Centre for Economic Policy Research [redacted] The Pinhas Sapir Center for Development Tel Aviv University [redacted] TEL AVIV UNIVERSITY The Gordon Faculty of Social Sciences Department of Public Policy

C I C N NC N A U I N AL AN A N

o ed y

The Eitan Berglas School of Economics, Recanati School of Business, Department of Public Policy at Tel Aviv University

ppo ed y

The Pinhas Sapir Center for Development, Tel Aviv University
Recanati School of Business, Tel Aviv University
Department of Public Policy, Tel Aviv University
Journal of Industrial Economics (JIE)
CEPR

el Av v M y 0

n er nd y er o v la e y o eq An App c on o e A oro o le Ind y

Richard Friberg (Stockholm School of Economics and CEPR)
*Cristian Huse (Stockholm School of Economics)

Using demand systems to evaluate risky projects: An application to the automobile industry[♠]

Richard Friberg[♣], Stockholm School of Economics and CEPR

Cristian Huse[♦], Stockholm School of Economics

This version: February 20, 2011

Abstract

We examine how the risk-return profiles of carmakers BMW and Porsche depend on whether car models are produced in the US or Europe. Using data from the US car market we combine a demand system for differentiated products with counterfactual paths to macroeconomic variables. We let prices and quantities respond to counterfactual values of exchange rates and consumer confidence. This allows us to generate counterfactual profit distributions at different horizons for alternative domestic and foreign production configurations. For plausible costs of building a plant, production in the US is attractive for BMW, but not for Porsche.

JEL: F23, G32, L16, L62

Keywords: Exchange rate exposure, net present value, certainty equivalent valuation, macroeconomic exposure, operational hedging, natural hedging, demand for cars.

♠ An earlier version of this paper was entitled "Simulations of Operating Exposure to Risk". We are grateful to the Swedish Research Council (VR) and Jan Wallanders and Tom Hedelius Stiftelse for financial support. We thank Elisa Alonso, Marcus Asplund, Johannes van Biesebroeck, Rickard Sandberg and seminar audiences at CEMFI, EARIE in Istanbul, ESSEC, Foro de Finanzas in Elche, HECER, Lund, the Finance seminar at Stockholm School of Economics, Uppsala and Queen Mary for valuable comments.

♣ Email: nerf@hhs.se. Correspondence address: Stockholm School of Economics, Dept of Economics, Box 6501, SE-113 83 Stockholm, Sweden.

♦ Email: cristian.huse@sse.edu. Correspondence address: Stockholm School of Economics, Dept of Finance, Box 6501, SE-113 83 Stockholm, Sweden.

Introduction

The German carmaker Volkswagen is building a plant in Tennessee and states in its annual report 2009 (p 188) that "Foreign currency risk is reduced primarily through natural hedging, i.e. by flexibly adapting our production capacity at our locations around the world, establishing new production facilities in the most important currency regions and also procuring a large percentage of components locally". There are many other examples of firms using risk considerations to motivate strategic choices of what to produce, and where to produce it. These operational choices are potentially important not only for firm profitability but may also have wider consequences for current account adjustment and labor markets.[1]

To make a well-informed choice of what strategy to pursue in the face of risk a firm needs to calculate counterfactual profits that reflect different macroeconomic conditions and different strategic choices. Our goal in the present paper is to develop tools to generate such counterfactual profits. We use two building blocks. Firstly, we estimate demand for differentiated products using methods from empirical Industrial Organization. We follow Berry, Levinsohn and Pakes (1995, BLP hereafter) and model demand using a random-coefficients logit model. Secondly, we generate counterfactual future paths of macroeconomic variables that act as sources of risk (exchange rates and a commonly used measure of macroeconomic conditions: consumer confidence). We model the univariate processes that govern these variables using GARCH specifications. We use a copula to model dependence between these variables. Feeding the counterfactual shocks into the demand system, and letting all prices and quantities respond, we thus generate probability distributions for profits. We then use these counterfactual profits to examine how risk profiles and discounted cash flows depend on firm choices of production location.

To anchor our analysis we focus on the US auto market. Volkswagen is not unique in using risk considerations to motivate production facilities in the US. BMW produces a number of models in the US and states in the annual report for 2007 (p 62) that "From a strategic point of view, i.e. in the medium and long term, the BMW Group endeavours to manage foreign exchange risks by 'natural hedging', in other words by increasing the volume of purchases denominated in foreign currency or increasing the volume of local production."[2] Several Asian carmakers also have significant production capacity in North America and natural hedging is one stated reason for this.[3] Other carmakers follow different strategies. Porsche for instance produces exclusively in the euro area but has 30-40 percent of its sales in North America. Would Porsche be better off producing in the US as well?[4] Should BMW focus all its production in Europe? We use product level data for the top

---

[1] See for instance Bergin, Feenstra and Hanson (2009) for evidence that employment in Mexican plants acts as an important margin of adjustment for US manufacturing in response to demand shocks.

[2] Mercedes also produces its SUVs and CUVs in the US (more precisely, its M-class, R-class and GL-class models).

[3] In Toyota's annual report (2007, p 77) it is for instance written that "Localizing production enables Toyota to locally purchase many of the supplies and resources used in the production process, which allows for a better match of local currency revenues with local currency expenses."

[4] Indeed, Porsche is enough of a schoolbook case on exchange rate exposure that it is featured as mini cases in two of the leading textbooks in international finance (Eiteman, Stonehill and Moffett (2007, p 322) and Eun and Resnick (2007, p 236) and a popular business school case: Porsche exposed (Moffet and Petitt (2004). In the

segments of the US auto market for 1995-2006 to estimate demand that serves as the main input in our counterfactuals. Throughout we focus our presentation on BMW and Porsche.

The idea to use a large number of counterfactual shocks in a system of demand for differentiated products, of the type now standard in Industrial Organization, seems trivial. Despite this we are only aware of one precursor that follows this path: Friberg and Ganslandt (2007) generate counterfactual profits following the same logic as in the current paper. The present paper extends their methodology in several ways. They use a nested logit specification for demand whereas we model demand in a much less restrictive fashion. They use shocks that are bivariate normal and consider only one counterfactual period, whereas we generate counterfactual paths of shocks that easily extend to other settings. Most importantly, we adapt the methodology to examine different operating strategies. Finally, one can argue that the US automobile market is a more interesting application of risk measurement than the Swedish market for bottled water.

As exemplified by the annual reports from auto manufacturers, and textbooks in corporate finance, the concepts of natural hedging and operational hedging are part of the vocabulary of firms. Natural hedging is typically taken to describe a situation where the firm tries to match the currency of revenue and costs. Operational hedging is a broader concept and also captures other strategies that aim to modify the risk-return profile of firms. There is little empirical work examining operational hedging: A recent exception is Jin and Jorion (2006) who find that both financial and operational hedging (gas storage, cash holding, diversification) lower the variability of stock returns for firms in the natural gas industry.[5]

If we turn from descriptive to prescriptive work, how should a firm value foreign production capacity? Consider a set of mutually exclusive investment opportunities. If the profit streams associated with the investments are certain, the firm should choose the investment with the highest discounted profits, the highest net present value (NPV). This insight from economic theory (Fischer (1930), Brennan (2003)) has found its way into textbooks (see Brealey and Myers (2003) or Damodaran (2010)). NPV has also found its way into practice. For instance, in the survey of Graham and Harvey (2001), 75 percent of firms used NPV to evaluate projects. The method is straightforward to apply in the case when the future cash flows are known with certainty. In contrast, when there is uncertainty, we need to create counterfactual profit distributions. How should such counterfactuals be generated? Textbooks in finance and international business suggest that one selects a probability distribution for each of a set of variables that affect profits, such as price and market size, and then use these distributions to generate counterfactuals.[6] Hertz (1964) is an early proponent of this method. Despite its use in business and teaching, the academic literature on the method is

present paper we want to move beyond qualitative discussions in these works and examine the quantitative implications of different strategies.

[5] See also Allayannis, Ihrig and Weston (2001) who relate accounting measures of firm value to the geographic dispersion of activity for 265 US multinationals over 1996-1998. They interpret geographic dispersion as operational hedging and find no evidence that operational hedging by itself raises firm value.

[6] Alternatively these sources suggest that one can use a decision tree to analyze future values of the firm or consider a limited set of alternative scenarios. We are not offered any guidance on how to generate quantitative estimates for the different scenarios or branches however, which is the aim of the present project.

slight. The *ad hoc* nature of assumptions regarding the risk distributions are the probable reason for the limited attention of academics.[7] A burgeoning field in finance examines risk distributions for financial assets using value at risk (VaR) methods (see for instance Jorion (2006)). The generation of cash flow distributions for non-financial firms is sometimes known as cash-flow at risk (C-FaR). A fundamental difficulty lies in generating profit distributions from a short time series. Stein el al (2001) match firms based on a few observables, such as market capitalization, to generate a larger number of realizations of shocks that can be used to create a probability distribution. While potentially useful, the end result is very much a black box. We hope to show in the present paper how to ground counterfactual profits in empirical applications of demand theory, rather than in ad hoc assumptions.

A potential use for the methods we propose is to examine the exchange rate exposure of firms. In a seminal contribution Adler and Dumas (1984) note that a linear regression of firm value on the exchange rate can be used to measure the sensitivity of firm value to exchange rate changes. Given a large number of observations on firm value, we can relate these to different values of exchange rates and to other macroeconomic shocks (Stulz (2002)). The question becomes, how do we generate these counterfactual firm values? One strategy has been to relate historical stock market valuation to changes in exchange rates (see for instance Jorion (1990), Dominguez and Tesar (2006) or Muller and Verschoor (2006) for a survey). This strand of literature has concluded that exporters tend to be positively affected by a depreciation of the exchange rate, but that coefficients tend to be unstable. For a firm's own purposes the application is clearly hampered by that any hedging programs will affect the measured impact of an exchange rate change. Further complications are that the stock market may have imperfect knowledge of firm's operations and that it is difficult to use the coefficients to examine different scenarios with respect to firm strategy.

The method that we propose may also be useful input to firms' decisions on financial hedges. Contrary to what we would expect from a frictionless Modigliani-Miller world, there is much evidence that firms use financial instruments to manage exposures. For instance 50 percent of the responding firms in Bodnar, Hayt and Marston (1998) report using derivatives. Reasons for hedging may be to smooth tax payments, avoid bankruptcy or to ensure sufficient cash flow to finance investments also in tough times (see Stulz (2002) for an overview of the arguments and Tufano (1996) or Adam and Fernando (2006) for empirical examinations of the motivations for hedging and its effects on firm value). In the current paper we largely disregard the why's, the when's and the how's of financial hedges. These are important issues but before taking a view on how to use financial hedges one needs to understand the relation between profits and risk factors. We focus on this first step in the decision process. In a second step one could use the counterfactual profits that we generate to evaluate different strategies for financial hedging. Brealey and Kaplanis (1996) do such comparisons for a simple stylized example.

[7] One response to these difficulties is to generate the "certainty equivalent" cash flow for each future period and then discount this using the risk-free rate (Cox and Ross (1976)). Note however that this also presumes that we know the expected value and variability of future cash flows as well as take a stand on the risk preferences in future periods.

Producing in several locations can not only limit variability of profits but we can also see it as a real option. Mello, Parson and Triantis (1995) examine hedging and production decisions of a firm that can produce a fixed output in any of two locations - the price of the output is fixed but the attractiveness of producing in the different locations varies with the exchange rate. They show how the value of the real option to produce in different locations increases with the volatility of the exchange rate. In the present paper we want to give empirical content to such a stylized model.[8] Most empirical applications of real options analysis have considered resource extracting industries such as mining (see for instance Slade (2001) or Moel and Tufano (2002)). The basic predictions of the real options model are supported, for instance that higher volatility increases the value of the real option. An exogenous output price that follows a Brownian motion is typically the principal source of risk in real option applications. While these assumptions may be appropriate for the gold mining industry, they are less satisfying for a price setting oligopolistic firm. In our simulations we compare counterfactual cash flows in the case where firms can easily switch production between different locations, to the case where they cannot. This gives us a straightforward way to value the real option of switching production locations.

We have chosen to apply our tools to the auto industry partly because operational hedging is the source of much interest in the industry. The auto industry has also been the testing ground for the class of demand models that we use and we can compare our demand results to a rich previous literature. Our demand estimations build closely on BLP (1995) who estimate a demand system for the US automobile market. Related work on US car markets is found in Goldberg (1995) who simulates exchange rate pass-through and in Train and Winston (2007) who show that the declining share of US manufacturers can be largely explained by observable product characteristics. Using similar tools, Berry, Levinsohn and Pakes (1999) examine the impact of Japanese voluntary export restrictions and Petrin (2002) simulates the welfare effects of the introduction of the minivan in the 1980s.

In the next section we present the data and describe the product ranges of BMW and Porsche in some detail. In Section 3 we present our demand estimation and how we generate counterfactual profits. In Section 4 we show the results from demand estimation and from the generation of counterfactual macroeconomic conditions. The counterfactual profits are then presented and analyzed in Section 5. We conclude in Section 6.

