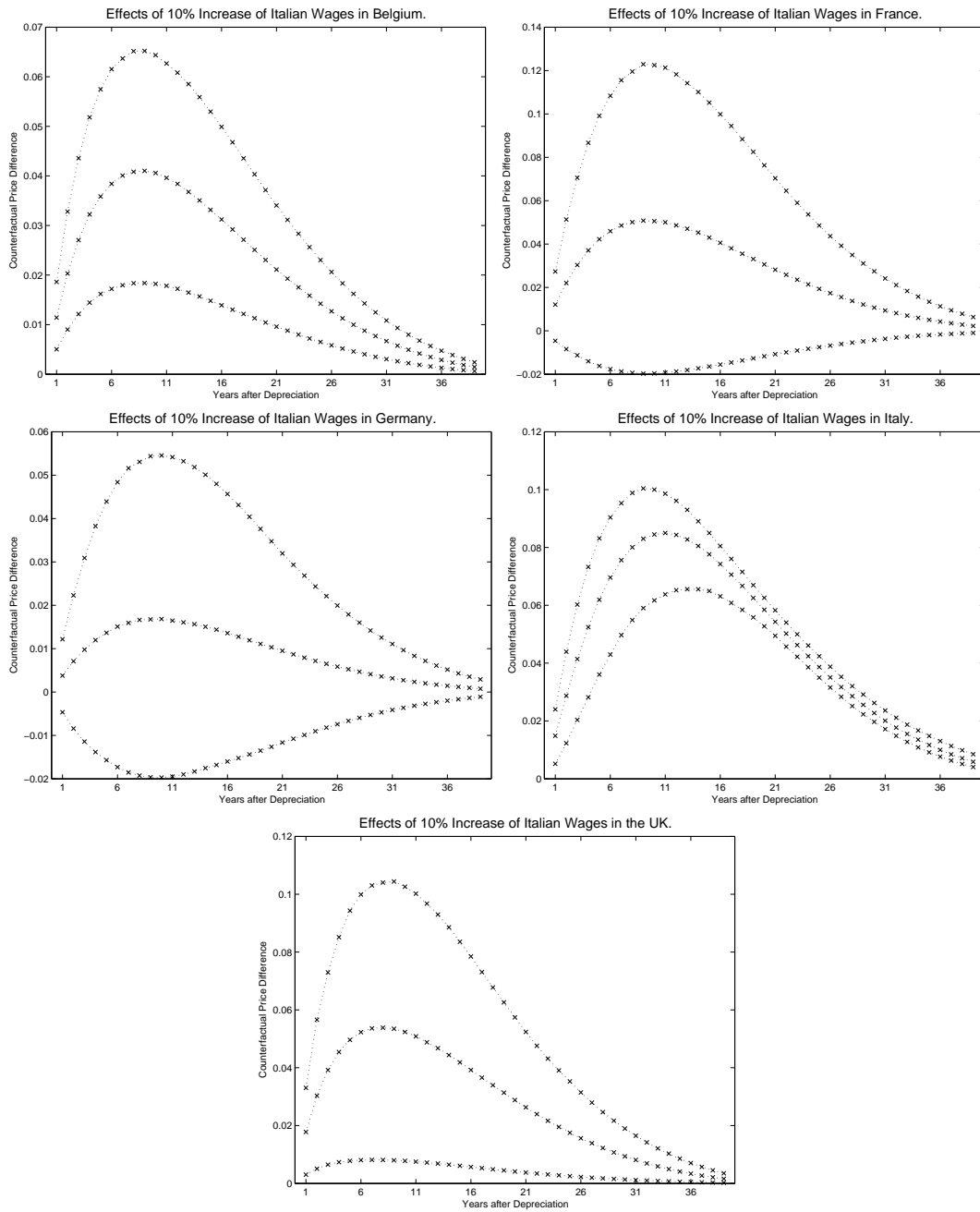


Figure E.4: Price path across Europe after a 10% increase in British wages

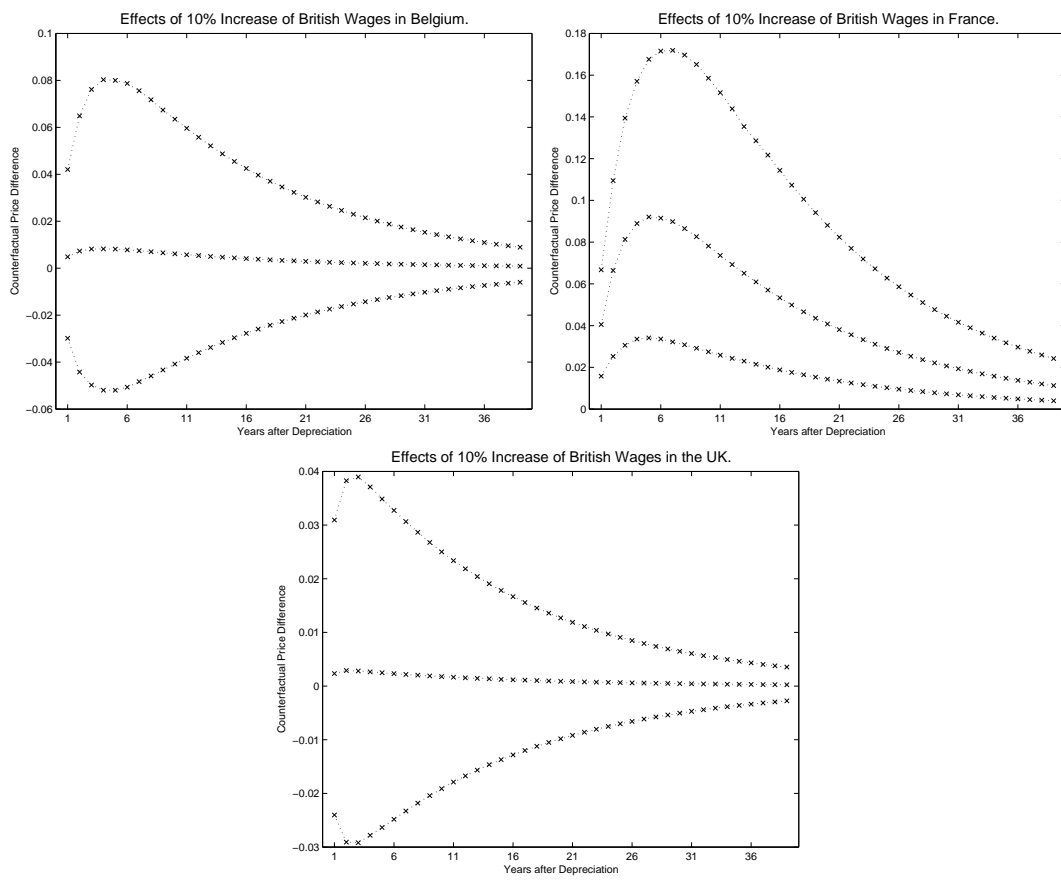
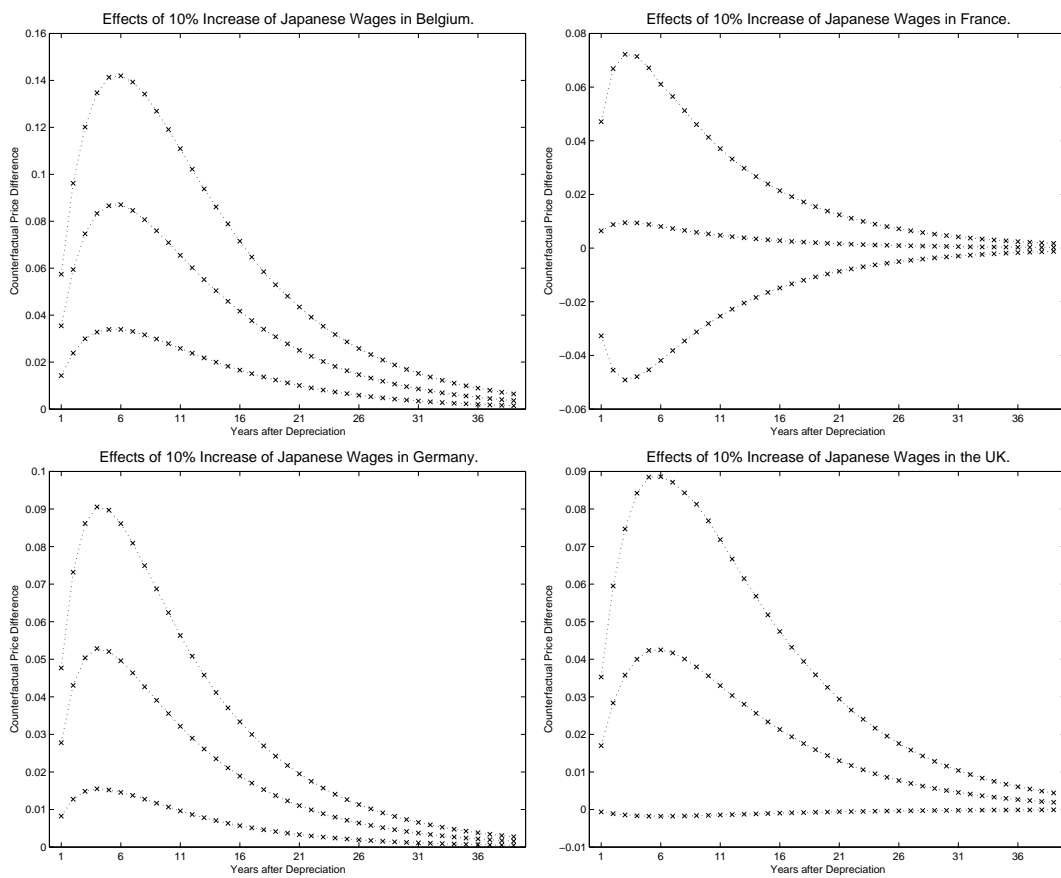


Figure E.5: Price path across Europe after a 10% increase in Japanese wages



Appendix F

Quarterly Estimates and Yearly Processes

This appendix section describes the procedure to use the quarterly data estimates and construct the yearly process required for the forward simulation stage.

