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Microeconomic evidence on demand-side real rigidity and implications for monetary non-neutrality

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Microeconomic evidence on demand-side real rigidity and implications for monetary non-neutrality*

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Preliminary.

Abstract

To model the observed slow response of aggregate real variables to nominal shocks, macroeconomic models augment nominal rigidities with real rigidities. One popular way of modelling such a real rigidity is to assume a non-constant demand elasticity. While there has been conducted ample empirical work on the degree and importance of nominal rigidities, there exists very little direct evidence on real rigidities so far. By using a unique, very rich data set on micro prices, quantities bought and consumer characteristics we provide comprehensive new evidence on the degree of real rigidities across several European goods markets. We find that consumer goods markets are characterized by non-constant demand elasticities. However, the data suggests that super-elasticities are much smaller than what is usually assumed in macroeconomic models. We calibrate a menu-cost model augmented with demand-side real rigidity and find that this type of real rigidity can, at most, explain 3% of the monetary non-neutrality observed in the data.

JEL classification: E30, E31, E50, D12, C3

Keywords: Demand curve, price elasticity, super-elasticity, price-setting, monetary non-neutrality.

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1 Introduction

Empirical studies employing macro data generally come to the conclusion that aggregate nominal shocks have relatively large and persistent real effects.¹ To explain this sizable degree of monetary non-neutrality most state-of-the-art macro models assume some form of nominal rigidity, most often in the form of stickiness in goods prices. To match the empirically observed patterns of the response of real variables to nominal shocks a considerable degree of nominal rigidity would be required (Maćkowiak and Smets, 2009).

However, there is now broad-based evidence that prices at the micro level change quite frequently (Bils and Klenow, 2004; Nakamura and Steinsson, 2008; Dhyne et al., 2005) and that nominal price rigidity alone cannot explain the large real effects of monetary policy. Nakamura and Steinsson (2010), for example, show that a menu-cost model with only nominal rigidity calibrated to the observed frequency of price adjustment explains only about 5% of the business cycle.

Taken together, the micro-macro disconnect suggests that multiplier effects, which amplify the effect of nominal rigidity at the micro level and increase persistence of aggregate variables, might be important. One way of introducing such a multiplier effect is the assumption of some form of real rigidity (Ball and Romer, 1990). Because real rigidities slow down the response of the desired price to a shock, the micro price flexibility and the macro price rigidity can be reconciled.

There are two classes of real rigidities (Klenow and Willis, 2006). One is the class of supply-side real rigidities, which include real-wage rigidities (as used, e.g., by Blanchard and Gali (2007)), firm-specific inputs (as used, e.g., in Gertler and Leahy (2008) or Altig et al. (2011)) or the use of intermediate inputs as proposed by Basu (1995) and employed by Nakamura and Steinsson (2010). The other class is demand-side real rigidities, which relax the assumption of constant-elasticity demand curve a la Dixit and Stiglitz (1977). This concept was introduced into the macro literature by Kimball (1995), examples for the application of such so-called Kimball-type demand curves include Eichenbaum and Fisher (2005), Dotsey and King (2005), or Gopinath and Itskhoki (2010), amongst others. One reason for the

¹See Christiano et al. (1999) for an overview of this literature.

popularity of the demand-side approach is that it generates an almost arbitrary amount of persistence, if the parameters governing real rigidities are chosen appropriately (Klenow and Willis, 2006).

If firms face demand curves with a non-constant elasticity of substitution, the response of prices to shocks is slowed down. The basic mechanism is that consumers demand relatively few goods with high relative prices but do not excessively demand goods with low relative prices (Klenow and Willis, 2006). That is, the price elasticity is a positive function of the relative price and profits decline more steeply around the maximizing relative price of one, compared to the case of a constant-elasticity of demand. This makes firms' profits more sensitive to prices of competitors and thereby increases strategic complementarity in price-setting.

How large are demand-side real rigidities assumed in macroeconomic models? The extent of real rigidity is measured by the super-elasticity, which is the price elasticity of the price elasticity (Klenow and Willis, 2006). Models embracing Kimball-type preferences have used a broad range of values for the calibration of the super-elasticity parameter. Chari et al. (2000) point out that the preference specifications employed by most of these studies imply highly implausible behavior on the side of consumers. To illustrate their argument, Figure 1 plots the demand and profit functions which result from specifications assumed in recent contributions to this literature, nicely summarized in Table 1 in Dossche et al. (2010).

The values for the super-elasticity of demand assumed in most studies imply very strong responses of consumers to even very small changes in relative prices. In all cases but the one of Bergin and Feenstra (2000), an increase in the relative price of only around (or little more than) 10% implies a complete extinction of a firm's sales.

Some indirect empirical evidence on the extent of demand-side real rigidity is provided in Klenow and Willis (2006). They show that demand-side real rigidities, which generate a reasonable amount of aggregate persistence, are generate frequent price adjustments, but

Figure 1: Demand and profit functions for various values of the price elasticity and the curvature of demand as employed in the literature

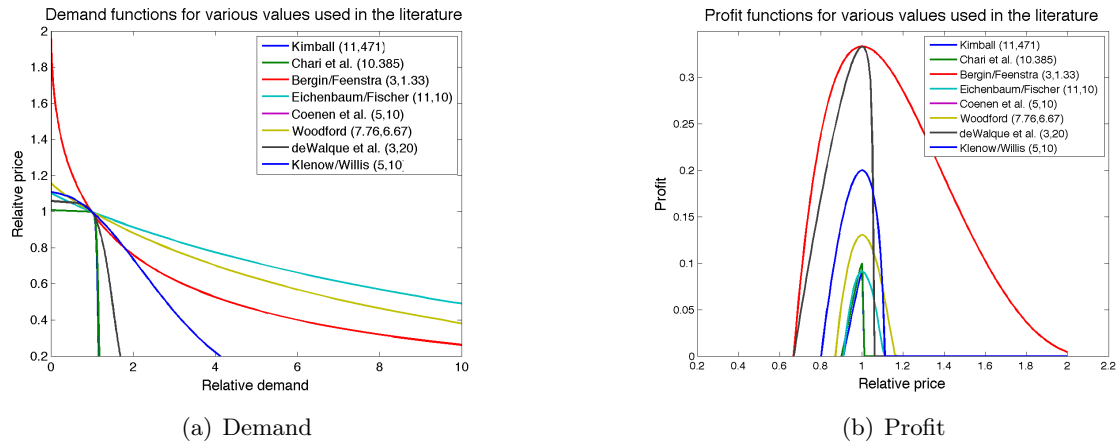


Figure 1 plots the demand functions and the resulting profit functions implied by the values of the elasticities and super-elasticities of demand as employed in the papers referred to in the legend. The representation and functional form of the Kimball aggregator is borrowed from Klenow and Willis (2006). These article include (Kimball, 1995, (Kimball)), (Chari et al., 2000, Chari et al.), (Bergin and Feenstra, 2000, Bergin/Feenstra), (Eichenbaum and Fisher, 2005, Eichenbaum/Fischer), (Coenen et al., 2007, Coenen et al.), (Woodford, 2003, Woodford) and (Klenow and Willis, 2006, Klenow/Willis). The selection of papers is taken from Dossche et al. (2010), who provide an overview of these studies. The number in the brackets after the author name(s) indicate the value of the elasticity and super-elasticity employed by the respective study.

are difficult to reconcile with the large absolute average size of price adjustments.² As a consequence, these authors conclude that demand-side real rigidities are arguably not very large.³

Direct evidence for single products or retailers on non-constant elasticity demand curves can be obtained by estimating demand curves and the curvature of demand. The latter is closely related to the size of the super-elasticity. Using Dominick’s *Finer Foods* data, (Goldberg and Hellerstein, 2013) estimate a super-elasticity for beer of 0.8. (Nakamura and Zerom, 2010) match data for retail and wholesale prices with commodity price data for coffee

²This is because strategic complementarities lead to a larger desire of firms to keep their price close to their competitors prices. If an aggregate shock hits the economy and firms adjust to the shock, they do not fully incorporate the shock in the first price adjustment round due to the joint presence of nominal and real rigidities, which lead to a coordination failure. Instead, firms that adjust take into account the aggregate price level and therefore largely the price of non-adjusters. Over time, more and more firms adjust to the shock and the aggregate price level moves slowly. This also implies that prices of a single firm respond only partially to the aggregate shock and therefore it takes a couple of price adjustments to fully incorporate the aggregate shock. Prices at the micro level then change frequently, but only by small amounts, conditional on adjustment. One should thus observe many small price changes in the data.

