Shocks vs Menu Costs: Patterns of Price Rigidity in an Estimated Multi-Sector Menu-Cost Model *

Erwan Gautier† Hervé Le Bihan‡

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Abstract

Relying on a menu cost model augmented with a time–dependent (Calvo) component, we investigate the structural sources of cross-sectoral heterogeneity in patterns of price setting. We use a large microdataset of French consumer prices to estimate the model at the product level for 227 products. The Calvo component is found to be large in most sectors. Heterogeneity in structural parameters is found to be substantial. These two features combined result in a sizable amplification of the degree of monetary policy non-neutrality, as compared to a single sector pure menu–cost model estimated with aggregate moments.

Keywords: price rigidity, menu cost, (S, s) models, adjustment cost.
JEL Codes: E31, D43, L11

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†Banque de France and Université de Nantes. Email adress: erwan.gautier@banque-france.fr
‡Banque de France Email adress: herve.lebihan@banque-france.fr

1 Introduction

Patterns of price adjustments both in the United States and the euro area have been described in a voluminous literature (see for instance Klenow and Malin (2010) and Nakamura and Steinsson (2013) for surveys). Among other characteristics, two salient features of price adjustments are reported by most of those empirical studies. First, there is a relatively high apparent degree of price rigidity: the frequency of price changes is rather small (especially if price changes due to sales are disregarded). Second, cross sectoral heterogeneity in the frequency of price changes is pervasive: for instance prices changes are very frequent for gasoline whereas they are quite rare in services. A still open question is to what extent such patterns as the apparent degree of price rigidity, and the cross–product heterogeneity in price rigidity, reflect structural frictions to price adjustments (such as adjustment costs), or rather reflect differences in the size of shocks affecting different sectors. This question is relevant for monetary policy, as both the source of price rigidity and the degree of cross sectoral heterogeneity matter for monetary policy.

In this paper we investigate to what extent the characteristics of price adjustments reflect intrinsic rigidity or the pattern of shocks affecting each sector. To address this issue we rely on a structural multi-sector menu cost model, which nests the standard menu cost model and the Calvo model of "exogenous" price rigidity - a set-up close to the CalvoPlus model of Nakamura and Steinsson (2010). Using this model, and a minimum distance estimation procedure, we estimate the value of the menu cost, that of the Calvo component (the probability of drawing a free opportunity to change prices), and the parameters characterizing the variance and persistence of sectoral productivity shock process at the product level. We estimate this model for more than 200 different products of the French CPI. Empirical moments are obtained using a large microeconomic data set of more than 25 million of individual consumer price quotes. The general equilibrium set-up used allows us to simulate the response of the economy to a monetary shock, and assess the degree of the monetary non-neutrality. We compare the aggregate response for different estimations of parameters of the model (one sector vs. multi-sector, augmented menu cost model vs Calvo or pure menu cost model) and we also compare the impulse response functions obtained for France and the US economy.

Our main results are the following. First, there is a substantial degree of heterogeneity in structural parameters across sectors. Second, the Calvo component is sizable and crucial to fit the data. Thus the genuine "menu cost" component contributes only partially to the overall degree of price rigidity. Across sectors, the heterogeneity in the Calvo component (as opposition to heterogeneity in cost shocks) explains most of the heterogeneity in the frequency. Third, heterogeneity matters for monetary policy: the degree of monetary non neutrality is larger considering a multi sectoral model, than using one sector model calibrated on the same average moments. At the same time, a model fitting median aggregate moments is able to approximate quite closely the degree of monetary non–neutrality obtained from a multi-sector model. Fourth, comparing models estimated using moments calculated for the United States and France, we find that the impulse response functions are quite similar for both economies, when assuming identical parameters for parameters other than those related to costs and price-setting friction.[1]

Our results builds on a large literature that has provided new theoretical and empirical results on price rigidity in the last decade or so. Overall we believe we contribute to this literature along three dimensions.

First, we contribute to the literature relating cross–sectoral heterogeneity of price rigidity indicators to models of price rigidity. Several papers provide descriptive evidence on the large sectoral heterogeneity of apparent price rigidity such as Bils and Klenow (2004) on the US, Dhyne et al. (2006), Baudry et al. (2007), on the euro area and France, whereas some microeconometric contributions Dhyne et al. (2011) or Fougere, Le Bihan, and Sevestre (2007) relate this sectoral heterogeneity to theoretical predictions of price rigidity models. We here provide a structural interpretation to this cross–product heterogeneity. We find that there is a substan-

[1]One restriction to our comparison is that we exclude sales from our analysis. Sales are much less prevalent in France than in the US. Whether sales are significantly adding to price flexibility in the case of the US is the topic of a substantial controversy, see e.g. Kryvtsov and Vincent (2014), Gagnon, Lopez-Salido, and Sockin (2015), Coibion, Gorodnichenko, and Hong (2015),Anderson et al. (2017). Our analysis takes no stand on this issue.

tial degree of heterogeneity in structural parameters across sectors, and that heterogeneity in pricing friction parameters is more important than heterogeneity in shocks to replicate French stylized facts. One specific feature of this contribution is that we provide structural estimates of price rigidity for a European economy and to compare them to the ones obtained for the United States. To our knowledge, no previous menu cost model has been estimated on micro data for an economy of the euro area. Previous work on European economies include Karadi and Reiff (2014) and Carlsson (2017) who have estimated parameters of menu-cost models respectively using food CPI Hungarian data and on Swedish producer price data[2]. Moreover, we here cover a large number of CPI sectors including services whereas most macro models are calibrated using micro data for some specific sectors (Nakamura and Steinsson (2010) is one exception) or using grocery price data. In our augmented menu–cost framework, we find that if we exclude sales, price adjustment costs are a little larger in the United States than in France, whereas productivity shocks have a larger variance in the United States than in France. However, we obtain that the real aggregate effect of monetary policy is very similar in France than in the United States. By contrast Alvarez and Burriel (2010) (based on a time dependent generalized Calvo with heterogeneous sectors calibrated to fit the distribution of price durations in both Euro area and the United States) find that monetary non neutrality is larger in Europe than in the United States (in a study that takes on board price changes due to sales).

A second contribution is to estimate the relative importance of time-dependent (Calvo) and state-dependent (menu cost) mechanisms in price-setting in a single set-up. This contribution builds on the recent literature featuring random menu cost models which encompass the Calvo and menu–cost model, including Nakamura and Steinsson (2010) and Alvarez, Le Bihan, and Lippi (2016) (see also Luo and Villar (2015) Blanco (2017) for papers using a similar set-up).[3] This literature has shown that the degree of monetary policy non-neutrality is larger when as-

[2]Hobijn, Ravenna, and Tambalotti (2006) estimate a menu-cost model using sectoral price data for Italian restaurants

[3]Early models with random cost of adjustment have been introduced by Caballero and Engel (1999) and Dotsey, King, and Wolman (1999).

suming a random menu cost than in the "standard", fixed menu cost model of Golosov and Lucas (2007).[4] Our contribution here is to provide an estimation of the relative contribution of the Calvo component in generating price rigidity (with respect to the menu cost). In this respect we relax an assumption of Nakamura and Steinsson (2010) who set the probability of being in the low menu cost regime to be equal to the frequency of price changes. Our approach is also complementary to the sufficient statistics approach Alvarez, Le Bihan, and Lippi (2016) [5]. We find the Calvo component to be sizeable and crucial to fit the data in most sectors. The "time dependent" motive for price changes is estimated to generate between 50% and 75% of all price changes. In addition, across sectors, the heterogeneity in the Calvo component (as opposition to heterogeneity in cost shocks) is found to explain most of the heterogeneity in the frequency. With some qualifications, our results thus provide some support to the literature that has studied inflation dynamics in multi-sector models relying on a Calvo set-up: see for instance, Bils and Klenow (2004), Carvalho (2006), Eusepi, Hobijn, and Tambalotti (2011), Le Bihan and Matheron (2012), and **?** for models calibrated with CPI micro data, or Bouakez, Cardia, and Ruge-Murcia (2009) who estimate a model based on sectoral aggregate data.

Our third contribution is to assess, in a single set-up, the degree of amplification of monetary policy non-neutrality brought along by the Calvo component, and by heterogeneity in price-setting. This follows prominent contributions by Carvalho (2006) and Nakamura and Steinsson (2010) who mainly focus on amplification effect resulting from sectoral heterogeneity and by Midrigan (2011) and Alvarez, Le Bihan, and Lippi (2016) who focus on amplification effect resulting from the assumption of random menu cost and/or multiproduct firms. Heterogeneity matters : we find that the degree of monetary non neutrality is twice larger when considering a multi–sector model, than if we consider a one–sector model calibrated on the same average

[4]Another recent strand of literature has proposed alternative mechanisms to rationalize small price changes and monetary non neutrality, these mechanisms consist of multi-product firms (Midrigan (2011)), strategic complementarities (Burstein and Hellwig (2006)), information capacity constraint (Woodford (2009)) or errors in price revisions (Costain and Nakov (2011, 2012)). In these papers, the decision rule is observationally equivalent to that derived under a random menu cost model.

[5]We do not rely on zero trend inflation, or Brownian motion cost shock approximations, that are used to derive analytical solutions in that paper – but have to rely on numerical techniques and a simulation approach

moments. At the same time, a model fitting median aggregate moments is able to approximate quite closely the degree of monetary non–neutrality obtained from a multi-sector model. The Calvo component also matters: the real effect of monetary policy is obtained to be more than 1.5 times the real effects obtained using a fixed menu–cost model a la Golosov and Lucas (2007) (when we rely on one-sector model estimated on aggregate median moments).

Our paper is structured as follows. Section 2 reviews the micro data as well as the main facts our model seeks to explain. Section 3 presents the augmented menu cost model we use, and presents its main properties, allowing to identify which moments identify the parameters. Section 4 provides evidence on the structural parameters, and investigates to what extent heterogeneity in price stickiness is driven by the properties of the shock processes, or the heterogeneity in menu costs. Section 5 examines the aggregate real response of the economy to a 1% monetary policy shock and compares the results for different set-ups of the models and also compares results obtained for France and the US economy. Section 5 concludes.

2 Data and Micro Facts

We first present stylized facts on the cross sectoral heterogeneity of usual price rigidity indicators (i.e. the frequency and the size of price adjustments) in France.

2.1 Data

To obtain our price rigidity micro facts, we here rely on longitudinal data sets of monthly price quotes collected by the Institut National de la Statistique et des Études Économiques (INSEE) to compute the monthly French CPI. We have stacked data sets used in Baudry et al. (2007), Berardi, Gautier, and Le Bihan (2015) and Berardi and Gautier (2016) to obtain a long sample covering a period of about 20 years between August 1994 and May 2014.[6] The data set contains

[6]French micro price data are presented with much more details in these papers.

more than 25 million price quotes and covers a little less than 65% of the CPI weights.[7] On average, the sample contains between 120,000 and 130,000 individual price quotes each month, collected from over 20,000 different retailers for several thousand different products and services. To compute price rigidity indicators, we have first dropped data collected during a VAT change (i.e. in Aug. and Sept. 1995, Sept. Oct. 1999, April and May 2000, July-Sept. 2009, Jan-Feb. 2012 and Jan-Feb. 2014) and before and after the euro cash changeover (Aug 2001 - June 2002). We have also dropped outliers. We define as outliers price change observations involving upward or downward changes by a factor larger than 5, and trimmed them from the data, we have also dropped out-of-season items from our data set. We have also dropped price changes smaller than 1% in absolute values in order to control for possible small price changes due to measurement errors (Eichenbaum et al. (2014)).

Our price rigidity indicators are computed excluding seasonal sales and promotions using a flag variable that identifies whether a price corresponds to a sale price, either in the form of seasonal sales or temporary promotional discounts. Berardi, Gautier, and Le Bihan (2015) find that in France price changes due to sales are less responsive to economic shocks than regular prices. Moreover, sales and promotions are mostly concentrated in some sectors (i.e. clothing and shoes and furnishings). Our model does not reproduce price changes due to sales. In particular, we exclude clothing from our analysis since price adjustment patterns in this sector are essentially driven by sales and are difficult to replicate using a standard menu cost framework.

Finally, our aim is also to compare price rigidity observed in France and in the United States. To perform this comparison, we rely on moments computed by Nakamura and Steinsson (2008) for disaggregated US products and released in their web appendix (Nakamura and Steinsson (2008)). We also use a bridge table to match the European CPI classification (COICOP) and the US one (ELI) (see Berardi, Gautier, and Le Bihan (2015) for details).[8] Overall, we are able

[7] Some categories of goods and services are not available in our sample: centrally collected prices, among which car prices and administered prices (e.g. tobacco) or public utility prices (e.g. electricity), as well as other types of products such as fresh food or rents.

[8] The bridge table is available from the authors

to match 206 French products (over a total of 227 products) with corresponding US products (i.e. more than 54% of the French CPI). The main products excluded from the US data set consist of cars, electricity and gas, medical services, airline fare, telephone services and fresh food.[9] Those products are typically associated with rather high frequencies of price changes (for the US, the average frequency of regular price changes for those products is higher than 30%). To perform an accurate comparison, we rely on the moments excluding sales. As mentioned in the introduction this is a potential limitation as the extent of sales is substantially larger in the United States.

2.2 Facts

We here briefly the main stylized facts of the data. For that, we compute standard statistics characterizing price adjustment patterns, at a disaggregated level (the 5-digit level of the COICOP nomenclature): the frequency of price changes, the share of price increases among price changes and the quartiles of the price change distribution. We obtain such statistics for 227 products and services. Table 1 reports simple weighted statistics both at the aggregate level, and for 5 broad sectors: Food, Manufacturing goods (split into durables and others goods), Energy and Services. The main stylized facts are the following. Price changes are infrequent: the weighted median frequency of price changes over all 227 products is 8.4%. Price decreases are not rare: about 70% of price changes are price increases. Price changes are rather sizable: the median size of price changes is about 5%, but large price changes are not rare since the 75th percentile of price changes is 8%.

Another important salient feature of the data is the large degree of heterogeneity across products. Price are more frequent for energy and food products (75% for energy and about 15% for food) whereas they are quite rare for services or durables (about 5%) (Table 1). Figure 1 plots the distribution of product specific frequencies of price changes and proportions of price

[9] The INSEE did not include in the data set available to us the set of prices that are mainly collected at the national level rather than in retail outlets, which match this list of items.

increases. About one half of the products have a frequency of price changes of less than 5%, whereas the frequency of price changes is larger than 10% for more than one third of products. Turning to share of price increases among price changes, in some sectors (mostly services) it is above 80%. Figure 2 plots the distribution of the quartiles of the distribution of price changes across products. Here again, there is a pervasive degree of sectoral heterogeneity.