2 The Data

We use quantity sold, recommended dealer price and product characteristics for all cars sold in the luxury, sport, SUV (sports utility vehicles) and CUV (cross over utility vehicles) segments in the US.[9] The main source of data is WARDS who supplied us with a panel of

[8] There is a closely related literature in the operations management tradition that in a similar way examines very stylized settings – thus the results are qualitative rather than quantitative (see for instance Dasu and Li (1997) or Kazaz, Dada and Moskovitz (2005)).

[9] More precisely we use sales data for the following segments, as classified by WARD's: Upper Luxury, Middle Luxury, Lower Luxury, Luxury Sport, Luxury Specialty, Small Specialty, Large Luxury CUV, Middle Luxury CUV, Large CUV, Middle CUV, Small CUV, Large Luxury SUV, Middle Luxury SUV, Large SUV, Middle SUV, Small SUV.

monthly sales by model line (BMW 3 series, Porsche 911 etc).[10] We examine the period from August 1995 to July 2006. In our regression analysis we aggregate sales to 12-month periods. Rather than use calendar years we note that new models, and a new recommended dealer price, appear in late summer each year. [11] Our time unit of analysis therefore runs from August to July the following year and we use the term model-year.

In Table 1 below we show some descriptive statistics for our set of cars. We examine the upper segments of the car market and the mean real price is roughly stable at 35 000 dollars. The lowest price is for a Pontiac G5 and the highest is for a Porsche Carrera GT.[12] On average some 30 000 to 40 000 cars are sold per model in a given model-year. The largest selling name plate in the data is the Ford Explorer. The number of models in the data increases substantially over the period, mainly reflecting growth in the CUV and SUV segments.

[Table 1 about here]

We focus on three macroeconomic variables in the analysis – the real exchange rates between the dollar and the euro (usd/eur), between the dollar and the Japanese Yen (usd/jpy) and the measure of consumer confidence published by the Conference Board. Consumer confidence is frequently mentioned in the industry as an important covariate of demand for cars. This is confirmed by Ludvigson (2004) who also examines the relation between different measures of consumer confidence. The dollar appreciated against the euro and yen up until the middle of the period, after that it depreciated against the euro but remained rather stable against the yen. The consumer confidence measure of the business cycle shows substantial variability as well.

2.1 The US market for BMW and Porsche, a closer look

BMW

German-based BMW is one of the ten largest car manufacturers in the world. Over the period, on average, 23.7 percent of BMW deliveries of cars are in North America.[13] Compared to other auto manufacturers the accounting figures point to BMW as a profitable firm with high margins: its' return on assets is on average 5.3 percent and the profit margin is 15.6 percent

---

[10] Product characteristics are available at a more disaggregated level than sales. We therefore map sales volume to product characteristics (horse power, price etc) using the characteristics of the baseline model (the model selling for the lowest price), as is now standard in the literature, see BLP (1995).

[11] According to WARDS over these years the new model-year production starts between June and August and the next model-year vehicles are available in showrooms between July and September. In the data set August is the month in which the new prices take effect. According to WARDS the recommended prices are not changed during the year. We use the recommended dealer price as our measure of price -- a simplification that we share with previous work examining the car market at this level. In practice dealers buy from the manufacturer and rebates on the car are given, either in the form of lower prices, discounted financing or buy-in's of the customers' old car: see Busse, Silva-Risso and Zettelmayer (2006) for an analysis of pricing at a sample of Californian retailers.

[12] We follow WARD's classification of segments, arguably the Carrera GT is closer to cars like Ferrari or Lamborghini that are not in the data set. Since it is produced by Porsche, which is our focus, we retain it in the data. The second highest price is for the Ford GT, retailing for an average of 128 000 dollars.

[13] Source. BMW Annual reports 2005 and 2000.

(EBITDA operating margin before interest, taxes, depreciation and amortization).[14] The main products for BMW over this period are the luxury cars in the 3, 5 and 7 series. At the start of the period it also sells the luxury sports car Z3. BMW further controlled the Land Rover and Range Rover lines that were produced in the UK. In 2000 Ford Motor Company took control of these brands. Since 1999 BMW has production capacity in a US factory in Spartanburg. In 2005-2006 the luxury sports car Z4, as well X3 and X5, that are classified as middle luxury CUVs are produced in this plant. All other products are produced in the euro area, apart from the Mini, which is produced in the UK. We therefore expect a potentially important role for the usd/euro exchange rate on BMW profits. Indeed the annual report for 2005 (p. 56) notes that "Of all the currencies in which the BMW group does business, the US dollar represents the main single source of risk; fluctuations in the value of the US dollar have a major impact on reported revenues and earnings."

[Table 2 about here]

Porsche

The North American market accounted for an average of 35 percent of sales revenue for Porsche.[15] During this period all production of Porsche cars is located in Europe. With a substantial share of revenue from the North American market but all costs in Europe we expect that Porsche profits are exposed to the US dollar. Indeed, prior to our period of study Porsche's profits had a strong relation to the dollar. In the mid 1980s, at the peak of the strong dollar, more than 60 percent of Porsche's sales were to North America. Over the latter part of the 1980s, and early 1990s, the dollar weakened against the German mark and by the early 1990s Porsche was having grave financial difficulties. During the time period that we examine however, accounting profitability and operating margins are high at Porsche: the return on assets is on average 19.7 percent and the operating margin is 24.7 percent.[16]

[Table 3 about here]

Porsche's main product over the period is the 911 - a name plate that was introduced in 1963 and still accounts for almost half of US revenue at the end. At the start the 911 is the only model marketed by Porsche in the US. The small roadster Boxster is then introduced in late 1996. The Cayenne is introduced in 2003 (identified as a middle luxury CUV by WARDS) and the sports car Cayman in 2005. In 2004 Porsche adds the top of the line sports car Carrera GT. After only having had assembly in Germany, Porsche starts production of its Boxster in Finland in 1997 (under an agreement with Finnish producer Valmet). Since 2005 also the Cayman model is produced in Finland which, like Germany, is part of the euro zone.

[14] Source: Orbis. Average over August 1999 to July 2006. Corresponding return on assets for Daimler (1.5%), Ford (-0.4%), Toyota (6.8%) and Volkswagen (2.4%). Corresponding EBIDTA margins for Daimler (8.1%), Ford (6.8%), Toyota (13.9%) and Volkswagen (10.5%)

[15] Source: Orbis.

[16] Source: Orbis.

To illustrate the potential for exposure of profits to the usd/eur exchange rate we graph monthly revenue flows in euros stemming from US sales of Porsche 911's over the period. During 1996 to 2001 the dollar appreciated against the euro and revenues from US sales, when converted into euros show a trendwise increase. Conversely, the weakening of the dollar in 2002 and 2003 is associated with lower revenue in euros. If marginal costs are stable in euro such a pattern is clearly consistent with substantial exchange rate exposure on the part of Porsche. The figure is also consistent with the idea that business cycle effects, as captured by consumer confidence, are an important influence on sales of Porsche cars.

[Figure 1 about here]

Typical work in the literature on exchange rate exposure would use time series data as in Figure 1 and regress cash flows on the usd/eur exchange rate along with some variables thought to influence demand (see for instance Williamson (2001)). We have experimented with such regressions both at the firm level and at the product level for BMW and Porsche. Effects broadly correspond to intuition. However, standard errors are large, parameter estimates are in several cases not stable across specifications and we have not taken account of changing product attributes or the endogeneity of prices. Such problems are commonly faced in estimating demand for differentiated products (see for instance Davis and Garcés (2010) for an accessible discussion of such problems) and are the motivation for the demand estimation approach that we describe in the following Section.

3 The Empirical Model

3.1 Demand

Demand Specification

We follow BLP (1995) who estimate a random-coefficients (RC) logit model for automobiles in the US market. We do not develop every detail of the model in this section, but rather refer authors to previous treatments including, in particular, BLP (1995) and Berry (1994). Define the conditional indirect utility of individual i when consuming product *j* from market *m* as:

$$u_{ijm} = \sum_{k=1}^{K} x_{jmk}\beta_{ik} + \xi_{jm} + \varepsilon_{ijm},\ i = 1,\ldots,I; j = 1,\ldots,J; m = 1,\ldots,M$$

where x_{jmk} are observed product characteristics such as size, HP/weight, brand, country of production, ξ_{jm} represent unobserved (by the econometrician) product characteristics, assumed observed by all consumers. Following the literature, we decompose the individual coefficients $\beta_{ik} = \overline{\beta}_k + \sigma_k v_{ki}$ where β_k is common across individuals, v_{ki} is an individual-specific random determinant of the taste for characteristic *k*, which we assume to be Normally distributed $(v_{1i},\ldots,v_{Ki})' \sim \mathcal{N}(0,\Sigma)$ and σ_k measures the impact of *v* on characteristic *k*. Finally, ε_{ijmt} is an individual and option-specific idiosyncratic component of preferences, assumed to be a mean zero Type I Extreme Value random variable independent from both the

consumer attributes and the product characteristics. The specification of the demand system is completed with the introduction of an outside good with conditional indirect utility $u_{i0}=\xi_{0m}+\sigma_0+\nu_i+\varepsilon_{i0}$, since some consumers decide not to buy any car.

This demand specification abstracts from explicitly modeling intertemporal substitution (see, for example, Nevo and Hendel (2006) and Gowrisankaran and Rysman (2007) for an alternative approach). This clearly represents a pragmatic modeling approximation to actual consumer choice behaviour in the industry in light of the lack of information of transactions at the consumer level and given that the focus of our paper lays not directly in the dynamics on the demand side.

Identification Strategy

We treat price as endogenous in our demand specification. To estimate our model, besides the exogenous characteristics, we use the BLP instruments (following BLP (1995)), a set of polynomial basis functions of exogenous variables exploiting the three-way panel structure of the data, consisting of the number of firms operating in the market, the number of other products of the same firm and the sum of characteristics of products produced by rival firms.

Following the literature on merger simulation, we back out marginal costs from the first-order condition faced by the firms under the maintained assumption of Bertrand-Nash conduct. These US dollar-denominated marginal costs are assumed fixed in our analysis - we abstract from any efficiency gains (or losses) from relocating production and allow marginal costs to change only due to exchange rate fluctuations, as emphasized below.

3.2 Counterfactual shocks

We need to take a stand on stochastic processes to generate counterfactual levels of exchange rates and consumer confidence. Note that this step is completely separate from the demand estimation. This can be useful if we want to include several business cycles to generate macroeconomic shocks but only have data on a shorter time period for the relevant product markets. We use bimonthly data for consumer confidence and the real exchange rates for the period January 1973 to July 2006 to estimate the statistical properties of these variables. Our reading of the evidence is that the forecasting ability of macroeconomic models of exchange rates is weak and we instead opt for a simpler, purely statistical, approach.[17] A number of studies have modeled exchange rate behavior over shorter horizons using autoregressive processes. A frequent finding is that a GARCH (1,1) model performs well (see for instance Hansen and Lunde (2005) or Rapach and Strauss (2008)). Patton (2006) also uses GARCH(1,1) processes to model the daily exchange rates of the US dollar against the yen and the euro.

We want the counterfactual shocks to capture the co-dependence between variables. For instance shocks to US monetary policy are likely to affect the exchange rate

[17] The igniting spark to the large literature on the forecasting ability of exchange rates of macro models was Meese and Rogoff's (1983) finding that a random walk beat all the proposed models. While some of the ensuing studies point to some predictive power of macro based models (for instance Mark (1995)), other studies point to very weak predictive power (Sarno and Valente (2009)).

against both the euro and the yen. In recent years copulas have been used to model the interdependencies between asset prices (see for instance Jondeau and Rockinger (2006), Kole et al (2007) or Patton (2009) for a survey)[18]. Consider three random variables X_1, X_2, X_3. The joint cumulative density function (cdf) is given by $H(x_1, x_2, x_3)=Pr[X_1\leq x_1, X_2\leq x_2, X_3\leq x_3]$. For each X_i, $i=1,2,3$, the marginal cdf is given by $F_i(x_i)=Pr[X_i\leq x_i]$. A concern is that the standard multivariate distributions, such as the multivariate normal, would force all marginal distributions to follow the same processes. The attractiveness of the copula approach is that it allows modeling of the univariate processes separately from their dependence. The core result with regard to copulas is due to Sklar (1959) who showed that any joint distribution of random variables can be decomposed into two parts: The marginal univariate distributions and a function, the copula function, that captures the dependency between the marginals.[19] Using C to denote the copula function we can thus write

$$H(x_1, x_2, x_3)=C(F_1(x_1), F_2(x_2), F_3(x_3)).$$

We use a multivariate t-copula to model the dependence between our three stochastic variables of interest. Define $F_i(x_i) \equiv u_i$. The t-copula is then defined by

$$C(u_1, u_2, u_3; \rho, \nu) = T_{\nu,\rho}\left(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2), t_\nu^{-1}(u_3)\right)$$

where $T_{\upsilon,\rho}$ is the cdf of the multivariate Student's t distribution with correlation matrix ρ and degrees of freedom υ. The cdf of the univariate student's t distribution with υ degrees of freedom is denoted by t_υ. An attractive feature of the t copula is that it allows for a higher dependence between extreme events than for instance the Gaussian copula. As $\upsilon\rightarrow\infty$ the t copula converges to the Gaussian copula.