³Nakamura and Steinsson (2010) show that this criticism does not apply to their modeling of real rigidities using intermediate input goods.

and estimate a median super-elasticity of demand of 4.6. Using scanner data from six stores of a Belgian retailer, (Dossche et al., 2010) find super-elasticities in the range of 4 for goods with an elasticity of 3 or larger. This is the case for five product categories: smoked salmon, wine, airing cupboards, tap, and toilet soap.

In this paper, we add to this evidence by providing some broader-based evidence on the amount of demand-side real rigidity in the data. To this end, we estimate the price elasticity of demand and the super-elasticity of demand from a rich homescanner dataset for 280 goods categories in three European countries: Belgium, Germany and the Netherlands. The national data providers normally use the data to sell consultancy services to companies in the area of marketing. This implies that the analysis of this dataset is basically intended to serve the same objectives as the ones of our study, i.e. to investigate consumer demand behavior and to inform firms about the demand for their products. One advantage of homescanner data is that we can directly track consumers' shopping behaviour over time and we can control for important consumer characteristics, such as income or age, which should influence the shape and location of demand curves.

We find the median demand elasticity in the range of 3 to 4, in line with the IO literature, but somewhat lower than the demand elasticities that are usually implemented in macroeconomic models.⁴ We furthermore document that there is heterogeneity across goods and households. Nevertheless, 75% of our elasticity estimates, which are allowed to vary over goods categories and households, are below ten. Our estimates of the super-elasticity suggest that it is between 1 to 2, in line with Bergin and Feenstra (2000) and the findings of (Goldberg and Hellerstein, 2013).

We calibrate a menu-cost model augmented with demand-side real rigidity to quantify what our median estimates imply for a macro model. We first calibrate the model with nominal rigidity only and then add the real rigidity with the elasticity and super-elasticity parameters equal to our median estimates. We find that the model with nominal rigidities only generates hardly any monetary non-neutrality, **about x%** of the variance of detrended real output

⁴There are exceptions, which use lower demand elasticities, more in line with our estimates, such as Nakamura and Zerom (2010), or Gopinath and Itskhoki (2010), for example. However, setting the demand elasticity to ten seems to be the prevalent parameter choice in macro models.

can be generated by the model. This is largely because the price changes in our data are quite frequent and large. Adding the real rigidity raises the variance of output, that can be generated by the model, by a **factor of x**. However, the bulk of monetary non-neutrality remains unexplained.

Our results support previous empirical evidence and the criticisms of Chari et al. (2000) or Klenow and Willis (2006): demand-side real rigidities in the data are rather small and are arguably not able to generate a reasonable amount of monetary non-neutrality. Supply-side real rigidities, such as employed in Nakamura and Steinsson (2010), seem a more promising modelling choice.

The rest of this paper is structured as follows: In section 2 we will describe our data set and provide some descriptive statistics on the frequency and size of price changes across the countries and sectors considered in our sample. Section 3 describes the estimation approach which we use to estimate demand curves, section 4 presents the estimation results, section 5 outlines the model and will discuss the obtained quantitative results. Section 6 summarizes and concludes.

2 Data and descriptive statistics

We employ a unique and very rich database on European scanner-price data which, to our best knowledge, has not been employed by the macro literature before. The data is provided by AiMark (Advanced International Marketing Knowledge) which is a non-profit cooperation that promotes research in the area of retail markets and to this end provides data originally compiled by Europanel and its partners Gesellschaft für Konsumforschung (GfK), Kantar Worldpanel and IRI. As will be outlined in more detail below, our data is best comparable to the IRI data used in Coibion et al. (2013) with the major difference that their data set covers U.S. data whereas our data comprises information from three European countries.

2.1 Description of the dataset

For each country in the data set (Belgium, Germany, and the Netherlands), the data providers construct a representative panel of households. Each household in the panel is endowed with a scanning technology which it uses to scan all the products belonging to the categories of *fast-moving costumer goods* it buys at retail outlets including, e.g., all major supermarket chains (such as Rewe or Aldi in Germany or Albert Heijn and C1000 in the Netherlands), drugstores, small corner shops and internet stores. This scanning technology is similar to the one underlying the Nielsen HomeScan database.

For each product bought, the household scans the bar-code which uniquely identifies the product via the Global Trade Item Number (GTIN)⁵ and enters the number and associated price for this product into the homescanner⁶. The data set contains a description of each product and a classification system of the goods into different (more aggregate) product categories.⁷ The household also provides a description of the type of store where it bought the product - including the name and location of the retail chain. The products belong to the categories of *fast-moving costumer goods*, which include (among others) grocery products, home and personal care products, and beverages. In addition to the detailed data on the individual transactions, we also have access to information household characteristics which comprises the location of the household, its income group and age.

Table 1 reports some sample information. As mentioned above, we have available scanner price data for the countries Belgium, Germany, and the Netherlands. The sample period is from 2005 - 2008. The number of households is around 2,000 for Belgium, 12,000 for Germany, and 4,000 for the Netherlands, and we observe more than 2 million individual shopping trips in the data set. The number of available observations is quite large: It ranges

⁵The GTIN-12 code corresponds to the Universal Product Code (UPC) which is used in the U.S. and Canada. In Europe, the GTIN was formerly known as European Article Number (EAN).

⁶In case the product does not have a bar-code, the household enters this information manually.

⁷We constructed a common classification scheme for the products in our data-set for all countries which rests on the one employed by the national data providers. However, the grouping systems of the individual providers can slightly differ across countries. We thus constructed comparable categories of goods by using the classification scheme of Germany as a basis and assigning the categories of the other countries to their German counterpart. The classification was done using both the assistance by country representatives of GfK and the extensive documentation of the different classification schemes, to which we had access at the data providers offices.

from around 2 millions for Belgium to more than 9 millions for Germany. These observations include the purchases of more than 190,000 unique products. The products come from 208 different categories (such as pasta or coffee). To evaluate the representativeness of the data, we calculate a simple measure of inflation as a weighted average of monthly price levels at the category level as in Coibion et al. (2013). We compare the average month-on-month inflation rate in our sample and compare it to the inflation rate in the national CPIs. Even though we do not match inflation exactly, the numbers are not very different, and we observe that they comove with official inflation rates (see Figure B in the Appendix).

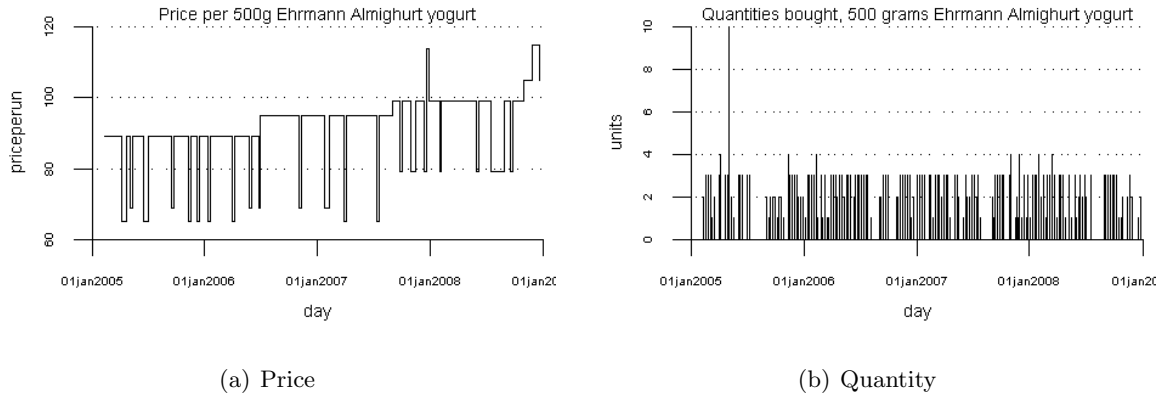
Table 1: *Database - Overview*

Country	Househ.	Products	Categ.	Purch.	Observ.	Infl.	CPI
Belgium	1,746	49,808	71	0.7	2.1	2.1	2.3
Germany	11,631	72,617	98	4.1	9.4	3.1	1.6
Netherlands	4,030	68,909	111	2.3	10.4	0.7	1.5
Total	17,407	191,334	280	7.0	21.8	2.0	1.8

Note: Purchases and observations in 1,000,000. Products is the number of different GTINs, which are included in our estimation sample, categories are the number of categories included in the sample. A purchase occasion is one shopping trip by one consumer to one retailer (identified by the shopping data and the retailer). Inflation refers to a simple measure of inflation calculated in our estimation sample, and CPI is the average month-on-month growth rate of the Harmonized Index of Consumer Prices (HICP) for 2005-2008 (source: Eurostat).

