Time Variation in Price Setting and Monetary Non-Neutrality*

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Abstract

This paper studies the implications of changes in price-setting behavior for the transmission of monetary policy. The analysis is based on a multi-sector menu cost model which is estimated separately for each quarter using Swiss CPI microdata from 2008 to 2022. The impulse responses suggest that the increase in the frequency of price changes revealed by the data has marginally reduced the cumulated response of output to a monetary policy shock. This result is corroborated by evidence from non-linear local projections. Using a time series of the sufficient statistic proposed by Alvarez et al. (2016a) to identify states with lower and higher degrees of monetary non-neutrality, we show that the responses of output and inflation to a monetary shock differ as expected between the two regimes.

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1 Introduction

Two facts about price setting emerge consistently from a large empirical literature examining price adjustments in microdata: Prices are sticky, and the frequency of price changes varies considerably across sectors.[1] Both facts play an important role in describing the transmission of monetary policy in standard models. The degree of price rigidity determines the persistence of output growth and inflation after monetary shocks (Golosov and Lucas, 2007; Woodford, 2009), while its cross-sectional heterogeneity amplifies their real effects (Carvalho, 2006; Carvalho and Nechio, 2011; Nakamura and Steinsson, 2008; Gautier and Le Bihan, 2022; Pastén et al., 2024).

Beyond its variation across sectors, price rigidity also varies over time. Several empirical studies document that the frequency of price changes increases with inflation (e.g., Gagnon, 2009; Nakamura et al., 2018; Alvarez et al., 2019; Karadi and Reiff, 2019), most recently during the post-pandemic inflation surge (e.g., Montag and Villar, 2022; Blanco et al., 2024; Cavallo et al., forthcoming). In Switzerland, we make the same observation for the frequency of consumer price changes in 2021 and 2022, although it has already been preceded by a steady, long-term increase over the decade leading up to the pandemic, independent of fluctuations in inflation (Rudolf and Seiler, 2022). At the same time, heterogeneity in the frequency of price adjustments increased across sectors. Similar to its cross-sectional heterogeneity, such time variation in price rigidity is likely to affect the transmission of monetary policy.

In this paper, we investigate the sources of the observed changes in price-setting behavior over time in Switzerland and analyze their implications for monetary non-neutrality. The model used for this analysis is the multi-sector menu cost model introduced by Nakamura and Steinsson (2010), also known as the "CalvoPlus" model. This model describes price adjustments as a combination of time-dependent and state-dependent pricing mechanisms. Following Gautier and Le Bihan (2022), we employ the method of simulated moments (MSM) to estimate the model. While Gautier and Le Bihan (2022) consider a 227-sector version of this model to analyze the heterogeneity of price-setting behavior in the French economy, we focus on analyzing price-setting behavior over time by estimating the model sequentially for each quarter. To keep our model computationally tractable, our version consists of four sectors: food, non-energy industrial goods (NEIG), energy, and services. This choice is rationalized by earlier findings which suggest that a model with only a few sectors can generate the same degree of monetary non-neutrality as a more complex model with numerous products (Carvalho, 2006; Carvalho and Nechio, 2011; Gautier and Le Bihan, 2022).

[1] Klenow and Malin (2010) and Nakamura and Steinsson (2013) provide comprehensive reviews of the literature on price-setting behavior based on micro price data.

The method of simulated moments aims to determine model parameters such that the simulated moments generated by the model closely match the actual moments computed from the data (McFadden, 1989). We target five conventional price-setting moments: two related to the extensive margin of price adjustments (i.e., the frequency of price adjustments and the share of price increases in all price changes), and three related to the distribution of price changes (i.e., the median absolute size of price adjustments, the interquartile range, and the kurtosis of the distribution of price changes). We obtain these moments from our dataset, which consists of more than 5.3 million individual price quotes underlying the Swiss Consumer Price Index (CPI) from January 2008 to December 2022 and covers up to 40 percent of the CPI by expenditure weights. We estimate two parameters reflecting pricing frictions (i.e., the Calvo probability of price adjustment and a menu cost parameter) and the standard deviation of the idiosyncratic productivity shocks.

The estimation results reveal that the time-dependent Calvo parameter explains most of the observed price stickiness in the data, whereas the menu cost parameter contributes only modestly to the overall degree of price rigidity. This result aligns with Gautier and Le Bihan (2022), who highlight the significant role of the Calvo mechanism compared to menu costs in driving price stickiness. Over time, both the Calvo parameter and, to a lesser extent, the menu cost parameter exhibit upward trends. By contrast, the volatility of idiosyncratic productivity shocks shows no trend over time but a strong cyclical variation.

To analyze the implications of time variation in price-setting behavior on the effectiveness of monetary policy, we generate output responses to a monetary policy shock using our estimated multi-sector menu cost models for each quarter from 2008 to 2022. We use the cumulated output responses each quarter to measure monetary non-neutrality. Our analysis shows that the observed changes in price setting have reduced the impact of monetary policy shocks on real output over the observation period.

We complement the analysis of monetary policy effectiveness with an additional measure of monetary non-neutrality that can be derived directly from the price-setting moments. In particular, we use the "sufficient statistic" proposed by Alvarez et al. (2016a), according to which the cumulated response of output to a monetary policy shock is proportional to the ratio of the kurtosis of the steady-state distribution of price changes to the frequency of price changes. Using Swiss CPI microdata to compute the sufficient statistic for each quarter from 2008 to 2022, we find that the time series is similar to the cumulated response of output to a monetary shock obtained from the model. It declines over time, suggesting that the real effects of monetary policy have become smaller in recent years.

Finally, we analyze the relevance of time variation in monetary non-neutrality on the transmission of a monetary shock. Using nonlinear local projections with both the cumulated output response obtained from the model and the sufficient statistic computed from the CPI microdata as state variables, we assess whether the real effects of monetary policy differ between states with higher and lower degrees of monetary non-neutrality. Our results show significantly larger real effects of monetary policy in states with a higher degree of monetary non-neutrality. In addition, prices react sluggishly, in contrast to their rapid response and quick reversion in states with a lower degree of non-neutrality. Overall, our findings empirically validate our two measures of monetary non-neutrality. Furthermore, by validating the theoretical sufficient-statistic proposition of Alvarez et al. (2016a) over time, they underscore its potential as an indicator of monetary non-neutrality that can be assessed in real time using the relevant price-setting moments from microdata.