We use GARCH(1,l) models to estimate the exchange rate processes. Use y_{it} to denote the logarithmic returns (first-differences of logarithmic series) in the real usd/eur and real usd/jpy respectively between time t and $t-1$. We assume that the process followed by y_{it} is given by

$$y_{it} = C_i + \varepsilon_{it}$$

$$\sigma_{it}^2 = \kappa_i + \alpha_{i1}\sigma_{it-1}^2 + \alpha_{i2}\varepsilon_{it-1}^2.$$

So the exchange rates are assumed to follow an autoregressive process of order 1. Today's realization is equal to the last period's value plus a random shock. The error term ε is assumed to follow a t distribution with mean zero. We allow the shocks to have time varying volatility.

We model the process followed by consumer confidence in first differences, such that Y_{it} is the difference in consumer confidence between time t and and $t-1$.

$$Y_{it} = C_i + \varepsilon_{it}$$

[18] Copulas are also finding applications in marketing, see Danaher and Smith (2010).
[19] See for instance Nelsen (1999).

As seen in Appendix A, the decreases in consumer confidence are greater than increases. To capture this asymmetry we model the shocks using an exponential GARCH model, EGARCH(1,1). Again let the error term ε follow a t distribution with mean zero and define $z=\varepsilon/\sigma$. Following Nelson (1991) we then assume that volatility can be modeled as

$$\ln(\sigma_{it}^2) = \kappa_i + \alpha_{i1}\ln(\sigma_{it-1}^2) + \alpha_{i2}z_{t-1} + \gamma(|z_{t-1}| - E|z_{t-1}|).$$

If γ is negative, the conditional volatility will be greater for negative shocks than for positive shocks. We fit a Student's t-copula to the residuals that we estimate by the GARCH and EGARCH processes. Based on the estimated copula we then generate 200 random shocks for each future period in the forecast horizon and let the shocks in each period follow the copula relation. We use

as a motivation for producing abroad, which we would argue is a reasonable simplification. For BMW and Porsche we compare production in Germany with production in the US. Average differences in factor prices are limited between these two countries. For instance, over 1992 to 2005 wages in manufacturing are on average 6.8 percent higher in US than in Germany.[23] The swings in exchange rates are, for these production locations and a given technology, likely to overwhelm level differences in production costs. As seen in Table 1 the usd/eur exchange rate fell from 1.4 in 1996-7 to 0.88 in 2001-2 and then rose again to 1.22 by 2005-6. Inflation is low in both countries during this time so such changes translate into cost differences of production. Counterfactual demand, $\hat{q}$, finally depends on the vector of counterfactual prices for all producers $\hat{p}$, and on the counterfactual realization of $\widehat{cc}$, the consumer confidence.

If a producer located in the EU instead produces a model in the US the cash flow from that model is

$$\Pi_{i,t+n}^{US} = \left(\frac{eur}{usd}\right)_{i,t+n} \left(\hat{p}_{i,t+n} - \hat{c}_{i,t+n}^{US}\right)\hat{q}_{i,t+n}\left(\widehat{cc}_{i,t+n}, \hat{p}_{i,t+n}(e)\right). \quad (2)$$

When production is in the EU, as in equation (1), costs are thus stable in euro whereas the exchange rate has a large effect on revenue. In contrast, in (2) costs and revenue are in the same currency and it is only the net profit that is affected by the exchange rate.

There are several ways one could introduce price adjustments. First, given marginal costs and the (unchanged) ownership structure, one can calculate the corresponding new equilibrium by iterated best response. Despite its elegance, this has a number of drawbacks. One is that, for each given scenario and horizon, we compute 200 simulated draws of the exchange rates and consumer confidence index and calculate about ten strategies. Another is that the number of products is about 150, potentially requiring a large number of iterations, even with a clearly dominant diagonal in the elasticity matrix. More importantly, however, the static Bertrand-Nash pricing assumption generates too much pass-through. Indeed, Goldberg and Hellerstein (2008) point to that demand systems that imply more plausible substitution patterns tend to generate excessive pass-through if coupled with static Bertrand-Nash pricing. Our counterfactual prices need to capture the empirical fact that consumer prices are stable but quantities vary over the business cycle. Introducing dynamic considerations into pricing is a possible solution but will generate the need for additional iterations, see Goldberg and Hellerstein (2010) or Nakamura and Zeron (2010) for studies that introduce dynamic price adjustment in a framework similar to ours. While increases in computing speed may make this the preferred scenario in future work, we have instead opted for hedonic price regressions as a straightforward way to generate empirically plausible counterfactual prices. We regress real prices on forward exchange rates interacted with country of origin, product characteristics (HP, size, transmission) and product fixed effects.[24]

[23] Source: OECD, labor compensation per employee in manufacturing, expressed in USD using PPP-adjusted exchange rates.

[24] Note that we do not include consumer confidence in this regression. In preliminary regressions we included the same interactions between segments and consumer confidences as in Specification II in Table 4. These interactions were not significant however and using the point estimates to generate the counterfactual prices

In practice it makes little difference if we use forward rates or actual exchange rates in this specification. However if we take the forward rate as the best predictor of the exchange rate that will prevail in the future, it is the natural candidate. We then use the coefficients from these hedonic regressions to generate counterfactual prices.

4. Results from estimation

4.1 Demand Estimates

Table 4 reports estimates of two RC logit specifications for the US car market. Both use characteristics such as price, engine power (HP), size and whether non-manual transmission is included in the baseline model, as well as a random coefficient for price. Both also include time (model-year), country of origin, and brand fixed-effects. The stance in which Specifications I and II differ is in the treatment of consumer confidence and market segment variables.[25]

[Table 4 about here]

Specification I uses consumer confidence and separate fixed-effects for market segments. In contrast, Specification II uses interactions of market segments and consumer confidence. Specification II thus allows differential responses in market shares according to the market segment a model belongs to, according to which economic outlook consumers expect to prevail.[26] Both specifications have significant coefficients for the mean and dispersion price coefficients, whereas the remaining characteristics are usually not significant. In fact, most of the explanatory power for market shares tends to come from brand and market segment fixed-effects.

The (own) price elasticities (equivalently, markups) of the models in Specification II are in the range 3.7-7.3 with an average elasticity 6.0, thus in line with previous studies of the car industry, notably Petrin (2002) RC logit estimates using micro data (see, for instance, column 6 of his Table 9). For the sake of comparison, our elasticities seem to be somewhat higher than those of Goldberg (1995), BLP (1995) and Goldberg and Verboven (2001). Goldberg's average price elasticities, reported in her Table II, are in the range 1.1-6.2 across specifications and market segments. BLP's price elasticities reported in

---

resulted in excessive variability of prices and profits. That prices respond to cost shocks but only to a limited degree to demand shocks fits well with a number of studies for many markets (see Okun (1981) for a seminal reference). Note that we use list prices which are likely to be even less affected by demand shocks than transaction prices. Copeland and Hall (2009) use transaction prices for the big three US carmakers and show that demand shocks have a small impact on price and are absorbed almost entirely by sales and production decisions.

[25] The car industry is characterized by a number of market niches and highly heterogeneous products. See, for instance, Goldberg (1995) for estimates of a nested logit model incorporating market segment information.

[26] Following the definition used by WARDS, we adopt 16 market segments as explained in Section 2. Goldberg (1995) uses nine market segments in her study of the US market, namely Subcompacts, Compacts, Internediate, Standard, Luxury, Sports, Pick-ups, Vans and Other, besides an indicator of whether the car's origin is domestic or foreign. The segments with the lowest price elasticities are Sports (both foreign and domestic cars), followed by Luxury (domestic), whereas the ones with the highest price elasticities are Intermediate (foreign-made), followed by Standard (domestic) and Vans (foreign). Our market segments reflect a much more segmented market, thanks partly to the development of relatively new market niches such as Luxury SUVs and CUVs (cross-utility vehicles) in the last 15 years or so.

their Table V are in the range 3-6.5, while Goldberg and Verboven's estimated elasticities for European markets, reported in their Table 6, are in the range 3-6. These results are consistent with the RC logit markup estimates (without microdata) reported in Petrin (2002)'s Table 9, whose 10th and 90th percentiles are 0.28 and 0.63, with an average markup of 0.4 , compared to, respectively, 0.11, 0.25 and 0.17 for his RC logit with microdata. Equivalently, the 10th and 90th percentile of Petrin's elasticities are 4 and 8.9 in his specification using microdata.

[Figure 2 about here]

Interestingly, the estimates for Specification II suggest an intuitive "pecking order" effect of the interaction terms. For instance, demand for the "Upper Luxury" segment tends to be more sensitive to consumer confidence than that of the "Middle Luxury" segment, which in turn is more sensitive than that of the "Lower Luxury" segment.[27] Similarly, the "Large Luxury SUV" segment is more sensitive to consumer confidence than the "Middle Luxury SUV" segment, the "Large CUV" segment is more sensitive to the "Middle CUV" and "Small CUV" segments etc. We interpret these results as evidence that, conditional on buying a car, consumers are more likely to purchase models from high-end segments the more confident they are about the economic outlook.

4.2 Price Hedonics

As discussed above we regress (real) prices on product characteristics (HP, size, transmission), model fixed effects and forward exchange rates. To gauge if the results are reasonable we report the elasticities in Table 6. The exchange rate pass-through in this regression is 0.146 for the euro exchange rate and 0.116 for the Yen.[28] Both are significant at the 5 percent level. Comparing to other estimates they are somewhat on the low side of what we expect. A number of studies examine pass-through in import prices (see Goldberg and Knetter (1997) for an early survey) and find pass-through elasticities that are frequently equal to about one half. Pass-through elasticities in the retail prices are typically lower yet. We can also compare to another non-structural estimate for the US auto market, Hellerstein and Villas-Boas (2010). The 24 models in their study exhibit an average pass-through of exchange rates into transaction prices of around 38 percent, but with large standard deviations.

[Table 6 about here]

4.3 Counterfactual shocks

We model the marginal distributions to the macroeconomics variables as GARCH(1,1) processes - the estimation output is given in Table 7. The significant coefficient on lagged volatility in the usd/eur relation points to that volatility is indeed time varying at this frequency. The process for consumer confidence reflects a pattern where the typical change is

[27] This amounts to saying that a positive economic outlook results on a larger impact on the market shares of, say, an Audi A8 (or BMW 7 series) than on those of an Audi A6 (respectively, BMW 5 series), which in turn are more sensitive to consumer confidence than those of an Audi A4 (BMW 3 series).

[28] The elasticity with respect to horsepower is 0.166 and significant at the 1 percent level. Size and transmission are not significant, but clearly the car model fixed-effects capture much of the variation that could identify these elasticities; the adjusted R-square for this regression is 0.986.

an upward drift but that negative shocks are associated with greater volatility (captured by the negative coefficient on the leverage term). See Appendix 1 for graphs of the time series of these variables.

[Table 7 about here]

The degrees of freedom for the t-copula are estimated to 21.65. The estimated correlation coefficients using the t-copula are -0.085 between usd/eur and consumer confidence, 0.063 between usd/jpy and consumer confidence and 0.522 between usd/eur and usd/jpy. Combining these estimates allows us to generate counterfactual shocks where the marginal distributions follow the GARCH processes and the co-dependence follows a t-copula in each period. Adding the succession of these shocks to the starting values in July 2006 then gives us counterfactual paths of the exchange rates and consumer confidence. As an example of our results, Figure 3 shows the distributions for counterfactual draws for these three variables 12 months ahead from July 2006. The histograms show the densities for the respective variable and the scatter plots the relation for each bilateral comparison. The scatter plot in the lower left hand corner for instance plots counterfactual draws of usd/eur against counterfactual draws of usd/jpy.

As seen, the draws reflect substantial dispersion for all three variables. The skewness of consumer confidence is visible. The starting value in July 2006 is 134 and we see predictions for 12 months ahead centered at this level (median across the draws is 146, mean 139) but a long tail of weaker realizations. As seen in the scatter plots in the middle row, the relation between the consumer confidence and the exchange rates is weak. The positive relation between the two exchange rates on the other hand is clearly visible in the scatter plots in the upper right and lower left corner. These then are the counterfactual levels of macro variables that are fed into the demand system when we consider the 12 month horizon ahead. Note that by the additive nature of the shocks we can view our results as simulating 200 possible paths of the underlying variables. As we expand the forecast horizon some of the paths for consumer confidence are predicted to be too low, or even negative. In these cases we replace the value with a hypothesized lower threshold of 10. The lowest level in the time period covered by our data is 15.8 (December 1982). Let us now turn to the reporting of the results

5. Simulation Results

5.1 Per period distributions of profits

First we consider predicted profits up to 4 years ahead. In generating these counterfactuals we use data up to July 2006 only so the counterfactual profits for 2007 is one year out and, for 2010, 4 years out. We take counterfactual values for July of the respective year and use these values to generate counterfactual profits for the whole year. As an example of the results from this analysis consider the cash flows of BMW when it produces all the models in the US and the cash flows if it produces all the models in the EU. In terms of operational hedging, these can be seen as two extreme cases capturing the case where marginal costs are perfectly stable in the currency of the market or perfectly stable in the currency of the producer. Sourcing

more materials in the US or producing in a country with a tight link to the dollar would be ways to achieve intermediate results.

