Large shocks travel fast*

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Abstract

We leverage the recent inflation upswing, and granular data provided by PriceStats, to identify robust price setting patterns following a large supply shock. We show that the frequency of price changes increases dramatically. We setup a simple NK model and calibrate it to fit the steady state data before the shock. The model features a significant component of state-dependent decisions, and implies that large cost shocks incite firms to react more swiftly than usual. Understanding this feature is crucial for interpreting the recent inflation dynamics.

PRELIMINARY

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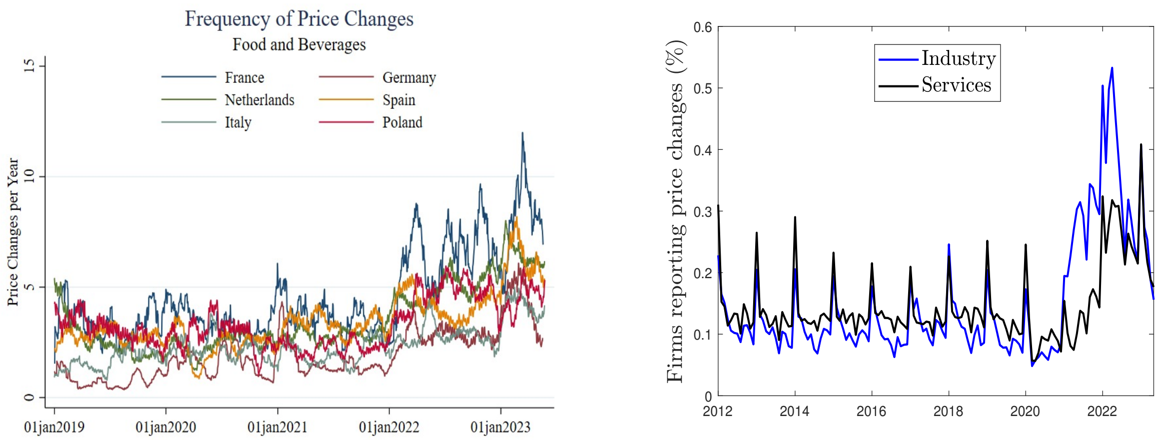
1 Introduction

The inflation surge that followed the sizeable increases of energy prices in several countries has revived interest on inflation and its welfare costs. After more than three decades of stable prices, in 2022 inflation peaked at about 10% in the Euro area and the US.

Figure 1: Frequency of price changes

Food and Beverages Sector | Industry and Services Sectors (France)



Note: The left panel data source is PriceStats (see Section 3). The right panel data source is Banque de France Monthly Business Survey (see Dedola et al. (2023))

We set up a new-keynesian model and parametrize it using a granular data set for the food and beverages sector for several European countries (see Cavallo (2018)). A founding principle of our analysis is to identify a model that is broadly consistent with the recent observed price setting behavior. It is apparent that the credibility of the analysis on retail price inflation requires that the model is consistent with the facts about price-setting behavior by retailers. Matching the model fundamentals to the price setting patterns observed in the granular data will lead us to reject the Calvo model, because of its impossibility to account for the significant increase in the frequency of price setting observed in the data, shown in Figure 1, and because of its failure to fit other features of price setting behavior, such as the size distribution of the price changes.

The paper is organized as follows. Section 2 presents the New Keynesian setup that guides our analysis of the price-setting activity of firms and will (later) be used to quantify the welfare costs. The model is inspired by the seminal work of Caballero and Engel (1993a,b) and nests several well-known cases such as the Calvo (1983) model or the menu cost model of Golosov and Lucas (2007). Section 3 describes the model's predictions for the frequency and the size-distribution of price changes and compares them with cross-sectional facts observed from the low inflation period before 2021. This part of the analysis relies on a granular dataset for several European countries provided by PriceStats.[1] These data contain detailed information on the frequency and size of daily price changes for a large number of firms, and provide the necessary information to identify the structural model parameters. The daily price data collection with uncensored spells allows for an accurate identification of sales and price changes (Cavallo, 2018).