The data structure allows us to track prices and quantities-bought trajectories for all households and products in the sample. To give an example of the data structure, we extract the purchases of one type of product for one household. Here, we choose one household from Germany, which frequently buys strawberry yogurt of the brand Ehrmann at the same retailer. The consumer is 40-45 years old and has an income of 2,250-2,499 EUR. We show the quantity bought and the associated price at a given shopping occasion in Figure 2. The price trajectory shown in Panel a) looks very much like the price trajectories we observe in CPI micro data sets: the reference price changes about one per year, while temporary price cuts, and even increases are not uncommon. We observe that the household usually buys one to three pots of yogurt, while at sales prices, the household sometimes buys four.

Figure 2: *Example of the data structure*



Note: Example: 500 grams *Ehrmann Almighurt* yogurt (strawberry flavour) bought on 168 occasions by one consumer aged 40-45 years, income 2,250-2,499 EUR, Germany.

For the econometric analysis, we first split the data in categories (yogurt, pasta, beer, etc.). This is the level at which we will estimate demand elasticities. We then aggregate the data to brand groups and rank the brands by expenditure share. We use the four top brands and construct a fifth good, which is a composite of all other brands in the category. This fifth good is the outside good in the estimation.

2.2 Descriptive statistics

The frequencies of price changes are comparable to evidence for CPI and PPI micro data for the euro area. We find a median frequency of price changes (fpc) of 15.24 on a monthly basis. Álvarez et al. (2006) report a frequency of 28% for unprocessed food, of 14% for processed food in the CPI, and 12% for non-durable, non-food items in the PPI. Most of the products in our data set fall in one of these non-durable goods categories, which suggests that the mean frequency of 19% and the median frequency of 15% seem reasonable. Excluding sales, we find a median frequency of 13%, suggesting that sales in our data set do not change the frequency of price changes substantially. This might of course be due to the fact that we can identify sales only via a v-shaped sales filter. We do not have a sales flag in the data set. The share of price increases in all price changes ($fraction^{up}$) reported in the evidence collected in Dhyne et al. (2005) is 54%, very close to our median.

Table 2: *Sample statistics on the monthly frequency and size of price changes*

	Mean	Median
Including sales		
fpc	19.06	15.24
$fraction^{up}$	50.93	54.38
$size$	6.38	3.73
$size^{abs}$	18.91	17.47
$size^{up}$	20.66	17.02
$size^{down}$	-15.48	-18.09
Excluding sales		
fpc_{exs}	16.54	13.10
$fraction_{exs}^{up}$	53.38	54.55
$size_{exs}$	6.12	4.27
$size_{exs}^{abs}$	20.98	17.25
$size_{exs}^{up}$	25.14	19.27
$size_{exs}^{down}$	-15.48	-14.56

Note: The figures for the frequency are computed as the percentage of prices which are changed within a given month at a given retailer. The figures for the size correspond to the percentage change of a price conditional on a price change. Sales are identified using a simple V-shaped filter. The superscripts *abs*, *up*, *down* indicate absolute values, price increases and price decreases, respectively.

The average absolute size of price changes conditional on a price change, $size^{abs}$, is 18% in our data, which is larger than the statistics reported in Dhyne et al. (2005). They report an average size of price changes of 15 to 16% for unprocessed food, and of 7 to 8% for processed food for the euro area. One explanation for this result might be that many small price changes are erratic, as shown in Eichenbaum et al. (2014): they find that many small price changes in CPI micro data are due to measurement issues and that the median price change of 10% found in their data, corrected for measurement bias, is roughly 30%, which is more in line with our statistics. In particular, we can clearly identify a product replacement, because any small change in a good requires the use of a new GTIN number.

3 Empirical Method

In this section, we briefly describe the econometric model used. We estimate demand elasticities using a nested multinomial logit model with random coefficients. We use the control function approach developed by Petrin and Train (2010) and applied to estimate demand elasticities by, for example, Gordon et al. (2012) to control for price endogeneity.

3.1 Discrete choice specification

The model consists of two nests. In the upper nest, consumers choose whether or not to buy in a given category c . Conditional on choosing that category, they decide on the brand within the category. For example, a household chooses to buy in the category pasta, and within this category, it chooses to buy a certain brand.

The probability of household i choosing an alternative within category c is the product of the conditional probability of choosing a brand j within the category c $P_{ij|c_i}$, given the category c is chosen, and the marginal probability of choosing category c , P_{ic} ,

$$P_{ic} = P_{ij|c_i} P_{ic}.$$

It is convenient to decompose the probabilities, because the marginal and the conditional probabilities take the form of logits (Train, 2009),

$$\begin{aligned} P_{ic} &= \frac{e^{W_{ic} + \lambda_c IncVal_{ic}}}{\sum_C e^{W_{ic} + \lambda_c IncVal_{ic}}} \\ P_{ij|c_i} &= \frac{e^{Y_{ij}/\lambda_c}}{\sum_J e^{Y_{ij}/\lambda_c}}, \end{aligned}$$

where $IncVal_{ic} = \ln \sum_J e^{Y_{ij}/\lambda_c}$ is the inclusive value, which is the expected utility household i receives from choice alternatives in category c . λ_c is the log-sum coefficient, and Y_{ij} are the explanatory variables, that vary over alternatives within the category c . W_{ic} is a vector of variables that describe category c , and does not vary over j .

The conditional utility of household i purchasing brand j in category c at shopping occasion t in the *lower* nest is

$$U_{ijt|c_{it}=1} = \beta_{ij} - \alpha_i p_{ijt} + \delta x_{ijt} + \varepsilon_{ijt}. \quad (1)$$

where β_j is a vector of brand-specific effects, p_{jt} is the price of brand j , and x_{ijt} includes other controls. We let α and β vary over households, and model heterogeneity by assuming normal mixing distributions for β_j and a lognormal distribution for α . The error term ε_{ijt} is distributed iid extreme value and the outside option of buying the other good is normalized

to ε_{i5t} .⁸

Utility from purchasing in category c in the upper nest is given by

$$u_{ict} = \rho w_{ict} + \Psi IncV_{ict} + \nu_{ict}. \quad (2)$$

where w_{ict} counts the number of weeks since the household last purchased in the category and $IncValue_{ict}$ is the inclusive value from (1), $\ln \sum_C \hat{\beta}_{ij} - \hat{\alpha}_i p_{jt} + \hat{\gamma}_i loyal_{ijt} + \hat{\delta} x_{it}$. The parameter ρ describes a need to buy some products regularly, while Ψ captures the effect of utility household i obtains from consuming in category c . The error term ν_{ict} is distributed iid logistic.

We use the control function approach to control for endogeneity in prices (Petrin and Train, 2010).

$$p_{jt} = \theta'_j Z_{jt} + \mu_{jt}, \quad (3)$$

where Z_{jt} is the mean price of the same brand in other NUTS1 regions within the same country (Hausman, 1996; Nevo, 2001).

Suppose the error term is decomposed into $\varepsilon_{ijt} = \underbrace{E(\varepsilon_{ijt}|\mu_{jt})}_{=\lambda\mu} + \tilde{\varepsilon}_{ijt}$, where $\tilde{\varepsilon}_{ijt}$ is by construction not correlated with μ_{jt} . Suppose $\varepsilon_{ijt} = \varepsilon_{ijt}^1 + \varepsilon_{ijt}^2$, where ε_{ijt}^1 is correlated with price. ε_{ijt}^1 and μ_{jt} are jointly normal and ε_{ijt}^2 , which is uncorrelated with price, is iid extreme value. Then $\varepsilon_{ijt}^1 = E(\varepsilon_{ijt}^1|\mu_{jt}) + \tilde{\varepsilon}_{ijt}^1$. The conditional distribution of ε_{ijt}^2 is same as unconditional, because it is independent.