[Figure 4 about here]

In Figure 4 we see that there is a much weaker relation between the usd/euro exchange rate and cash flows if BMW were to produce locally in the US than rather than in the EU. This follows from equations (1) and (2). In both production scenarios a weaker dollar is associated with lower cash flows when expressed in euro terms, but when producing in the US only the net revenue is exposed to exchange rate risk.

The dispersion of the estimates unrelated to the usd/euro exchange rate may seem surprisingly low. Two comments are in order. Firstly, the draws of the underlying shocks reflect only shocks to consumer confidence and exchange rates. Product recalls because of mechanical failure[29], unusually successful advertising campaigns and a myriad other factors have the potential to affect cash flows. We could add purely random noise to our simulated cash flows to capture such randomness. We have refrained from doing so to keep the presentation simple – we mention it as a possible factor to include in applied work. At least since Frank Knight (1921) made the distinction between risk and uncertainty it has also been noted that some events are not apt to be captured by probability theory. Note though that several such events can be examined in the current framework as separate scenarios. For instance, what would be the effect on the risk profile of the entry of a low priced substitute to the BMW 3 series? Indeed Petrin (2002) uses the kind of framework that we do but applies a backward looking simulation to examine the impact of the introduction of the minivan segment. Given the backward looking nature of the counterfactual, different shocks to demand and exchange rates are not an issue in his study.

[Figure 5 about here]

Another useful way of presenting simulated cash flows is to examine the probability distribution. In Figure 5a we graph kernel density estimates of simulated cash flows for BMW at different horizons. As is to be expected, the further ahead, the more dispersed is the distribution. In 5a we present simulated profits for the case where the CUV's X3, X5, X6 and the roadster Z4 are produced in the US. This corresponds to the actual production locations in July 2006. In 5b we compare simulated profits under the current production locations with a counterfactual where there is only production in the EU (3 years ahead). As seen, average profits are similar and there is considerable dispersion in both scenarios. By having more production in the US, BMW makes cash flows less sensitive to the usd/euro exchange rate such that the probability distribution has a higher peak – a testament to that producing in the US can be seen as operational hedging. Also note that the lower tail of the profit distribution is shifted inwards. Conversely, the upward tail is somewhat higher when producing only in the EU.

[29] Recalls are not uncommon in the automotive industry, see for instance www.recall.gov for a list of recalls or witness Toyota executives' testimony before the US Congress on quality problems (see The Economist: "The machine that ran too hot", Feb 25th 2010).

In Table 8 below we present some statistics on the 3 year ahead profit distributions for a wider range of strategies. First compare the current production structure for BMW with a scenario where all production would be in the EU. We thus compare cash flows in the first row of Table 8 to cash flows in the second row at different points on the distributions. The current production pattern limits downside risk substantially. Also the upper tail is affected and the shrinking of the distribution in the tails is roughly symmetric.[30] At both the 1st and 5th percentile the increase associated with having the current production locations is on par with the decrease at the 99th and 95th percentile. At the 10th percentile the increase in profits from having the current locations is higher than the decrease at the 90th percentile. Evaluated at a concave utility function, these numbers point to the attractiveness of the natural hedge for BMW. The overall pattern for both BMW and Porsche is that the more production that takes place in the US, the lower is the variability of cash flows.

[Table 8 about here]

An alternative for a risk-averse owner is to use financial hedges. Note that a financial hedge in itself does not affect the cash flows from the operations.[31] Rather, a financial hedge gives rise to a financial gain or loss, that weighs in the opposite direction from the direct effect of an exchange rate change on cash flows. As argued in the introduction, we see issues on financial hedging as largely separate from the relation between operational cash flows and shocks that is our focus here. To nevertheless highlight two issues on the interplay between financial hedging and operating policies, we also consider profits in the case where expected profits are sold forward on the futures market. Use $t+n$ to denote the realization of the exchange rate and f to denote the forward rate available at time t. We assume that the forward rate is unbiased such that it is equal to the expected value (at time t) of the exchange rate at time $t+n$. In our scenarios we assume that the firms sell all the expected dollar revenue forward where E denotes the expectations operator.

$$\Pi_{i,t+n}^{H} = \left(\left(\frac{eur}{usd}\right)_{i,t+n}\hat{p}_{i,t+n} - \hat{c}_{i,t+n}^{EU}\right)\hat{q}_{i,t+n}\left(\widehat{cc}_{i,t+n}, \hat{p}_{i,t+n}(e)\right) - \left[f\left(\frac{eur}{usd}\right)_{i,t} - \left(\frac{eur}{usd}\right)_{i,t+n}\right] E\left(\left(\frac{eur}{usd}\right)_{i,t+n}\hat{p}_{i,t+n}\hat{q}_{i,t+n}\left(\widehat{cc}_{i,t+n}, \hat{p}_{i,t+n}(e)\right)\right).$$

We can compare profits from the strategy where all production is in the US, to one where all production is in the EU, but all the expected cash flow is sold forward. A first thing to note is that in this case financial hedging lowers profit variability even more than the operational hedging does. An unexpected weakening of the euro will lead to higher cash flows but will be balanced by the loss made on the forward contract. A second observation is that the profit variability due to consumer confidence shocks is not perfectly correlated with exchange rates

[30] At the minimum and maximum values there is some asymmetry however; the minimum is 920 million euro higher under the current production locations then if all production were in the EU. The maximum is 1669 million lower under the current production locations.

[31] The literature, that examines the motivations for hedging, points to some situations where hedging may affect future cash flows. The mechanisms are indirect however – avoiding financial distress may for instance allow you pursue more aggressive strategies in a downturn or keep a steady flow of investments (Froot, Stein and Scharfstein (1993)).

and some variability remains. Clearly, financial hedging is possible also when producing in the US and the resulting variability in profits is the lowest in this scenario.

The scenario with the highest expected profits is the one where firms can seamlessly switch across locations according to the level of the exchange rate. Having this possibility amounts to having a real option. Firms reap the upside when the euro is depreciated and limit the downside when the euro is strong.

As suggested by Adler and Dumas (1984) we may also use regressions to analyze the links between cash flows and the risk factors. In Table 9 we report results from such regressions on the same 3-year-ahead projections as in Table 8. Again we see how production in the US is a way of lowering exposure to the exchange rate. We also note that financial hedging eliminates the effect of the exchange rate on profits. This points to one reason why regressions using stock prices to measure exposure are likely to be of limited use in learning about the exposure of firms if they are hedging. Given the widespread use of financial hedges (see for instance Bodnar, Hayt and Marston (1998)) it is therefore not surprising that estimates of exchange rate exposure are weak in the literature that examines the exchange rate exposure using stock market valuation of firms.[32]

[Table 9 about here]

5.2 Net present value of different production locations

The previous section illustrated one use for the simulation tools that we develop. To generate probability distributions for cash sh t7at we a9(Give)74( )-39(76( )-79(to)-109(e)4(x)-9(a)4(mi)-3(e)-5( )-87(

NPV. We thus calculate the NPV of each of the 200 streams of cash flows and report summary statistics on these streams in Table 10.

[Table 10 about here]

The last component we need is the cost of building a plant in the US. For simplicity we take the production capacity in EU to be in place and treat it as a sunk cost. The cost of building a plant in the US will be dependent on a large number of assumptions. To avoid clutter we report the discounted profit streams only in Table 10 and discuss separately what plant investments that these might motivate. To gauge the order of magnitude of costs, notice that the cost of establishing Volkswagen's new plant in Chattanooga is reported to be 1 billion USD (equivalent to about 0.7 billion euros at the prevailing exchange rate in January 2010).[35] BMW opened a new plant in Leipzig, Germany, in 2005. A total of 1.3 billion euro had been invested in this plant prior to its opening (Annual report 2005, p 19).

Consider first the differences in the mean NPV and compare BMW's NPV in the current scenario with that of a case where all production is in the EU. The difference in NPV between the two scenarios is around 0.8 billion euro. The difference is of the same magnitude as the cost of establishing a new plant and from this perspective we would expect BMW to be roughly indifferent between the two. Producing all models in the US would increase the mean NPV by around 2.5 billion. We expect that the greater the flexibility that BMW has in switching production locations, the more will a US plant be worth. Indeed, in our simulations the NPV for the case where production is perfectly flexible between the EU and the US is some 12.2 billion higher than when production is in the EU only.

Now turn to differences in mean NPV for Porsche. The ranking of scenarios is the same as for BMW but differences are lower in absolute terms. Say that Porsche would want to follow BMW and produce their CUV, the Cayenne, in the US. The difference in mean NPV between that scenario and the current one is only 0.14 billion euro. This is much below the back-of-the-envelope costs of a new plant mentioned for BMW and Volkswagen. Also in the extreme case of perfectly flexible production, the increase in mean NPV is only 1.3 billion relative to the current scenario. These numbers stress that Porsche operates on a much smaller scale than BMW. For the model-year 2005-6 for instance BMW sold 73 800 cars of the models that it produces in the US (see Table 2). In the same period only 12 500 cars were sold of Porsche's Cayenne. Porsche's total US sales for the same time period are 34 800. If the minimum efficient scale for an auto plant is rather high, it can clearly make sense for BMW to make the investment but not for Porsche. For comparison we can turn to Hall's (2000) study of minimum efficient scale using data from 14 North American plants operated by Chrysler. He finds a minimum efficient scale of around 3000 cars per week (his Figure 6) and that the average plant operated 83 percent of the weeks. The yearly minimum efficient scale would thus be around 130 000 cars. There can clearly be important differences across time and manufacturers. Nevertheless the evidence presented here points to differences in scale as a plausible explanation for why Porsche has not pursued the strategy of starting production in the US.

[35] New York Times, "Students See a Creek and Imagine a Bridge for VW", Jan 26 2010.

Let us also consider the full distribution of NPV's. Again examine BMW first. We see from Table 10 that the lower tail of cash flows is shifted inwards by producing some models in the US. The worst path implies a negative NPV of around -8.7 billion euro with the current set of locations rather than a negative value of -25.4 billion euro in the case where all production is in the EU. Now compare the first percentile of the NPV for different scenarios: with the current production locations, it takes a modest negative value of -0.9 billion euros rather than -15.9 billion euros for the case where all production is in the EU. Moving all production to the US is associated with a drastic shrinking of the standard deviation of NPV. The logic is the same as that illustrated in figure 4 above: If only net revenue is affected by the exchange rate, the variability of cash flows is much lower. Differences in mean profits are slight across scenarios. This reflects the assumption that marginal costs of production are the same in the final pre-simulation period. Patterns for Porsche are similar as for BMW, but NPV is much lower reflecting Porsches smaller scale of operation. How the firm should weigh these figures depend on risk preferences and on the value attached to avoiding negative outcomes. Compare the case of current locations for BMW with the counterfactual of having all production in the EU. The shrinking of the tails in the NPV distribution is then roughly symmetric. The difference between NPV's at the first percentile is roughly 15 billion euro, which is close to the difference in NPV's at the 99th percentile. The difference at the 5th percentile is also close to the difference at the 95th percentile and the difference at the 10th percentile is greater than that at the 90th percentile. For a decision maker that attaches a larger weight to outcomes in the lower tail of the distribution natural hedging appears attractive in this case.

Following Markowitz (1952) a common way of illustrating choice under risk is to relate expected values to standard deviations for different investments. In Figure 6 below we do so for the NPVs for BMW that we reported in Table 10. Consider a case where the preferences of the firm (or its non-diversified owners) can be described by a mean-variance utility function. If we abstract from investment cost, such a firm would clearly either produce entirely in the US or choose flexible production since these alternatives dominate the others in a mean-variance sense.

[Figure 6 about here]

6. Concluding comments

We make no claims as to the novelty of our qualitative results. Production capacity abroad can act as a natural hedge and there is an option value associated with being able to shift production between locations. We believe that our contribution comes from showing how we can give quantitative content to these strategies for firms in a differentiated products industry.