Mapping the model to the observables allows us to select a data-consistent structural model of price setting. We show that a main feature of the selected price setting model is a sizeable component of state-dependent decisions. This means that the firms' responsiveness to the shocks depends on the size of the shocks.[2] This finding differs markedly from the time-dependent models that are widely used in several central banks, such as the workhorse model of Calvo (1983). A main finding implies that large cost shocks, such as those triggered by the recent energy shocks, induce firms to react faster than in normal times. This is important to understand the dynamics of inflation after a large shock, as also noted by Alvarez and Neumeyer (2019); Karadi and Reiff (2019). We show that the selected model can qualitatively replicate the response of the frequency of price changes after a large cost shock, such as the ones recently observed.[3]

[1] Our data was provided by PriceStats, a private company related to the The Billion Prices Project (see Cavallo and Rigobon (2016)). This dataset is a comprehensive collection of retail prices obtained from the websites of large, multichannel retailers. It is generated using a technology known as web scraping, which automatically scans the code of publicly available webpages daily to gather and store relevant data.

[2] See Gagnon (2009); Alvarez et al. (2019); Karadi et al. (2023) for an extensive documentation of the importance of state dependent pricing in several countries including the US and Europe.

[3] The idea of using large shocks to discuss model selection has been used by other authors, such as Gopinath and Itskhoki (2010); Alvarez, Lippi, and Paciello (2016); Bonadio, Fischer, and Sauré (2019).

2 A generalized setup for NK models

This section presents a New Keynesian setup that nests several models, from the well known Calvo (1983) to the menu cost model of Golosov and Lucas (2007). The setup describes the firm's price setting decisions by means of a generalized hazard function as in Caballero and Engel (2007), relating the probability of price adjustment to the firm's state, measured by the distance between the firm's current price from the profit maximizing price. The notion of a generalized hazard function was developed in seminal papers by Caballero and Engel (1993a,b), a derivation from first principles based on random adjustment costs was provided in Caballero and Engel (1999) and Dotsey et al. (1999), and later revisited using information theoretical foundations by Woodford (2009) and Costain and Nakov (2011b).

Household Preferences. Time is continuous and $t \in [0, \infty)$. The preferences of the representative agent are given by the discounted present value

$$\int_0^\infty e^{-\rho t} U\left(C(t), H(t)\right) dt \quad \text{where} \quad U(C, H) \equiv \frac{C^{1-\epsilon}}{1-\epsilon} - \alpha H, \tag{1}$$

where $C(t)$ is an aggregate of $i \in [0, 1]$ goods and $H(t)$ is the labor supply. There is a preference shock $A_i(t)$ associated with good i at time t, which acts as a multiplicative shifter of demand for each good i. Let $c_i(t)$ be the consumption of the product i at time t. The Dixit-Stiglitz consumption composite $C(t)$ is

$$C(t) \equiv \left[\int_0^1 A_i(t)^{\frac{1}{\eta}} \, c_i(t)^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}}. \tag{2}$$

Labor supply is an aggregate of the labor that each firm hires so that $H(t) = \int_0^1 h_i(t)di$.

Households maximize preferences in equation (1) subject to a budget constraint choosing consumption and labor for each good i and time t. There is a distortionary labor subsidy to allow the flexible price equilibrium to coincide with the efficient allocation.

The supply side. We consider an economy populated by a unit mass of firms, indexed by $i \in [0,1]$, and each of them produces one good. For firm i to produce $c_i(t)$ of the good i at time t requires both labor (h_i) and energy (m_i) inputs, according to the production function

$$c_i(t) = \left(\frac{h_i(t)}{Z_i(t)}\right)^{1-\beta} m_i(t)^{\beta} \tag{3}$$

where $\beta \in (0,1)$ is the energy share in production and firm i's marginal cost of production at time t is: $\text{mc}(t) = K E(t)^{\beta} \, (W(t) Z_i(t))^{1-\beta}$ where $W(t)$ is the nominal wage and $E(t)$ is the price of the energy input.[4] The technology exhibits constant returns to scale. We assume that $A_i(t) = Z_i(t)^{\eta-1}$ so the (log of) marginal cost and the preference shock are perfectly correlated. We assume that $Z_i(t) = \exp(\sigma \, z_i(t))$ where $\{z_i\}$ are standard Brownian motions independent across i.