A second important finding is that differences between France and the United States are smaller than differences across products. Table 2 compares, with a fairly high degree of precision, price adjustment patterns for similar French and US products. The frequency of price changes in the United States is only slightly higher than in France. As already underlined by Berardi, Gautier, and Le Bihan (2015) the main difference comes from a higher share of sales in the United States. The share of price increases is also very similar. The main difference between the two countries is in the size of price adjustments: regular price adjustments are about twice larger in the US than in France.

Our aim in the remaining of this paper is to relate these differences to structural parameters of a menu cost model and investigate possible implications in terms of monetary non-neutrality.

3 A Multi–Sector Menu Cost Model

To understand the sources and consequences of cross–sectoral heterogeneity in price rigidity that is prevalent in price data, we set-up a sectoral menu cost model, building on Nakamura and Steinsson (2010). The model features heterogeneity in price rigidity structural parameters and in sectoral shock processes.

3.1 Model

3.1.1 Household behavior

The representative household maximizes an intertemporal utility function given by:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\gamma} C_{t+\tau}^{1-\gamma} - \omega L_{t+\tau} \right]$$

where the disutility of labor is linear, L_t is Labor, C_t is a Dixit-Stiglitz consumption aggregate, β is a discount factor, γ the intertemporal elasticity of substitution, ω a labor disutility parameter Aggregate consumption C_t is given by an aggregation of goods produced in different sectors. There are K sectors in the economy. A continuum of firms indexed by i operates in each sector k, and produce differentiated products. The level of consumption of the aggregate composite good C_t is given by a Dixit-Stiglitz index of the differentiated goods produced by the K different sectors: $C_t = \left[\sum_{k=1}^{K} \omega_k^{\frac{1}{\theta}} C_{k,t}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$. In the latter expression, the level of consumption of the good produced by the sector k is given by: $C_{k,t} = \omega_k \left[\int_0^1 C_{i,k,t}^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}}$ where θ is the elasticity of substitution between the different goods (which is assumed to be identical within a sector and across sectors), and ω_k is a sectoral weight that in the empirical application will be set equal to the CPI weight.

The maximization program of the households is subject to a budget constraint:

$$P_t C_t + E_t \left[Q_{t,t+1} B_{t+1} \right] \leq B_t + W_t L_t + Others$$

where "Others" include dividends and the proceeds of a complete set of Arrow Debreu securities, W_t is nominal wage, B_t is the quantity of riskless one-period bonds maturing at date $t+1$ held by the household, $Q_{t,t+1}$ is the stochastic discount factor (the expectation of which is the price of the bond).

From the first-order conditions, in each state of the world, the stochastic discount factor is given by:

$$Q_{t,t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left(\frac{P_t}{P_{t+1}} \right)$$

The price of goods produced by firm i price operating in sector k will be denoted $P_{i,k,t}$. Demand addressed to the firm i, resulting from optimal allocation across goods is the following:

$$C^d_{i,k,t} = C_t \left(\frac{P_{i,k,t}}{P_t} \right)^{-\theta}$$

Finally, first-order condition also determine the real wage, given by:

$$\frac{W_t}{P_t} = \omega C_t^{\gamma}$$

3.1.2 Firms

We consider the pricing decision of a firm that operates in a monopolistic competition environment *à la* Dixit-Stiglitz.

The production function of firm i in sector k is linear and given by:

$$Y_{i,k,t} = A_{i,k,t} N_{i,k,t} \tag{1}$$

where $A_{i,k,t}$ is idiosyncratic productivity and $N_{i,k,t}$ hours worked. Output is $Y_{i,k,t}$, and in the baseline version of the model output equals here to consumption.

The law of motion for productivity is an auto-regressive process, with parameters that are identical within a sector:

$$lnA_{i,k,t} = \rho_k lnA_{i,k,t-1} + \varepsilon_{i,k,t} \tag{2}$$

where $\varepsilon_{i,k,t}$ is a i.i.d Gaussian idiosyncratic shock with variance $\sigma_k^2 = E\varepsilon_{i,k,t}^2$. Persistence parameter ρ_k, and the volatility parameters σ_k^2 will be parameters of interest that vary across sectors.

A recent literature has relied on alternative processes for productivity shocks. In particular, Midrigan (2011) and Karadi and Reiff (2014) have used cost processes featuring a Poisson component, resulting in leptokurtik cost shocks. This is an alternative mechanism to generate the fat-tails observed in the empirical distributions of price changes. We do not allow for such a process in our baseline version of the model for two reasons. First, there is an identification issue, resulting in a difficulty to disentangle this mechanism, from the Calvo type of price friction. Second, the assumption of fat-tailed shocks is debatable when actual price changes are rare since the cost shock will be the accumulation of cost shocks over a large period of time (see **?**).

We also consider, following Nakamura and Steinsson (2010), an alternative version of the model when there are intermediate inputs in the production function. The extension of the model is presented in the Appendix. By adding inter-firms relations through intermediate inputs, we are introducing some degree of strategic complementarity in our economy.

The aggregate price level is given by: $P_t = \left[\sum_{k=1}^{K} \omega_k P_{k,t}^{1-\theta}\right]^{\frac{1}{1-\theta}}$ The sectoral price level is given by: $P_{k,t} = \left[\int_0^1 P_{i,k,t}^{1-\theta} di\right]^{\frac{1}{1-\theta}}$

The per-period real profit function is then:

$$\Pi_{i,k,t} = \frac{P_{i,k,t}}{P_t} C_t \left(\frac{P_{i,k,t}}{P_t}\right)^{-\theta} - \left(\frac{W_t}{P_t}\right) \frac{C_{i,k,t}}{A_{i,k,t}}$$

In addition, price adjustment is costly: when changing prices, a menu cost is incurred. The menu cost $c_{i,k,t} W_t$ is assumed to be time-varying. As emphasized by Klenow and Kryvtsov (2008) "first-generation" menu–cost model with fixed menu costs are not able to fit the extent of small price changes seen in most data sets. With a probability λ_k, the price change is free: $c_{i,k,t} = 0$; with a probability $1 - \lambda_k$, $c_{i,k,t} = \mu_k$. Thus μ is the cost paid by the firm conditional on drawing a non-zero menu cost.

The model is close to Nakamura and Steinsson (2010)'s "CalvoPlus" model. It encompasses both the pure menu cost model (in which $\lambda_k = 0$) and the Calvo model ($\mu = \infty$), in which price changes are triggered only by free adjustment opportunities. Sector-specific price rigidity parameters of interest are: μ_k and λ_k.

For a firm i, in the sector k, we denote the vector of state variables: $\mathcal{S}_{i,t} = \{P_{i,t-1}/P_t, A_{i,t}, C_t\}$. The present value of profits is:

$$V(\mathcal{S}_{i,t}) = \max[V^{nc}(\mathcal{S}_{i,t}), V^{c}(\mathcal{S}_{i,t})] \tag{3}$$

where V^c is value if price is changed:

$$V^{c}(\mathcal{S}_{i,t}) = \max_{P_{i,t}}[\Pi(P_{i,t}/P_t, A_{i,t}, C_t) + E_t Q_{t+1} V(\mathcal{S}_{i,t+1})] - c_{i,t} W_t \tag{4}$$

and V^{nc} is value if price is not changed.

$$V^{nc}(\mathcal{S}_t) = \Pi(P_{i,t-1}/P_t, A_{i,t}, C_t) + E_t Q_{t+1} V(\mathcal{S}_{i,t+1}) \tag{5}$$

The model is solved by numerical methods and value function iteration. As is common in the menu cost set-up, the solution will give rise to a "range of inaction", rationalizing infrequent price changes.

3.2 Solution of the model and equilibrium

To close the model, we assume the monetary authority targets a path for nominal value added: $S_t = P_t C_t$. Nominal output S_t follows a random walk with drift:

$$log(S_t) = \pi + log(S_{t-1}) + \eta_t$$

where π is trend inflation and η_t is an aggregate policy shock.

The firm program is solved by value-function iteration. A sketch of the approach is as follows, assuming for now, for exposition purpose, that the process for P_t is known. Given S_t and P_t, real aggregate consumption C_t derives from the nominal value added identity. For a representative firm in sector k, with a given set of parameters λ_k, μ_k, σ_k and ρ_k, the processes for productivity, menu costs, and aggregate inflation are discretized on a grid. We assume an initial set of values characterizing function $V(.)$ on the grid. We then solve the program of the firm to derive the policy function and a resulting new value function using equations (3),(4),(5). Iterations on function $V(.)$ are carried out until convergence. Upon convergence, the resulting policy function is used to simulate the model and produce simulated statistics on the distribution of price changes.

In general equilibrium, one needs to acknowledge that P_t is endogenous. The firm's problem is infinite-dimensional, as P_t is the aggregate of all individual prices. Following Krusell and Smith (1998) and the implementation of their procedure by Nakamura and Steinsson (2010), we assume that firms perceive the evolution of the price level as a function of a small number of moments of the price distribution, namely:

$$\frac{P_t}{P_{t-1}} = \Gamma\left(\frac{S_t}{P_{t-1}}\right) \tag{6}$$

The computation of the general equilibrium is performed as follows. The above iteration is carried out to find the policy function. The aggregate price change is then computed, and compare with prediction from (6). Function Γ is then updated, and we iterate over Γ and value-function iteration loops until convergence. Upon convergence function the perceived aggregate law of motion Γ is consistent with individual policy rules.

Following Nakamura and Steinsson (2010), and for robustness purposes we also consider a model with intermediate inputs (see the Appendix for the specification in that case). Introducing such an ingredient allows us to consider strategic complementarities in the models since firms buying intermediate inputs to other firms take into account prices of other firms to set their own price.

3.3 Predefined parameters

Some parameters of the model have been calibrated prior to the estimation. The calibration of these parameters is presented now, as they are also useful for illustrating the model properties. Following Nakamura and Steinsson (2008), we assume log utility $\gamma = 1$ and set the discount factor to $\beta = 0.96^{1/12}$, and the elasticity of demand to $\theta = 4$. These values fall in standard ranges, and the latter is consistent with a mark-up of 1.33. We also impose the parameters associated with the inflation process. The mean of the process for overall inflation is set to $\pi = 0.125\%$ and the standard deviation of η_t^P to $\sigma_\eta = 0.28\%$ from the aggregate French CPI data over our sample period (note that there is no growth in the model so we consider inflation rather than nominal GDP growth). In the model where we allow intermediate inputs, we calibrate the share of inputs to 0.7 as in Nakamura and Steinsson (2010) and close to the value calculated using National Accounts time series for France (see Table F in Appendix). Over the period 1994-2014, the average share of intermediate inputs is equal to 50% of total production. The cost share of intermediate inputs is equal to the revenue share (0.5) times the markup ($\frac{\theta}{\theta-1} = 4/3$), which leads a weighted average cost share of intermediate inputs close to 70%. This figure is larger when considering only manufacture ($s_m = 0.8$ to 0.9).

3.4 Model Properties

To illustrate the properties of the model and investigate how moments can help identify structural parameters, we plot simulated moments obtained from our theoretical model for a range of different values of the 4 parameters of interest. [10] Our chosen simulated moments correspond to those used in our estimation procedure: the frequency of price change, the share of price increases, and the quartiles of the price change distribution. These results are produced considering a two-sector model ($K = 2$), featuring one small sector and one large sector. We run large simulations of the model under various parametrizations: each parameter in the small sector is varied in turn on a grid, away from a baseline parameter value. The parameters of the larger

[10] In the following we omit the sector index to alleviate notations, when there is no ambiguity.

sector are kept unchanged across simulations. The moments of the small sector are reported to illustrate how sensitive moments are to variations in the parameters. A large sensitivity of moments to variations of the parameters will increase the precision of the estimation. Figure 3 plots simulated moments for different values of parameters driving the menu cost process, whereas Figure 4 plots simulated moments for different values of parameters driving the productivity process. Before describing in details the results, it is worth stressing that none of the parameters is pinned down by a single moment, a property which motivates our use of an SMM estimation technique.

The effect of increasing λ, the probability of a free menu cost – i.e. the Calvo component of the model– are reported in the top panel of Figure 3. The frequency of price change is an approximately linear increasing function of λ. Price decreases are also more frequent with a larger λ, and the share of price increases drops. Because trend inflation is positive in the model, any price decrease is due to firm-specific positive productivity shocks. With a larger value of λ, the contribution of the productivity shocks to price changes is much larger. For a given set of other parameters, firms are more willing to decrease prices with a larger value of λ. Indeed, the perspective of a future need to increase their price again does not prevent them from doing so, given that the opportunity of free price adjustment is more frequent. Thus, they can more easily adjust their prices downwards following positive productivity shocks. Finally, a larger λ generates price changes of smaller size. When λ increases say from 1% to 5%, the first quartile of price changes decreases from 4% to less than 2%, whereas the median and the third quartiles are decreasing but more slightly. The reason is that when drawing randomly a free opportunity of price changes, firms will adjust their prices whereas they may have already adjusted in the recent period, inducing some small price change. The parameter λ thus mitigates the standard "selection effect" of menu cost model.

The effect of varying the size of the menu cost μ is described in the bottom panel of Figure 3. As predicted by a standard menu cost model, the frequency of price changes is a decreasing function of the size of the menu cost μ. In the set-up where $\lambda = 0$ and σ_ϵ is small, the model is close to a fixed menu cost model (Sheshinski and Weiss (1977)) where price changes mostly driven by the trend inflation. When the menu cost is larger, firms wait longer before adjusting their prices. Similarly, the share of price increases is increasing rapidly to 100% since the larger menu cost deter firm from adjusting to positive productivity shock (in the baseline, the variance of productivity shock is set at a small value) in a set-up of positive trend inflation. The size of price changes is increasing with the menu cost because of the strong selection effect. Finally, the interquartile range is small, as expected since standard menu cost models predict a very small variance of price adjustments.

Turning to the effect of varying productivity parameters σ_k and ρ_k (Figure 4), a larger standard deviation of the innovation of productivity shock σ_k increases the frequency of price changes, and reduces the share of price increases other things equal. More volatile productivity shocks do indeed increase the occurrence of decreases in marginal costs, and thus of price decreases. The variance of the productivity shock also boosts the size of price changes, since firms will typically be hit by shocks of larger sizes. The dispersion in the size of price changes, measured by the inter-quartile range of price changes, is also larger for large values of the productivity shock variance, since the variability in the desired price changes is much higher with a larger variance of productivity shock. Very similar patterns emerge with respect to the auto-correlation of the productivity shock varies, as increasing the parameter ρ lifts up the unconditional variance of the productivity shock.

4 Empirical Results

This section presents our estimation results. Using a simulated moment method (SMM) technique, we estimate parameters associated with both the menu cost and the productivity process and we consider one-sector and multi-sector versions of the model.