Our paper adds to the extensive empirical literature on price rigidity by documenting variations in price adjustment patterns over time and investigating their sources. Several empirical studies document that the frequency of price changes increases with inflation (e.g., Gagnon, 2009; Nakamura et al., 2018; Alvarez et al., 2019; Karadi and Reiff, 2019), most recently during the post-pandemic inflation surge (e.g., Montag and Villar, 2022; Blanco et al., 2024; Cavallo et al., forthcoming). Unlike these studies, we examine a long-term trend in the frequency of price adjustments, which was not reported in previous studies. For example, in the euro area, the average frequency shows neither an upward nor a downward trend from 2005 to 2019 (Gautier et al., forthcoming), but there are slight increases in individual[2] euro-area countries. We provide a structural interpretation of the observed changes in price-setting behavior by estimating the CalvoPlus model of Nakamura and Steinsson (2010). Gautier and Le Bihan (2022) have used this model to explore the cross-product heterogeneity of price rigidity. Building on earlier results that a model with only a few sectors can produce the same level of monetary non-neutrality as a more complex multi-sector model with numerous products (Carvalho, 2006; Carvalho and Nechio, 2011; Gautier and Le Bihan, 2022; Pastén et al., 2024), we estimate the model sequentially over time to obtain time-varying parameters that speak to the structural features that drive the observed changes in price-setting behavior over time.

This paper further relates to a growing body of empirical work documenting state-dependent effects of monetary shocks across states such as interest rate cycles (Alpanda et al., 2021), credit cycles (Alpanda and Zubairy, 2019), financial frictions (Ottonello and Winberry, 2020), business cycles (Tenreyro and Thwaites, 2016) or

[2] Gautier et al. (forthcoming) find an increase in the average frequency of price changes in Austria (1996:01–2017:02), France (2003:03–2019:09), Germany (2010:01–2019:12), and Latvia (2010:01–2018:12).

inflation (Jordà et al., 2020; Ascari and Haber, 2022). By using the cumulated output responses to a monetary shock and the sufficient statistic to uncover variations in the degree of monetary non-neutrality over time, our empirical evidence for the state dependence of monetary policy arises from price-setting mechanisms derived from both model estimations and microdata moments.

Finally, our paper contributes to the broad empirical literature examining the implications of price-setting patterns for the propagation of shocks in general (e.g., Burstein et al., 2005; Auer et al., 2021; Bonomo et al., 2023), and to the more specific literature testing the sufficient-statistic proposition for monetary policy shocks. The evidence is mixed. Alvarez et al. (forthcoming) find that the sufficient statistic is negatively correlated with the cumulated impulse response of sectoral prices to a monetary shock in French PPI industries and CPI categories. Gautier et al. (2023) document the same relationship for the kurtosis-frequency ratio of French gasoline prices. By contrast, Hong et al. (2023) find that the kurtosis of US producer price changes is uninformative about the real effects of monetary policy. Our results provide empirical support for the theoretical prediction of Alvarez et al. (2016a). Moreover, while the existing papers test the theoretical prediction along the cross-sector dimension, the novelty of this paper is to provide an empirical test in the time-series dimension. By validating the theoretical prediction, it confirms the potential of the sufficient statistic as an indicator of the degree of monetary non-neutrality that can be computed from microdata in real time.

The paper is organized as follows. Section 2 describes the micro price data underlying the Swiss consumer price index and presents stylized facts on the dynamics in price-setting moments from 2008 to 2022. Section 3 describes the model and the estimation strategy. Section 4 presents the estimation results. Section 5 analyzes the macroeconomic implications of the observed changes in patterns of price rigidity. Section 6 provides nonlinear local projections to test the relevance of time variation in monetary non-neutrality for the transmission of a monetary shock. Section 7 concludes.

2 Data and stylized price-setting facts

This section presents the micro price data (Section 2.1) that consist of monthly consumer prices in Switzerland from 2008 to 2022 and characterizes stylized facts about price setting, both for average moments (Section 2.2) and their variation over time (Section 2.3). We focus on five conventional price-setting moments: two that capture aspects of the extensive margin of price adjustments (i.e., the frequency of price adjustments and the share of price increases in all price changes), and three that capture aspects of the distribution of price changes (i.e., the median absolute size of price adjustments, the interquartile range, and the kurtosis of the price change distribution).

2.1 Swiss CPI microdata

The data consist of monthly price quotes collected by the Swiss Federal Statistical Office (FSO) to construct the Swiss Consumer Price Index (CPI).[3] The sample covers 15 years from January 2008 to December 2022 and includes 5.3 million price quotes for 397,000 individual products and services, representing 266 expenditure items, collected from 1,777 stores throughout Switzerland.

To minimize the impact of compositional shifts over time, we restrict the sample to expenditure items (corresponding to the five-digit COICOP level) that are available throughout the sample period and for which prices are collected at a frequency of quarterly or higher. To further improve the informativeness of the data and to control for measurement errors, we exclude administered prices, prices based on unit value indices, and others.[4] Our remaining sample consists of 120 expenditure items, representing up to 40 percent of the CPI basket by expenditure weights.

We compute price changes as monthly log differences in the unit prices of the products. Our baseline sample excludes price changes due to temporary sales and product substitution. We present stylized facts about price setting using five conventional moments of price rigidity: the frequency of price adjustments (f), the share of price increases in all price changes ($\frac{f^+}{f}$), the median absolute size of price adjustments ($|\Delta p|$), the interquartile range ($\mathrm{IQR}(\Delta p)$), and the kurtosis[5] of the price change distribution ($\mathrm{Kur}(\Delta p)$). We compute these moments at the disaggregated level by pooling price changes per expenditure item over the months of a quarter, thus converting monthly data to quarterly data. To compute aggregate statistics, we use average basket weights and take weighted median moments across items.

2.2 Average price-setting moments

Table 1 reports average moments for all products and four sectors: food, non-energy industrial goods (NEIG), energy, and services. Five stylized facts emerge that are

[3] The data have been provided by the FSO to the Swiss National Bank and the KOF Swiss Economic Institute at ETH Zurich under a confidentiality agreement and cannot be shared.

[4] Appendix A.1 provides more details on our data treatment and sampling decisions.

[5] Heterogeneity at the lowest level of product identification in CPI microdata may bias the measurement of the kurtosis of price changes (Alvarez et al., 2016a). To address this issue, we compute the kurtosis based on price changes standardized at the ten-digit COICOP level. We standardize price changes at the ten-digit COICOP level by subtracting their mean (for all non-zero price changes) and dividing them by their standard deviation.

broadly consistent with previous national (e.g., Kaufmann, 2009; Rudolf and Seiler, 2022) and international evidence (e.g., from Nakamura and Steinsson (2008) for the United States or Gautier et al. (forthcoming) for the euro area) and robust to the treatment of price changes due to temporary sales and product substitution.[6] First, Swiss consumer prices are sticky. The median frequency of price changes is 17.4 percent, and the mean frequency is 26.9 percent per month, meaning that one in four prices changes every month. Second, price increases are more common than price decreases. About 60 percent of all price changes are price increases. Third, price changes are large compared to the average inflation rate of 0.3 percent over the sample period. The median absolute size of price changes is 4.3 percent. Fourth, the size distribution has a large proportion of small and large price changes. The interquartile range of the distribution is 6.2 percentage points, and its median kurtosis is 4.1. Fifth, the frequency of price changes varies considerably across sectors. Price changes are most frequent for energy items (frequency of 84.2 percent) but rare for services (frequency of 2.8 percent). Food and NEIG are in the middle, although price changes for food items (frequency of 23.5 percent) are twice as frequent as for NEIG (frequency of 12.8 percent).