We have made a number of simplifying assumptions and let us briefly discuss them here. Most of these assumptions are made for convenience. We only considered the US market for instance. Time and resource constraints hindered us from assembling similar quality data for BMW's and Porsche's other markets. If a firm were to perform calculations such as these for themselves they would want to include other important markets in the analysis as well. A further simplifying assumption is that costs are fixed in the currency of

production. In reality prices of steel and other inputs are likely to fluctuate and affect marginal costs. To accurately model the relation between input prices and world market prices of raw materials however one should take account of the long term nature of supplier relations for auto manufacturers. Porsche for instance states that "A further increase in crude oil and raw material prices could also restrict Porsche's profitability…Porsche monitors the raw materials market and endeavors to minimize the cost risk by way of long-term supplier arrangements" (Annual report 2005-6, p 18). Examining marginal costs that are fixed in either the market currency or the home currency is a simple way of capturing two polar cases in terms of the correlation between exchange rates and marginal costs. The impact of tax rules on profits, retailer markups and economies of scale and scope at the plant level are other issues that we disregard in our simulation. Again, the difficulties are not conceptual. We focused on one source of operational hedging, the decision of where to produce. Another margin would be in terms of how to produce. By determining the technology in a plant a firm can also affect how the marginal cost develops over different ranges. Investing in a way such that marginal costs

Berry, Steve (1994), Estimating discrete choice models of product differentiation, RAND Journal of Economics 25, 242-262.

Berry, Steve, James Levinsohn and Ariel Pakes (1995), Automobile prices in market equilibrium, Econometrica 63, 841-890.

Berry, Steve, James Levinsohn and Ariel Pakes (1999), Voluntary export restraints on automobiles: Evaluating a trade policy, American Economic Review 89, 400-430.

Bodnar, Gordon M., Gregory Hayt and Richard C. Marston (1998), Wharton 1998 survey of risk management by U.S. non-financial Firms, Financial Management 27, No. 4

Bartram, Söhnke and Gordon M. Bodnar (2005), The foreign exchange exposure puzzle, Managerial Finance 33, 642-666.

Brealey, Richard A and Evi C Kaplanis (1995), Discrete exchange rate hedging strategies, Journal of Banking and Finance 19, 765-784.

Brealey, Richard A. and Stewart C. Myers (2003), Principles of Corporate Finance, 7th edition, New York: McGraw-Hill.

Brennan, Michael J. (2003), Corporate investment policy, in George M. Constantinides, Milton Harris and René M. Stulz (ed.) Handbook of the Economics of Finance, Amsterdam: Elsevier, 167-214.

Busse, Meghan, Jorge Silva-Risso and Florian Zettelmeyer (2006), $ 1,000 cash back: The pass-through of auto manufacturer promotions, American Economic Review 96, 1253-1270.

Copeland, Adam and George Hall (2009), The response of prices, sales and output to temporary changes in demand, forthcoming, Journal of Applied Econometrics.

Cox, John and Stephen Ross (1976), The valuation of options for alternative stochastic processes, Journal of Financial Economics 3, 145-66.

Damodaran, Aswath (2010), Applied Corporate Finance, 3d edition, John Wiley & sons.

Danaher, Peter J. and Michael S. Smith (2009), Modeling multivariate distributions using Copulas: Applications in marketing, forthcoming, Marketing Science.

Dasu, Sriram and Lode Li (1997), Optimal operating policies in the presence of exchange rate variability, Management Science 43, 705-722.

Davis, Peter and Eliana Garcés (2010), Quantitative Techniques for Competition and Antitrust Analysis, Princeton: Princeton University Press.

Dominguez, Kathryn M.E. and Linda L. Tesar (2006), Exchange rate exposure, Journal of International Economics 68, 188-218.

Eiteman, David K., Arthur I. Stonehill and Michael H. Moffett (2007), Multinational Business Finance, 11th edition. New York: Pearson.

Eun, Cheul S. and Bruce G. Resnick (2007), International Financial Management, Second Edition, New York: McGraw-Hill.

Fisher, Irving (1930), The Theory of Interest, New York: Macmillan.

Friberg, Richard and Mattias Ganslandt (2007), Exchange rates and cash flows in differentiated product industries: A simulation approach, Journal of Finance 62, 2475-2502.

Froot, Ken, David Scharfstein and Jeremy Stein, (1993), Risk Management: co-ordinating corporate investment and financing policies, Journal of Finance 48, 1629–1658.

Goldberg, Pinelopi K. (1995), Product differentiation and oligopoly in international markets: The case of the U.S. automobile industry, Econometrica 63, 891-951.

Goldberg, Pinelopi K. and Michael M. Knetter (1997), Goods prices and exchange rates: What have we learned?, Journal of Economic Literature 35, 1243-1272.

Goldberg, Pinelopi K. and Frank Verboven, (2001), The evolution of price dispersion in the European car market, Review of Economic Studies 68, 811-48.

Goldberg, Pinelopi K. and Rebecca Hellerstein (2008), A structural approach to explaining incomplete exchange-rate pass-through and pricing-to-market, The American Economic Review 98, 423-29.

Goldberg, Pinelopi K. and Rebecca Hellerstein (2010), A Structural approach to identifying the sources of local-currency price stability, manuscript, Federal Reserve Bank of New York.

Gowrisankaran, Gautam and Marc Rysman (2007), Dynamics of consumer demand for new durable goods, manuscript, Boston University.

Graham, John R. and Campbell R. Harvey (2001), The theory and practice of corporate finance: Evidence from the field, Journal of Financial Economics 60, 187-243.

Hall, George J. (2000), Non-convex costs and capital utilization: A study of production scheduling at automobile assembly plants, Journal of Monetary Economics 45, 681-716.

Hansen, Peter R. and Asger Lunde, (2005), A forecast comparison of volatility models: Does anything beat a GARCH(1,1)?, Journal of Applied Econometrics 7, 873-879.

Hellerstein, Rebecca and Sofia Berto Villas-Boas (2010), Outsourcing and pass-through, Journal of International Economics 81, 170-183.

Hendel, Igal and Aviv Nevo (2006), Measuring the implications of sales and consumer inventory behaviour, Econometrica 74, 1637-73.

Hertz, David B. (1964), Risk analysis in capital investment, Harvard Business Review, 95-106.

Jin, Yanbo and Philippe Jorion (2006), Firm value and hedging: Evidence from U.S. oil and gas producers, Journal of Finance 55, 107-152.

Jondeau, Eric and Michael Rockinger (2006), The copula-GARCH model of conditional dependencies: An international stock market application, Journal of International Money and Finance 25, 827-853.

Jorion, Philippe (1990), The exchange rate exposure of US multinationals, Journal of Business 3, 331-345.

Jorion, Philippe (2006), Value at Risk: The New Benchmark for Managing Financial Risk, third edition, New York: McGraw-Hill.

Kazaz, Burak, Maqbool Dada and Herbert Moskovitz (2005), Global production planning under exchange-rate uncertainty, Management Science 51, 1101-1119.

Knight, Frank H (1921), Risk, Uncertainty and Profit, Boston MA: Houghton Mifflin.

Kole, Erik, Kees Koedijk and Marno Verbeek (2007), Selecting copulas for risk management, Journal of banking and finance 31, 2405-2423.

Ludvigson, Sydney C. (2004), Consumer confidence and consumer spending, Journal of Economic Perspectives 18, 29-50.

Mark, Nelson C. (1995), Exchange rates and fundamentals: Evidence on long-horizon predictability, American Economic Review 85, 201-218

Markowitz, Harry (1952), Portfolio selection, Journal of Finance 7, 77-91.

Meese, Richard A. and Rogoff, Kenneth, (1983), Empirical exchange rate models of the seventies: Do they fit out of sample?, Journal of International Economics 14, 3-24.

Mello, Antonio S., John E. Parsons and Alexander J. Triantis (1995), An integrated model of multinational flexibility and financial hedging, Journal of International Economics 39, 27-51.

Moel, Alberto and Peter Tufano (2002), When are real options exercised? An empirical study of mine closings, Review of Financial Studies, 35-64.

Moffett, Michael H. and Barbara S. Petitt, (2004) Porsche exposed, mini-case, Thunderbird School of Global Management.

Muller, Aline and Willem F.C. Verschoor (2006), Foreign exchange risk exposure: Survey and suggestions, Journal of Multinational Financial Management 16, 385-410.

Nakamura, Emi and Dawit Zerom (2010), Accounting for incomplete pass-through, forthcoming, Review of Economic Studies.

Nelsen, Roger B., (1999), An Introduction to Copulas, New York: Springer Verlag.

Nelson, Daniel B. (1991), Conditional heteroskedasticity in asset returns: A new approach, Econometrica 59, 347-370.

Nevo, Aviv (2002), Measuring market power in the ready to eat cereal industry Econometrica 69, 307-342

Okun, Arthur M (1981), Prices and Quantities: A Macroeconomic Analysis, Washington D.C.: Brookings Institution.

Patton, Andrew (2006), Modelling asymmetric exchange rate dependence, International Economic Review 47, 527-556.

Patton, Andrew (2009), Copula-Based Models for Financial Time Series, in Torben G. Andersen, Richard A. Davis, Jens-Peter Kreiss and Thomas Mikosch (eds.) Handbook of Financial Time Series, New York: Springer Verlag.

Petrin, Amil (2002), Quantifying the benefits of new products: The case of the Minivan, Journal of Political Economy 11, 705-729

Sarno, Lucio and Giorgio Valente (2009), Exchange rates and fundamentals: Footloose or evolving relationship?, Journal of the European Economic Association 7, 786-83.

Slade, Margaret (2001), Managing projects flexibly: An application of real-option theory to mining investments, Journal of Environmental Economics and Management 41, 193-233.

Stein, Jeremy, Stephen E. Usher, Daniel La Gattuta and Jeff Youngen (2001), A comparables approach to measuring cashflow-at-risk for non-financial firms, Journal of Applied Corporate Finance 13, 100-109.

Stulz, René M. (2002), Risk Management and Derivatives, Mason OH: Thomson Southwestern.

Train, Kenneth E. and Clifford Winston (2007), Vehicle choice behavior and the declining market share of U.S. automakers, International Economic Review 48, 1469-1496.

Tufano, Peter (1996), Who manages risk? An empirical examination of risk management practices in the gold mining industry, Journal of Finance 51, 1097-1137.

Van Biesebroeck, Johannes (2003), Productivity dynamics with technology choice: An application to automobile assembly, Review of Economic Studies 70, 167-198.

Weitzman, Martin K. (2007), Subjective expectations and asset-return puzzles, American Economic Review 97, 1102-1130.

Williamson, Rohan (2001), Exchange rate exposure and competition: evidence from the automotive industry, Journal of Financial Economics 59, 441-475.

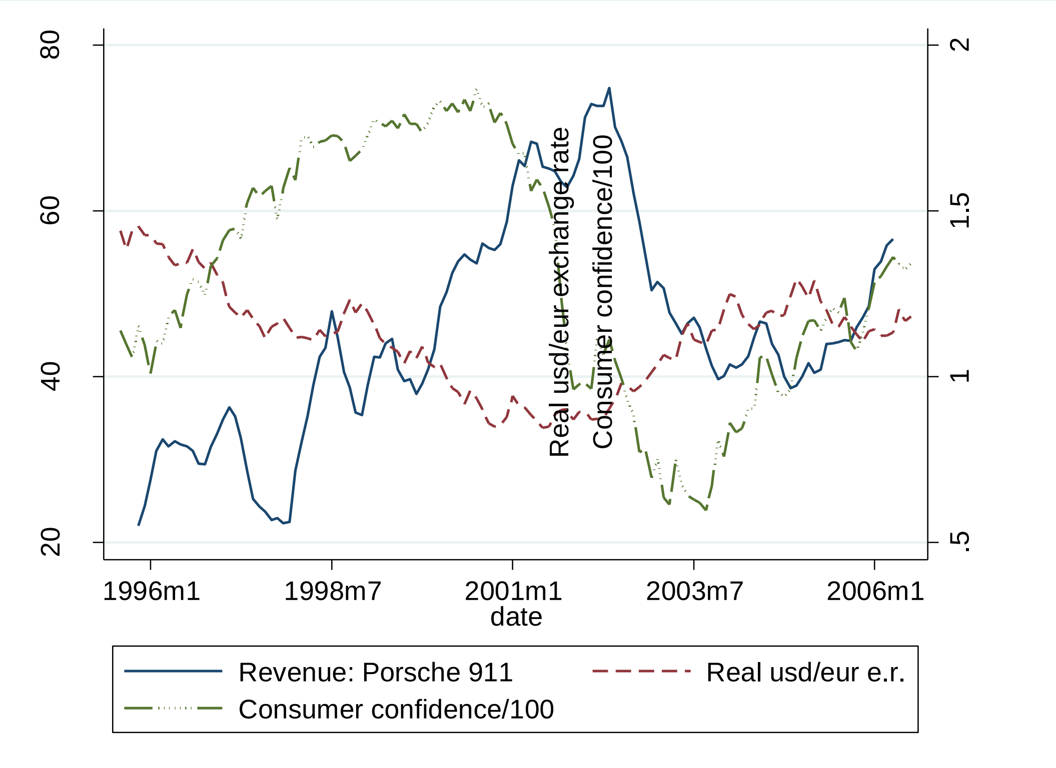

Figure 1. Porsche revenues from US sales of 911 measured in euro, real usd/eur exchange rate and consumer confidence.