We consider the profit maximization problem for a firm in steady state using the generalized hazard function of Caballero and Engel (1999) and Caballero and Engel (2007). The setup embeds a broad class of sticky-price models, including well known cases such as the canonical Golosov and Lucas (2007), the pure Calvo (1983) model and the hybrid Calvo-Plus model by Nakamura and Steinsson (2010). The state of the firm x is given by its "price gap", defined as the price currently charged by the firm relative to the price that maximizes current profits:

$$P_i^*(t) = \frac{\eta}{\eta - 1} \text{mc}_i(t)$$

namely the marginal cost times the constant markup $\frac{\eta}{\eta-1}$, implied by the CES demand system. Note that $P^*(t)$ depends on time because productivity is stochastic and because the marginal costs can change over time, for instance following a large energy shock.

More precisely, the price gap $x_i(t)$ for firm i is the time t wedge between the actual price

[4] The constant is $K \equiv \beta^{-\beta}(1-\beta)^{\beta-1}$.

$P(t)$ and the desired price $P_i^*(t)$:

$$x_i(t) \equiv \log P_i(t) - \log P_i^*(t) \tag{4}$$

Absent pricing frictions the gap is identically zero, i.e. each firm charges the optimal price $P_i(t) = P_i^*(t)$. If the price is not adjusted, the price gap changes due to trend inflation (increasing nominal costs) and the idiosyncratic productivity shocks, so that the law of motion of the price gap for each i is

$$dx_i(t) = -\mu dt + \sigma dz_i(t),$$

where z_i is a standard Brownian motion and μ is the growth rate of nominal wages per unit of time i.e. the inflation rate.[5]

The price-setting problem. The firm's value function $v(x)$ solves the following problem:

$$\rho\, v(x) = B\, x^2 - \mu v'(x) + \frac{\sigma^2}{2} v''(x) + \min_{\ell \geq 0} \{\ell \cdot (v(x^*) - v(x)) + (\kappa\, \ell)^\gamma\} \tag{5}$$

where the quadratic term represents a second order expansion of the profit function around the profit-maximizing price, with $B \equiv \frac{\eta(\eta-1)}{2}$, and x^* is the profit maximising reset price-gap that satisfies $v'(x^*) = 0$.[6] At every moment the firm chooses an optimal effort rate ℓ for price resetting, so that with probability ℓ per unit of time the firm will be able to adjust its price, i.e., to control x.[7] The optimal choice balances the benefit of a price reset, given by $v(x^*) - v(x)$, with the cost of effort, given by the convex power function $(\kappa\, \ell)^\gamma$, with $\gamma > 1$ and $\kappa > 0$. We note that the units of the cost function are expressed as a fraction of forgone (steady state) profits. Given the CES demand system, to express these units in terms of the

[5] This is can be rationalized by assuming the money supply grows at an exogenous rate μ.

[6] See Appendix A of Alvarez and Lippi (2014).

[7] We could enrich the model by assuming the firm can also change its price by paying the menu cost $\Psi > 0$. We ignore this possibility for simplicity but we note that little is lost in generality, as proven in proposition XX in Alvarez et al. (2022).

revenues (and output) they must be divided by η.

Policy Rules. The optimal price setting behavior implied by equation (5) is summarized by a *generalized hazard function* (GHF), $\Lambda : \mathbb{R} \to \mathbb{R}_+$, which gives the probability (per unit of time) that a firm with price gap x will change its price. The first order condition gives the generalized hazard function $\Lambda(x)$ which is the optimal value ℓ^* for a given value of x, namely:

$$\Lambda(x) = \kappa^{\frac{\gamma}{1-\gamma}} \left(\frac{v(x) - v(x^*)}{\gamma}\right)^{\frac{1}{\gamma-1}}, \quad \text{for each } x \in (-\infty, \infty) \ . \tag{6}$$

Intuitively, the optimally chosen probability of adjustment is increasing in the distance between x and the optimal reset gap x^*. The value function $v(\cdot)$ and the generalized hazard function $\Lambda(\cdot)$ have a minimum at x^* and are increasing in $|x - x^*|$. Intuitively, the larger the distance between x and x^* the bigger are the incentives to adjust.