[6] Table A.1 in the appendix shows the average price-setting moments for all products and the four sectors for the sample that includes price changes due to temporary sales and product substitution.

Table 1: Average price-setting moments in Swiss CPI microdata

	Weight	Frequency		Size		
		f	$\frac{f^+}{f}$	$\lvert\Delta p\rvert$	IQR(Δp)	Kur(Δp)
All products						
Mean	0.363	0.269	0.610	0.053	0.088	4.646
Median		0.174	0.587	0.043	0.062	4.148
Standard deviation		0.286	0.202	0.043	0.088	2.636
By sector (median moments)						
Food	0.115	0.235	0.537	0.033	0.060	4.782
NEIG	0.086	0.128	0.592	0.037	0.057	4.314
Energy	0.036	0.842	0.543	0.027	0.037	2.831
Services	0.126	0.028	0.734	0.059	0.076	4.165

Notes: The table shows average price-setting moments in Swiss CPI microdata. The sample ranges from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution. Moments are calculated at the disaggregated item level (corresponding to the five-digit COICOP level) and aggregated across items as weighted medians using average CPI expenditure weights. Over time, the aggregate moments are simple time averages. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat.

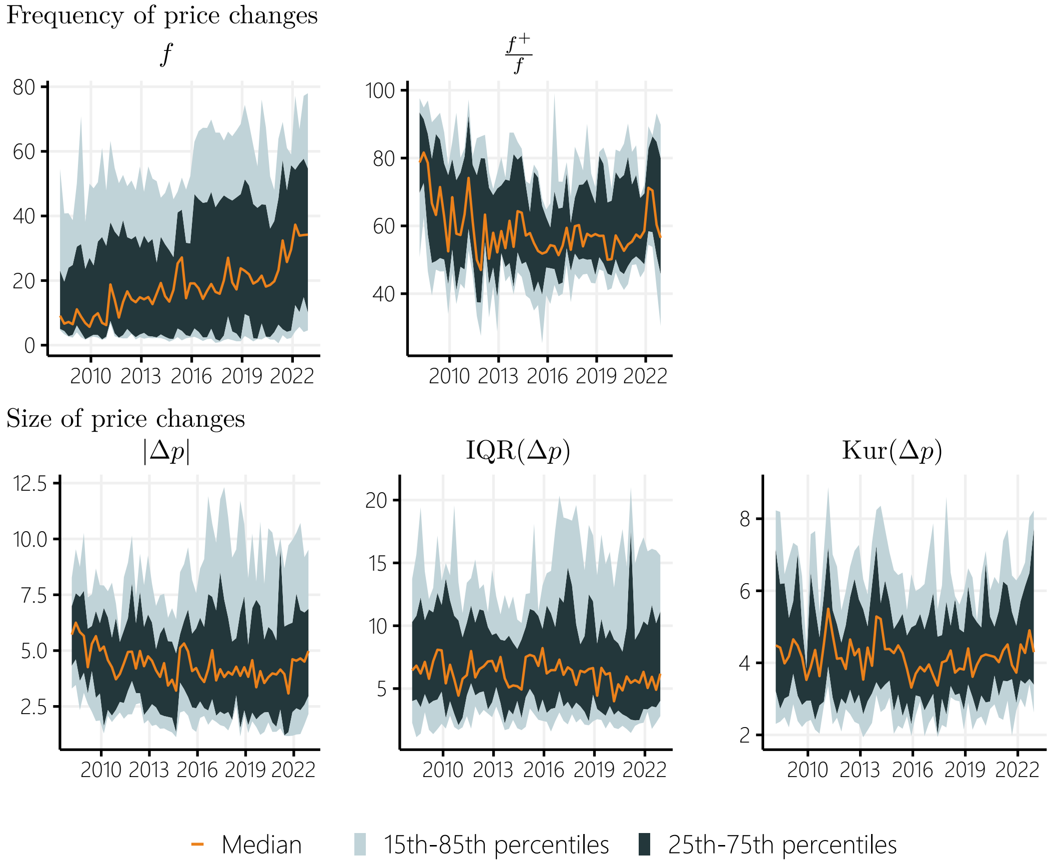
2.3 Price-setting moments over time

In this paper, we complement the evidence on the cross-sectional characteristics of price-setting moments with additional evidence from a time-series perspective. To this end, Figure 1 plots the evolution of the price-setting moments over time from 2008:I to 2022:IV using the sample that excludes price changes due to temporary sales and product substitution.[7] For each quarter, the figures show the median, the interquartile range (dark-shaded area), and the 15th to 85th percentile range (light-shaded area) of the moments calculated across expenditure items.

We note the following five facts about the evolution of price-setting moments over time. First, the frequency of price changes increases over the sample period, implying

[7] Figure A.1 in the appendix shows the distribution of the price-setting moments across expenditure items over time for the sample that includes price changes due to temporary sales and product substitution. Our conclusions are broadly robust to the treatment of temporary sales and product substitution.

Figure 1: Distribution of price-setting moments across expenditure items over time



Notes: The figure shows the distribution of price-setting moments across expenditure items in Swiss CPI microdata and their evolution over time. The sample ranges from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution. The panels show the frequency of price changes and the share of price increases in all price changes (in the top row), the median absolute size of price adjustments, the interquartile range, and the kurtosis of the price change distribution (in the bottom row). For each quarter, the panels depict the median, the interquartile range (dark-shaded areas), and the 15th to 85th percentile range (light-shaded areas). The frequency and size of price changes are reported in percent.

that prices have become more flexible on average.[8] The median frequency increases slightly but steadily from 7.4 percent in 2008 to 19.5 percent in 2020 and accelerates further to 34.9 percent in 2022 with the rise in inflation in the last years of the sample due to both more frequent price increases and price decreases.[9] The share of price increases fluctuates relatively steadily around 60 percent after falling slightly at the beginning of the sample period.