Utility then becomes

$$U_{ijt|y_{it}=1} = \beta_{ij} - \alpha_{ij} p_{jt} + \gamma_i loyal_{ijt} + \delta x_{ijt} + \lambda \mu_{jt} + \tilde{\varepsilon}_{ijt}^1 + \varepsilon_{ijt}^2, \quad (4)$$

where $\tilde{\varepsilon}_{ijt}^1 = \sigma \eta_{ijt}$ is normal with zero mean and constant variance and η_{ijt} is standard normal.

To estimate the model, we apply a three-step approach. First, we estimate control function and retain residual $\hat{\mu}_{jt}$. Second, we estimate the mixed logit for the lower nest with $\hat{\mu}_{jt}$ and

⁸We index the shopping occasion by t , which does not refer to a well-defined constant frequency, but to the date at which household i goes shopping and buys in category c .

income and age (interacted with brand-specific dummies), brand-region fixed effects, a dummy for a sale, and a proxy for loyalty as explanatory variables summarized in x_{ijt} in equation(1).⁹ Third, we estimate the logit for the *upper* nest using the inclusive value calculated from the results obtained in the second step. We then calculate the elasticities and super-elasticities for each household within a category.

3.2 Demand elasticities and super-elasticities

Demand elasticities can be derived from the nested mixed logit model. We derive the elasticity of the upper and the lower nest in the Appendix. The elasticity for the upper nest is given by

$$\theta_u = \alpha_i P_{ij|c_i} (1 - P_{ic}) p_{ijt} \quad (5)$$

The elasticity for the lower nest is

$$\theta_l = \frac{\alpha_i}{\Psi} p_{ijt} (1 - P_{ij|c_i=1}). \quad (6)$$

Because the probability can be written as the product of the marginal and the conditional probability, the total elasticity is just the sum of the upper and the lower elasticities $\theta = \theta_u + \theta_l$.

One advantage of the mixed logit model is that the price elasticity depends on the price and therefore allows us to derive super-elasticities directly from the estimates, without having to assume a quadratic functional form (Hellerstein, 2008). This is because the model allows for heterogeneity in consumers price sensitivity, which contribute to the curvature of demand. It nests the CES with a super-elasticity of zero as a special case (Goldberg and Hellerstein, 2013).

⁹Region is defined by the first level NUTS (Nomenclature of Territorial Units for Statistics) regions, which reference the administrative divisions of European countries for statistical purposes. For Belgium, these are the three regions Brussels Capital Region, Flemish Region and Walloon Region. For Germany, these are the 16 German Länder. For the Netherlands, there are four regions: north-, east-, west- and south Netherlands. Loyalty is proxied by a count variable, which gives the number of purchases of the same brand in the same category in the past.

The super-elasticity of the upper nest is

$$\epsilon_u = 1 + \theta_l - \Psi \alpha_i P_{ij|c_i} P_{ic} p_{ij} \quad (7)$$

and for the lower nest

$$\epsilon_l = 1 - \frac{\alpha_i}{\Psi} p_{ij} P_{ij|c_i=1} \quad (8)$$

The total super-elasticity is the sum of the upper and the lower super-elasticities $\epsilon = \epsilon_u + \epsilon_l$.

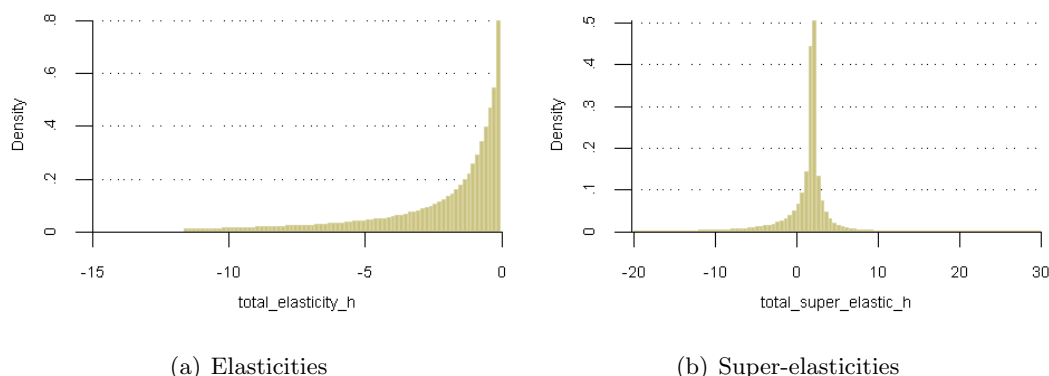
4 Empirical results

The distributions of all estimates of the elasticity and super-elasticity for each category and household are shown in the upper Panels in Figure 3. The distribution of estimated elasticities is highly skewed, which is largely due to the assumption of a lognormally distributed price coefficient (Panel a)). Furthermore, the distribution is wide, suggesting that there is a substantial heterogeneity in price elasticities across categories and households. This does not carry over to the estimates of the super-elasticity, which we do not restrict to be strictly positive or negative. Here, we find a tighter distribution, showing that most estimates are in the range between zero and five (Panel b)). There are only a few estimates with a value of 10 or larger, suggesting that the assumptions often used in many macroeconomic models reviewed in the introduction seem rather unlikely.

How large should the parameters for price elasticities and super-elasticities be in macroeconomic models? In the median, the price elasticity is rather small, at a value of 3.85 (Table 3). The mean and weighted mean are a bit lower. Many macroeconomic models assume a price elasticity of 10. This seems a relatively large value, given that more than 80% of our estimates are below 10.

Super-elasticities are clearly below ten. The median estimate for the super-elasticities is 1.39. This is close to the estimates for the beer market found in Goldberg and Hellerstein (2013), and slightly lower than the estimates for the coffee market in Nakamura and Zerom

Figure 3: *Distribution of elasticities and super-elasticities*



Notes: The distributions are shown for a trimmed sample, where we cut off the upper and lower 5% of the estimates, both for elasticities and super-elasticities. This is because we estimate a very large number of coefficients, and there are a few outliers, which would otherwise contaminate estimates of the mean.

Table 3: *Descriptive Statistics Estimates*

	Mean	Median	W. mean
Demand elasticity			
Total elasticity	1.91	3.58	2.08
Upper nest	0.19	0.13	0.20
Lower nest	1.65	2.99	1.84
Super-elasticity			
Total super-elasticity	1.65	1.39	1.47
Upper nest	-0.55	0.10	-0.71
Lower nest	2.06	1.31	2.08

Notes: The first two columns show the mean/median values of all estimated elasticities/super-elasticities. The third column shows weighted means (by expenditure share).

(2010) or for the European retailer in Dossche et al. (2010). 90% of our estimates are below a value of 5. Taking these pieces of evidence together, the data does not support assumptions of a super-elasticity parameter in the range of ten or even larger.

5 A menu-cost model with Kimball-type preferences

5.1 Model setup

The baseline specification of our theoretical model closely follows Nakamura and Steinsson (2010). As in their case, our economy is inhabited by a representative household, a continuum

of firms and a monetary authority that controls the evolution of nominal GDP. The household supplies labor to firms, decides how to allocate income between aggregate consumption and saving and determines the amount it wants to consume of each good available in the economy. Firms produce goods using labor (subject to idiosyncratic changes in labor productivity) and set prices to maximize profits. Changing prices is subject to a cost. The monetary authority determines the growth rate of nominal GDP by injecting money into the economy. Deviating from Nakamura and Steinsson (2010) we incorporate real rigidities into the model in the form of a Kimball-type preference structure (which embeds the standard CES case used by Nakamura and Steinsson (2010) as a special case) rather than a roundabout production setup.

5.1.1 Households

The representative household maximizes expected discounted life-time utility, which depends positively upon aggregate consumption, C_t , and negatively upon labor supply, L_t , and is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{1}{1-\gamma} C_t^{1-\gamma} - \frac{\omega}{1+\psi} L_t^{1+\psi} \right], \quad (9)$$

where E_0 denotes the rational expectations operator conditional on information available to the households at date 0. β (with $0 < \beta < 1$) represents the subjective discount factor. The period utility function is assumed to be additive separable in consumption and labor supply. The parameter γ governs the degree of relative risk aversion while ψ determines the convexity of the dis-utility of labor. ω is a weighting term determining the relative extent of the dis-utility of labor. The composite consumption good, C_t , is generated via a Kimball aggregator as specified in equation (13) below.