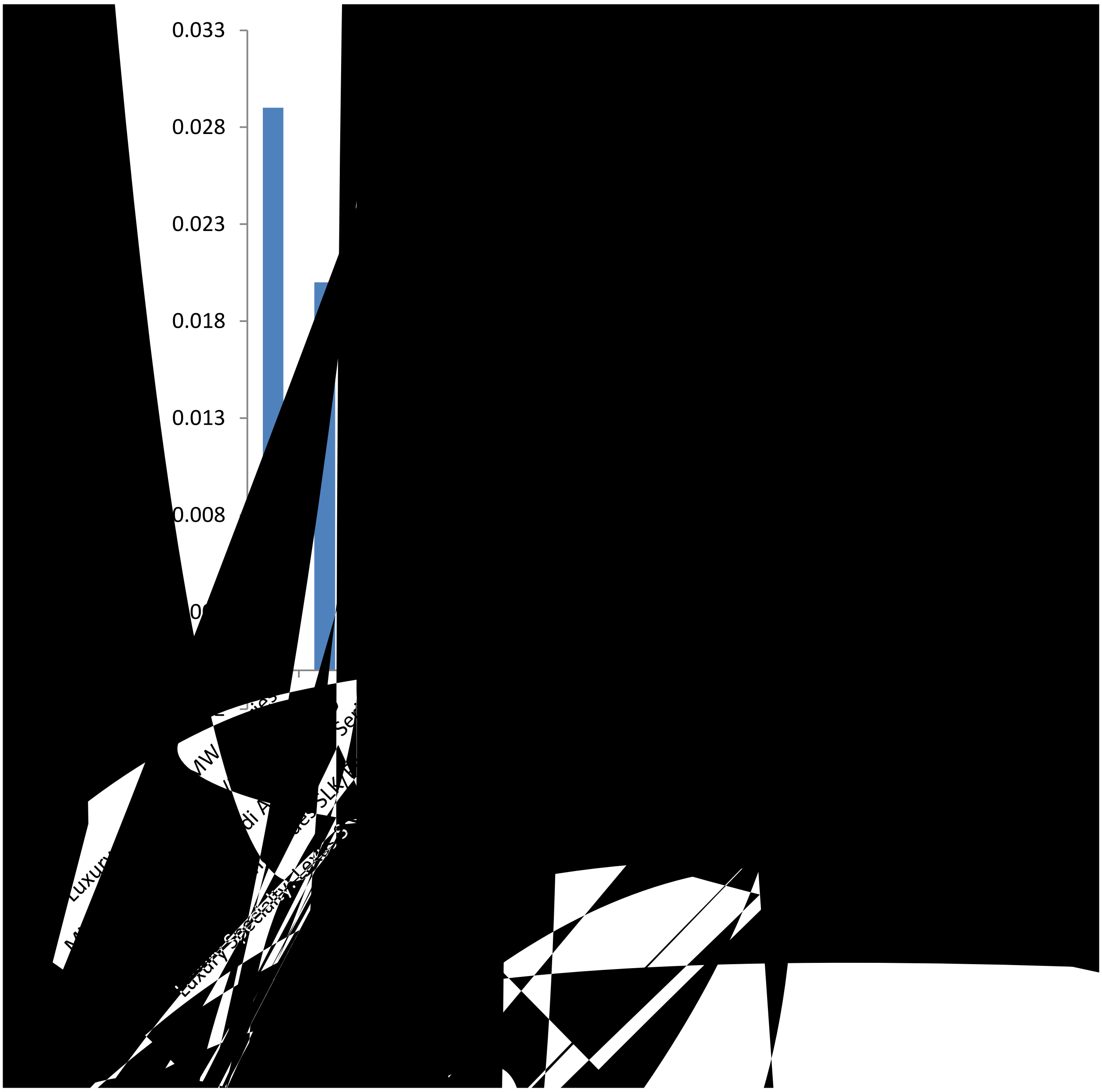

Figure 2. Interaction effects between market segment fixed effects and consumer confidence. Estimates from Table 4, Specification II.

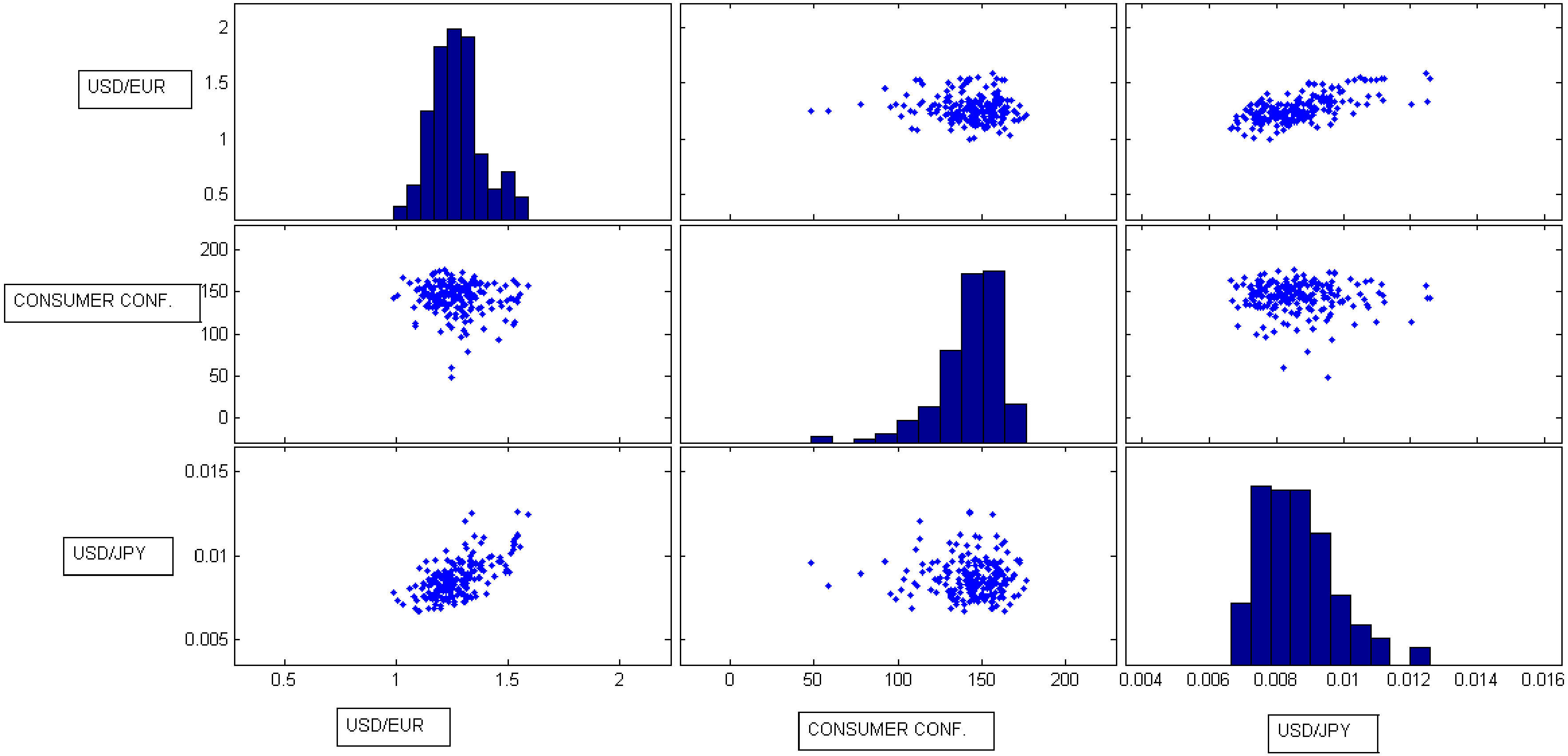

Figure 3. Counterfactual values of exchange rates and consumer confidence at the 12 month forecast horizon using July 2006 as start date.

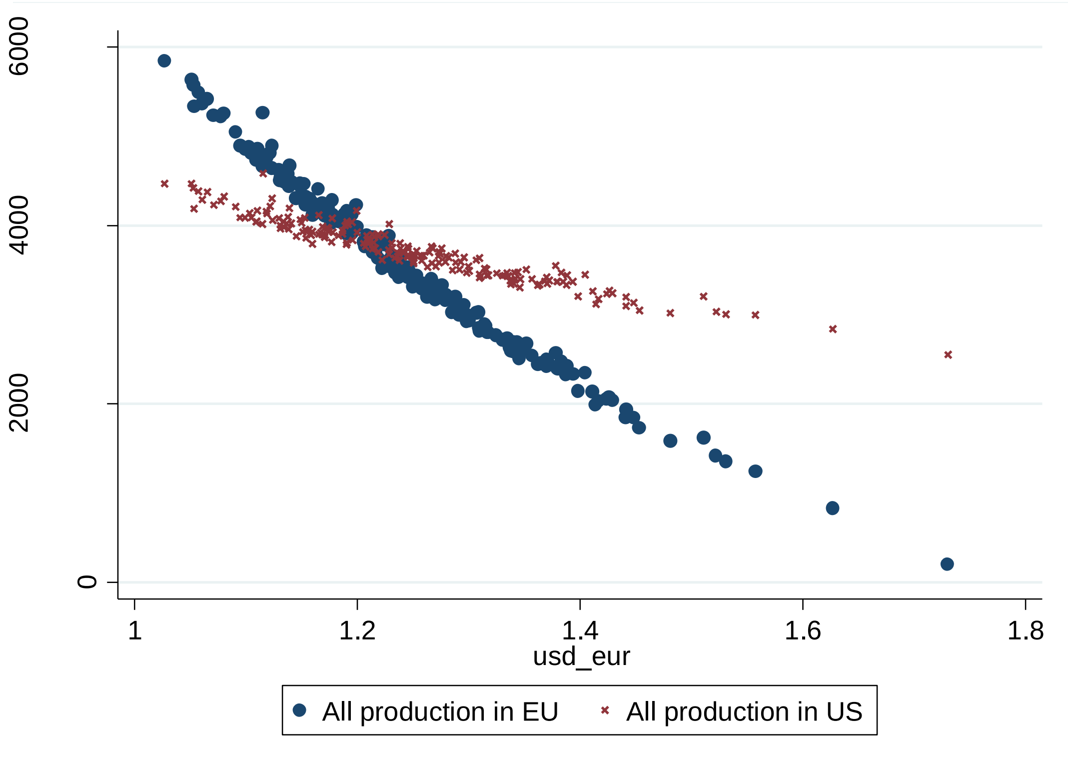

Figure 4. Counterfactual cash flows in relation to the real usd/euro rate from US sales for BMW at the 12 month forecast horizon. Production of all models locally in US or all in the EU.

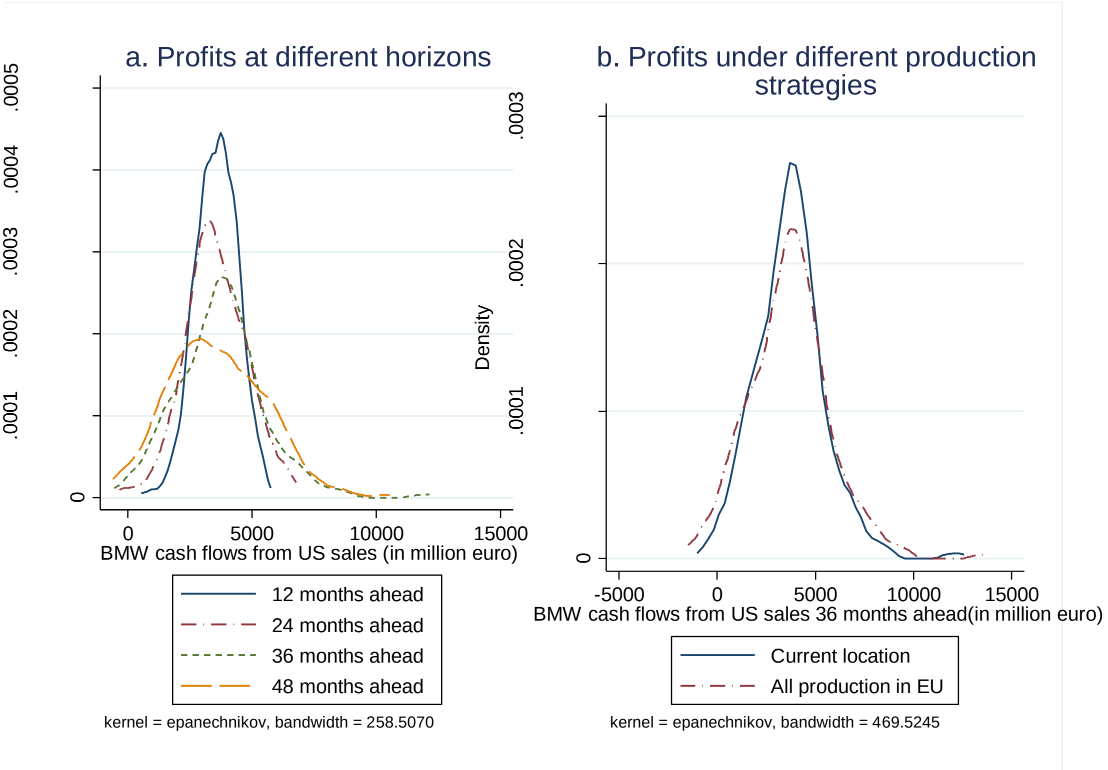

Figure 5. Counterfactual distributions of cash flows for BMW. Figure a, current production locations (X3, X5, X6 and Z4 in US and others in EU) at different horizons. Figure b, current production structure vs. all production in the EU at the 36 month ahead horizon.