Second, we find an increase in the cross-sectional heterogeneity of price rigidity. In particular, the interquartile range of the price adjustment frequencies widens over time, with the 75th percentile increasing more than the 25th percentile. This suggests that the increase in the average frequency is not the result of a broad-based tendency towards more frequent price changes but rather the result of a marked increase in the price adjustment frequencies in a subset of the CPI. In particular, the increase is driven by more frequent price changes of both food items and NEIG.[10] This contrasts with the last years of the sample, where we observe a broad-based increase in the frequency of price adjustments, as reflected in the upward shift of the entire frequency distribution.

Third, the absolute size of price changes declines slightly. The median size is 5.9 percent in 2008 and 4.7 percent in 2022. The decrease is due to both smaller price increases and (absolute) price decreases.[11] Thus, smaller price changes occur relatively more often at the end of our sample than at the beginning.

Fourth, price changes have become more dispersed across sectors. This is evident in the widening distribution of the size of price changes, especially from the second half of our sample onwards. Before 2015, 15 percent of all price changes are larger than 8.0 percent in absolute terms. After 2015, the top 15 percent of all price changes exceed 9.8 percent. This increase also reflects the broader distribution of the interquartile range of price changes.

[8] This contrasts with the results reported by Kaufmann (2009) for the earlier period from 1993 to 2005 in Swiss CPI microdata, for which the trend in the frequency of price changes was flat. For the euro area, the average frequency shows neither an upward nor a downward trend from 2005 to 2019 but increases slightly in individual euro-area countries: Gautier et al. (forthcoming) find an increase in the average frequency of price changes in Austria (1996:01–2017:02), France (2003:03–2019:09), Germany (2010:01–2019:12) and Latvia (2010:01–2018:12). With the rise in inflation following the pandemic, an increase in the frequency of price changes has been documented in various countries and data sources, such as US CPI microdata (Montag and Villar, 2022), French survey data (Dedola et al., 2023), and online prices from different countries (Cavallo et al., forthcoming).

[9] The top row of Figure A.2 in the appendix shows the distributions of the frequency of price increases and decreases across expenditure items over time.

[10] Figure A.3 in the appendix shows the median price-setting moments per sector in Swiss CPI microdata and their evolution over time. Rudolf and Seiler (2022) show that the NEIG with a significant decrease in price rigidity include items for which prices are collected online, reflecting the greater price transparency and increased competition in online markets with the rise of e-commerce.

[11] The bottom row of Figure A.2 in the appendix shows the distributions of the median absolute size of price increases and price decreases across expenditure items over time.

Thus, small and large price changes are relatively more common at the end of our sample than at the beginning. This observation is summarized in a fifth and final fact: the evolution of the kurtosis of price changes over time. Apart from its high-frequency fluctuations, the kurtosis remains relatively constant, fluctuating around four over the entire sample period.

3 Estimation of a multi-sector menu cost model

The previous section has revealed considerable dynamics in price setting over time. To explore the sources of the observed changes in price-setting behavior in the Swiss CPI microdata and investigate their implications for monetary non-neutrality, we rely on the multi-sector menu cost model developed by Nakamura and Steinsson (2010). Section 3.1 outlines the main building blocks of the model. To identify the structural parameters related to firms' price-setting decisions with the data moments, we use price-setting moments derived from the Swiss CPI microdata to estimate the parameters corresponding to pricing frictions and the standard deviation of idiosyncratic productivity shocks (as detailed in Section 3.2), while we calibrate the remaining parameters prior to estimation (as detailed in Section 3.3).

3.1 Multi-sector menu cost model

This section presents the building blocks of the multi-sector menu cost model, which consists of households (Section 3.1.1), firms (Section 3.1.2), and a path for nominal output targeted by the monetary authority (Section 3.1.3) to close the model. The model is similar to the CalvoPlus model introduced by Nakamura and Steinsson (2010). It generalizes the state-dependent pricing model of Golosov and Lucas (2007) into a multi-sector framework and further incorporates time-dependent price adjustment features from Calvo (1983).

3.1.1 Households

The infinitely-lived household maximizes an intertemporal utility function

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{1}{1-\gamma} C_{t+\tau}^{1-\gamma} - \frac{1}{\varphi+1} L_{t+\tau}^{\varphi+1} \right], \tag{3.1}$$

where C_t is a composite consumption aggregate and L_t is labor input. The parameter β denotes the discount factor, $\gamma > 0$ is the coefficient of relative risk aversion (or, equivalently, the inverse elasticity of intertemporal substitution in consumption), and φ determines convexity of labor disutility. E_t denotes the expectation operator conditional on the information available in t.

Aggregate consumption, C_t, is given by a Dixit-Stiglitz aggregator (Dixit and Stiglitz, 1977) of the sectoral goods demanded by households. There are K different sectors in the economy with a continuum of firms indexed by $i \in [0, 1]$, involved in the production of sectoral output, $C_{k,t}$,

$$C_t = \left[\sum_{k=1}^{K} \omega_k^{\frac{1}{\theta}} C_{k,t}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \quad \text{and} \quad C_{k,t} = \left[\int_0^1 C_{i,k,t}^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}}, \tag{3.2}$$

where ω_k represents the sectoral weights and $\theta > 1$ denotes the elasticity of substitution between goods across sectors and across varieties within a given sector.

In each period, the household optimizes its expenditure on each sectoral good, $C_{k,t}$, in such a way as to obtain the highest level of the consumption bundle, C_t, for a given level of expenditure. The optimal demand for each sectoral good, $C_{k,t}$, follows from maximizing the value of the bundle with respect to each differentiated good and subject to a given level of expenditure and is given by

$$C_{k,t} = \left(\frac{P_{k,t}}{P_t} \right)^{-\theta} C_t \quad \text{and} \quad C_{i,k,t} = \left(\frac{P_{i,k,t}}{P_{k,t}} \right)^{-\theta} C_{k,t}, \tag{3.3}$$

where P_t is the aggregate price level and $P_{k,t}$ is the price index of sector k,

$$P_t = \left[\sum_{k=1}^{K} \omega_k P_{k,t}^{1-\theta} \right]^{\frac{1}{1-\theta}}, \quad P_{k,t} = \left[\int_0^1 P_{i,k,t}^{1-\theta} di \right]^{\frac{1}{1-\theta}}. \tag{3.4}$$

Equation (3.3) states that the demand for the sectoral product k varies with the aggregate demand for consumption, C_t, and with its relative price, $P_{k,t}/P_t$.