Households choose composite consumption and labor to maximize (9) subject to the following budget constraint

$$P_t C_t + E_t [D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \Pi_t(z) dz \quad t = 0, 1, \dots \quad (10)$$

This equation requires that aggregate consumption expenditure C_t and investment in financial assets $D_{t,t+1} B_{t+1}$ cannot be larger than available resources consisting of the stock of financial

assets carried over from the previous period B_t , wage income $W_t L_t$ and profits distributed by firms $\int_0^1 \Pi_t(z) dz$. $D_{t,t+1}$ is the period- t price of a financial assets that pays off one unit in period $t + 1$.

The first-order conditions for the household's optimization problem are given by:

$$D_{t,T} = \beta^{T-t} \left(\frac{C_T}{C_t} \right)^{-\gamma} \frac{P_t}{P_T} \quad (11)$$

$$\frac{W_t}{P_t} = \omega L_t^\psi C_t^\gamma. \quad (12)$$

Equation (11) represents the standard inter-temporal Euler equation linking consumption growth to the real interest rate while equation (12) states that labor supply adjusts such that the real wage is equal to the marginal (dis)-utility of labor.

The composite consumption good, C_t , is created by the costless aggregation of a continuum of differentiated goods, $c_t(z)$, which are supplied by monopolistic firms. Following Kimball (1995) and Klenow and Willis (2006), we implicitly define the composite consumption good, C_t , using an aggregator of the form

$$\int_0^1 \Upsilon \left(\frac{c(z)}{C} \right) dz = 1, \quad (13)$$

where the function $\Upsilon(\cdot)$ satisfies the conditions $\Upsilon(1) = 1$, $\Upsilon'(\cdot) > 0$ and $\Upsilon''(\cdot) < 0$ and where time indices are dropped for notational ease. In our simulations below, we report the outcomes of two specifications for the aggregation function $\Upsilon(\cdot)$. In the baseline case, we specify the function $\Upsilon(\cdot)$ to be given by

$$\Upsilon \left(\frac{c(z)}{C} \right) = \left(\frac{c(z)}{C} \right)^{\frac{\bar{\theta}-1}{\bar{\theta}}} \quad (14)$$

which amounts to assume standard CES preferences as proposed by Dixit and Stiglitz (1977). We denote this as the CES case below. In this specification, $\bar{\theta}$ denotes the (constant) elasticity of substitution.

Alternatively, we employ the Kimball aggregator function proposed by Klenow and Willis (2006) and used, among others, by Gopinath and Itskhoki (2010). We denote this as the

NON-CES case below. In this case, the aggregation function $\Upsilon(\cdot)$ is given by

$$\Upsilon(x) = 1 + (\bar{\theta} - 1) \exp\left(\frac{1}{\bar{\epsilon}}\right) \bar{\epsilon}^{\left(\frac{\bar{\theta}}{\bar{\epsilon}} - 1\right)} \left[\Gamma\left(\frac{\bar{\theta}}{\bar{\epsilon}}, \frac{1}{\bar{\epsilon}}\right) - \Gamma\left(\frac{\bar{\theta}}{\bar{\epsilon}}, \frac{x^{\frac{\bar{\epsilon}}{\bar{\theta}}}}{\bar{\epsilon}}\right) \right], \quad (15)$$

with $x = \frac{c(z)}{C}$ and $\Gamma(u, z)$ denoting the incomplete gamma function.

Given an optimal decision about overall consumption expenditure, C , household choose the optimal amount of each good $c(z)$ by minimizing the overall cost of purchasing C . For the CES case, the optimal demand for good z is given by

$$c(z) = \left(\frac{p(z)}{P}\right)^{-\bar{\theta}} C, \quad (16)$$

showing that the demand for good z depends positively upon overall consumption C and negatively upon the price of good z relative to the overall price level P . $\bar{\theta}$ is a parameter of the aggregation function Υ and can be interpreted as the elasticity of substitution between good z and some other good z' .

When employing the Kimball aggregator function, the demand function for good z is given by

$$c(z) = \left[1 - \bar{\epsilon} \ln\left(\frac{p(z)}{P}\right) \right]^{\frac{\bar{\theta}}{\bar{\epsilon}}} C, \quad (17)$$

where again the demand for good z depends positively upon overall consumption demand C and negatively upon the relative price of good z . $\bar{\theta}$ and $\bar{\epsilon}$ are parameters of the aggregation function Υ determining the steady-state size and behavior of the elasticity of demand. For $\bar{\epsilon} = 0$ this demand function reduces to the CES case.¹⁰

The major difference between the setups of Dixit and Stiglitz (1977) and Klenow and Willis (2006) consists of their differing implications for the behavior of the price elasticity of demand. To illustrate these differences we first define the price elasticity of demand, $\theta(p)$, as

$$\theta(p) = \frac{\partial \ln c(z)}{\partial \ln p} \quad (18)$$

¹⁰In deriving equation (17), we made use of an approximation result obtained by Gopinath and Itskhoki (2010, Appendix).

and the super-elasticity of demand, $\epsilon(p)$, as

$$\epsilon(p) = \frac{\partial \ln \theta(p)}{\partial \ln p}, \quad (19)$$

where we allow both the elasticity and the super-elasticity of demand to be non-constant and depending on the (relative) price of a good.¹¹

In the CES case, the (steady-state value of the) elasticity of demand is $-\bar{\theta}$ and the super-elasticity is 0, i.e., the price elasticity is constant for all values of the relative price of good z . For the NON-CES case, the price elasticity of demand is given by

$$\theta^{NON-CES} = -\frac{\bar{\theta}}{1 - \bar{\epsilon} \ln \left(\frac{p(z)}{P} \right)}, \quad (20)$$

whereas the super-elasticity of demand is given by

$$\epsilon^{NON-CES} = \frac{\bar{\epsilon}}{1 - \bar{\epsilon} \ln \left(\frac{p(z)}{P} \right)}. \quad (21)$$

In the steady state where $\frac{p(z)}{P} = 1$ holds we get:

$$(\theta^*)^{NON-CES} = \bar{\theta} \text{ and } (\epsilon^*)^{NON-CES} = \bar{\epsilon}. \quad (22)$$

These equations show that for $\bar{\epsilon} > 0$ the elasticity of demand in the NON-CES case increases in the relative price of good z and will be larger than for the CES case. This difference in the behavior of the elasticity of demand has profound implications for the response of price setters to macroeconomic shocks (such as a change in nominal aggregate demand induced by the monetary authority) as documented in the simulation exercises below.

¹¹Dossche et al. (2010) note that different authors use slightly different measures for the super-elasticity (curvature) of demand. Our notation follows that of these authors which is also employed, e.g., by Gopinath and Itskhoki (2010).

5.1.2 Firms

Monopolistically competitive firms denoted by z produce differentiated products via the production function

$$y_t(z) = A_t(z)L_t(z), \quad (23)$$

where $A_t(z)$ denotes firm-specific productivity and $L_t(z)$ is the amount of labor employed by firm z . We assume that firm-specific productivity follows a first order auto-regressive process of the form

$$\ln A_t(z) = \rho \ln A_{t-1}(z) + \epsilon_t(z), \quad \epsilon_t(z) \sim N(0, \sigma_{\epsilon,t}^2). \quad (24)$$

Firms aim to maximize the discounted value of expected profits,

$$E_0 \sum_{t=0}^{\infty} D_{0,t} \Pi_t(z), \quad (25)$$

where profits $\Pi_t(z)$ are given by

$$\Pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - KW_t I_t(z) - P_t U. \quad (26)$$

$y_t(z)$ denotes firm's z sales which are equal to $c_t(z)$ as discussed above. $p_t(z)y_t(z)$ represent firm's z revenue, $W_t L_t(z)$ are labor cost, $KW_t I_t(z)$ are costs ("menu costs") of changing prices ($I_t(z)$ is an indicator function taking the value 1 if the firm changes its price in period t and 0 otherwise). $P_t U$ denote fixed nominal costs of production. Based on our empirical results for the estimated elasticities we follow Nakamura and Steinsson (2010) and introduce this term to justify the co-existence of empirically estimated large markups with observed relatively small firm profits in the national accounts.