4.1 Estimation approach

Estimated parameters include two parameters for the menu cost process: the probability of drawing a free adjustment cost λ and the menu cost μ and two parameters for the productivity process: the standard deviation of the productivity shock σ_ε and the auto-correlation of the productivity process ρ. We rely on a SMM technique which consists of finding parameter values that minimize the distance between actual moments calculated from the data and the simulated moments coming from our model. We proceed as follows: we select a vector of moments m computed from the actual micro CPI price data. For a given candidate set of parameters Ω, we solve the policy function, we simulate large price trajectories from the model, and compute the simulated moments $\hat{m}(\Omega)$. For each set of parameters Ω, we can calculate the difference between actual moments and simulated moments, which gives the vector $m - \hat{m}(\Omega)$. The SMM estimation technique consists of finding the set of parameters $\hat{\Omega}$ that minimizes the weighted difference between the actual and simulated moments:

$$\hat{\Omega} = argmin_{\Omega} \left[(m - \hat{m}(\Omega))' W (m - \hat{m}(\Omega)) \right]$$

where the weighting matrix W is here chosen as the inverse of the actual moments to give more weight to the smaller moments.[11] Minimization is performed using a numerical routine.[12]

Our implementation of the SMM uses five moments as targets: the frequency of price changes, the frequency of price increases, the median and the first and third quartiles of the distribution of absolute price changes. We choose these moments in the baseline, as one of our aim is to compare our results with the ones obtained for the United States, and comparable moments are only available at the product level from Nakamura and Steinsson (2008). [13]

[11] As a robustness exercize – still in progress at the time of this version of the paper – we carry out estimation using the inverse of variance of the moments (obtained from bootstrap) as weighting matrix W.

[12] As is not uncommon in work with large micro datasets (e.g. Acemoglu et al. (2016)), we do not report standard errors of SMM parameters since they are bound to be very small and weakly informative given the huge size of the data set

[13] As a robustness exercize, we carry out estimation using kurtosis and interquartile range as additional moments

We run the estimation both at the aggregate level, using either average or median moments of the data, and at the product-level for all of the 227 products we identified in the micro price data set. In this latter case, the joint estimation of a multi-sector menu cost model with such a large number of sectors and parameters would not not tractable. To perform product-level estimate, we then follow a two–step approach. In a first step, we estimate a single sector version of our model based on the *median* moments of the aggregate economy. Following Nakamura and Steinsson (2010) and our own results (detailed in further section), this model captures quite well the behaviour of the aggregate economy. Then, in a second step, for each of the 227 sectors in turn, we estimate a two-sector model featuring i) a small sector, which is our sector of interest, and ii) a large sector which features the "rest of the economy". The parameters for the latter large sector are treated as fixed, auxiliary parameters and set to the values obtained in the first step. Estimation targets the moments in each small sector. The weight of the small sector in the overall economy is set to its value in the French CPI, whereas the weight of the large sector is set to the fraction of the total size CPI covered by our full sample. Overall, we thus estimate 227 two-sector general equilibrium models. By following such an approach, we are able to estimate sets of structural parameters of a large number of sectors, while relying on are a general equilibrium approach. The potential bias stemming from having the small sector pooled with the other sectors at the estimation stage should remain very limited since the average sectoral weight is less than 0.5%.

4.2 Results from a one-sector model and aggregate moments: France vs the United States

Table 3 first presents results obtained for a one-sector version of the model estimated using either median moments or mean moments, both for the French and the US economies. Results also include the version of the model where we consider intermediate inputs in the production

(see Tables A and C and Figure A in Appendix). Preliminary results are presented in Appendix in Table B for one-sector models and Table D for sectoral models.

function of the firm. As Nakamura and Steinsson (2010) have shown it is the most relevant shortcut model for an actual multi-sector economy, we mainly comment results from the model fitting median moments. One first salient result is that the value of λ estimated from median moments is a little larger than 4% in France and close to 5% in the United States. Thus, the share of price changes triggered under the zero menu cost regime accounts for a little more than half of the median frequency of price changes for both countries. The role of the Calvo component is even larger when using the model assuming intermediate inputs in the production function (6.5 and 7.1 percent respectively). Thus, for the typical sector, the Calvo component of the model is rather large as compared to the menu cost component. This finding matches evidence reported on producer prices by Carlsson (2017) using Swedish micro data and Alvarez, Le Bihan, and Lippi (2016) on the same French CPI data using a sufficient statistics approach. The "selection effect" typical of menu cost model is expected to be much attenuated. The estimated average menu cost μ - when price adjustments are not free - is between 1.6 and 2% of total revenues in France but much larger in the United States (between 4 and 5%). A larger menu cost is here needed to fit the larger size of price changes in the US, when at the same time frequencies of price changes and shares of price increases are rather similar in the US and France. We can compute the average amount paid by firms per period for adjusting their prices as $\mu \times (f - \lambda)$: in France, such average cost represents less than 0.1% of total revenues whereas in the US it is between 0.1 and 0.2%. Nakamura and Steinsson (2010) find very close results with an average menu cost actually paid of about 0.5% when $s_m = 0$ and close to 0.1% when $s_m = 0.7$. Studies using "direct" evidence such as Levy et al. (2005), Dutta et al. (1999) or Zbaracki et al. (2004) report values between 0.5% and 1% of revenues for different types of supermarkets, drugstores or industrial firms. Overall, menu-costs are estimated to be larger in the United States when we exclude from the calculations sales and promotions and consider very similar products.

Concerning the parameters associated with the productivity process, the unconditional standard deviation of the productivity shock (say $V_a = \sigma_\epsilon / \sqrt{(1-\rho^2)}$) recovered by theses estimates lies between 5% and 8% in France, whereas it is much higher in the United States, lying between

9% and 12%. Nakamura and Steinsson (2010) report values between 6 and 10% for σ_ϵ, which implies values between 8 and 13% for V_a. In both countries, the volatility of idiosyncratic shocks is found to be large compared to the aggregate shock on inflation, since the standard deviation of η_t is calibrated on aggregate CPI data to $\sigma_\varepsilon^P = 0.28\%$. Thus idiosyncratic productivity shocks are the main drivers of price change decisions and explain the dispersion in the size of price adjustment. Also, to a large share extent, the difference in size of price adjustments between France and the United States is explained by differences in the variance of the productivity shock.

4.3 Multi-sector estimates and the sources of cross–sectoral heterogeneity

Figure 5 plots the weighted distribution of the parameters estimated for all 227 products using the multi-sector version of the model. For all four parameters of the model, the degree of heterogeneity is large. The distributions of λ_k's and μ_k's feature the largest dispersion. In a attempt to standardize the dispersion indicators, we compute the following relative dispersion indicator. Namely, we calculate the ratio between the interquartile difference (q3-q1) and the median of the distribution of parameters. For λ and μ, the dispersion indicator is larger than 1.3 (i.e. the interquartile range represents more than 130% of the median parameter) whereas it is much smaller than 1 for σ (0.55) and ρ (0.33).

Table 4 summarizes our cross sectoral results, by reporting median values of parameters for all products, as well as by broad categories of products. First, the proportion of price changes stemming from the opportunity of free price adjustment (the ratio of λ to the frequency) is very high, in the order of 60%, for food, other manufactured goods and services whereas this proportion is smaller for durables or energy. Some sectoral differences are also observed for the menu cost parameters. This menu cost is larger in services and durables. Overall, differences across sectors in average menu costs (in terms of percentage of total revenues) are quite small in the case without intermediate inputs, but appear larger when considering the case with intermediate inputs. In particular, average menu costs are larger for services and durables. As a results the share of free price changes is smaller in those than in other sectors. Concerning the parameters characterizing the productivity process, some differences are quite sizable. The median $\sigma_{\epsilon k}$ is smaller for energy and services than for food or manufactured goods. However the median ρ parameter is much larger in these latter sectors, which leads to a rather similar median unconditional standard deviation of the productivity process across sectors.

To illustrate how differences in price adjustment characteristics relate to structural parameters of price-setting, Figures 6, 7, 8 and 9 plot each moment of the data against estimated parameters. In most cases, no simple relationship emerges, illustrating that various parameters play a role. However some patterns are noticeable. Figure 6 suggests that a large share of the cross–product heterogeneity in frequency of price changes is explained by variations of λ and μ, whereas productivity parameters play a smaller role. As expected, cross–product differences in the share of price increases seem better related to cross–product differences in productivity parameters than in menu–cost parameters (Figure 7). Finally, cross–product differences in the median size of price changes and in the dispersion of price change appear to be related with the variance of productivity shocks and of the menu cost μ.

To investigate more formally to which extent cross–product heterogeneity in parameters can explain cross product heterogeneity in data moments, we run a series of counterfactual experiments. For each of the 227 CPI product categories, we run four counterfactual exercizes, each corresponding to one the parameters of interest. In each exercize, we simulate moments from the multi-sector model holding one of the four parameters *constant across sectors*, and setting it equal to the median value of parameter estimate distribution. For instance, in all sectors we set λ_k equal to the median value of λ's, and for all product categories in turn, we simulate a model using actual estimated parameter values except for λ. We then calculate the relative dispersion of cross–product distribution of the moments simulated by the counterfactual exercises (i.e. standard deviation divided by the mean) and compare it to the relative dispersion in the data. Table 5 summarizes the results. The relative dispersion across products of the frequency of price changes in the data is very large since the standard deviation is close to 1.4

times the average frequency. When considering the counterfactual where λ_k is set to its median value $Median(\lambda_k)$ for all products, the dispersion of the frequency of price changes is a little larger (1.49), whereas it decreases a lot (to 0.71) in the exercize where μ_k is set to its median value. A feature driving this result is however that the frequency of price changes in the energy products is an outlier, and resultingly a large share of the variations in the frequency of price changes is due to energy products. As the high frequency of price changes in the energy sector is captured in the model by very small estimated menu costs, the standard deviation of the frequency decreases a lot when μ is set equal its median value (and thus substantially increased for energy goods). By contrast when excluding energy items, as evidenced in the second row of Table 5, heterogeneity in λ_k is shown to be a key contributor to variations in the frequency of price changes. Indeed if when λ_k is set to its median value for all products the relative dispersion of the frequency of price changes is more than halved from 64% to 31%. Productivity parameters play a minor role to explain cross product heterogeneity in the frequency of price changes.[14] Turning to the share of price increases, the cross–product relative dispersion is rather small (18.5%). λ and μ appear to play a rather limited role to explain this cross–product heterogeneity: the corresponding counterfactual relative dispersion is only reduced to 13%. For that moment, productivity parameters turn out to play almost no role. The relative dispersion in the median size of price changes does not seem to be driven by any single parameter. Finally the cross product heterogeneity in the dispersion of price changes (as captured by the relative dispersion of interquartile of price changes, equal to 40.5%) seems to be related to cross product differences in both λ_k and $\sigma_{\epsilon k}$ parameters.

To summarize estimation and counterfactual exercizes, there is evidence of heterogeneity in all parameters. In particular we find evidence both of substantial "menu costs" and of a Calvo component in price adjustments. Heterogeneity in the frequency of price change is mainly driven by those parameters. In turn, heterogeneity in the idiosyncratic productivity/cost process plays

[14]The counterfactual cross–product relative dispersion in the frequency moment is even larger than the baseline relative dispersion when either ρ or $\sigma_{\epsilon k}$ are set equal to their median. This reflects the fact that the ρ_k and σ_{ϵ_k} are negatively correlated across products.

more of a role explaining the variability in size of price changes.

5 Implications for Monetary Non Neutrality

This section investigates to what extent cross–product heterogeneity, and the weight of the Calvo component, do matter for the effect of a monetary policy shock, based on our estimated set of parameters and the multi-sector menu cost model. Using function Γ obtained from the Krusell and Smith (1998) procedure, as well as the law of motion for aggregate output, we are able to simulate the real effects of a 1% shock in the nominal output (i.e. a shock to η_t). Our aim is to estimate the impact of sectoral heterogeneity on the degree of monetary non-neutrality and also whether differences in structural parameters between France and the United States have implications for the real effect of monetary policy in both countries.[15]

5.1 Sectoral Heterogeneity and Monetary Non Neutrality

To investigate implications of sectoral heterogeneity, we analyze the real response to a monetary policy shock in three variants of the general equilibrium model: a single-sector model calibrated to fit average moments across sectors, a one–sector model calibrated to fit median moments, and a multi–sector model. As previously mentioned, simulating a 227 sectors general equilibrium multi-sector model would not be tractable. Therefore in this exercize we rely on a five sector menu cost model, parametrizing each of the five sectors using the median parameters obtained from Table 4. To the extent that there is residual heterogeneity within each sector, our results will underestimate the bias of using a one–sector model.

Figure 10 displays the response of output to a 1% monetary policy shock in the three models in the case $s_m = 0$. Figure 11 plots the results for results with $s_m = 0.7$. We find that the response is much short-lived in the one–sector model fitting the average moments of the data

[15] Obviously our exercize is primarily an analytical one: characterizing a realistic monetary policy shock would require a more sophisticated set-up, in particular because France is part of the European Monetary Union. However to the extent that existing studies of price rigidity point that price adjustment patterns in France are even quantitatively representative of those in the euro area, the exercize can be thought as a euro-area-wide shock.

than in the multisector model: the half life in is about one year in the multisector model versus 6 months for the one sector model. Thus, the persistence is severely underestimated when neglecting sectoral heterogeneity. We also find that the real effect of the monetary shock is much smaller in the case of the one–sector model fitting the average moments of the data.

Table 6 reports a summary indicator on the degree of monetary policy non-neutrality in three models, namely the cumulated response of output after a monetary shock. Taking into account sectoral heterogeneity increases the degree of monetary policy non-neutrality by a factor of 2, in the model with intermediate inputs. Such an amplification is in line with the results of Nakamura and Steinsson (2010), although they report an amplification factor of 3.[16] Finally, as already underlined by Nakamura and Steinsson (2010) for the United States, we find that using a multi-sector model fitted to the median moments does a better job of approximating the response in the multi-sector economy than a model fitting the average moments. For instance in the model fitted to median moments the cumulative output effect equal 7.41 percent, against 8.12 in the multi-sector model, arguably the closest to the true data-generating process in this set-up. The degree of non-neutrality is higher by a factor of 1.6 when comparing the one–sector model estimated on median moments and the one–sector model estimated using average moments.

We also note that, as was underlined in Nakamura and Steinsson (2010), considering intermediate inputs increase a lot the monetary non-neutrality, reflecting of strategic complementarities (the cumulated output responses being boosted up from 3.09 to 8.12 in our experiment). If we compare cumulated real effects obtained from the different models assuming the presence of intermediate inputs, we find very similar amplification factors as in the case with no intermediate inputs: compared with the model estimated on average models, the degree of non-neutrality is 1.7 times higher when we consider model estimated on median moments and 1.9 higher when considering a multi-sector model.