Assuming that all households face identical decision problems and that markets are complete, the aggregate flow budget constraint faced by households takes the form

$$W_t L_t + B_t + T_t \leq P_t C_t + E_t Q_{t,t+1} B_{t+1}, \tag{3.5}$$

where W_t is the nominal wage rate, B_t is the quantity of one-period risk-free bonds held by the household between time t, $Q_{t,t+1}$ is the stochastic discount factor, and T_t denotes distributed profits and other transfers. Households supply labor to the producing firms and are the owners of the firms. Income consists of labor income, $W_t L_t$, capital income, B_t, and claims on the profits of monopolistically competitive firms plus other transfers, T_t. It is used for nominal consumption, $P_t C_t$, and is invested in bond holdings, $E_t Q_{t,t+1} B_{t+1}$.

The first-order conditions of the representative household's maximization of lifetime utility (Equation 3.1) subject to the flow budget constraint (Equation 3.5) give the optimal labor supply condition (Equation 3.6) and the Euler equation for consumption (Equation 3.7), together with a transversality condition and a condition excluding ”Ponzi schemes” (i.e., the flow budget constraint holds in every period):

$$L_t^{\varphi} C_t^{\gamma} = \frac{W_t}{P_t}, \tag{3.6}$$

$$E_t Q_{t,t+1} = \beta E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \frac{P_t}{P_{t+1}} \right]. \tag{3.7}$$

According to Equation (3.6), the optimal labor supply indicates that the marginal rate of substitution between leisure and consumption is equal to the real wage. The Euler equation for consumption (Equation 3.7) implies that the time path of consumption varies with the asset price, Q_t.

3.1.2 Firms

We consider the pricing decision of a firm $i \in [0, 1]$ operating in sector k in a monopolistic competitive environment. Each firm faces a linear production function of the form:

$$Y_{i,k,t} = A_{i,k,t} L_{i,k,t}, \tag{3.8}$$

where $A_{i,k,t}$ is an idiosyncratic productivity process and $L_{i,k,t}$ is the labor input of firm i, assuming a perfectly competitive labor market. The law of motion for log productivity is an AR(1) process:

$$\ln A_{i,k,t} = \rho_k \ln A_{i,k,t-1} + \varepsilon_{i,k,t}, \tag{3.9}$$

with sector-specific persistence parameter, ρ_k, and an idiosyncratic shock, $\varepsilon_{i,k,t}$, which is a realization of an i.i.d. Gaussian process with variance σ_k^2.

With a common production technology and a fully competitive labor market, the real marginal cost of firm i in sector k is given by $MC_{i,k,t} = W_t / A_{i,k,t}$. The real profit in t can thus be written as

$$\Pi_t = \left(\frac{P_{i,k,t}}{P_t} \right) C_{i,k,t} - \left(\frac{W_t}{P_t} \right) \frac{C_{i,k,t}}{A_{i,k,t}}, \tag{3.10}$$

where the demand for goods of firm i in sector k is given by

$$C_{i,k,t} = \left(\frac{P_{i,k,t}}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{P_t} \right)^{-\theta} C_t. \tag{3.11}$$

The mechanism describing the price-setting behavior of the firms follows the modifications of Gautier and Le Bihan (2022) of the CalvoPlus model developed by Nakamura and Steinsson (2010). In particular, firm i in sector k can adjust its price in t for free with probability λ_k and can incur a sector-specific menu cost $c_{i,k,t} = \mu^*_{k,t}$ with probability $1 - \lambda_k$. Sector-specific menu costs vary over time and are expressed in labor units.

The firm's pricing problem involves determining the optimal time to adjust and the optimal price to set in the event of an adjustment to maximize the firm's net present value. Formally, the firm's decision problem can be written as:

$$V\left(\Xi_{i,k,t}\right) = \max\left[V^{nc}\left(\Xi_{i,k,t}\right), V^{c}\left(\Xi_{i,k,t}\right)\right], \tag{3.12}$$

where $\Xi_{i,k,t} = \{P_{i,k,t-1}/P_t, A_{i,k,t}, C_t\}$, V^c is the value when the price is adjusted in t, and V^{nc} is the value when the price is not adjusted in t. V^c and V^{nc} are determined by

$$V^c(\Xi_{i,k,t}) = \max_{P_{i,k,t}}\left[\Pi\left(\frac{P_{i,k,t}}{P_t}, A_{i,k,t}, C_t\right) + E_t Q_{t+1} V(\Xi_{i,k,t+1})\right] - c_{i,k,t}\frac{W_t}{P_t} \tag{3.13}$$

and

$$V^{nc}(\Xi_{i,k,t}) = \max_{P_{i,k,t}}\left[\Pi\left(\frac{P_{i,k,t-1}}{P_t}, A_{i,k,t}, C_t\right) + E_t Q_{t+1} V(\Xi_{i,k,t+1})\right]. \tag{3.14}$$

3.1.3 Closing and solving the model

The model is closed by assuming that the monetary authority targets a path for nominal output $S_t = P_t C_t$. The log of nominal output is assumed to follow a random walk with drift:

$$\ln S_t = \pi_t + \ln S_{t-1} + \eta_t, \tag{3.15}$$

where π_t denotes the growth rate of the nominal output, and η_t can be interpreted as representing an aggregate policy shock.

The model is solved using numerical methods and value function iteration. We assume an initial set of values characterizing the function $V(\cdot)$ in Equation (3.12) and solve the firms' optimization problem to derive the policy function and obtain a new value function. We iterate on the function $V(\cdot)$ until convergence. Once converged, we use the resulting policy function to simulate the model and generate price-setting moments.

It is important to note that the firm's problem becomes infinite dimensional since P_t is the aggregation of individual prices. Following the method proposed by Krusell and Smith (1998) and implemented by Nakamura and Steinsson (2010), we assume that the firms perceive the evolution of the price level as a function of a small number of moments in the price distribution.

3.2 Estimation

We estimate the multi-sector menu cost model described in Section 3.1 using the method of simulated moments (MSM) introduced by McFadden (1989). This method has also been used by Gautier and Le Bihan (2022), who estimate a 227-sector version of the model outlined in the previous section using CPI microdata from France from 1994 to 2014.[12] The method of simulated moments aims to find model parameters such that the simulated moments generated by the model match the actual moments derived from the data. Accordingly, the MSM estimator $\hat{\theta}_{MSM}$ minimizes the distance between the empirical data moments $m(x)$ and the simulated model moments $m(\tilde{x}|\theta)$:

$$\hat{\theta}_{MSM} = \theta : \min_{\theta} \parallel m(\tilde{x}|\theta) - m(x) \parallel, \tag{3.16}$$

where x represents the empirical data, and $\tilde{x}|\theta$ denotes the data simulated by the model conditional on the parameter vector θ. We define the distance metric $\parallel \cdot \parallel$ as the percentage difference between simulated model moments and data moments, i.e.,

$$e(\tilde{x}, x|\theta) = \frac{m(\tilde{x}|\theta) - m(x)}{m(x)}. \tag{3.17}$$

This way, the moment error function $e(\tilde{x}, x|\theta)$ is a strictly positive scalar, and all moments are expressed in the same units, ensuring that no moment is unintentionally weighted differently due to its unit. Consequently, the MSM estimator is the solution to the minimization problem:

$$\hat{\theta}_{MSM} = \theta : \min_{\theta} e(\tilde{x}, x|\theta)' W e(\tilde{x}, x|\theta), \tag{3.18}$$

where W is a $k \times k$ weighting matrix to control the weight of each moment. We assume that W is an identity matrix[13], which implies that all moments are equally weighted, reducing the minimization problem to the sum of the squared distance between the data and model moments.