As in Caballero and Engel (2007) the policy rule implies that price changes occur probabilistically, with a probability that is governed by the GHF. Compared to the workhorse Calvo (1983) model, where the adjustment probability is constant, a generalized hazard function $\Lambda(x)$ allows it to depend on the state x, the firm's desired adjustment. Such state dependence is appealing theoretically, see e.g. Barro (1972); Sheshinski and Weiss (1977); Dixit (1991); Golosov and Lucas (2007), and has been found to be relevant empirically, see e.g. Fougere et al. (2007); Dias et al. (2007); Eichenbaum et al. (2011); Gautier and Le Saout (2015).[8] A large number of models are nested by this framework, including the canonical Calvo model with a constant hazard $\Lambda(x) = 1/\kappa$ as $\gamma \uparrow \infty$, the Golosov and Lucas (2007) model with x bounded by the adjustment thresholds where the hazard is flat (almost zero) over a range of x and then spikes up with a big slope. Intermediate cases cover the so called Calvo-Plus model by Nakamura and Steinsson (2010) and the random menu cost problem of Dotsey and

[8] Several authors have employed the generalized hazard function in applications and empirical work. For recent applications see e.g. Costain and Nakov (2011a); Carvalho and Kryvtsov (2018); Sheremirov (2020); for empirical work see e.g. Berger and Vavra (2018); Petrella et al. (2018), and for related theoretical work Baley and Blanco (2021).

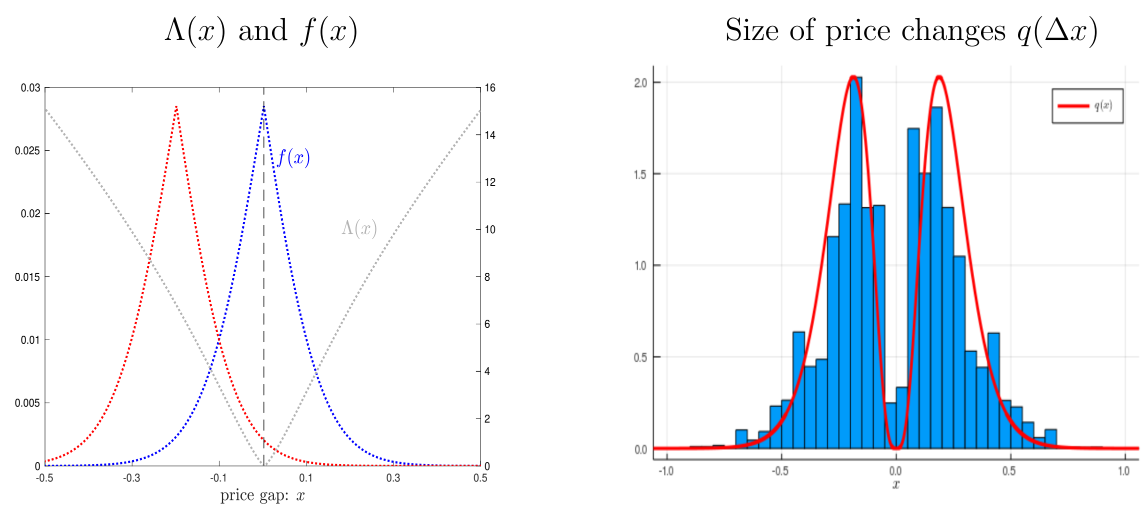
Wolman (2020).

Aggregation of the firm's decisions: $f(x)$. The policy rule for the firm's problem together with the law of motion of price gaps imply a transition for any initial cross sectional distribution of price gaps. Focusing on a steady state, the hazard $\Lambda(x)$, summarizing the policy rule, together with μ, σ^2, summarizing the law of motion of price gaps, uniquely determine the steady state distribution of firm's price gaps. Let us define this distribution by the density function $f : \mathbb{R} \to \mathbb{R}_+$ which satisfies the following Kolmogorov forward equation

$$\Lambda(x) \cdot f(x) = \mu f'(x) + \frac{\sigma^2}{2} f''(x), \quad \text{for each } x \neq x^*. \tag{7}$$

with boundary conditions $\lim_{x \downarrow x^*} f(x) = \lim_{x \uparrow x^*} f(x)$; $1 = \int_{-\infty}^{\infty} f(x)dx$, and $\lim_{x\to\infty} f(x) = \lim_{x\to-\infty} f(x) = 0$. The density function f, represented in the left panel of Figure 2, depicts the distribution of price gaps that arises in steady state.