[16]We conjecture however that part of the discrepancy in the amplification factor reflects that our data set does not include some specific sectors with large frequencies of price change like used cars, electricity...

The amplification effect related to sectoral heterogeneity we find on French data is also in line with the analytic computations of Alvarez, Le Bihan, and Lippi (2016). Alvarez, Le Bihan, and Lippi (2016) show that in a menu–cost model with random opportunity of free price change and assuming multiproduct firms, the cumulated output effect of a small monetary policy shock is a function of the kurtosis of non-zero price changes and of the frequency of price changes. Assuming an homogenous economy, and using the average moments to calibrate such an economy, the output response is shown to be proportional to $R \equiv Kur/Freq$, where $\overline{Kur}$ and $\overline{Freq}$ are the average kurtosis and frequency of the economy. Assuming an economy, with heterogeneous sectors, the cumulated output response is $R^{het} \equiv \sum_{k=1}^{K} w_k Kur_k/Freq_k$, where w_k Kur_k $Freq_k$ are CPI weights, kurtosis of price changes, and frequency of price changes in sector k (see Appendix E in Alvarez, Le Bihan, and Lippi (2016)). Our set-up differs from Alvarez, Le Bihan, and Lippi (2016) since we do not have multiproduct firms, we allow for positive inflation rate and have freely estimated AR(1) shock for costs rather than Brownian motions, and moreover, we work with discrete time and approximate solutions rather than analytical solutions derived under continuous time. To compare our results with those provided by the analytical results of Alvarez, Le Bihan, and Lippi (2016), we calculate the ratio of kurtosis over frequency, using our micro data and considering different level of aggregation. Table E in Appendix reports our results. First, we find that if we use average or median moments, the ratio R is 1.4 times higher using median moments rather than average moments. Table 6 reports a factor of 1.6 to 1.7 when using our numerical simulations. Second, based on the sample of our 227 products, using product-level weights, frequencies and kurtosis we find an amplification factor R^{het}/R of 2.35. This amplification factor is a little smaller – close to 1.9 – when using a five-sector aggregation (i.e. first calculating R for five aggregate sectors and then calculate the weighted average R over the 5-sectors). This is of the same order of magnitude as the value of 2.0 we obtained with our estimated model.

5.2 The Amplification Effect of the Calvo Component

Figure 13 presents (in the case $s_m = 0$, and using the median moment approximation of the multi–sector economy) the response of our baseline model along with two polar benchmarks models our set-up encompasses. One is a pure menu cost model (λ=0) (Golosov and Lucas (2007)) calibrated on the median moments. The other is a the baseline Calvo model (μ=0), again calibrated to reproduce median moments. The output response in our augmented menu–cost model is larger than in the menu–cost model. The amplification factor (due the the Calvo component) is of the order of 1.5, that is the cumulated output response is 50 percent larger than in a pure menu–cost model. The overall response is closer to the menu cost impulse response function than to the Calvo one according to the cumulated response we have chosen. Notice indeed that although about half of price changes are triggered by the Calvo mechanism, our model has an amplification factor of around 1.5, while the amplification factor is estimated to be 2.3 for the Calvo model. The results are qualitatively similar to Alvarez, Le Bihan, and Lippi (2016) or Nakamura and Steinsson (2010): introducing a fraction of state–dependent agents in a Calvo set-up reduces non-neutrality more than proportionally. In other terms, the output response is a convex function of the share of Calvo price setters (for a given frequency of price change). The quantification of this effect we obtained is in line with Alvarez, Le Bihan, and Lippi (2016) (although the effect of the pure Calvo set-up relative to pure menu cost, is found to be lower in our set-up than in their results).

5.3 France versus United States

Finally, Figure 12 plots the real responses to a 1% monetary policy shock in France and in the United States. As our calibration implies that all parameters other than the "price-setting" parameters of interest are the same for both countries, differences between the two countries can only be attributed to differences in productivity or menu costs. Considering both cases with or without inputs and using the one sector model fitting the median moments, we find that the real response to a monetary shock is very close in both countries. This suggests that differences in menu costs or productivity parameters can not explain differences in monetary non-neutrality (to the extent that sales are not regarded as mainly responding to aggregate shocks).

6 Conclusion

Motivated by the recurrent finding in empirical micro prices studies that prices are much more frequent in some sectors than others, this paper has investigated the role of menu costs and of productivity shocks in the level, and in the cross–sectoral dispersion, of price rigidity in France. A structural model of price rigidity has been used to disentangle the effects of price rigidity on one side and the effects of productivity shocks on the other side on the moments of price adjustment patterns (i.e. frequency and size of price changes). The augmented menu cost model used, nests both the standard Calvo model and a fixed menu-cost model. Using a SMM estimation technique and price rigidity moments computed on French CPI micro data, we have estimated deep parameters of this random menu cost model for more than 200 different CPI product categories. Matching US and French data moments, we have also compared estimation results for both the United States and France.

Our main results are the following. First, the Calvo dimension of price rigidity is crucial to fit the patterns of micro data and a large proportion of price changes are associated with the free opportunity to change prices. The "menu cost" component of price rigidity contributes only little to price rigidity differences. Second, there is a substantial degree of heterogeneity in structural parameters across sectors. The cross sectoral heterogeneity in the frequency of price changes in the data reflects large differences in price rigidity deep parameters rather than differences in productivity shocks. In particular, cross–sectoral variance of the Calvo parameter (the probability of free opportunity to change prices) contributes a lot to the cross–sectoral variation in the frequency of price changes. We also find only small difference in parameter estimates between United States and France: the larger size of price changes in the US is replicated through a larger variance of productivity shocks and larger menu costs. Finally, at the aggregate level, cross–product heterogeneity is found to matter for monetary policy. The cumulated response of output to money in a multi–sector economy is twice as large as in a single sector model featuring the same average moments. When we compare impulse response functions to a monetary shock in the United States and France (assuming identical parameters for parameters other than those related to costs and price-setting friction), we find highly similar impulse response functions, suggesting that differences in the degree of monetary non-neutrality between the two economies are not driven by differences in the rigidity of regular prices.

References

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr. 2016. "Transition to Clean Technology." *Journal of Political Economy* 124 (1):52–104.

Alvarez, Fernando, Herve Le Bihan, and Francesco Lippi. 2016. "The Real Effects of Monetary Shocks in Sticky Price Models: A Sufficient Statistic Approach." *American Economic Review* 106 (10):2817–51.

Alvarez, Luis J. and Pablo Burriel. 2010. "Micro-Based Estimates of Heterogeneous Pricing Rules: The United States vs. the Euro Area." *Scandinavian Journal of Economics* 112 (4):697–722.

Anderson, Eric, Benjamin A. Malin, Emi Nakamura, Duncan Simester, and Jn Steinsson. 2017. "Informational Rigidities and the Stickiness of Temporary Sales." *Journal of Monetary Economics* 90:64–93.

Baudry, L., H. Le Bihan, P. Sevestre, and S. Tarrieu. 2007. "What do Thirteen Million Price Records have to Say about Consumer Price Rigidity?" *Oxford Bulletin of Economics and Statistics* 69 (2):139–183.

Berardi, Nicoletta and Erwan Gautier. 2016. "Adjustments in consumer prices in France in periods of low inflation." *Quarterly Selection of Articles* 41.

Berardi, Nicoletta, Erwan Gautier, and Hervé Le Bihan. 2015. "More facts about prices: France before and during the great recession." *Journal of Money, Credit and Banking* 47 (8):pp. 1465–1502.

Bils, Mark and Peter J. Klenow. 2004. "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy* 112 (5):947–985.

Blanco, Andres. 2017. "Optimal Inflation Target in an Economy with Menu Costs and a Zero Lower Bound ." Working paper, University of Michigan.

Bouakez, Hafedh, Emanuela Cardia, and Francisco J. Ruge-Murcia. 2009. "The Transmission Of Monetary Policy In A Multisector Economy." *International Economic Review* 50 (4):1243–1266.

Burstein, Ariel and Christian Hellwig. 2006. "Prices and market shares in state-dependent pricing models." 2006 Meeting Papers 375, Society for Economic Dynamics.

Caballero, Ricardo J. and Eduardo M. R. A. Engel. 1999. "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S,s) Approach." *Econometrica* 67 (4):783–826.

Carlsson, Mikael. 2017. "Microdata Evidence on the Empirical Importance of Selection Effects in Menu-Cost Models." *Journal of Money Credit and Banking* .

Carvalho, Carlos. 2006. "Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks." *The B.E. Journal of Macroeconomics* 6 (3):1–58.

Coibion, Olivier, Yuriy Gorodnichenko, and Gee Hee Hong. 2015. "The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications." *American Economic Review* 105 (3):993–1029. URL `http://www.aeaweb.org/articles?id=10.1257/aer.20121546`.

Costain, James and Anton Nakov. 2011. "Price Adjustments in a General Model of State–Dependent Pricing." *Journal of Money, Credit and Banking* 43:385–406.

———. 2012. "Distributional dynamics under smoothly state-dependent pricing." *Journal of Monetary Economics* forthcoming.

Dhyne, Emmanuel, Luis J. Alvarez, Herve Le Bihan, Giovanni Veronese, Daniel Dias, Johannes Hoffmann, Nicole Jonker, Patrick Lunnemann, Fabio Rumler, and Jouko Vilmunen. 2006. "Price Changes in the Euro Area and the United States: Some Facts from Individual Consumer Price Data." *Journal of Economic Perspectives* 20 (2):171–192.

Dhyne, Emmanuel, Catherine Fuss, M. Hashem Pesaran, and Patrick Sevestre. 2011. "Lumpy Price Adjustments: A Microeconometric Analysis." *Journal of Business & Economic Statistics* 29 (4):529–540. URL https://ideas.repec.org/a/bes/jnlbes/v29i4y2011p529-540.html.

Dotsey, Michael, Robert G. King, and Alexander L. Wolman. 1999. "State-Dependent Pricing And The General Equilibrium Dynamics Of Money And Output." *The Quarterly Journal of Economics* 114 (2):655–690.

Dutta, Shantanu, Mark Bergen, Daniel Levy, and Robert Venable. 1999. "Menu Costs, posted prices and multiproduct retailers." *The Journal of Money, Credit and Banking* 31 (4):683–703.

Eichenbaum, Martin S., Nir Jaimovich, Sergio Rebelo, and Josephine Smith. 2014. "How Frequent Are Small Price Changes?" *American Economic Journal: Macroeconomics* 6 (2):137–155.

Eusepi, Stefano, Bart Hobijn, and Andrea Tambalotti. 2011. "CONDI: A Cost-of-Nominal-Distortions Index." *American Economic Journal: Macroeconomics* 3 (3):53–91.

Fougere, Denis, Herve Le Bihan, and Patrick Sevestre. 2007. "Heterogeneity in Consumer Price Stickiness: A Microeconometric Investigation." *Journal of Business & Economic Statistics* 25:247–264. URL https://ideas.repec.org/a/bes/jnlbes/v25y2007p247-264.html.

Gagnon, Etienne, J. David Lopez-Salido, and Jason A. Sockin. 2015. "The Cyclicality of Sales, Regular and Effective Prices: Comment." Finance and Economics Discussion Series 2015-52, Board of Governors of the Federal Reserve System (U.S.). URL https://ideas.repec.org/p/fip/fedgfe/2015-52.html.

Golosov, Mikhail and Robert E. Jr. Lucas. 2007. "Menu Costs and Phillips Curves." *Journal of Political Economy* 115:171–199.

Hobijn, Bart, Federico Ravenna, and Andrea Tambalotti. 2006. "Menu Costs at Work: Restaurant Prices and the Introduction of the Euro." *The Quarterly Journal of Economics* 121 (3):1103–1131.

Karadi, Peter and Adam Reiff. 2014. "Menu Costs, Aggregate Fluctuations, and Large Shocks." Working Paper Series 10138, CEPR.

Klenow, J. Peter and Benjamin Malin. 2010. "Microeconomic Evidence on Price-Setting." *Handbook of monetary economics* 3:231–284.

Klenow, Peter J. and Oleksiy Kryvtsov. 2008. "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?" *The Quarterly Journal of Economics* 123 (3):863–904.

Krusell, Per and Anthony A. Smith. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *Journal of Political Economy* 106 (5):867–896.

Kryvtsov, Oleksiy and Nicolas Vincent. 2014. "On the Importance of Sales for Aggregate Price Flexibility." Staff Working Papers 14-45, Bank of Canada. URL `https://ideas.repec.org/p/bca/bocawp/14-45.html`.

Le Bihan, Herve and Julien Matheron. 2012. "Price Stickiness and Sectoral Inflation Persistence: Additional Evidence." *Journal of Money, Credit and Banking* 44 (7):1427–1442.

Levy, Daniel, Mark Bergen, Shantanu Dutta, and Robert Venable. 2005. "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains." Macroeconomics 0505012, EconWPA.

Luo, Shaowen and Daniel Villar. 2015. "The Skewness of the Price Change Distribution: A New Touchstone for Sticky Price Models." mimeo, Columbia University.

Midrigan, Virgiliu. 2011. "Menu Costs, Multi-Product Firms, and Aggregate Fluctuations." *Econometrica,* 79 (4):1139–1180.

Nakamura, Emi and Jon Steinsson. 2008. “Five Facts about Prices: A Reevaluation of Menu Cost Models.” *The Quarterly Journal of Economics* 123 (4):1415–1464.

———. 2010. “Monetary Non-Neutrality in a Multisector Menu Cost Model.” *The Quarterly Journal of Economics* 125 (3):961–1013.

———. 2013. “Price Rigidity: Microeconomic Evidence and Macroeconomic Implications.” *Annual Review of Economics* 5 (1):133–163.

Sheshinski, Eytan and Yoram Weiss. 1977. “Inflation and Costs of Price Adjustment.” *Review of Economic Studies* 44 (2):287–303.

Woodford, Michael. 2009. “Information-Constrained State-Dependent Pricing.” *Journal of Monetary Economics* 56:s100–s124.

Zbaracki, Mark J., Mark Ritson, Daniel Levy, Shantanu Dutta, and Mark Bergen. 2004. “Managerial and Customer Costs of Price Adjustment: Direct Evidence from Industrial Markets.” *The Review of Economics and Statistics* 86 (2):514–533.