5.1.3 Monetary policy

Following Nakamura and Steinsson (2010) and Midrigan (2011) we assume that aggregate nominal GDP, $Y_t^N = P_t C_t$, grows at a constant long-run rate μ and is subject to temporary shocks. More specifically, we assume that the monetary authority controls the path of nominal

GDP according to the process

$$\ln Y_t^N = \mu + \ln Y_{t-1}^N + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2). \quad (27)$$

5.2 Model solution

An equilibrium in this model is a set of policy rules for the endogenous variables that is consistent with the household's and firms' maximization, market clearing and the evolution of the exogenous processes for total factor productivity and nominal GDP. To solve for the equilibrium we first rewrite the firms' profit function employing both the labor demand and supply function and replacing firm's output by the corresponding demand function in real terms as follows:

$$\begin{aligned} \Pi_t^R(z) = & \left(\frac{p_t(z)}{P_t} \right) \mathcal{F} \left(\frac{p_t(z)}{P_t} \right) \frac{Y_t^N}{P_t} - \omega L_t^\psi C_t^\gamma \left(\frac{1}{A_t(z)} \right) \mathcal{F} \left(\frac{p_t(z)}{P_t} \right) \frac{Y_t^N}{P_t} - \\ & - K \omega L_t^\psi \left(\frac{Y_t^N}{P_t} \right)^\gamma I_t(z) - U, \end{aligned} \quad (28)$$

where $\mathcal{F}(\cdot)$ corresponds to equation (16) in the CES-Case and to equation (17) in the NON-CES-Case.

We solve the firm's optimization problem using dynamic programming.¹² The state variables for the firm's optimization problem are given by the level of idiosyncratic productivity $A_t(z)$, aggregate real GDP as represented by the ratio of nominal GDP and the price level, $\frac{Y_t^N}{P_t}$, and the firm's relative price at the end of the previous period $\frac{p_{t-1}(z)}{P_t}$. Given these state variables, each firm maximizes the value function

$$V \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right) = \max \left\{ V^{NC} \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right), V^C \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right) \right\}, \quad (29)$$

where $V^{NC}(\cdot)$ denotes the value function when the firm does not change its price and $V^C(\cdot)$ denotes the value function when the firm changes its price. The expressions for these two

¹²To solve the model, we made intensive use of the Matlab programs used by Nakamura and Steinsson (2010). We would like to thank these authors for providing their code.

function are given by:

$$V^{NC} \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right) = \Pi \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right) + E_t \left[D_{t,t+1} V^{NC} \left(A_{t+1}(z), \frac{p_{t-1}(z)}{P_{t+1}}, \frac{Y_{t+1}^N}{P_{t+1}} \right) \right]$$

$$V^C \left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{Y_t^N}{P_t} \right) = \max_{p_t} \left\{ \Pi \left(A_t(z), \frac{p_t(z)}{P_t}, \frac{Y_t^N}{P_t} \right) + \right.$$

$$\left. + E_t \left[D_{t,t+1} V^{NC} \left(A_{t+1}(z), \frac{p_t(z)}{P_{t+1}}, \frac{Y_{t+1}^N}{P_{t+1}} \right) \right] \right\}$$

To solve this optimization problem, the firm needs to form expectations about the future path of the state variables. This can be done in a straightforward manner for A_t and Y_t^N which both follow exogenous stochastic processes. In the case of the price index, P_t , however, one faces the following fixed point problem: The optimal decision of a firm depends on the path of the price level and this optimal decision in turn impacts the determination of the equilibrium path of the price level. To address this issue, we follow Nakamura and Steinsson (2010) and use the method by Krusell and Smith (1998) to approximate the distribution of relative prices by the first moments of the expected price distribution and postulate that firms use the formula

$$\frac{P_t}{P_{t-1}} = \Gamma \left(\frac{Y_t^N}{P_{t-1}} \right) \quad (30)$$

to form expectations of the change in the aggregate price level (i.e. the inflation rate).

Given this forecasting rule, our procedure to solve for the equilibrium proceeds as follows:

- (1) We start by specifying a discrete grid vector for each of the three state variables, initialize the stationary distribution and make a first guess of the forecasting rule $\Gamma \left(\frac{Y_t^N}{P_{t-1}} \right)$.
- (2) Given the forecasting rule, we then solve for the firms' policy function using value function iterations.
- (3) As a next step we update the stationary distribution using the policy function.
- (4) Finally, we update the forecasting rule and check whether it is consistent with the aggregate inflation rate implied by the firms' policy function. If this is the case we stop, otherwise we return to (2).

5.3 Calibration

To calibrate the model we group the model parameters into two classes. The first set of parameters include those which are identical for all four countries of our sample or which govern the aggregate process of monetary supply. The parameters in this group including the values attached are listed in Table 4. Following Nakamura and Steinsson (2010) and others, we employ a discount factor $\beta = 0.96^{1/12}$ implying an annual (steady-state) interest rate of around 4%. The parameter of relative risk aversion, γ , is set equal to one which makes the utility function logarithmic in consumption. For the value of the elasticity of labor supply, ψ , we choose a value equal to zero yielding a utility function linear in working time. We set $\bar{L} = 1/3$ so that the steady-state labor supply is equal to one third of the total time endowment. Finally, for all countries the persistence parameter of the idiosyncratic productivity shock is chosen to be equal to $\rho = 0.7$. Employing country-specific historical nominal and real GDP data for the time period from 1996 to 2013 the parameters governing the evolution of nominal GDP are calibrated to be equal to $\mu = 0.0018$ and $\sigma_\eta = 0.0028$ for Belgium, $\mu = 0.0014$ and $\sigma_\eta = 0.0020$ for Germany, $\mu = 0.0019$ and $\sigma_\eta = 0.0020$ for the Netherlands and $\mu = 0.10 * 0.0018 + 0.76 * 0.014 + 0.14 * 0.0019$ and $\sigma_\eta = \sqrt{0.10^2 * 0.0028^2 + 0.76^2 * 0.020^2 + 0.14^2 * 0.0020}$ for the aggregate.

Table 4: *Model parameters common across countries and parameters for the country-specific monetary-policy process*

Parameters common across countries				
Subjective discount factor, β	0.96 ^{1/12}			
Relative risk aversion, γ	1			
Elasticity of labor supply, ψ	0			
Steady-state labor supply, L^*	1/3			
Pers. of mon. policy process, ρ	0.7			
Country-specific parameters for the monetary policy process				
	BE	DE	NE	ALL
Mean (monthly) inflation rate, μ	0.0018	0.0014	0.0019	0.0016
Std. dev. of mon. pol. shocks, σ_η	0.0028	0.0020	0.0020	0.0016

The remaining country-specific parameter values are presented in Table 5, where we differentiate between two alternative preference specifications for each of the four countries included in our sample: In the upper panel we report figures for a standard Dixit-Stiglitz CES specification for the aggregation function $\Upsilon(\cdot)$. Here, the elasticity parameter, $\bar{\theta}$, is chosen to be equal to its estimated steady-state value and the value for the super-elasticity parameter, $\bar{\epsilon}$, is (counter-factually) set equal to zero. In the lower panel of Table 5 (NON-CES case), we consider the specification for $\Upsilon(\cdot)$ employed by Klenow and Willis (2006) and Gopinath and Itskhoki (2010). In this case, the elasticity parameter, $\bar{\theta}$, is again chosen to be equal to its empirical counterpart as derived from equation and the parameter for the super-elasticity, $\bar{\epsilon}$, is set equal to the value found in the data. The values for the menu-cost parameters (*Menu costs*) and the standard deviations of the idiosyncratic shocks (*Std.dev. of id. shocks*) are chosen to match the empirical observations on the mean frequency and size of price changes as reported in the upper panel (values including sales) of Section 2. Menu costs are reported as a fraction of steady-state revenue.¹³

For the CES case, menu costs are all of a relatively moderate size, ranging from 0.29% for Belgium to 4.43% for the case of all countries. As one would expect there generally appears to exist a positive relationship between the size of menu costs and the frequency of price changes. However, this relationship is not perfectly clear-cut as other factors such as the consumers' preferences and the monetary environment also play an important role. The same is true for the NON-CES case. As anticipated, the size of the menu costs is now considerably larger though, ranging from a relatively modest value of 1.91% for Belgium to sizeable 10.06% for the Netherlands. The change in menu costs corresponds to an increase by a factor of close to 1.5 for all countries and around 4 for Belgium. A similar finding is reported by Klenow and Willis (2006) who document an increase in menu costs by a factor of two when comparing the CES with the NON-CES case. Looking at the absolute values of the menu costs implied by our model, they appear to be partly considerably higher than those provided by independent evidence on menu costs as reported for example by Levy et al. (1997) who find that costs of changing prices amount to around 0.7% of revenue.