Figure 2: Model objects: hazard function and cross sectional distributions



Note: The model uses the calibration for the Euro Area food and beverages sectorin Table 1.

3 Price setting behavior: data vs theory

This section presents a few key predictions of the model about the frequency and the size distribution of the price changes. We compare the predictions for the model's steady state with data for price setting behavior observed before the large energy shocks hit Europe in the years 2019-2021. We argue that the GHF model is able to account for several key patterns observed in the data. In Section 3.1 we use the model to study the response of prices to a large energy shock. This exercise provides a validation of the model by comparison of the predictions for the frequency of price changes with the actual data for 2022 and 2023.

To summarize, the main point of this section is to highlight that a data-consistent model of price setting implies that the economy's response to a large shock differs markedly from the response to a small shock. In particular, a large shock will give rise to a much faster pass-through from costs to prices, and hence face policymakers with a temporarily high inflation.

Frequency of price changes. The cross sectional density function $f(x)$ and the generalized hazard function $\Lambda(x)$ can be used to compute several objects that are observable in the data. The steady state frequency of price adjustments N is given by

$$N = \int_{-\infty}^{\infty} f(x)\Lambda(x)\, dx \tag{8}$$

The equation has a simple interpretation: it counts the total number of price adjustments, in a time period (say a year). These price adjustments originate from the firm's effort ℓ to control the price gaps, see equation (5) and equation (6).

Distribution of the size of price changes. Recall that upon any price change the firm resets its gap from x to the optimally chosen x^*, i.e. the size of the adjustment is $\Delta x = x^* - x$. This occurs with probability $\Lambda(x)$ per unit of time. Recall also that at steady state, there is a density $f(x)$ of firms with price gap x. The distribution of the size of price changes has the following density $q(\Delta x)$:

$$q(x^* - x) \equiv \frac{\Lambda(x) f(x)}{N}. \tag{9}$$

It is interesting to contrast the actual shape of the distribution of price changes observed in the actual data, $q(\Delta x)$, to select a data-consistent model of price-setting behavior. We pursue that effort and present a calibration of the parameters that yields a distribution of price changes $q(\Delta x)$ that approximately matches the data. The right panel of Figure 2 shows data that align closely to the predictions of the GHF model, in particular the ability to replicate a small mass of tiny price changes and the bimodality of the distribution.

A model that reproduces few observations of tiny price changes is economically appealing. Intuitively, when x is close to the optimal return gap x^*, the firm allows this deviation because the losses from the suboptimal price are low. Namely, the benefit of effort ℓ, which is given by $v(x^*) - v(x)$, is low (in absolute value). In contrast, one of the salient features of the Calvo model is that for any state, the probability of price adjustment is the same and independent of the benefit of adjustment. This implies that the mode of the distribution of price changes is given by a price change of infinitesimal size, a feature that is quite at odds with the data depicted in the right panel of Figure 2.

A brief description of the dataset. We base our analysis on granular data on price setting behavior, as in Cavallo (2018). These data contain detailed information on the frequency and size of daily price changes for a large number of firms, and provide the necessary information to solve the inverse inference problem mentioned above. Our data was provided by PriceStats, a private company related to the The Billion Prices Project (see Cavallo and Rigobon (2016)). It is generated using a technology known as web scraping, which automatically scans the code of publicly available webpages daily to gather and store relevant data. The dataset consists of product details, such as price, category, and sale status, collected on a daily basis from various retailers' websites. The data is uncensored and detailed, covering the entire lifespan of all products sold by these retailers, and provides prices that are similar to those obtained in offline stores (Cavallo et al., 2018). We use a subset of data from several European countries, from January 1st 2019 to May 1st 2023. We focus on the "Food and Beverages" category, which has experienced one of the highest rates of inflation during this period in many countries.

This dataset offers several advantages over traditional data sources such as Consumer Price Index (CPI) and Scanner Data . Firstly, it provides daily price updates, free from unit values, time-averaging, and imputations, which are common issues in CPI and Scanner Data. This high-frequency data collection allows for a more accurate identification of sales and price changes (Cavallo, 2018). Another major advantage of this dataset is the uncensored price spells. Unlike other data, prices here are continuously recorded from the day they are first offered to consumers until they are discontinued, offering a complete and unaltered view of the product's price life cycle. Furthermore, the data is comparable across countries, collected using identical techniques for similar categories of goods over the same time period. Finally, it offers real-time availability, providing up-to-date information without any processing delay. This makes it a potentially valuable tool for central banks and policymakers in real-time estimation of price stickiness and related statistics.