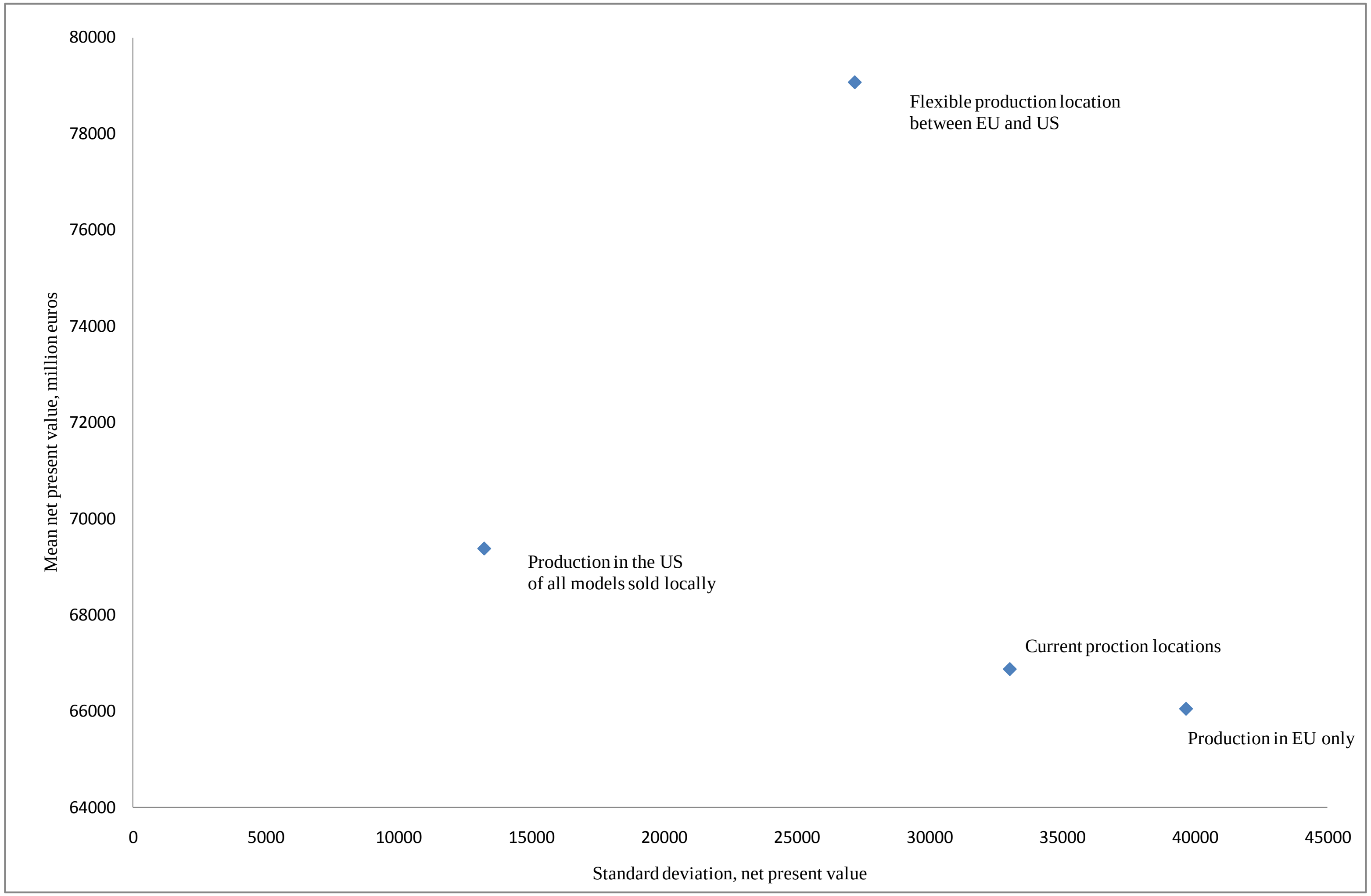

Figure 6. Net Present Value of different production strategies for BMW. Mean and standard deviations across 200 paths of simulated values for exchange rates and consumer confidence.

Table 1. Descriptive statistics, top segments of the US car market 1995-2006.

Model year	Price per model				Number of cars sold per model		# models	usd/euro	usd/jpy*100	Consumer Confidence
	Mean	SD	Min	Max	Mean	SD				
1995-6	38041.75	[redacted]3	12708.33	87966.01	[redacted]		[redacted]	970	1.0522	112.88
1996-7	37403.57	17539.10	14269.31	90906.66						

Table 2. Price, quantity and revenue share, BMW US market, 1995-1996 and 2005-2006.

	Price		Quantity		Share of revenue	
	1995-6	2005-6	1995-6	2005-6	1995-6	2005-6
3 series	23 562	26 730	49 868	118 377	0.22	0.31
5 series	41 273	36 544	28 439	56 266	0.22	0.20
6 series		61 713		9 741		0.06
7 series	65 472	61 332	18 478	19 270	0.23	0.12
8 series	81 495		552		0.01	
Z3	31 727		20 827		0.12	
L.R. Defender	37 151		1 418		0.01	
L.R. Discovery	35 005		16 324		0.11	
Range Rover	60 220		6 782		0.08	
Z4		29 606		10 215		0.03
Z8		111 840		9		0
X3		31 721		29 257		0.09
X5		36 544		34 326		0.12
Mini Cooper						0.06

The table shows means and standard deviations across months for a given model-year. Prices are in real 2000 dollars.

Table 3. Price, quantity and revenue share, Porsche US sales 1995-96 and 2005-06.

	Price		Quantity		Share of revenue	
	1995-6	2005-6	1995-6	2005-6	1995-6	2005-06
911	68 222	60 994	6 828	11 995	0.71	0.43
Boxster	43 718	38 743	4 500	5 770	0.29	0.13
Cayenne		36 392		12 501		0.27
Cayman		50 503		4 372		0.13
Carrera GT		374 788		208		0.05

The table shows means and standard deviations across months for a given model-year. Prices are in real 2000 dollars.

Table 4. Demand estimates, US car market 1995-2006. Random-coefficients logit model.

Variables	I	II	Examples	
Price	**-0.021**	**-0.030**		
	[-2.804]	[-4.475]		
HP	0.002	0.010		
	[0.247]	[1.394]		
Size	0.067	0.049		
	[1.360]	[0.790]		
Transmission	0.000	0.000		
	[.367]	[-0.754]		
Sigma price	**0.008**	**0.009**		
	[4.844]	[5.345]		
CONS. CONF.	0.016	-		
	[1.145]			
CONS. CONF. x Upper Luxury	-	**0.029**	Audi A8	BMW 7 Series
		[2.428]		
CONS. CONF. x Middle Luxury	-	**0.020**	Audi A6	BMW 5 Series
		[2.383]		
CONS. CONF. x Lower Luxury	-	**0.011**	Audi A4	BMW 3 Series
		[1.737]		
CONS. CONF. x Luxury Sport	-	**0.020**	Mercedes SLK	Porsche 911
		[1.843]		
CONS. CONF. x Luxury Specialty	-	0.013	Lexus SC430	Mercedes CLK
		[1.457]		
CONS. CONF. x Small Specialty	-	0.001	Mini Cooper	VW Beetle
		[0.079]		
CONS. CONF. x Large Luxury CUV	-	**0.016**	Acura MDX	Cadillac Escalade
		[2.166]		
CONS. CONF. x Middle Luxury CUV	-	**0.015**	Lexus RX330	Porsche Cayenne
		[2.108]		
CONS. CONF. x Large CUV	-	**0.020**	Chrysler Pacifica	Honda Pilot
		[2.274]		
CONS. CONF. x Middle CUV	-	0.012	Ford Escape	Hyundai Santa Fe
		[1.524]		
CONS. CONF. x Small CUV	-	0.005	Mitsub. Outlander	Toyota RAV4
		[0.623]		
CONS. CONF. x Large Luxury SUV	-	**0.030**	Cadillac Escalade	Range Rover
		[2.319]		
CONS. CONF. x Middle Luxury SUV	-	**0.016**	Land Rover Discovery	Lexus GX470
		[1.854]		

CONS. CONF. x Large SUV	-	**0.017**	Chevrolet Tahoe	Chevy Suburban
		[1.953]		
CONS. CONF. x Middle SUV	-	**0.015**	Land Rover Freelander	Nissan Xterra
		[1.930]		
CONS. CONF. x Small SUV	-	-0.004	Chevrolet Tracker	Jeep Wrangler
		[-0.531]		
Elasticities				
Min	-5.0	-7.3		
Mean	-3.9	-6.0		
Max	-2.5	-3.7		

Coefficients in bold denote significance at 5% level. T-stats in brackets. All specifications include time, country of origin and brand fixed effects. Specification I also includes segment fixed effects.

Table 5. Implied elasticities and price cost margins for selected models using demand estimates from Table 4.

			Specification I		Specification II	
Brand	Market Segment	Model	Elasticity	PCM	Elasticity	PCM
Audi	Lower Luxury	Audi A3	-3.656	0.274	-5.687	0.176
Audi	Lower Luxury	Audi A4	-3.861	0.259	-6.074	0.165
Audi	Middle Luxury	Audi A6	-4.406	0.227	-7.282	0.137
Audi	Upper Luxury	Audi A8	-4.098	0.244	-5.437	0.184
BMW	Lower Luxury	BMW 3 Series	-4.021	0.249	-6.402	0.156
BMW	Middle Luxury	BMW 5 Series	-4.374	0.229	-7.214	0.139
BMW	Luxury Specialty	BMW 6 Series	-4.039	0.248	-5.004	0.200
BMW	Upper Luxury	BMW 7 Series	-4.021	0.249	-4.981	0.201
BMW	Middle Luxury CUV	BMW X3	-4.298	0.233	-7.000	0.143
BMW	Middle Luxury CUV	BMW X5	-4.389	0.228	-7.243	0.138
Porsche	Luxury Sport	Boxster	-4.417	0.226	-7.303	0.137
Porsche	Middle Luxury CUV	Cayenne	-4.403	0.227	-7.268	0.138
Porsche	Luxury Sport	Porsche 911	-4.043	0.247	-5.069	0.197

Table 6. Hedonic regression elasticity estimates, US car market 1995-2006.

Variables	Estimates
Characteristics	
HP	**0.166**
	[8.67]
Size	0.028
	[0.88]
Transmission	0.000
	[0.56]
Exchange rates	
USD/EUR	**0.146**
	[3.10]
USD/JPY	**0.116**
	[1.99]
Fixed-effects	
Model	Yes

The table reports elasticities and associated t-statistics for the hedonic regression of real prices on product characteristics, real exchange rates and model fixed-effects. Parameters in bold are significant at the 5% significance level.

Table 7. Univariate processes for exchange rates and consumer confidence, Jan 1973-July 2006 bimonthly data.

	usd/eur	Consumer confidence	usd/jpy
Estimation	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)
C	0.0003	**1.5170**	0.0004
	[0.09]	[2.70]	[0.11]
κ	0.0004	**2.0786**	0.0011
	[0.80]	[2.84]	[0.50]
α_1 "GARCH"	**0.7392**	**0.5033**	0.5263
	[2.40]	[2.94]	[0.62]
α_2 "ARCH"	0.0960	**0.4531**	0.0549
	[1.09]	[2.54]	[0.68]
γ "Leverage"		**-0.3759**	
		[-3.26]	
Degrees of freedom	200	18.17	16.37
Log-likelihood	324.1647	-712.1135	309.1884

Regressions run on bimonthly data 1973:1 to 1996:6. T-stats in brackets. Coefficients in bold are significant at the 5% level.

Table 8. Distribution of cash flows (in million euro) 3 years ahead from US sales for BMW and Porsche under different scenarios.