¹³The corresponding values derived for the price statistics excluding sales are reported in Table 6 of Appendix A.

Table 5: *Sample-specific preference and production-process parameters and simulation results*

	BE	DE	NE	ALL ($\rho = 0.7$)	ALL ($\rho = 0.95$)
CES					
Elasticity	1.41	2.41	2.34	3.58	3.58
Superelasticity	0	0	0	0	0
Menu costs	0.285	2.527	3.946	4.427	4.151
Std.dev. of id. shocks	0.076	0.083	0.109	0.091	0.074
<i>fpc</i>	0.235	0.124	0.127	0.152	0.152
<i>fraction^{up}</i>	0.54	0.551	0.552	0.551	0.544
<i>size^{abs}</i>	0.137	0.164	0.213	0.175	0.175
<i>size^{up}</i>	0.134	0.159	0.206	0.168	0.17
<i>size^{down}</i>	0.14	0.169	0.221	0.184	0.181
CIR	1	1.6	1.26	0.77	0.95
Var. of C	0.02	0.03	0.02	0.01	0.01
NON-CES					
Elasticity	1.41	2.41	2.34	3.58	3.58
Superelasticity	1.91	2.74	2.54	1.39	1.39
Menu costs	1.339	6.742	10.06	6.659	6.263
Std.dev. of id. shocks	0.406	0.235	0.297	0.141	0.114
<i>fpc</i>	0.233	0.123	0.126	0.153	0.152
<i>fraction^{up}</i>	0.504	0.515	0.511	0.542	0.541
<i>size^{abs}</i>	0.137	0.164	0.212	0.174	0.175
<i>size^{up}</i>	0.144	0.17	0.222	0.17	0.171
<i>size^{down}</i>	0.131	0.156	0.201	0.179	0.18
CIR	7.7	2.59	3.15	1.32	1.59
Var. of C	0.16	0.06	0.05	0.02	0.03

Notes: 1) Menu costs are given by the percentage share of steady-state revenue $\frac{\theta-1}{\theta} \frac{K}{Y^*}$. 2) The values for the elasticity and super-elasticity are taken from the estimation results as reported in Table 3. 3) Menu cost and standard deviation parameters are chosen so as to match the median frequency and size of price changes reported in rows *fpc* and *size^{abs}* of the upper panel (descriptive statistics including sales) of Table 2. 4) CIR (cumulative impulse response) and Var of. Y (variance of aggregate real consumption) represent measures of monetary non-neutrality as described in the main text. The numbers for the the CIR are multiplied by 100, the number for the Variance of C are multiplied by 10^4 . (5) To compute the variance of real GDP we employ HP filtered quarterly real GDP for each country from 1995 to 2008. The source of the data is Eurostat.

The values for the standard deviations of idiosyncratic shocks reach from around 7.6% for Belgium to around 11% for the Netherlands in the CES case. The values for these parameters again reflect the combinations of the empirically observed frequencies and sizes of price changes in the respective country where higher values for the standard deviation correspond to higher frequencies and sizes of price changes, everything else equal. As expected and, e.g., previously observed by Klenow and Willis (2006) these values become considerably larger for the NON-CES case where they reach from around 14% for all countries to almost 40% for Belgium. The reason for this increase results from the change in firms' incentives to change prices in the presence of NON-CES preferences: In this environment, firms are very hesitant to change prices due to the potential large losses in market share (and hence revenue). To reconcile this aversion to change relative prices with the observed frequencies of price changes, firms have to be subject to frequent and substantial changes in their cost structure, which force them to change prices despite the considerable demand changes induced by them.

Comparing our findings for the sizes of the standard deviations with those found by Klenow and Willis (2006), we can see that the relative increase in values between the CES and NON-CES case is of similar extent. However, the absolute values appear to be considerably smaller, in particular if one conditions on the observed frequency of price changes: Looking, e.g., at Germany and the Netherlands which both exhibit a frequency of price changes of around 21 to 22% we find that the associated standard deviations of idiosyncratic shocks which are compatible with the observed price characteristics correspond to at most 28% in our model. This compares to around 35% which is the corresponding number for the standard deviation of idiosyncratic shocks in the model by Klenow and Willis (2006) compatible with an observed frequency of price changes of around 21.5%. As illustrated in the introduction to this section this of course reflects the lower values of the super-elasticities which we find in the data and accordingly use in our model specifications. Nevertheless, these values still appear to be very large. Bachmann and Bayer (2013), e.g., employ a comprehensive data set of firms in Germany and report values for the standard deviation of idiosyncratic productivity of around 9% annually using the Solow residual as their measure of productivity. In future research, we

intend to provide an explanation for these differences in results and will investigate to what extent these differences can be attributed to special features of the retail good market. For example, producers of retail goods may be subject to other idiosyncratic shocks which are not captured by changes in labor productivity.

5.4 Simulation results

Employing the calibrated parameter values, we next investigate the degree of monetary non-neutrality associated with the two different specifications of the demand structure described above. Following Nakamura and Steinsson (2010), we measure monetary non-neutrality using two different statistics: As a first statistic, we compute the area under the impulse response function of aggregate real consumption C following a shock to nominal GDP (i.e. after a positive realization of η_t in (27)). This statistics, denoted by CIR (Cumulative Impulse Response) in Table 5, captures the overall effect of a nominal shock on real consumption spending: The larger and longer-lasting the response of C to a nominal shock, i.e., the degree of monetary non-neutrality, is, the higher CIR will be. As a second statistic, we compute the variance of aggregate consumption spending ($\text{Var}(C)$) that results from model simulations where only nominal shocks hit the economy (i.e., where no idiosyncratic productivity shocks occur). Again, higher values of this statistic indicate a larger degree of monetary non-neutrality (where the statistic would take on the value 0, if no real effects of nominal changes were present).

The results are reported in the last two rows of the first and second panel of Table 5.¹⁴ Considering the CES case, we can see that there exists a negative relationship between the frequency of price changes and the degree of monetary non-neutrality, confirming the well-known fact that higher degrees of nominal rigidity (as indicated by the average length between price changes and measured by the frequency of price change (fpc)) are associated with larger monetary non-neutrality, everything else equal: Poland, e.g., which is characterized by very frequent price changes, exhibits a considerably lower degree of

¹⁴Results for the cases where values are calibrated to match price statistics excluding sales are reported in Table 6 of Appendix A and Figure ?? of Appendix ?. They qualitatively and quantitatively similar to the results reported in this Section.

monetary non-neutrality than Germany where price change much less frequent. Comparing the CES and NON-CES cases, we see that the introduction of real rigidity on the demand side has very sizeable effects on the degree of monetary non-neutrality in all countries apart from Belgium. The extent of monetary non-neutrality as measured by the CIR increases by a factor of two to more than four. When taking the variance of aggregate consumption as a measure, we obtain increases by a factor of two to more than ten. For Belgium we only document negligible differences in the degree of monetary non-neutrality though. This is clearly due to the very small estimated value for the super-elasticity in this country.