In Table 1 we present summary statistics of price setting behavior for several Euro area countries and some aggregate statistics from related studies.

The standard deviation of the size of price changes is similar across countries with the exception of Italy and Ireland. The kurtosis measure is also very similar across Euro Area countries and ranges between 2.1 and 2.7 with the exception of Ireland with a Kurtosis of 1.6. The frequency of price changes in the food and beverages sector is larger than the aggregate data and is also more heterogeneous across countries. For instance, the UK displays a frequency of 0.7 price changes a year whereas France features 3.6 price changes a year.

The measurement of kurtosis. To compute kurtosis in Table 1, we follow Alvarez et al. (2022) in order to account for unobserved heterogeneity. Recall that kurtosis is a scale-free statistic. Therefore if all firms had a normal distribution of price changes then kurtosis is

Table 1: Price Setting Behavior before 2022 and Calibration

	Mean (Δx)	STD (Δx)	Kurtosis (Δx)	N	σ	γ	κ
Euro area CPI data (PRISMA data, period 2005-19, Gautier et al. 2022)							
	0.025	0.10	$2.8^{(a)}$	1	0.10	3.30	0.21
Euro area supermarket data (IRi data, period 2013-17, Karadi et al. 2023)							
	Mean (Δx)	STD (Δx)	Kurtosis (Δx)	N	σ	γ	κ
	-	0.13	3.2	1.1	0.14	4.19	0.28
Euro area Food and Beverages data (PriceStats data, period 2019-21)							
	Mean (Δx)	STD (Δx)	Kurtosis (Δx)	N	σ	γ	κ
France	-0.001	0.13	2.3	3.6	-	-	-
Germany	0.008	0.13	2.5	1.4	-	-	-
Greece	0.003	0.10	2.7	2.0	-	-	-
Ireland	0.001	0.32	1.6	1.6	-	-	-
Italy	-0.002	0.23	2.1	2.1	-	-	-
Netherlands	0.009	0.11	2.3	2.8	-	-	-
Spain	0.008	0.16	2.5	2.9	-	-	-
EA Average	0.004	0.15	2.4	2.4	0.23	2.61	0.09
Other countries Food and Beverages data (PriceStats data, period 2019-21)							
	Mean (Δx)	STD (Δx)	Kurtosis (Δx)	N	σ	γ	κ
UK	0.002	0.29	1.9	0.7	0.24	1.95	0.38

Notes: The PriceStats data uses a sample of changes in regular prices (excluding sales). The statistics are computed after dropping price changes larger than 1.50 log points in absolute value and products with less than 3 price spells for the period 2019-2021. Kurtosis is computed using equation (10), a correction for unobserved heterogeneity proposed by Alvarez et al. (2022). The statistics from the Price-setting Microdata Analysis (PRISMA) network are obtained from Table 7 in (Gautier et al., 2022). These data covers the period from 2005 to 2019. Standard deviation and kurtosis figures were obtained in private exchanges with the authors. (a) The matched value of kurtosis for the PRISMA data of 4.1 is corrected for heterogeneity using a multiple from Alvarez et al. (2021) who perform the correction for French CPI data. The statistics from Karadi et al. (2023) are taken from their Table 2 and correspond to the average of 4 euro area countries; Germany, France, Italy and the Netherlands between 2013 and 2017. Parameters γ, κ are calibrated using a GMM estimator to match the standard deviation and kurtosis of price changes. The drift of price gaps is $\mu = 2\%$. The additional parameters are set to standard values: $\eta = 6$, $\rho = 0.05$.