Tables and Figures

Table 1: Stylized Facts on Price Rigidity in France (1994-2014)

	Nb	Frequency		Size of price changes			CPI Weight
	products	changes	increases	p25	p50	p75	
				Mean			
All	227	13.7	8.7	2.8	4.8	8.6	57.0
				Median			
All	227	8.4	6.1	2.6	4.4	8.0	57.0
Food	77	13.2	8.2	2.5	4.5	8.0	15.3
Durables	33	5.0	3.2	3.7	7.3	11.8	5.2
Other Manuf	59	7.2	5.1	2.4	4.4	8.2	12.7
Energy	6	74.4	45.3	1.8	2.9	4.5	5.0
Services	52	4.9	4.4	2.6	4.3	7.0	18.8

Note: Calculations made on the French CPI micro data set over the period 1994-2014 (25 million of monthly price quotes). Prices of rents, cars, fresh food products and electricity + clothing goods are excluded (around 60% of the CPI left). Price changes due to sales and promotions are excluded (flag). We have dropped VAT change and euro–cash changeover periods and price changes smaller than 1% in absolute values. Price rigidity moments are first calculated at the product level and we then compute the weighted median of those product-specific moments.

Table 2: Comparison of French and US price rigidity indicators

	Frequency		Size of price changes			CPI Weight
	changes	increases	p25	p50	p75	
Mean						
France	13.9	8.9	2.8	4.9	8.7	54.3
United States	14.9	9.3	3.9	8.5	17.1	54.3
Median						
France	8.4	6.1	2.6	4.5	8.0	54.3
United States	9.2	6.2	3.8	8.0	15.4	54.3

Note: Calculations made on the French CPI micro data set over the period 1994-2014 (25 million of monthly price quotes). Prices of rents, cars, fresh food products and electricity + clothing goods are excluded (around 60% of the CPI left). Price changes due to sales and promotions are excluded (flag). We have dropped VAT change and euro–cash changeover periods and price changes smaller than 1% in absolute values. Price rigidity moments are first calculated at the product level and we then compute the weighted (using French CPI weights median of those product-specific moments. For the US calculations, we are using moments calculated by Nakamura and Steinsson (2008) and released as a web appendix. We are using moments at the product level and for comparable French products, we are considering moments excluding sales (flag for the frequencies and filtered for the size of price changes). We calculate aggregate moments using French CPI weights

Table 3: Estimates of Price Rigidity Model - France vs United States

	Menu cost			Productivity			
	λ	μ	average (in %)	σ_ϵ	ρ	σ	$\frac{\lambda}{Freq}$
$s_m = 0.0$							
Mean moments							
France	0.078	0.016	0.097	0.046	0.493	0.053	56.9
United States	0.092	0.046	0.263	0.082	0.451	0.092	61.6
Median moments							
France	0.044	0.020	0.081	0.039	0.632	0.050	51.9
United States	0.048	0.053	0.234	0.071	0.544	0.085	53.0
$s_m = 0.7$							
Mean moments							
France	0.125	0.016	0.023	0.071	0.549	0.085	91.2
United States	0.134	0.049	0.073	0.138	0.460	0.156	90.6
Median moments							
France	0.065	0.016	0.030	0.062	0.617	0.079	77.5
United States	0.071	0.038	0.079	0.096	0.641	0.125	78.2

Note: The table reports results obtained from the simulated moments matching procedure. For each category, we report the median parameter obtained. μ is here calculated as $\frac{\mu}{\frac{\theta}{\theta-1}Y_{SS}}$ whereas the average menu cost is calculated as $mu \times (Freq - \lambda)$. $\frac{p_0}{Freq}$: fraction of price changes performed under $c_t = 0$. One-sector model estimated using aggregate median moments US versus France.

Table 4: Estimates of Price Rigidity Model - Multi-sector model -

	Menu cost			Productivity			
	λ	μ	average	σ_ϵ	ρ	σ	$\frac{\lambda}{Freq}$
$s_m = 0$							
All	0.041	0.030	0.129	0.038	0.675	0.052	48.8
Food	0.086	0.025	0.114	0.046	0.631	0.059	65.1
Durables	0.018	0.039	0.125	0.045	0.697	0.063	36.4
Other manuf	0.040	0.032	0.101	0.033	0.765	0.051	56.3
Energy	0.038	0.000	0.000	0.031	0.851	0.059	5.1
Services	0.030	0.059	0.113	0.026	0.832	0.047	61.5
$s_m = 0.7$							
All	0.059	0.029	0.071	0.046	0.743	0.069	70.2
Food	0.120	0.023	0.027	0.069	0.646	0.090	90.8
Durables	0.015	0.038	0.134	0.038	0.716	0.054	30.3
Other manuf	0.052	0.033	0.089	0.044	0.753	0.067	69.7
Energy	0.047	0.000	0.000	0.031	0.831	0.056	6.3
Services	0.031	0.065	0.116	0.025	0.917	0.063	63.5

Note: The table reports results obtained from the simulated moments matching procedure. For each category, we report the median parameter obtained.For each category, we report the median parameter obtained. μ is here calculated as $\frac{\mu}{\frac{\theta}{\theta-1}Y_S S}$ whereas the average menu cost is calculated as $mu \times (Freq - \lambda)$. $\frac{\lambda}{Freq}$: fraction of price changes performed under $c_t = 0$.

Table 5: Counterfactual Relative Dispersion of the Cross–Product Distribution of Moments

	Data	Counterfactual exercizes under homogeneity in:			
		λ	μ	σ_ϵ	ρ
Freq.	1.396	1.489	0.714	1.446	1.378
Freq. excl. energy	0.642	0.307	0.732	0.584	0.673
Share of price increases	0.185	0.132	0.129	0.174	0.225
Median size	0.434	0.528	0.661	0.505	0.832
Interquartile (q3-q1)	0.405	0.338	0.467	0.324	0.500

Note: We here report relative dispersion indicators computed as the standard deviation of the distribution across products of moments divided by the mean value of moments (statistics are weighted). For instance, the standard deviation of the frequency of price change is 140% higher than the average frequency of price change. The first column reports the relative dispersion observed in the data. The second column the relative dispersion in the counterfactual exercise where we set λ equal to its median value for all products of the sample and other parameters equal to their estimated value. Column (3), (4) and (5) report similar figures but using counterfactual exercises where the parameter set to its median value is respectively μ, σ_ϵ and ρ.

Table 6: Cumulated Real Output Effect of a 1% Monetary Shock

	One sector Average	Median	Multi sector 5 sectors	Amplif. Factor
$s_m = 0$	1.52	2.44	3.09	2.03
$s_m = 0.7$	4.35	7.41	8.12	1.86

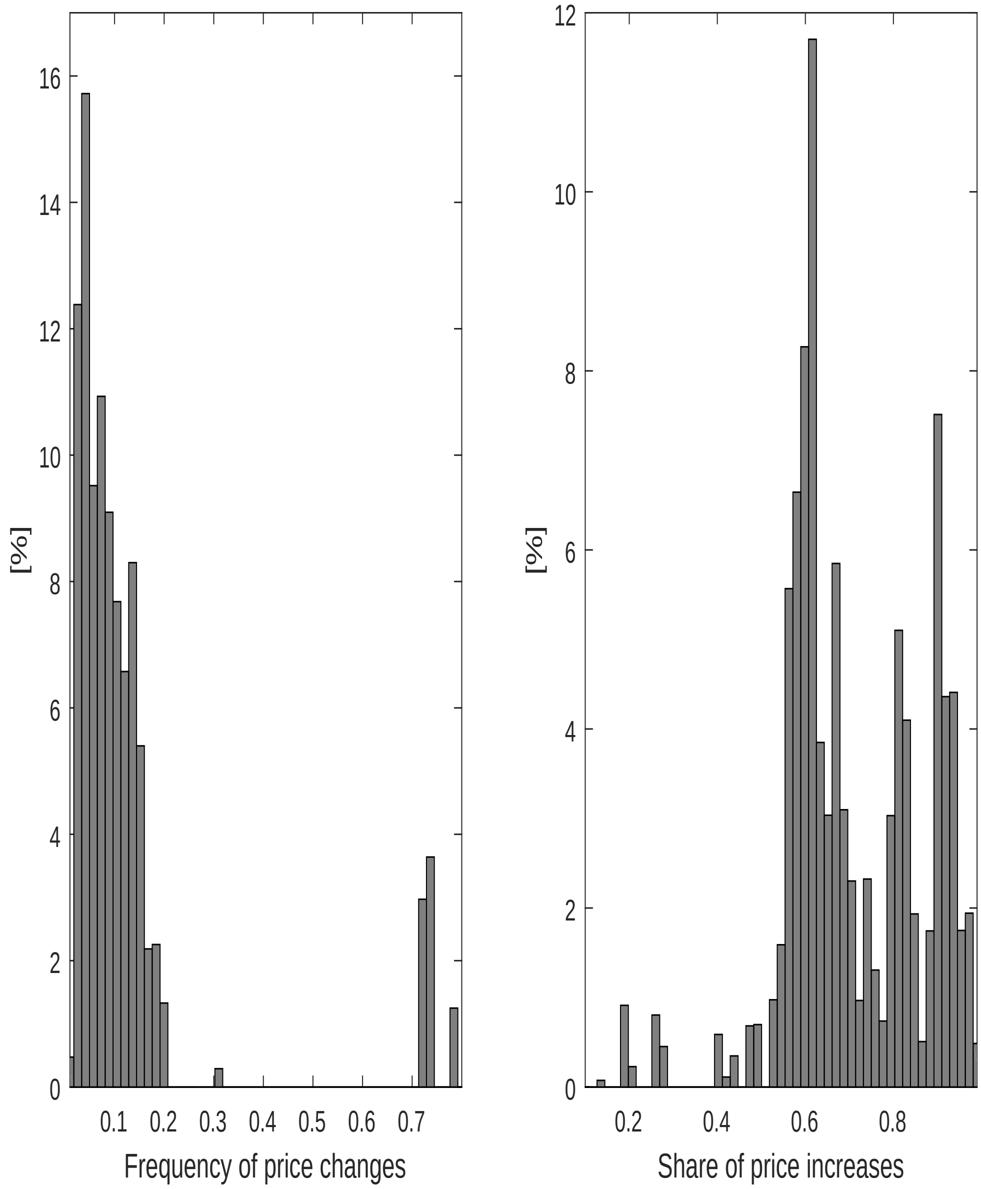
Note: Amplification factor is the ratio of column (4) to column (2), ie Multi sector vs. One sector "average" model

Table 7: Cumulated Real Output Effect of a One-Standard Deviation Money Shock

	Cumulated effect	Amplification Factor
Menu Cost	0.0048	1.000
Baseline	0.0076	1.582
Calvo	0.0111	2.317

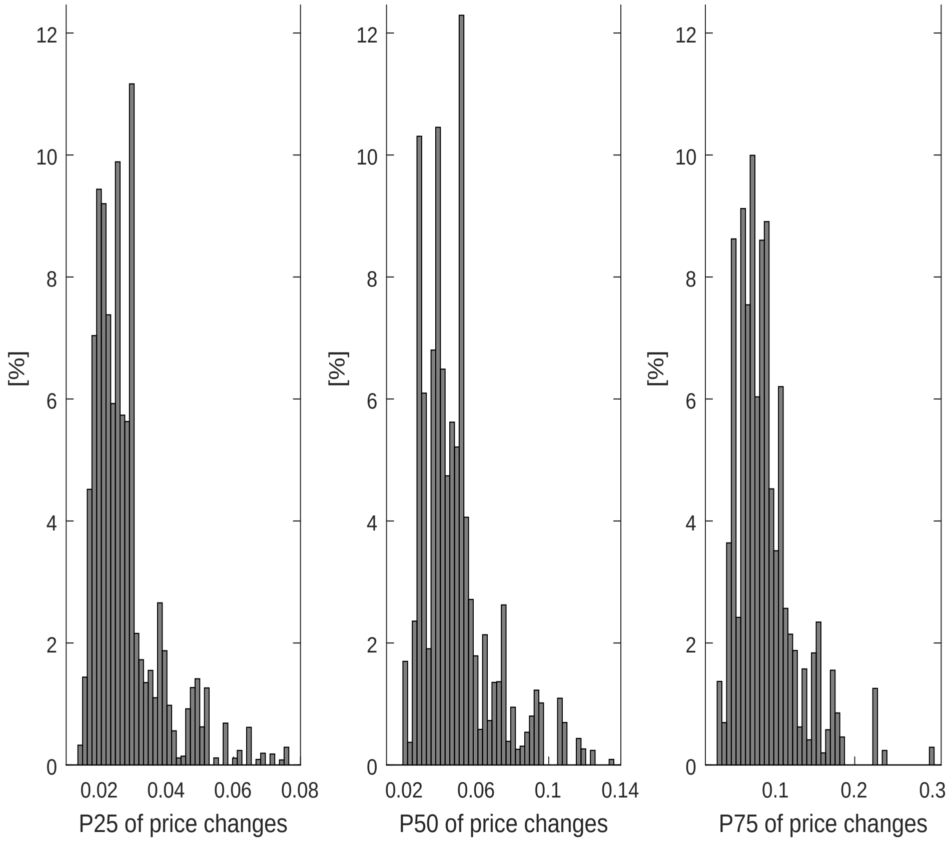
Note: We report in this table the cumulated real monetary effect (calculated after 45 periods) of a one-standard deviation money shock in different models. First line reports the results for a Menu–cost model estimated on our aggregate median weighted moments. Second line reports the results for our baseline model (menu cost with possibility of free price adjustment).Third line reports the results in a Calvo model estimated on our aggregate median moments. Amplification factor is the ratio of line (1) to other lines.

Figure 1: Frequency of Price Changes and Share of Price Increases



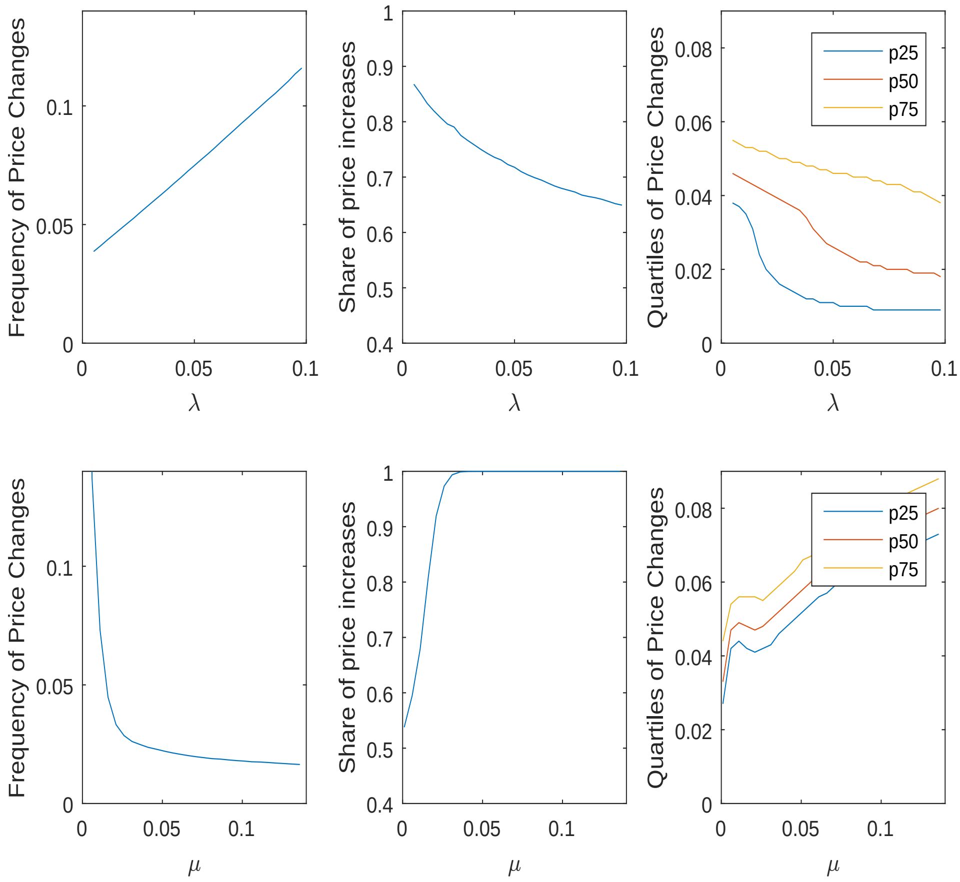
Note: The figure plots the distribution of the product-level frequency of price changes, frequency of price changes is computed using micro price data excluding price changes due to sales and product substitutions and price changes smaller than 1% in absolute values.