Suppose the quarterly process is given by:

$$e_t = \alpha + \rho e_{t-1} + u_t \quad (\text{F.1})$$

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:

$$\rho_{N \times N} = \begin{bmatrix} \rho_1 & 0 & \dots & 0 \\ 0 & \ddots & 0 & 0 \\ \vdots & \dots & \rho_{N-1} & 0 \\ 0 & \dots & 0 & \rho_N \end{bmatrix}$$

where 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 let us express the P correlation as follows:

$$E[e_t^i e_{t-P}^i] = E[\alpha_i + \rho_i e_{t-1}^i + u_t] e_{t-P}^i = \dots = \rho_i^P$$

We use the estimates of $\hat{\rho}$ and $\hat{\alpha}$ to do forward simulations over the yearly process \tilde{e}_t . Hence, we write yearly parameters $\tilde{\rho}$ and $\tilde{\alpha}$ as a function of the quarterly parameters ρ and α .

$$\tilde{e}_t = \tilde{\alpha} + \tilde{\rho}\tilde{e}_{t-1} + \tilde{u}_t \quad (\text{F.2})$$

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:

$$\begin{aligned} \tilde{\rho}_i &= E(\tilde{e}_t \tilde{e}_{t-1}) = E \left(\left[\frac{e_t + e_{t-1} + e_{t-2} + e_{t-3}}{4} \right] \left[\frac{e_{t-4} + e_{t-5} + e_{t-6} + e_{t-7}}{4} \right] \right) \\ &= \frac{1}{16} (\rho_i + 2\rho_i^2 + 3\rho_i^3 + 4\rho_i^4 + 3\rho_i^5 + 2\rho_i^6 + \rho_i^7) \end{aligned} \quad (\text{F.3})$$

The steady-state value for the i^{th} currency e_t^i of this average can be written as:

$$E(e_t^i) = E(\tilde{e}_t^i) \Leftrightarrow \frac{\alpha_i}{1 - \rho_i} = \frac{\tilde{\alpha}_i}{1 - \tilde{\rho}_i}$$

this expectation should match the quarterly steady state, so we have the relationship between the constants:

$$\tilde{\alpha}_i = \frac{\alpha(1 - \tilde{\rho}_i)}{1 - \rho_i} \quad (\text{F.4})$$

Finally I also need to describe the error parameter for

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

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

$$\tilde{\Omega} = E \left(\left[\frac{u_t + u_{t-1} + u_{t-2} + u_{t-3}}{4} \right] \left[\frac{u_t + u_{t-1} + u_{t-2} + u_{t-3}}{4} \right]' \right) = \frac{1}{4} \Omega$$

Appendix G

Alternative Adjustment Cost Function

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

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

The following tables replicate the results of tables 2.10 to 2.13 using the alternative specification for the adjustment cost function. The main findings still hold, although some rankings or estimates may change slightly.

Table G.1: **Cost components (%) using alternative adjustment cost function**

Exports	Local Cost	Destination Cost	Adjustment Cost
American	79.81	14.28	5.91
French	75.51	23.31	1.17
German	78.75	21.18	0.06
Italian	20.69	66.38	12.93
Japanese	59.75	26.99	13.26
Sold Domestically	Local Cost	-	Adjustment Cost
American	99.97	-	0.03
French	97.19	-	2.81
German	100.00	-	-
Italian	90.37	-	9.63

Table G.2: **Adjustment cost by destination market (alternative cost function)**

	Belgium	France	Germany	Italy	UK
American	7.2	0.1	0.0	9.3	0.0
French	3.4	2.1	0.0	0.4	0.5
German	0.0	0.0	0.0	0.1	0.0
Italian	18.8	10.6	8.6	9.6	3.5
Japanese	19.3	0.0	4.1	-	20.2

Table G.3: **Ratio of adjustment cost Ψ_{fm}/Ψ_{ff} (alternative cost function)**

	Belgium	France	Germany	Italy	UK
American	44.21	4.98	1.00	75.47	0.05
French	1.08	1.00	0.04	0.12	0.19
German	0.26	0.60	1.00	0.93	1.00
Italian	0.18	0.43	4.27	1.00	0.05
Japanese	0.44	0.03	1.00	-	0.18

Table G.4: **Implied markups in 1985 under alternative cost function**

	Mean	Std Dev
American	71%	40%
French	81%	36%
German	51%	46%
Italian	78%	33%
Japanese	86%	33%