equal to 3. However, mixing many normal distributions with different scale factors (standard deviation of price changes) gives rise to a kurtosis higher than 3. Alvarez et al. (2022) show that under the assumption that each product i within a category has a product-specific scale b_i, such that $\Delta x_{it} = b_i \Delta x$, kurtosis can be computed accounting for unobserved heterogeneity using

$$Kurt(\Delta x_t) = \frac{\mathbb{E}[(\Delta x_{it})^4]}{\mathbb{E}[(\Delta x_{it})^2(\Delta x_{is})^2]}, \tag{10}$$

where the empirical counterparts are estimated with

$$\begin{aligned}
\widehat{\mathbb{E}}[(\Delta x_{it})^4] = &\quad \frac{1}{\#I}\sum_{i\in I}\frac{1}{\#T(i)}\sum_{t\in T(i)}(\Delta x_{it})^4, \\
\widehat{\mathbb{E}}[(\Delta x_{it})^2(\Delta x_{is})^2] = &\quad \frac{1}{\#I}\sum_{i\in I}\frac{1}{\#T(i)(\#T(i)-1)}\sum_{t,s\in T(i),t\neq s}(\Delta x_{it})^2(\Delta x_{is})^2,
\end{aligned}$$

where $\#I$ are the number of products, $T(i)$ is the set of times where product i changes prices and $\#T(i)$ are the number of price changes for product i.

Calibration. We calibrate the model to match the standard deviation and the kurtosis of price changes as well as the frequency of price changes. We also set $\sigma^2 = N \cdot Var(\Delta x)$ since this relationship holds for a wide variety of models when $\mu \approx 0$, see Alvarez et al. (2022). We use standard values for the additional parameters of elasticity of substitution and intertemporal preference: $\eta = 6$ (which implies a markup of 20%) and a time discount $\rho = 0.05$. We choose an inflation rate of $\mu = 2\%$ consistent with inflation at steady state. We then use a GMM estimator to calibrate the parameters of the effort cost function κ, γ. The calibrated parameters are shown in Table 1. Recall that the kurtosis of a Calvo model is equal to 6, while the kurtosis of a canonical menu cost model is 1. The data suggest a somewhat intermediate situation.

The right panel of Figure 2 shows that the calibrated model is able to capture some key features of the data: the fact that the distribution of price changes is bimodal, with a dip at zero. The latter is a major difference compared to the prediction of the Calvo model where the constant hazard implies a mode at zero, i.e., that the most frequently observed price change has a tiny size. This prediction is counterfactual and it is a telltale of the fact that price setting behavior displays state dependence: price are adjusted only when necessary.

3.1 The propagation of an aggregate cost shock

In Figure 1 we saw that the frequency of price adjustments rose quickly after a large energy shock. In this subsection, we provide a thought experiment that rationalizes these facts. Namely, it takes an economy at steady state and hits it with a marginal cost shock as will be made precise below. We take calibrations of the price-setting model presented in Table 1 to study the propagation of large and small shocks. We will illustrate that, under a GHF model, large and small shocks have different implications for pass-through and the frequency of price adjustments.

Take an economy characterized by a steady state distribution of price gaps and a policy rule. The economy is then hit by an unexpected once-and-for-all shock to marginal cost that displaces the distribution of states δ percentage points to the left as in Figure 2. Firms then would like to increase their prices to close their price gap. This incentive shapes the dynamic response of the price level and the frequency of price changes after the shock. We will describe the transition of these variables back to steady state for small and large shocks.

After the shock, we assume that the policy rule does not change. However, the distribution of states does change and at the instant of the shock it is equal to $f(x+\delta)$. We define $\hat{f}(x,t) : \mathbb{R} \times [0,\infty) \to \mathbb{R}_+$ as the distribution of price gaps after t units of time have elapsed from the shock. Intuitively, the distribution depends on time elapsed because it will only converge to the steady state after the initial effect of the shock is gradually washed away by price adjustments and idiosyncratic shocks.

In Figure 2 we see the distribution of price gaps f, centered around the vertical line, and the distribution of firms' price gaps after the shock $\hat{f}(x, 0)$. We see that the distribution after the shock places most firms' prices in a region far from their desired prices (at around -20% price gap). In this region the probability of adjustment, $\Lambda(x)$, is larger so a large shock triggers an increase in number of price adjustments.