Variable	Mean	SD	Min	p1	p5	p10	p50	p90	p95	p99	Max
BMW											
Current production (X3,X5,X6,Z4 in US)	3703.16	1746.01	-545.32	-9.38	850.93	1515.48	3701.28	5699.56	6676.24	8307.92	12124.23
All in EU	3670.05	2093.76	-1465.8	-807.68	222.93	1059.98	3677.69	6055.46	7278.86	9030.07	13793.51
X6 and Z4 in US, rest in EU	3673.91	2056.24	-1358.6	-715.07	292.43	1104.19	3680.33	6016.13	7225.43	8938.13	13610.44
3-7 series in US, rest in EU	3795.63	755.30	2026.37	2240.42	2626.38	2886.78	3768.88	4665.56	5034.58	6284.16	7399.03
All in US	3800.30	710.14	2161.42	2382.69	2645.43	2925.40	3773.12	4641.49	4972.56	5912.23	7244.49
All in EU, expected profits sold forward	3670.05	192.56	3307.70	3329.76	3412.50	3466.17	3643.00	3891.40	3983.86	4353.40	4797.23
All in US, expected profits sold forward	3800.23	188.28	3439.84	3465.45	3544.67	3598.88	3769.34	4027.00	4123.49	4470.06	4728.37
Production flexible between EU and US	4264.78	1487.28	2161.41	2382.69	2645.43	2925.40	3781.31	6055.46	7278.86	9030.07	13793.51
Porsche											
All in EU	120.33	209.74	-427.66	-369.43	-201.46	-136.46	122.44	365.29	457.93	665.59	1160.40
Boxster in US, rest in EU	123.25	181.06	-346.48	-294.51	-155.83	-97.38	124.85	335.47	415.67	594.33	1021.55
Cayenne in US, rest in EU	126.51	144.21	-255.74	-221.03	-92.66	-46.30	128.05	289.62	356.57	514.82	846.18
911 in US, rest in EU	129.57	119.75	-171.06	-130.40	-65.05	-18.33	131.05	271.62	326.55	441.43	724.79
911 and Cayenne in US, Boxster EU	135.75	54.43	.85	18.00	49.18	69.87	133.96	201.60	225.59	285.87	410.57
911 and Boxster in US, Cayenne EU	132.49	91.28	-89.88	-59.79	-16.70	16.66	131.36	241.79	284.80	370.17	585.94
All in US	138.67	26.86	82.03	87.23	96.56	105.58	136.61	169.19	187.72	215.42	271.72
All in EU, expected profits sold forward	120.33	19.32	53.93	57.78	87.42	100.16	121.43	138.56	151.46	175.07	201.72
All in US, expected profits sold forward	138.67	10.69	111.52	114.25	120.69	125.02	138.20	152.79	156.07	162.12	164.39
Production flexible between EU and US	198.56	133.93	82.03	87.23	96.59	105.58	141.61	365.29	457.94	665.59	1160.40

The simulations use 200 values of real usd/eur, usd/jpy and consumer confidence as described in the text. The set of models is the same as 2006. Financial hedge constructed such that the entire expected inflow in US dollars is sold forward.

Table 9. The relation between cash flows from US sales and the dollar/euro exchange rate for BMW and Porsche (in million euros).

	(1) BMW: Current production locations	(2) BMW: All production in US	(3) BMW: All production in EU + financial hedge	(4) Porsche: All production in EU	(5) Porsche: All production in US	(6) Porsche: All production in EU + financial hedge
usd/eur	**-25,236.320**	**-8,612.512**	-405.934	**-2,425.065**	**-322.504**	18.372
	[-40.21]	[-20.04]	[-1.02]	[-36.15]	[-13.84]	[0.46]
$(usd/eur)^2$	**6,136.601**	**2,138.887**	164.519	**576.605**	**81.769**	-11.078
	[27.45]	[13.97]	[1.16]	[24.13]	[9.85]	[-0.78]
Adjusted R-squared	0.98	0.91	0.00	0.98	0.83	0.02

Regression run on simulated data. T-stats in brackets. Coefficients in bold significant at 5% level. The simulations use 200 values of usd/eur. The set of models is the same as 2006. Expected profits 3 years ahead. Financial hedge constructed such that the entire expected inflow in US dollars is sold forward.

Table 10. Net present value of cash flows under different production scenarios. Summary statistics over each of 200 simulated paths of exchange rates and consumer confidence.

Scenario (in EU unless stated)	Mean	SD	Min	p1	p5	p10	p50	p90	p95	p99	Max
BMW current production	66855.73	33035.98	-8757.34	-868.53	12832.64	27285.23	65230.56	107530.5	120723.8	146332.4	187041.5
BMW all in EU	66030.74	39677.0	-25389.7	-15891.3	1834.71	18491.26	64042.04	114141.8	131106.6	161588	210517.3
BMW all in US	69363.49	13232.33	40852.35	43184.86	47700.07	53559.51	68370.25	87052.16	91848.57	101463.8	118353.9
BMW flexible between EU and US	79062.57	27194.84	40852.35	43184.86	47700.07	53559.51	69520.16	114834.9	131106.6	161609.1	210517.3
Porsche current all in EU	1897.94	3728.70	-7475.31	-6652.55	-4079.24	-2452.23	1756.18	6442.18	7934.54	11078.23	15948.99
Porsche Cayenne in US	2044.99	2532.16	-4514.81	-3994.55	-1952.53	-839.8	1956.57	5286.83	6219.31	8331.30	11729.64
Porsche all in US	2344.86	464.34	1445.76	1474.16	1615.62	1751.25	2310.67	3001.04	3162.45	3571.10	4138.73
Porsche flexible between EU and US	3509.35	2246.67	1445.76	1474.16	1615.62	1767.92	2437.59	6518.42	7934.54	11081.14	15948.99

The table reports profits for simulations using 200 simulated paths of real usd/eur, usd/jpy and consumer confidence as described in the text. The set of models is the same as 2006. Financial hedge constructed such that the entire expected inflow in US dollars is sold forward.

Appendix (not for publication) Graphs of time series of consumer confidence and real exchange rates, Jan 1973-July 2006.

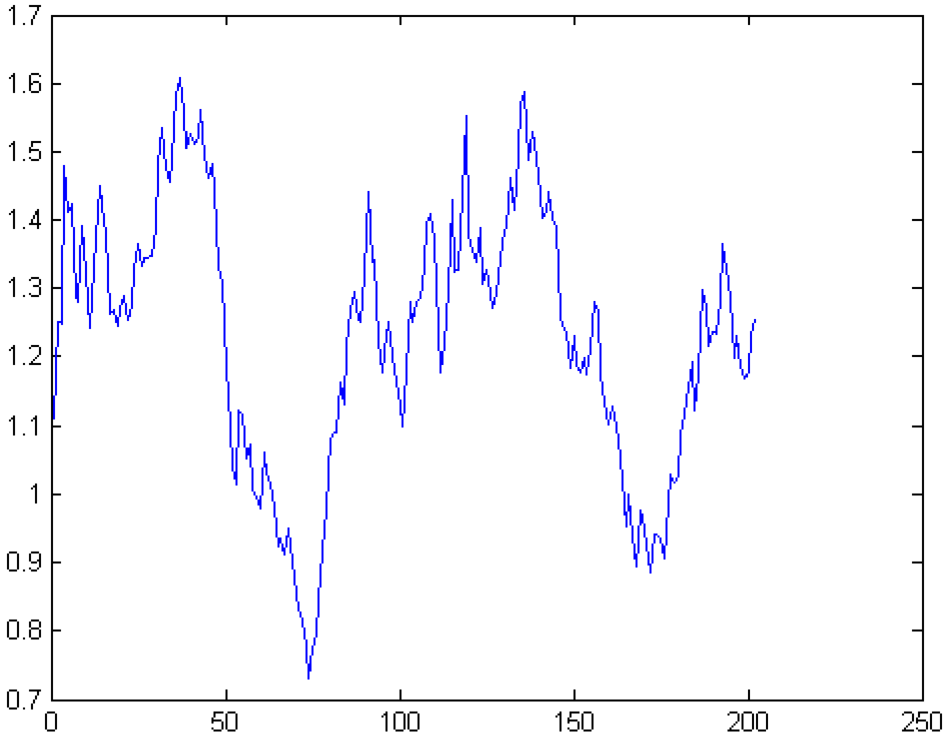

Figure A1, Real usd/eur exchange rate

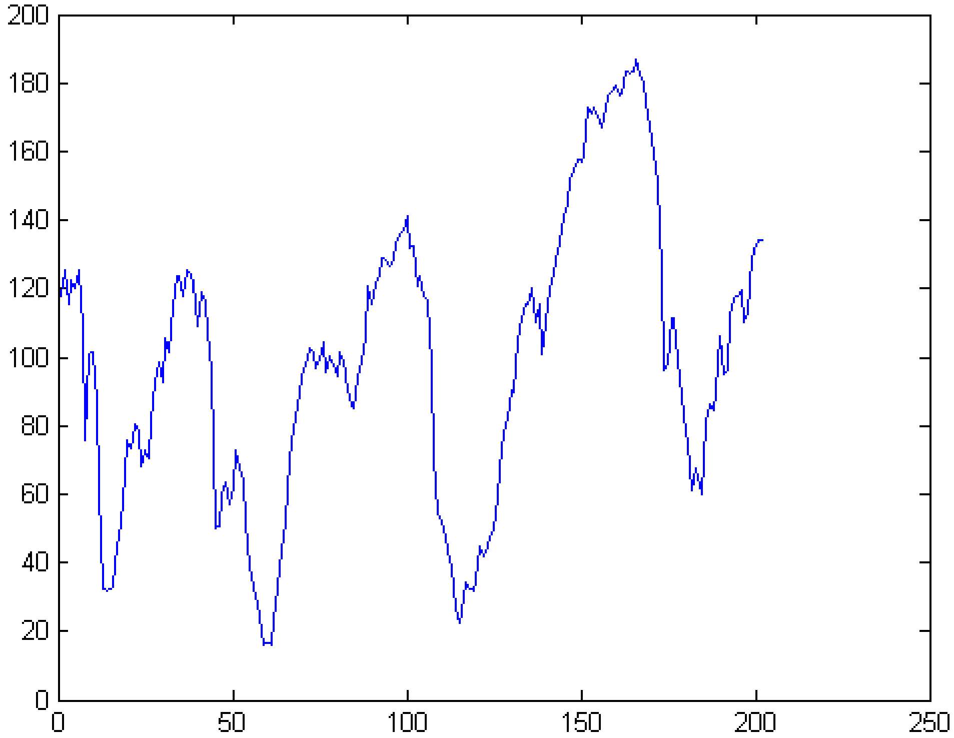

Figure A2. Consumer confidence.

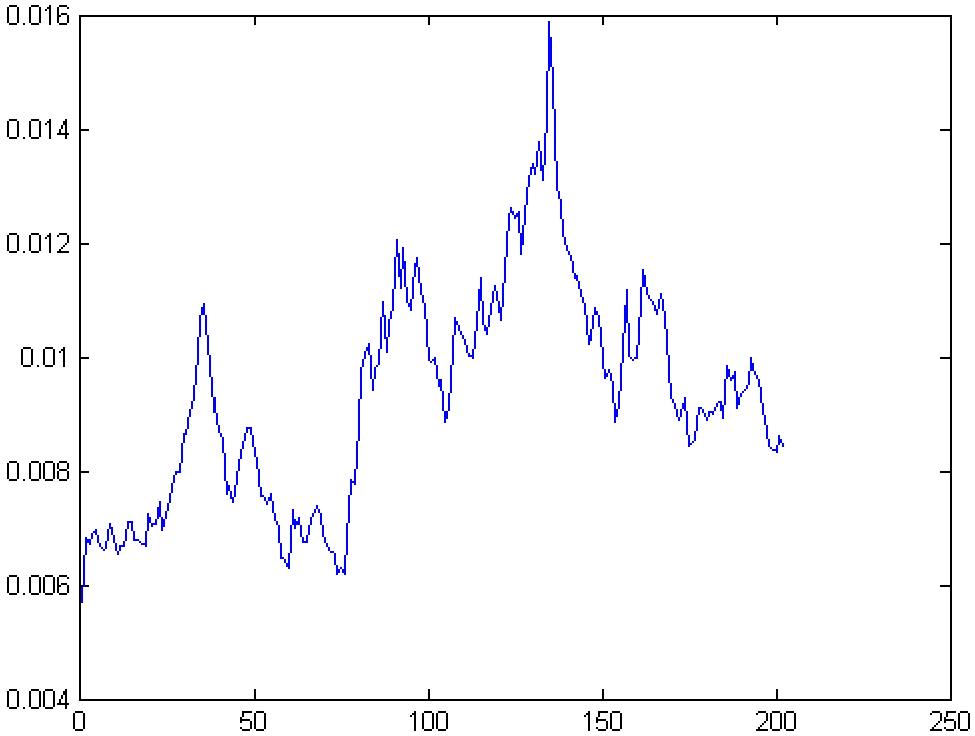

Figure A3, Real usd/jpy exchange rate.

Table A1. Descriptive statistics on real exchange rates and consumer confidence January 1973-July 2006.

	$Ln(usd/eur)_t - Ln(usd/eur)_{t-1}$	$Ln(usd/jpy)_t - Ln(usd/jpy)_{t-1}$	$Cons.Conf._t - Cons.Conf._{t-1}$
mean	.0036804	.0048591	.0810945
Sd	.0483109	.0513835	9.582596
skewness	.1684724	.3807809	-1.181214
kurtosis	2.985719	3.213163	6.375787