Figure 2: Size of Price Changes (1st quartile - median - 3rd quartile)



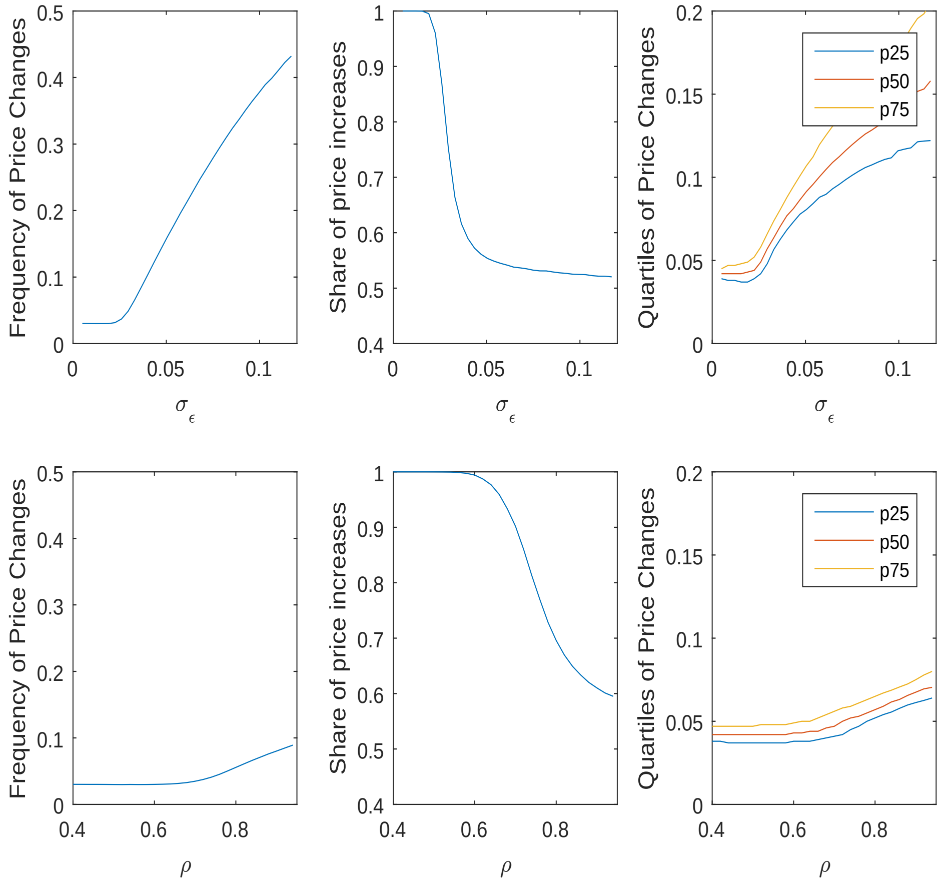
Note: The figure plots the distribution of the product-level quartiles of the distribution of price changes, quartiles of size of price changes are computed using micro price data excluding price changes due to sales and product substitutions and price changes smaller than 1% in absolute values.

Figure 3: Moments of the Model as a Function of Menu Cost Parameters



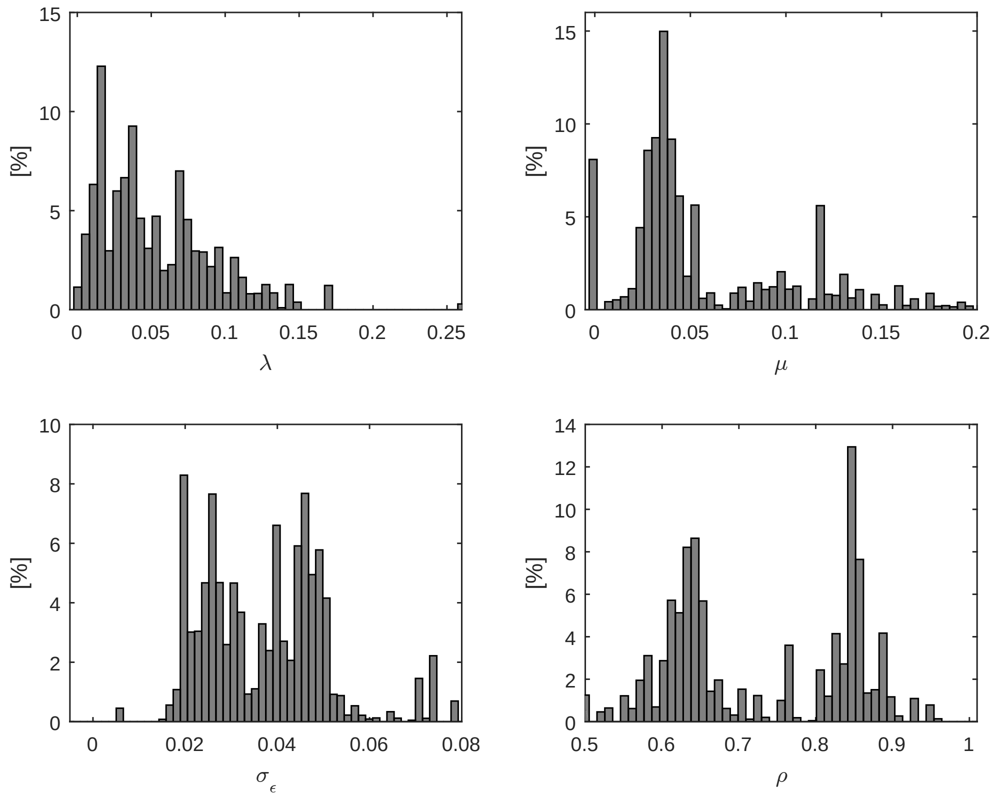
Note: Moments are simulated moments obtained from our theoretical model for a range of values of λ (first row) and of μ (second row). The frequency of price changes (column 1), the share of price increases (column 2) and the quartiles of the price change distribution (column 3) are obtained assuming that other parameters are fixed to a baseline low value ($\lambda = 0.00$, $\mu = 0.02$ and $\sigma_\epsilon = 0.025$).

Figure 4: Moments of the Model as a Function of Productivity Parameters



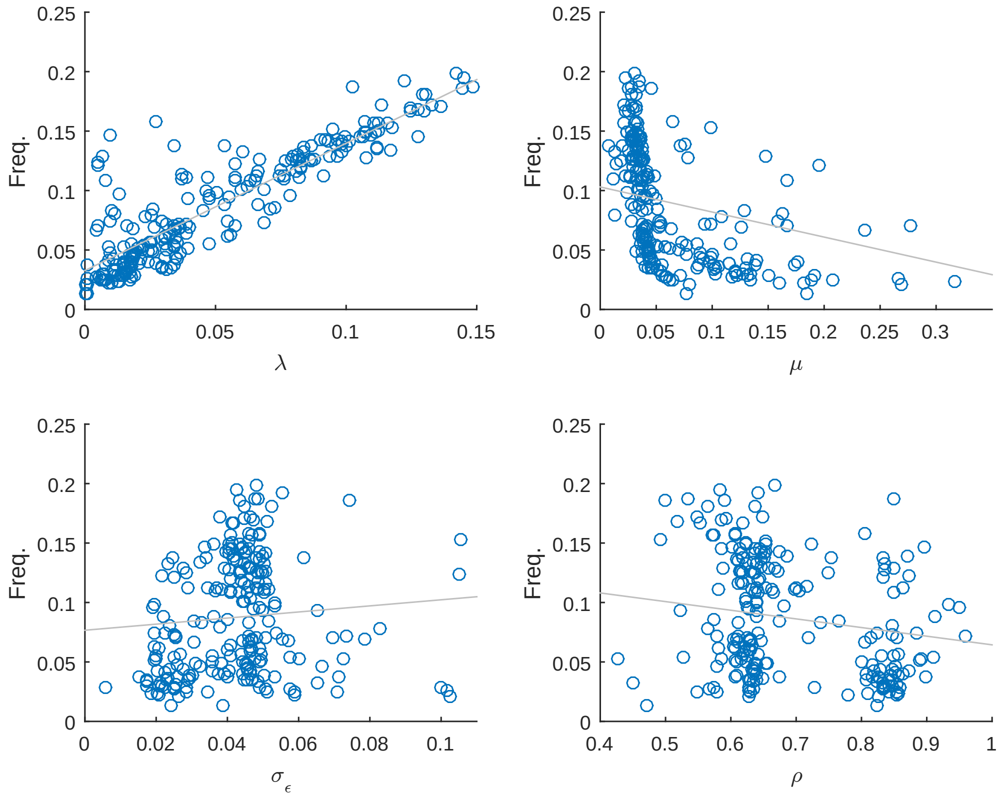
Note: Moments are simulated moments obtained from our theoretical model for a range of σ_ϵ (first row) and of ρ (second row). The frequency of price changes (first column), the share of price increases (column 2) and the quartiles of the price change distribution (column 3) are obtained assuming that other parameters are fixed to a baseline low value ($\lambda = 0.00$, $\mu = 0.02$ and $\sigma_\epsilon = 0.025$).

Figure 5: Distribution of estimated parameters across products



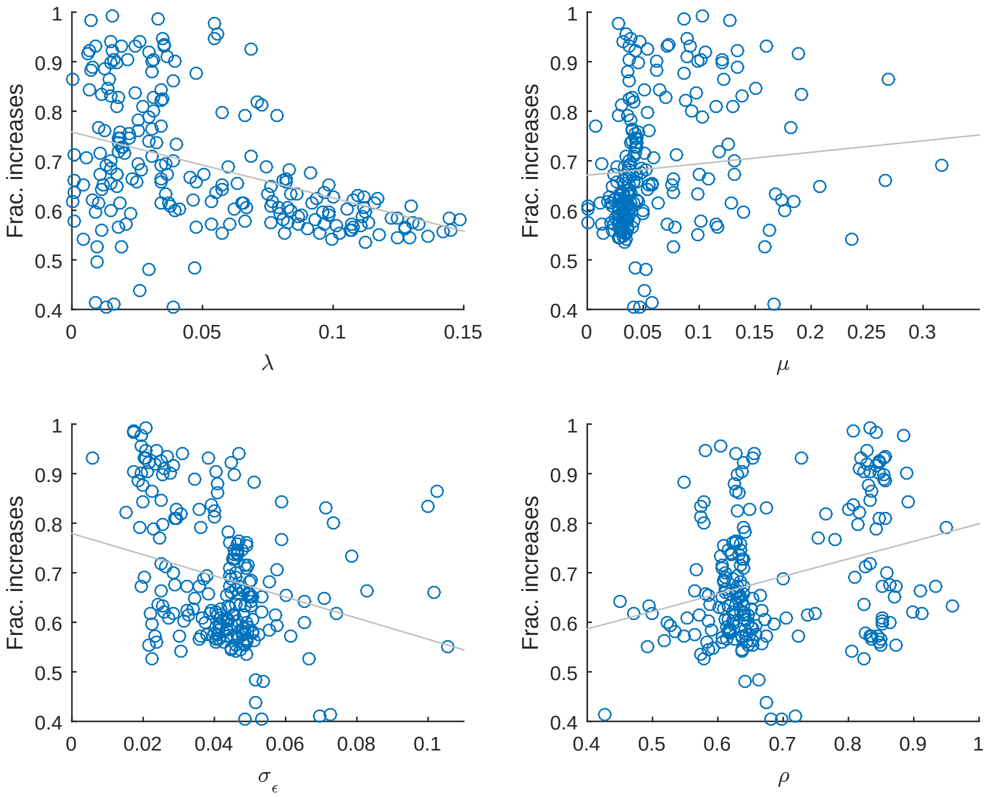
Note: The different histograms plot the distribution of each parameter estimated for all available CPI product categories.