This distribution $\hat{f}(x,t)$ is the solution of the Kolmogorov forward partial differential equation with initial condition $\hat{f}(x,0) = f(x+\delta)$, for each $x \in \mathbb{R}$. Using $\hat{f}(x,t)$ we can describe the path for the price level and the frequency of price changes after an aggregate shock, as

$$P(t) \approx P(0) + \int_{-\infty}^{\infty} x \cdot \hat{f}(x,t)\, dx \;-\; (X_{ss} - \delta), \tag{11}$$

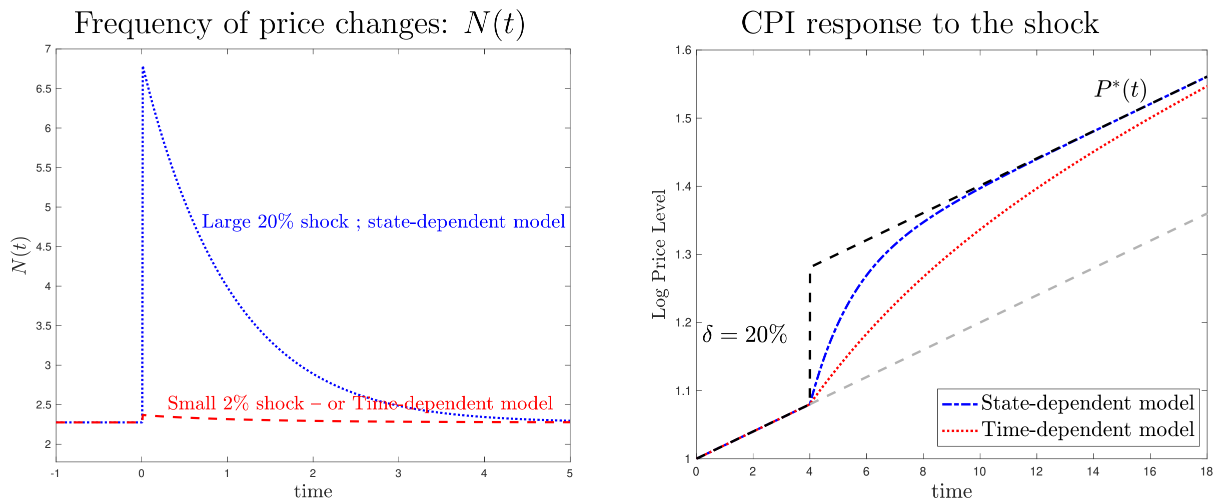
$$N(t) = \int_{-\infty}^{\infty} \Lambda(x) \cdot \hat{f}(x,t)\, dx \tag{12}$$

where $X_{ss} = \int_{\mathbb{R}} x \cdot f(x)\, dx$. The right hand side of equation (11) can be written more succinctly as $P(0) + X(t) - (X_{ss} - \delta)$ where $X(t)$ denotes the mean price gap at time t. Notice that the change in the price level is computed as deviations from $X_{ss} - \delta$ because that is exactly the aggregate price gap at the instant of the shock before any price change happens.

From the left panel of Figure 3 we can see that the frequency of price changes increases sharply after a large shock. This is due to many firms lying in a region far from their desired gap x^*, i.e. a region where the hazard, $\Lambda(x)$, is relatively high. This yields a persistent increase in the frequency of price adjustments. Notice that this effect is not present in the Calvo model.

Looking at the right panel we see that the propagation of a large shock features a much faster pass-through than one predicted by a Calvo model matching the same frequency and size of price changes. This is the flip-side of the observation about frequency. Upon a large shock the calibrated model is characterized by more firms adjusting prices upwards resulting in faster passthrough. Observing the slopes of the price level, the figure further depicts the

Figure 3: Propagation of a Large Shock



Note: The model uses the calibration for the food and beverages sector of euro area countries in Table **??**. The calibration matches a frequency of $N = 2.4$ price changes a year, the kurtosis and standard deviation of price changes of 2.4 and 15% respectively.

inflation dynamics and the forecast error associated with the use of a Calvo model. Failing to account for the large increase in the frequency of price revisions, the Calvo model leads to a substantial initial underestimation of inflation followed by a subsequent overestimation.

In summary, the state-dependent model features dynamic responses to large cost shocks that resemble the data on inflation and the increase in the frequency of adjustments for the recent surge in inflation in Europe. Furthermore, as we have shown, the forecast of the frequency of price changes and the path of inflation can be very different depending on the model that the analyst is using. For this episode, the implications of a purely time-dependent model are counterfactual.

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