[12] We thank the authors for making their codes publicly available (Le Bihan and Gautier, 2020).

[13] Gautier and Le Bihan (2022) use the inverse of the variance of the data moments to down-weight moments with a high variance. They obtain these variances from sector-level bootstrap simulations.

We estimate three parameters for each sector k: the probability of price adjustment, λ_k, the menu cost, μ_k, and the standard deviation of idiosyncratic productivity shocks, σ_k. In our setup, we use five moments as targets for the model: the frequency of price changes, the share of price increases in all price changes, the median absolute size of price changes, and the interquartile range and the kurtosis of the price change distribution. The literature shows these moments to be essential in determining menu costs and the relative importance of state-dependent and time-dependent components in pricing decisions (Nakamura and Steinsson, 2010; Midrigan, 2011; Karadi and Reiff, 2019).

We start by estimating a "one-sector" version of the model using the median moments of the data. We then estimate "multi-sector" versions of the model that include the four sectors of food, NEIG, energy, and services. Estimating a multi-sector model consisting of four sectors offers two main advantages over further cross-sector disaggregation. First, the model remains tractable enough to estimate the parameters of all sectors jointly.[14] Second, building on earlier results, a model with only a few sectors can generate the same degree of monetary non-neutrality as a more disaggregated multi-sector model (Carvalho, 2006; Carvalho and Nechio, 2011; Gautier and Le Bihan, 2022; Pastén et al., 2024).

Therefore, instead of examining the cross-section of the model in more than four sectors, we analyze its properties over time. We do this by estimating the model sequentially for each quarter. The resulting time-varying parameter estimates allow us to identify the sources and consequences of time variation in price adjustment patterns.

3.3 Calibration and initialization

As explained in Section 3.2, we estimate three parameters: Two parameters corresponding to the pricing frictions (i.e., the probability of price adjustment, λ, and the menu cost, μ) and the standard deviation of idiosyncratic productivity shocks (σ). We calibrate all other parameters of the model before estimation as follows, adopting the calibration assumption of Nakamura and Steinsson (2010) for most of them. We assume log utility ($\gamma = 1$) and linear disutility of labor ($\varphi = 0$). The elasticity of demand is set to $\theta = 4$, which implies an average markup over marginal costs of 33.3

[14] When estimating their multi-sector model at the most disaggregated level consisting of 227 products, Gautier and Le Bihan (2022) effectively estimate a two-sector model to handle the complexity of estimating a large number of sectors and parameters. First, they estimate the one-sector model representing the aggregate multi-sector economy using median moments. Then, for each of the k sectors, they use a two-sector model with a small sector (the sector k of interest) and a large sector (the rest of the economy). The parameters for the large sector are set to the parameters obtained from estimating the one-sector model in the first step and hence treated as exogenous. The estimation targets are the moments computed for each sector k.

percent. We deviate from the parameterization of Nakamura and Steinsson (2010) with respect to the discount factor ($\beta = 0.98^{1/12}$) and the growth rate of nominal aggregate output, π_t, which we assume to be time-varying and equal to Swiss core inflation (excluding fresh and seasonal products, energy, fuels, and administered prices) in every quarter. We do this because the estimates of the risk-free short-term real interest rate and the long-term nominal growth are lower for Switzerland than for the United States. For the persistence parameter of the aggregate policy shock and the sectoral productivity shock process, we set $\rho_\eta = 0.65$ and $\rho_k = 0.7$, consistent with the calibration assumption of Gautier and Le Bihan (2022). Finally, the standard deviation of the aggregate policy shock is calibrated to $\sigma_\eta = 0.0097$, based on aggregate core inflation over our sample period.

We estimate the model sequentially for each quarter over our sample period from 2008:I to 2022:IV. For the first period, we initialize the set of parameters with the values from Gautier and Le Bihan (2022). For each subsequent period, we initialize the parameters with the estimated values from the previous period.

4 Time variation in price setting

In this section, we present our estimation results of the multi-sector menu cost model (described in Section 3.1) obtained using the method of simulated moments (described in Section 3.2). We first estimate the pricing parameters in the one-sector model and compare them with the parameters obtained from a four-sector version of the model (in Section 4.1). We then present the estimation results over time (in Section 4.2). Finally, we investigate the sources of the observed shifts in the price-setting moments in the estimated pricing parameters of the model (in Section 4.3).

While we do not elaborate on the fit of the model here, the values of the actual and simulated moments obtained from our baseline estimates are presented in Appendix B.1 (for the one-sector model) and in Appendix B.2 (for the four-sector model) and indicate that most of the target moments are relatively well fitted.

4.1 Average parameters

Table 2 provides averages of the quarterly estimation results. In the top panel, the parameters are obtained from the one-sector model, which we estimate in two versions using the median and mean moments of the data.[15] In the bottom panel,

[15] The baseline sample of CPI microdata excludes price changes due to temporary sales and product substitution. In Table B.1, we provide the estimation results for the sample including price changes due to temporary sales and product substitution.

the parameters are obtained from the four-sector model and averaged across sectors using CPI expenditure weights.

First, we note that the parameters differ considerably depending on whether they are based on mean or median price-setting moments. For example, the probability of price adjustment, λ, is much lower for the model estimated with median moments than for the model estimated with mean moments (13.6% versus 23.6%). This result reflects the strong asymmetries in the cross-sectional distribution of the price-setting moments.

Next, we compare the results from the one-sector model with the aggregated results from the four-sector model. The parameters aggregated across the four sectors are similar to those estimated using median moments in the one-sector model. By contrast, they are far from the estimates using mean moments in the one-sector model. This result illustrates the bias introduced by estimating the CalvoPlus model with aggregate mean moments and suggests that median moments in the one-sector setup provide a good proxy for a multi-sector economy (Nakamura and Steinsson, 2010). Therefore, we focus on the estimates obtained using median moments in the remainder of the analysis.