Figure 6: Cross product differences in the frequency of price changes and estimated parameters



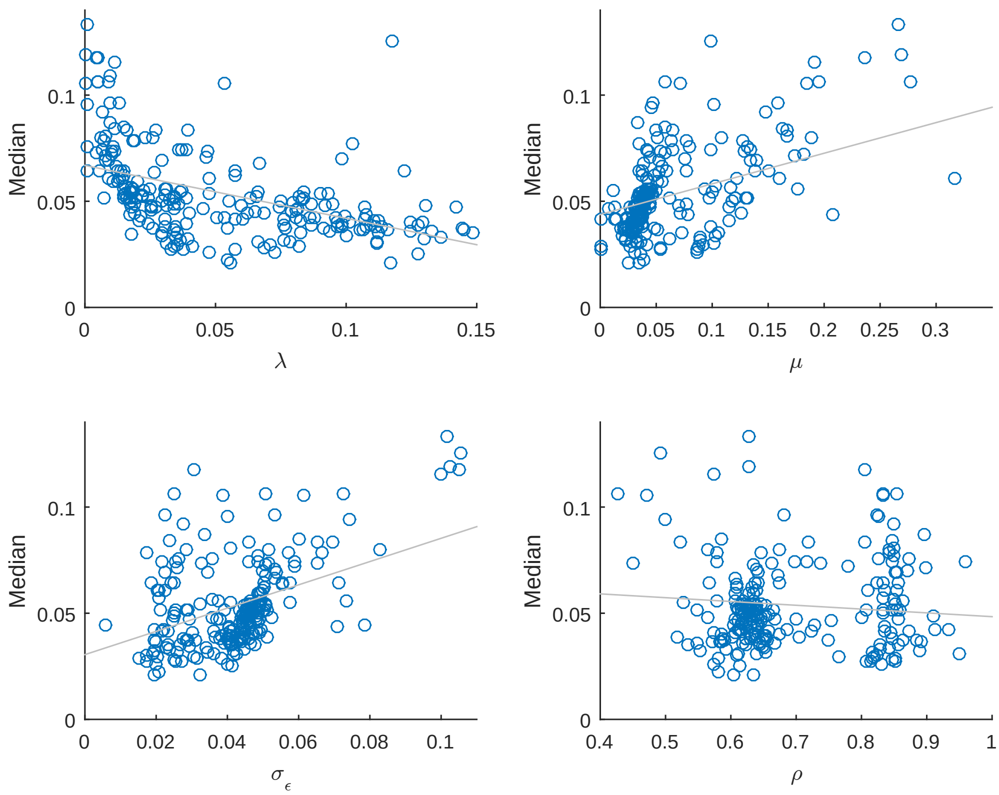
Note: Each point in the scatter plot is one of the 227 products, with values on the x-axis indicating the value of the estimated parameter of interest for that product, and values on the y-axis reporting the value of the moment in that sector. The scatter plot is truncated (sectors with frequencies larger than 25 percent are not plotted)

Figure 7: Cross product differences in the share of price increases and estimated parameters



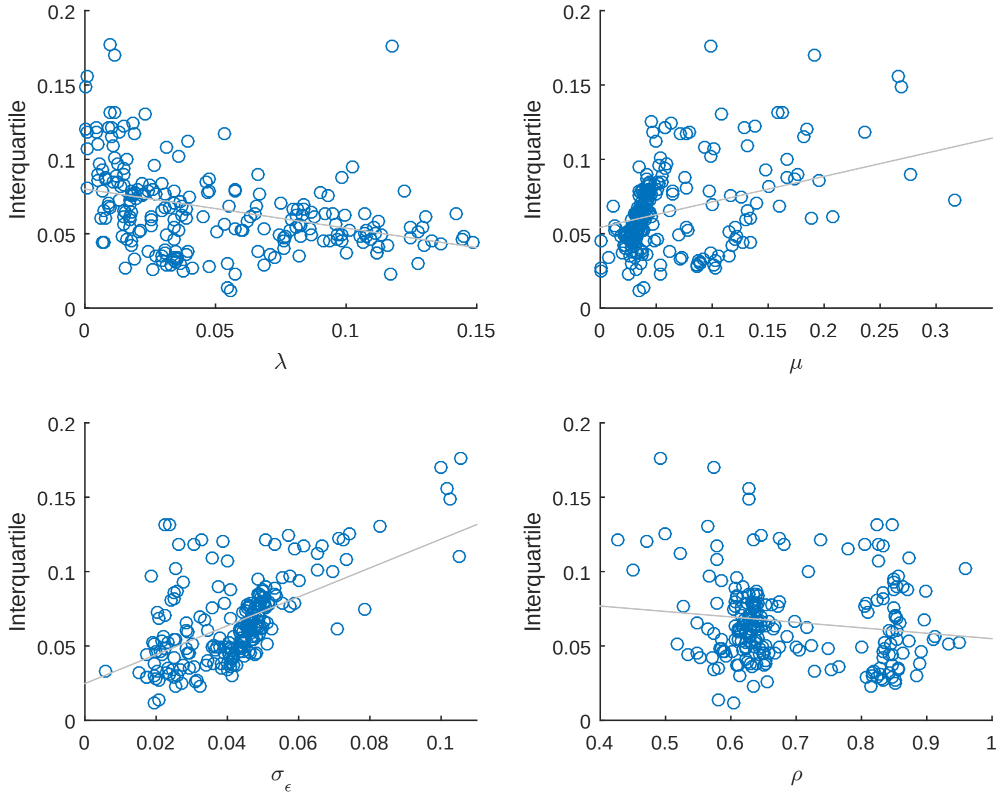
Note: Each point in the scatter plot is one of the 227 products, with values on the x-axis indicating the value of the estimated parameter of interest for that product, and values on the y-axis reporting the value of the moment in that sector.

Figure 8: Cross product differences in the median size of price changes and estimated parameters



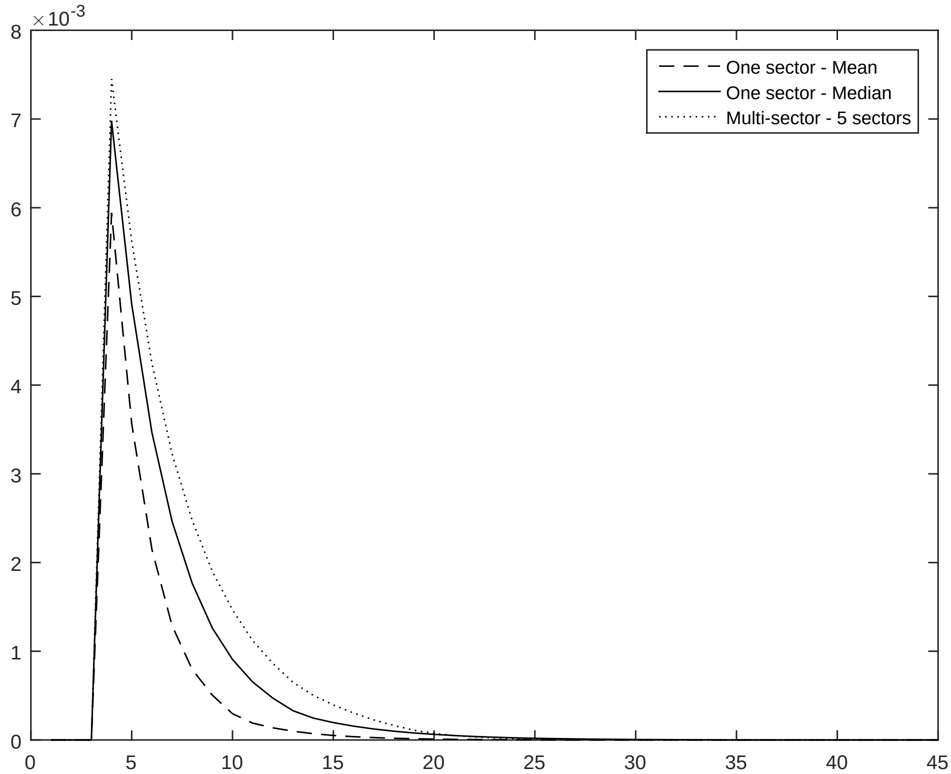
Note: Each point in the scatter plot is one of the 227 products, with values on the x-axis indicating the value of the estimated parameter of interest for that product, and values on the y-axis reporting the value of the moment in that sector.

Figure 9: Cross product differences in the interquartile size of price changes and estimated parameters



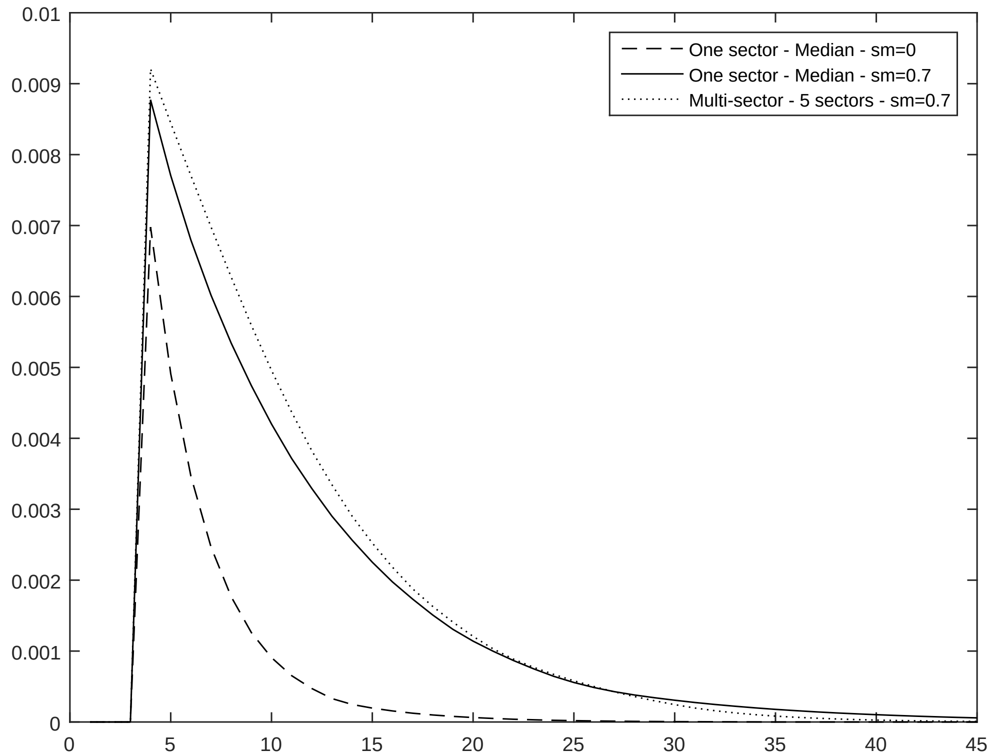
Note: Each point in the scatter plot is one of the 227 products, with values on the x-axis indicating the value of the estimated parameter of interest for that product, and values on the y-axis reporting the value of the difference between the third quartile of the distribution of price changes and the first quartile of this distribution (for each sector).

Figure 10: Impulse Response Function - One versus Multisector Model - $s_m = 0.0$



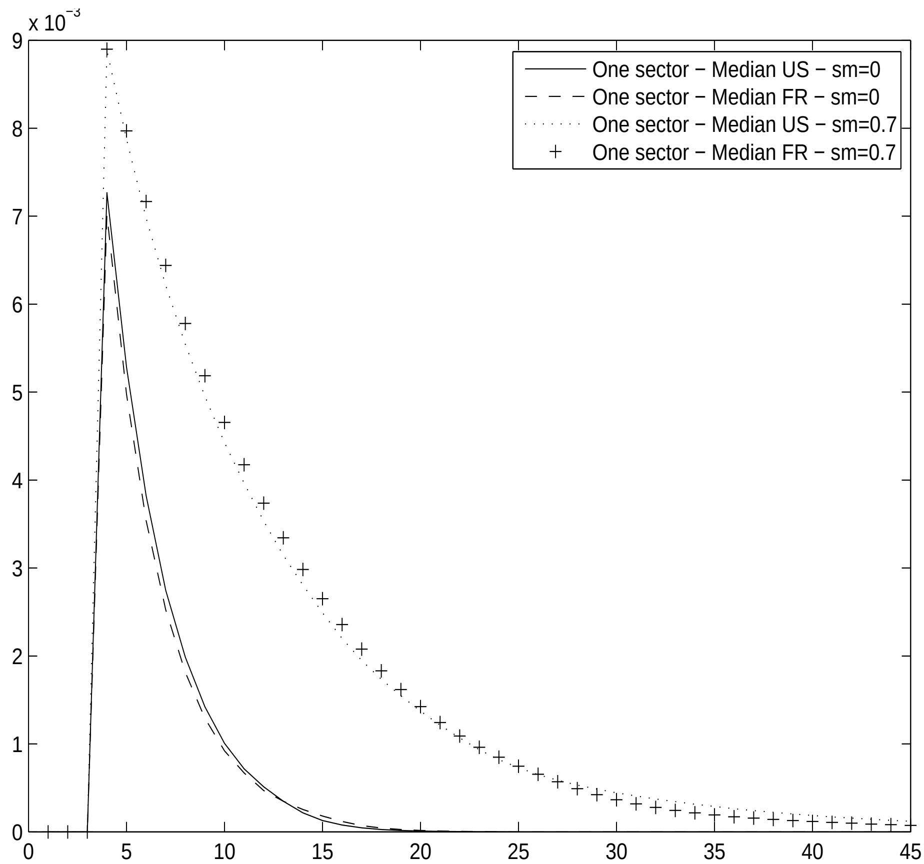
Note: In the model where the share of intermediate inputs is set to zero, we simulate a monetary policy shock of 1%. Using the function Γ, and estimated parameters of our models, we are able to calculate the aggregate response of output to this shock. We consider here different cases where we use different sets of parameter estimates. The first dashed line is the IRF corresponding to the model where we estimate a one sector model fitting average moments of the data, the black line is the IRF corresponding to the model where we estimate a one sector model fitting the median moments of the data, the dotted line is the IRF corresponding to the multi–sector model with 4 sectors where parameter estimates correspond to the median parameters of all products within one of the 4 sectors.

Figure 11: Impulse Response Function - One versus Multi–sector Model - $s_m = 0.7$



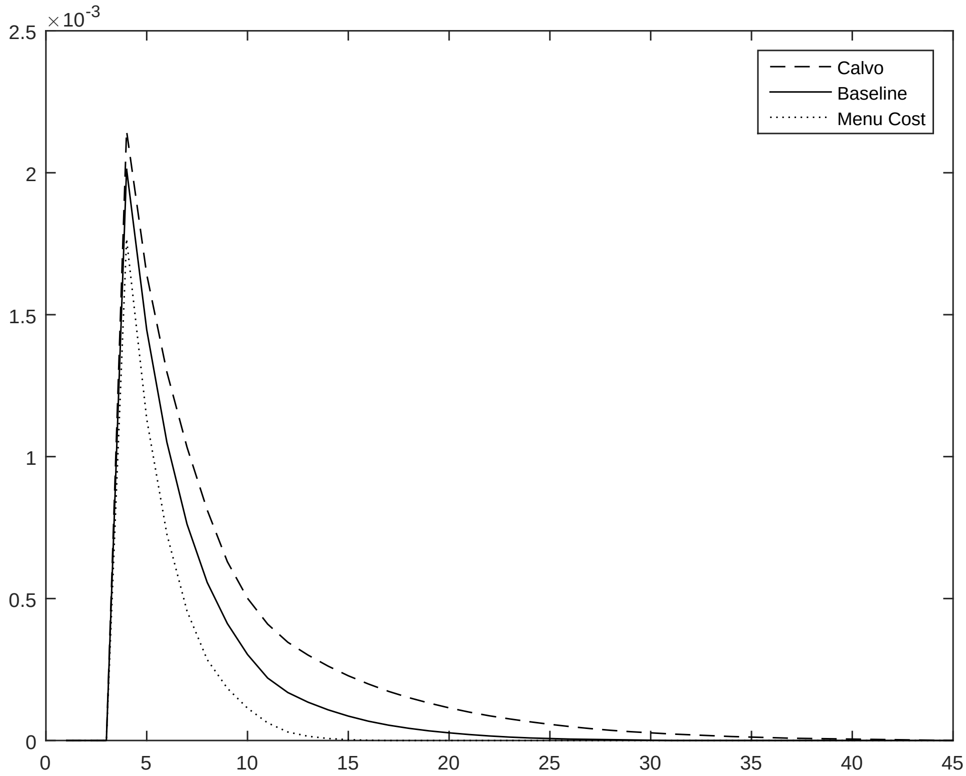
Note: In the model where the share of intermediate inputs is set to 0.7, we simulate a monetary policy shock of 1%. Using the Gamma function and estimated parameters of our models, we are able to calculate the aggregate response of output to this shock. We consider here different cases where we use different sets of parameter estimates. The first dashed line is the IRF corresponding to the model where we estimate a one sector model fitting average moments of the data, the black line is the IRF corresponding to the model where we estimate a one sector model fitting the median moments of the data, the dotted line is the IRF corresponding to the multi–sector model with 4 sectors where parameter estimates correspond to the median parameters of all products within one of the 4 sectors.