Figure 4: *Impulse response function*

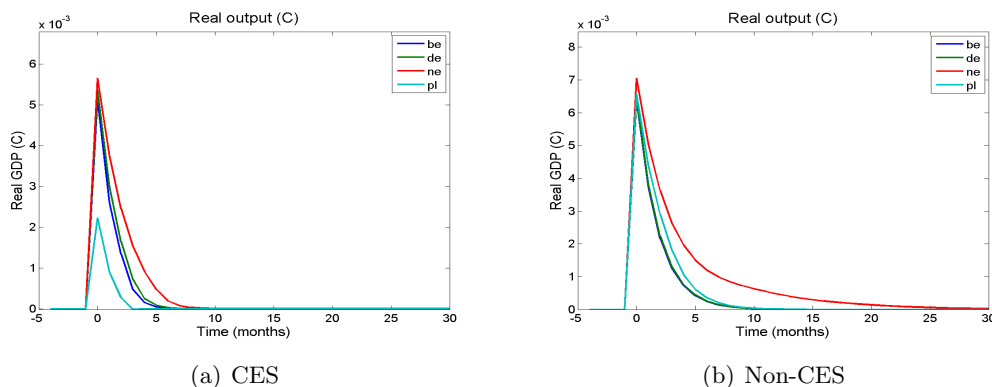


Figure 4 plots the impulse-response functions of real consumption expenditure after an unexpected (postivte) shock to nominal aggregate demand for the four countries under consideration for both the CES and NON-CES (labeled "Kimball" in the graph) demand functions.

This result is also clearly illustrated in Figure 4, which shows the impulse response functions of real aggregate consumption expenditure after a shock to nominal demand for the four countries under consideration. We see that for all countries except Belgium the initial response is larger for the NON-CES case compared to the CES case. Moreover, not only the effect on impact is larger, but also its persistence. Thus, real rigidity not just increases the effect on impact, but also adds persistence to the model's response to nominal shocks. This effect on persistence is most pronounced for the countries with a high degree of real rigidity (Germany, the Netherlands and Poland), where it takes almost twice as long (or longer) for the shocks effects to fade out. But even for Belgium we now observe a sizeable effect. In other words, our results indicate, that plausibly calibrated real rigidities on the demand side can contribute to

reconcile the slow response of real variables to nominal shocks.

On the other hand, when comparing our measures for monetary non-neutralities with those obtained by Nakamura and Steinsson (2010) when considering the case of intermediate inputs we can see that our results are much lower. In a next step, we thus plan to extend our analysis to consider the effects of sectoral heterogeneities.

6 Conclusions

The findings by Bils and Klenow (2004) that micro prices are changed relatively often and that both large price increases and decreases frequently occur has challenged the by then dominating view amongst most monetary economists that considerable nominal frictions exist in the economy. Since then, several attempts have been made to reconcile the micro evidence on relatively flexible prices and observed relatively large responses of real variables to nominal shocks. One of these attempts has been to introduce real rigidities resulting from kinked-demand curves into macro models. While very flexible in its implementation this approach has so far lacked appropriate microeconomic evidence. The aim of this paper was to provide this evidence and evaluate its quantitative implications.

To this end, we have employed a new data set on consumer retail transactions which contains detailed information on prices and quantities for four European countries and estimate demand systems that allow us to uncover evidence on the size and distribution (across different markets and across countries) of the elasticity and super-elasticity of demand. Our findings suggest values for the elasticity parameters which are in the range between 1 and 3. While these numbers are well below the values most often used in the macro literature they tend to be in line with the ones found in the marketing literature. Similarly, our findings for the super-elasticity parameter are much smaller than the values used in macro models with values being in the range between 0.5 and 3.

In a second step, we have used our estimated values for the elasticity and super-elasticity of demand to calibrate a menu-cost model. We have used this model, which extends the model of Nakamura and Steinsson (2010) by including the demand structure of Klenow and Willis

(2006), to investigate how the degree of monetary non-neutrality depends upon the assumed demand structure. We document that monetary non-neutrality increases greatly for models that include a real

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A Additional tables

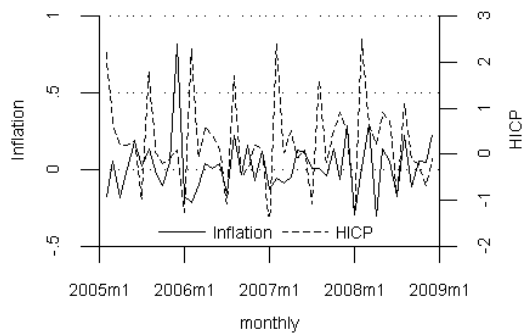
Table 6: *Country-specific preference and production-process parameters and simulation results based on estimated price statistics excluding sales*

	BE	DE	NE	PL
CES				
Elasticity	1.95	2.44	2.03	2.12
Superelasticity	0	0	0	0
Menu costs	0.73	2.94	3.43	0.507
Std.dev. of id. shocks	0.072	0.084	0.106	0.08
<i>fpc</i>	0.198	0.11	0.108	0.325
<i>fraction^{up}</i>	0.526	0.526	0.546	0.543
<i>size^{abs}</i>	0.133	0.168	0.21	0.131
<i>size^{up}</i>	0.132	0.164	0.205	0.13
<i>size^{down}</i>	0.133	0.173	0.216	0.132
CIR	1.0596	2.0364	2.1319	0.3092
Var. of C	0.0074	0.0244	0.0355	0.0254
NON-CES				
Elasticity	1.95	2.44	2.03	2.12
Superelasticity	0.79	2.98	2.22	2.65
Menu costs	1.385	7.476	8.614	1.642
Std.dev. of id. shocks	0.133	0.235	0.305	0.272
<i>fpc</i>	0.197	0.105	0.108	0.327
<i>fraction^{up}</i>	0.521	0.495	0.505	0.525
<i>size^{abs}</i>	0.134	0.165	0.21	0.13
<i>size^{up}</i>	0.135	0.171	0.222	0.134
<i>size^{down}</i>	0.133	0.159	0.199	0.127
CIR	2.0426	3.044	10.525	2.2842
Var. of C	0.0353	0.0636	0.1526	0.7869
Variance of real GDP				
Var. of Cons.	0.1324	0.2693	0.5424	0.6774
Var. of GDP	0.6587	1.0984	1.0324	1.5774
Var. expl.: CES	0.0112	0.0222	0.0344	0.0161
Var. expl.: Non-CES	0.0536	0.0579	0.1478	0.4989

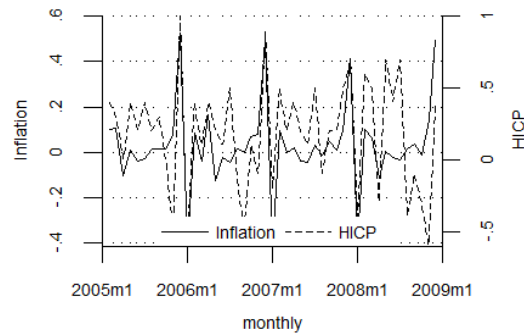
Notes: 1) Menu costs are given by the percentage share of steady-state revenue $\frac{\theta-1}{\theta} \frac{K}{Y^*}$. 2) The values for the elasticity and super-elasticity are taken from the estimation results as reported in Table 3. 3) Menu cost and standard deviation parameters are chosen so as to match the median frequency and size of price changes reported in rows *fpc* and *size^{abs}* of the lower panel (descriptive statistics excluding sales) of Table 2. 4) CIR (cumulative impulse response) and Var. of C (variance of aggregate real consumption) represent measures of monetary non-neutrality as described in the main text. The numbers for the the CIR are multiplied by 100, the number for the Variance of C are multiplied by 10^6 .

B Additional figures

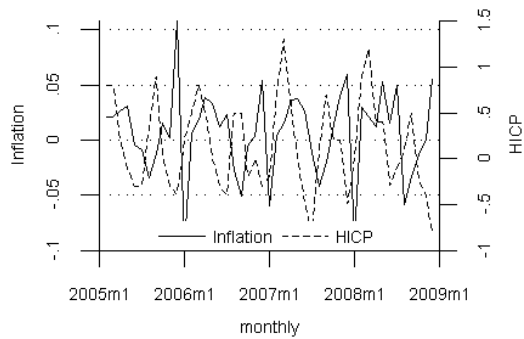
Figure 5: *Inflation in the sample and HICP inflation rates*



(a) Belgium



(b) Germany



(c) Netherlands

Notes: Monthly inflation rates in our data sample is calculated as the weighted (by expenditure share) average change in the price level of all products bought in the estimation sample. Monthly HICP inflation rates are taken from Eurostat and cover the same period as our sample (2005–2008).