We then assess the levels of the aggregated parameters. The probability of price adjustment, λ, is relatively high compared to the frequency of price changes, as indicated by the Calvo share. Price changes under the zero menu cost regime account for up to 80 percent of the median frequency of price changes. Thus, for the typical sector, the Calvo component of the model is quite large relative to the menu cost component, μ, consistent with previous evidence reported for CPI (Alvarez et al., 2016a; Gautier and Le Bihan, 2022) and PPI data (Carlsson, 2017). The estimated menu cost, μ, when price adjustments are not free, is slightly more than 8% of total revenue in the estimates from the four-sector model using median moments. Regarding the parameters associated with the productivity process, the unconditional standard deviation of the productivity shock (i.e., $\frac{\sigma}{\sqrt{1-\rho}}$) is about 5.5%. The volatility of idiosyncratic productivity shocks is large relative to the aggregate shock on inflation, whose standard deviation is calibrated to 0.97% using aggregate CPI data. Thus, idiosyncratic productivity shocks are important drivers of price changes and account for an important part of the distribution of the size of price adjustments.

Finally, we address the heterogeneity of the estimated parameters across sectors. Comparing the degree of heterogeneity across parameters is complex due to different scales. Therefore, we use the coefficient of variation, defined as the ratio of the standard deviation to the mean, as an indicator of dispersion. The coefficient of variation is higher for λ (0.21) than for μ (0.14) and σ (0.07). Part of the large dispersion in the price friction parameters is due to the energy sector, which has almost fully flexible prices and the largest λ. Conversely, the service sector has the smallest λ, and the menu cost parameter μ is relatively large.

Table 2: Average estimates of price rigidity parameters

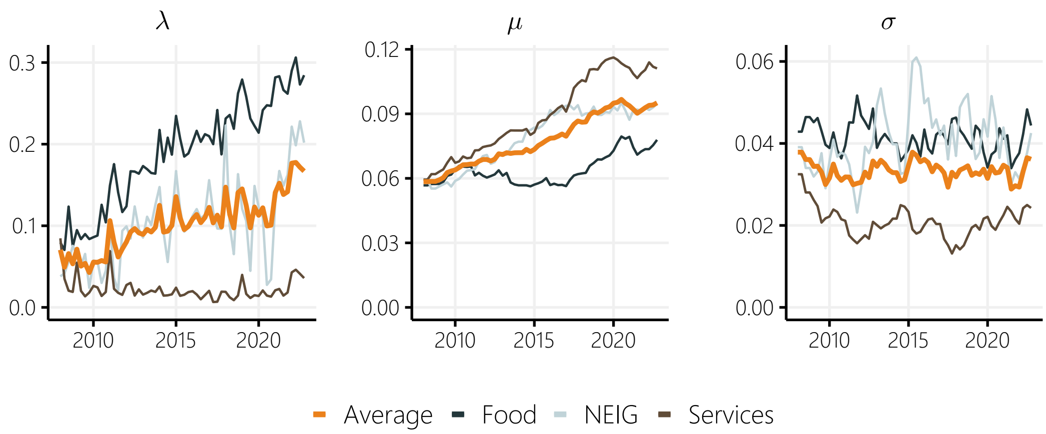
	Pricing frictions		Volatility	Calvo share
	λ	μ	σ	$\frac{\lambda}{f}$
One-sector model				
Mean moments	0.236	0.100	0.056	0.852
Median moments	0.136	0.041	0.039	0.711
Four-sector model				
Average	0.161	0.083	0.032	0.800
Food	0.190	0.064	0.042	0.808
NEIG	0.104	0.079	0.041	0.808
Energy	0.684	0.125	0.022	0.812
Services	0.022	0.089	0.021	0.784
Coefficient of variation	0.208	0.137	0.071	-

Notes: The table shows the estimated parameters obtained using the method of simulated moments. For the one-sector model, it reports two different versions: a model estimated using the median moments of the data and a model estimated using the mean moments of the data. The four-sector model uses median moments. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat. Moments are calculated at the disaggregated item level (corresponding to the five-digit COICOP level) and aggregated across items as weighted medians using average CPI expenditure weights. Over time, the average results are simple arithmetic means. Estimations are based on the sample of CPI microdata excluding price changes due to temporary sales and product substitution.

4.2 Parameters over time

Figure 2 plots the estimated parameters from the four-sector model[16] over time. It shows the estimates for each sector and the weighted average across sectors.[17] To improve the readability of the figure, we exclude the parameters estimated for the energy sector.[18]

Figure 2: Evolution of the parameters estimated using the four-sector model over time



Notes: The figure shows the evolution of each parameter estimated with the four-sector model using the median moments of the sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution. It shows the estimates for each sector and the weighted average across sectors using CPI expenditure weights, where the sectors correspond to the COICOP-HICP special aggregates defined by Eurostat. The results for energy are not reported but are shown in Figure B.5 in the appendix.

The parameter governing the probability of price adjustment, λ, increases steadily and substantially over the sample period. From the beginning of the sample in 2008 (when λ is 0.06 on average), it doubles to 0.12 in 2019 and accelerates further to 0.17 in the period since the pandemic. This development is mainly driven by the food sector, where λ is the highest at all times compared to the other sectors, rising from 0.09 in 2008 to almost 0.30 in 2022. This is in contrast to the service sector, where the estimated probability of price adjustment shows no trend and remains flat at a low level over time. The λ parameter for NEIG shows the most variation over time. It briefly rises from 0.05 at the beginning of the sample to over 0.20 before returning

[16] Figure B.4 shows the estimated parameters from the one-sector model. Our conclusions about the evolution of the parameters estimated with the four-sector model are broadly consistent with those obtained from the one-sector model.

[17] The baseline sample of CPI microdata excludes price changes due to temporary sales and product substitution. Figure B.3 provides the estimation results from the four-sector model based on the sample including price changes due to temporary sales and product substitution.

[18] As shown in Table 2, the pricing parameters of the energy sector take on extreme values compared to the other sectors. Figure B.5 in the appendix plots the estimated parameters over time, including the energy sector.

to 0.11 shortly before the pandemic in 2019. In the post-pandemic period, the NEIG sector experiences the largest increase in estimated price adjustment probability, rising from 0.07 to 0.21 in less than three years.

Compared to λ, the menu cost parameter μ evolves much more smoothly with a less pronounced increase over time. The average menu cost increases by about 60 percent, from less than 0.06 in 2008 to 0.09 in 2022. The period during the pandemic marks the only period in which the average μ decreases over a longer period and does not return to pre-pandemic levels by the end of the sample period. The increase in menu costs is seen in all sectors, although to varying degrees. It is strongest in the service sector, almost doubling to 0.11 between 2008 and 2022. By contrast, it is weakest in the food sector, where μ remains relatively flat from 2008 to 2016 and only increases after 2017. In the NEIG sector, menu costs initially rise at a similar pace to those in the service sector but plateau after 2015.