Figure 12: Impulse Response Function - France versus United States



Note: In the model where the share of intermediate inputs is set either to 0 or 0.7, we simulate a monetary policy shock of 1%. Using the Gamma function and estimated parameters of our one-sector models for France or the United States, we are able to calculate the aggregate response of output to this shock. We consider here different cases where we use different sets of parameter estimates. The black line is the IRF corresponding to the US model where we estimate a one sector model fitting US median moments of the data (with $s_m = 0$). The dotted line is the IRF corresponding to US median economy but assuming $s_m = 0.7$. The dashed line is corresponding to the French model where we estimate a one sector model fitting French median moments of the data (with $s_m = 0$). The cross line is the IRF corresponding to French median economy but assuming $s_m = 0.7$.

Figure 13: Impulse Response Function - Baseline versus Calvo and Fixed Menu Cost



Note: We estimate a Calvo model (where all price changes are due to the low menu cost state), and a Menu Cost model (where all price changes are due to the high menu cost state). Using obtained estimated parameters, we simulate a monetary policy shock of one standard deviation of inflation. Using the Gamma function and estimated parameters of our one-sector models for France, we are able to calculate the aggregate response of output to this shock. The black line is the IRF corresponding to the French model where we estimate a one sector model fitting FR median moments of the data (with $s_m = 0$). The dotted line is the IRF corresponding to a standard menu cost model (Golosov and Lucas (2007)) estimated on FR data. The dashed line is the IRF corresponding to a standard Calvo model estimated on FR data.

Appendix

I) Estimation results using interquartile range and kurtosis

The choice of moments used to estimate our model is crucial to identify our parameters. In Nakamura and Steinsson (2010), the frequency of regular price changes and the absolute size of price changes are used to estimate menu cost and the standard deviation of the productivity shock. In Midrigan (2011), 17 moments including quantiles of the distribution of price changes (10th, 25th, 50th, 75th, 90th percentiles) are used to estimate several parameters. More recently, Karadi and Reiff (2014) are using interquartile range and kurtosis of the distribution of price changes to calibrate their model.

In our baseline estimation, we are using moments that can be compared between France and the United States (interquartile range and kurtosis are not available in Nakamura and Steinsson (2008). In this appendix, we are describing results using the median and average moments of the kurtosis and interquartile range only for France. First we report in Table A the main statistics and their variance (we here obtain these variances using boostrap simulations). We also report the moments obtained from our models at the estimated value of our parameters, we consider models where $s_m = 0$ and $s_m = 0.7$. The Table B reports our estimation results. Results are broadly in line with what we obtain using other moments of the data. The share of price changes triggered by the zero-menu cost state is similar between 60 and 75% whereas the standard deviation of productivity shocks is estimated to be 0.05-0.06 when $s_m = 0$ and about 0.08 when $s_m = 0.7$. The estimated menu cost in the high menu-cost state is also quite similar depending on using kurtosis or percentiles of the price change distribution.

Table A: Price rigidity in France - Moments

	Freq. changes	Share of increases	Size of price changes p50	interquartile	kurtosis
Mean	0.137	0.710	0.047	0.073	5.287
	(0.001)	(0.005)	(0.001)	(0.002)	(0.246)
Model $s_m = 0.0$	0.129	0.631	0.049	0.075	2.659
Model $s_m = 0.7$	0.134	0.590	0.038	0.076	3.401
Median	0.084	0.674	0.044	0.070	4.462
	(0.001)	(0.004)	(0.001)	(0.001)	(0.106)
Model $s_m = 0.0$	0.091	0.695	0.047	0.073	5.150
Model $s_m = 0.7$	0.081	0.630	0.042	0.082	5.344

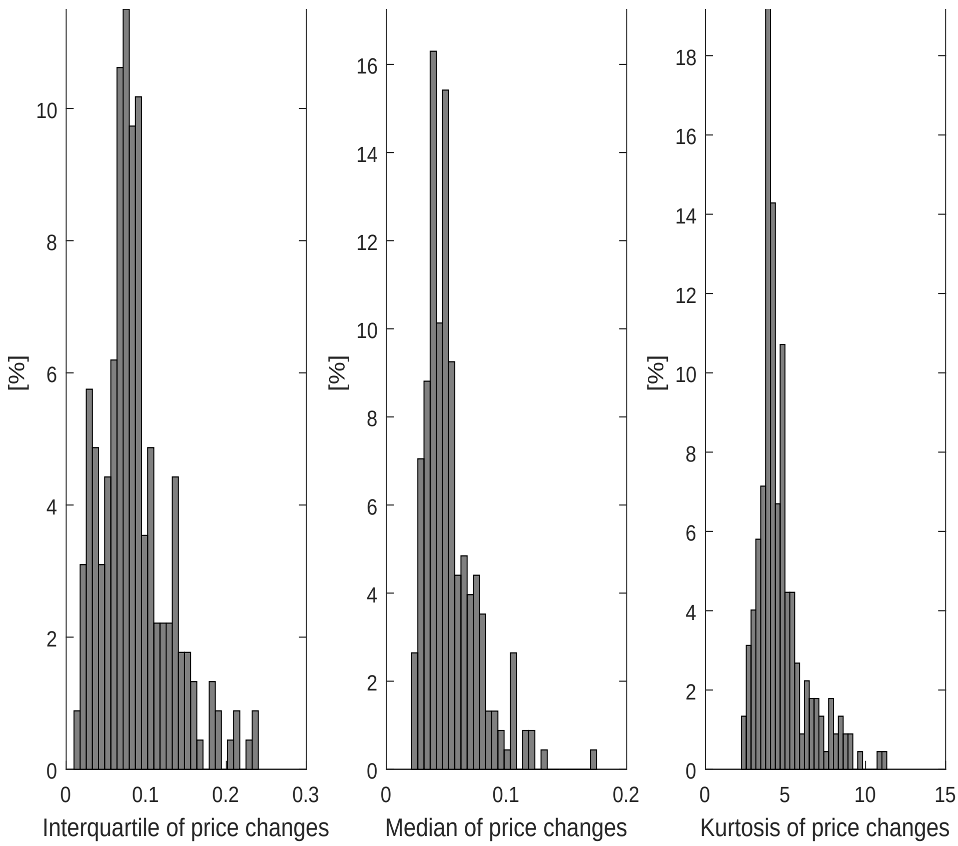
Note: Calculations made on the French CPI micro data set over the period 1994-2014 (25 million of monthly price quotes). Price rigidity moments are first calculated at the product level and we then compute the weighted (using French CPI weights) median of those product-specific moments. Standard deviation of moments are calculated using 100 bootstrap simulations. Moments generated by the models at estimated values are also reported for cases where $s_m = 0$ or $s_m = 0.7$

Table B: Estimates of Price Rigidity Model - Using kurtosis and interquartile ranges in fitted moments - Single sector model

	λ	μ	Menu cost average (in %)	Productivity σ_ϵ	ρ	σ	$\frac{\lambda}{Freq}$
$s_m = 0.0$							
Mean moments	0.066	0.011	0.080	0.031	0.760	0.063	48.1
Median moments	0.055	0.026	0.074	0.040	0.692	0.065	66.0
$s_m = 0.7$							
Mean moments	0.101	0.008	0.030	0.045	0.710	0.077	73.5
Median moments	0.064	0.026	0.052	0.071	0.719	0.124	76.0

Note: The table reports results obtained from the simulated moments matching procedure. For each category, we report the median parameter obtained. μ is here calculated as $\frac{\mu}{\frac{\theta}{\theta-1}Y_{SS}}$ whereas the average menu cost is calculated as $mu \times (Freq - \lambda)$. $\frac{p_0}{Freq}$: fraction of price changes performed under $c_t = 0$. The parameters have been estimated using the following 5 moments: frequency of regular price adjustments, the proportion of price increases, the median of absolute price changes, the interquartile of distribution of non-zero price changes and the kurtosis of the distribution of non-zero price changes.

Figure A: Size of Price Changes (median - interquartile and kurtosis)



Note: The figure plots the cross product distribution of moments of the price change distribution: median price change (in absolute value), the interquartile price change (difference between the first and third quartile of price change), kurtosis of price change distribution.

Table C: Price rigidity in France - Moments - 5 sectors

	Freq. changes	Share of increases	Size of price changes p50	interquartile	kurtosis
Food					
Data	0.132	0.609	0.044	0.081	3.995
	(0.001)	(0.004)	(0.000)	(0.001)	(0.08)
Model	0.130	0.609	0.041	0.083	3.211
Durables					
Data	0.050	0.603	0.072	0.121	3.850
	(0.001)	(0.006)	(0.001)	(0.003)	(0.102)
Model	0.056	0.682	0.074	0.102	2.893
Other manuf					
Data	0.075	0.674	0.043	0.076	4.727
	(0.001)	(0.005)	(0.001)	(0.001)	(0.139)
Model	0.076	0.679	0.043	0.077	5.222
Energy					
Data	0.744	0.609	0.028	0.055	2.804
	(0.001)	(0.002)	(0.000)	(0.000)	(0.016)
Model	0.733	0.526	0.028	0.055	2.488
Services					
Data	0.049	0.898	0.041	0.037	6.347
	(0.001)	(0.004)	(0.001)	(0.001)	(0.213)
Model	0.047	0.989	0.041	0.042	3.054

Note: Calculations made on the French CPI micro data set over the period 1994-2014 (25 million of monthly price quotes). Price rigidity moments are first calculated at the product level and we then compute the weighted (using French CPI weights) median of those product-specific moments. Standard deviation of moments are calculated using 100 bootstrap simulations. Moments generated by the models at estimated values are also reported for $s_m = 0$

Table D: Estimates of Price Rigidity Model - 5 sectors - using kurtosis and interquartile ranges in fitted moments

		Menu cost		Productivity			
	λ	μ	average (in %)	σ_ϵ	ρ	σ	$\frac{\lambda}{Freq}$
$s_m = 0.0$							
Food	0.088	0.023	0.100	0.041	0.326	0.043	66.9
Durables	0.021	0.044	0.125	0.053	0.580	0.065	43.0
Other manuf	0.050	0.038	0.095	0.047	0.518	0.054	66.4
Energy	0.586	0.001	0.018	0.028	-0.059	0.028	78.7
Services	0.031	0.033	0.060	0.008	0.424	0.008	63.2

Note: The table reports results obtained from the simulated moments matching procedure. For each category, we report the median parameter obtained. μ is here calculated as $\frac{\mu}{\frac{\theta}{\theta-1}Y_{SS}}$ whereas the average menu cost is calculated as $mu \times (Freq - \lambda)$. $\frac{\lambda}{Freq}$: fraction of price changes performed under $\mu_t = 0$. The parameters have been estimated using the following 5 moments: frequency of regular price adjustments, the proportion of price increases, the median of absolute price changes, the interquartile of distribution of non-zero price changes and the kurtosis of the distribution of non-zero price changes.

Table E: Amplification of real effects of monetary policy - Comparison with the "sufficient statistic approach" of Alvarez, Le Bihan, and Lippi (2016)

	Kurtosis	Freq.	Kur/Freq	Amplification Factor
One sector - mean	5.28	0.137	38.59	1
One sector - median	4.46	0.084	53.28	1.38
5 sectors - sector median	-	-	72.73	1.88
Fully heterogenous model	-	-	90.74	2.35

Note: The table reports the ratio of kurtosis on frequency of price changes using different weighted schemes. First line, we compute the weighted average kurtosis and the weighted average frequency of price changes and calculate the simple ratio between the two aggregate statistics. Second line we are using weighted median of moments calculated over all products and calculate the ratio. Third line we are first calculating the ratio between median kurtosis and median frequency for the 5 aggregate products and then we compute the weighted average ratio. Fourth line, we are calculating the ratio kurtosis on frequency for all products and then we calculate the average weighted ratio. The last column reports the ratio between R obtained in different scenarios (lines 2 to 4) and the R obtained for the scenario with one sector - average moments (line 1).

II) Model with intermediate inputs

Production function becomes:

$$Y_{i,k,t} = A_{i,k,t} L_{i,k,t}^{s_m} M_{i,k,t}^{(1-s_m)}$$

s_m: share of intermediate inputs

Index of intermediate input

$$M_{i,k,t} = \left[\int_0^1 m_{i,k,t}(j)^{\frac{1-\theta}{\theta}} dj \right]^{\frac{\theta}{1-\theta}}$$

where $m_{i,k,t}(j)$ is intermediate input produced by firm j and used by firm i

Table F: Share of intermediate inputs in production by aggregate sector - France - average 1994-2014

Sector	Code	Share of intermediate inputs	% of overall production
Overall		0.52	
Manufacture of food products, beverages and tobacco	CA	0.71	0.09
Manufacture of textiles, wearing apparels, leather and related products	CB	0.72	0.02
Manufacture of wood, paperand paper products	CC	0.67	0.03
Manufacture of chemicals and chemical products	CE	0.75	0.04
Manufacture of pharmaceutical products	CF	0.49	0.01
Manufacture of rubber and plastic products	CG	0.63	0.03
Manufacture of fabricated metal products except machinery and equipment	CH	0.67	0.05
Manufacture of computer, electronic and optical products	CI	0.59	0.02
Manufacture of electrical equipment	CJ	0.66	0.01
Manufacture of machinery and equipment nec	CK	0.67	0.02
Manufacture of transport equipment	CL	0.79	0.06
Other manufacturing and repairing	CM	0.57	0.04
Wholesale and retail trade; repair of motor vehicles and motorcycles	GZ	0.47	0.21
Accommodation and food service activities	IZ	0.45	0.05
Telecommunications	JB	0.48	0.03
Information	JC	0.34	0.03
Financial and insurance activities	KZ	0.61	0.10
Real estate activities	LZ	0.18	0.15

Note: The share of intermediate inputs is calculated using input-output tables provided by Insee national accounts over the period 1994-2014. The share of intermediate inputs is calculated as the share between intermediate inputs and production in a given sector whereas % of overall production is calculated as the share of a given sector in overall production of all sectors considered in this table.