For the parameter corresponding to the standard deviation of idiosyncratic productivity shocks, σ, we observe a constant trend over time. The average estimate ranges between 0.03 and 0.04 over the sample period. The largest fluctuations for σ occur in the NEIG sector, where it peaks at 0.06 in early 2015, presumably related to the discontinuation of the minimum exchange rate of CHF 1.20 per euro. Furthermore, we observe an increase in volatility at the end of our sample during the post-pandemic inflation surge across sectors. Otherwise, little systematic movement can be identified for the other estimates.

4.3 Investigating the sources of time variation in price setting

In this section, we investigate how the variations in the empirical price-setting moments over time relate to the structural parameters estimated by the CalvoPlus model. First, we infer dynamic relationships by plotting each moment of the data against the estimated parameters over time (in Section 4.3.1). Then, more formally, we conduct counterfactual experiments by holding one parameter constant at a time, simulating price-setting moments from the multi-sector model, and comparing these simulated moments to the empirical data moments (in Section 4.3.2).

4.3.1 Cross-period relationship between price-setting moments and parameters

For each point in time and each sector, Figure 3 plots each price-setting moment from the data against one of the three parameters estimated using the four-sector model.[19] In most cases, there is no simple relationship between the price-setting moments and the model parameters, reflecting a complex interplay of multiple parameters in generating the moments. However, certain patterns do emerge.

Figure 3 suggests that much of the variation in the frequency of price changes over time is explained by variations in λ. There is a strong positive relationship between the frequency and the probability of menu cost-free price adjustment. To a lesser extent, variations in the frequency are positively related to variations in μ. By contrast, the relationship between the share of price increases and pricing friction parameters is less clear. Differences in the share of price increases over time appear to be positively related to differences in the volatility of productivity shocks. Further from Figure 3, the size-related pricing moments appear to increase with the volatility of the productivity shock σ and decrease with the menu cost μ. Furthermore, the median size of price changes is negatively related to the probability of price adjustment, λ.

4.3.2 Counterfactual experiments

To investigate more formally how the variations in the empirical price-setting moments over time relate to the structural parameters, we conduct three counterfactual experiments, each corresponding to one of the parameters of interest. In each experiment, we simulate price-setting moments from the four-sector model[20], holding one parameter constant at its sector-specific average obtained from the baseline model while estimating the remaining two parameters as in the baseline.

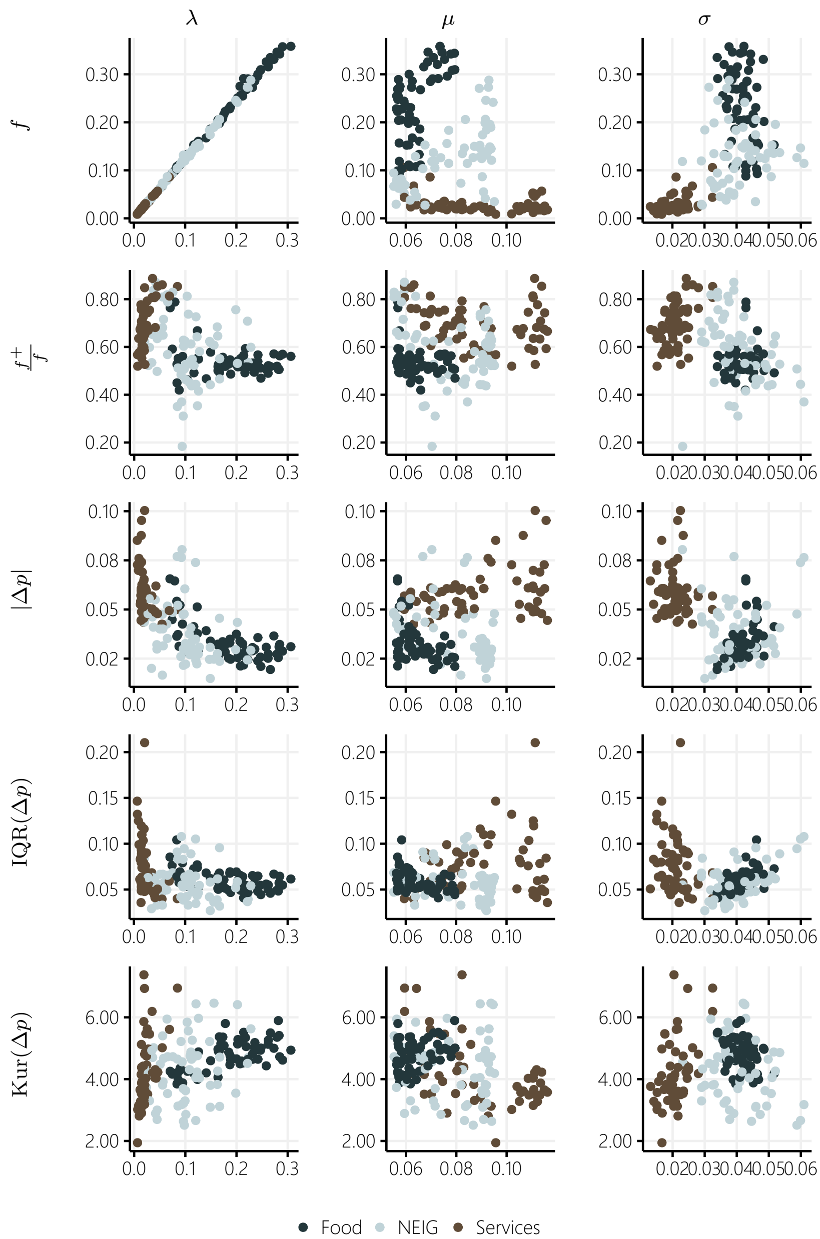
Figure 4 reports the results of these counterfactual exercises for each price-setting moment by plotting in each panel, for each quarter and sector, the data moment on the x-axis against the (counterfactual) model moment on the y-axis.[21] The first column of the figure reports scatter plots of data moments and simulated moments

[19] Figure B.6 illustrates the cross-period relationship between the price-setting moments and the parameters estimated using the four-sector model and aggregated across sectors using CPI expenditure weights. Figure B.7 illustrates the cross-period relationship between the price-setting moments and the parameters estimated using the one-sector model. Our conclusions remain broadly consistent with these alternative estimations.

[20] Figure B.8 provides the results for the same counterfactual experiments estimated with the one-sector model. Our conclusions are broadly consistent with this alternative estimation.

[21] In Table B.2, we supplement the evidence shown in Figure 4 by reporting the slope coefficients and adjusted R-squared values for each scatterplot and sector. Instances where the slope or R-squared is lower in an experiment than the baseline suggest that the respective parameter influences the time variation of a given moment.

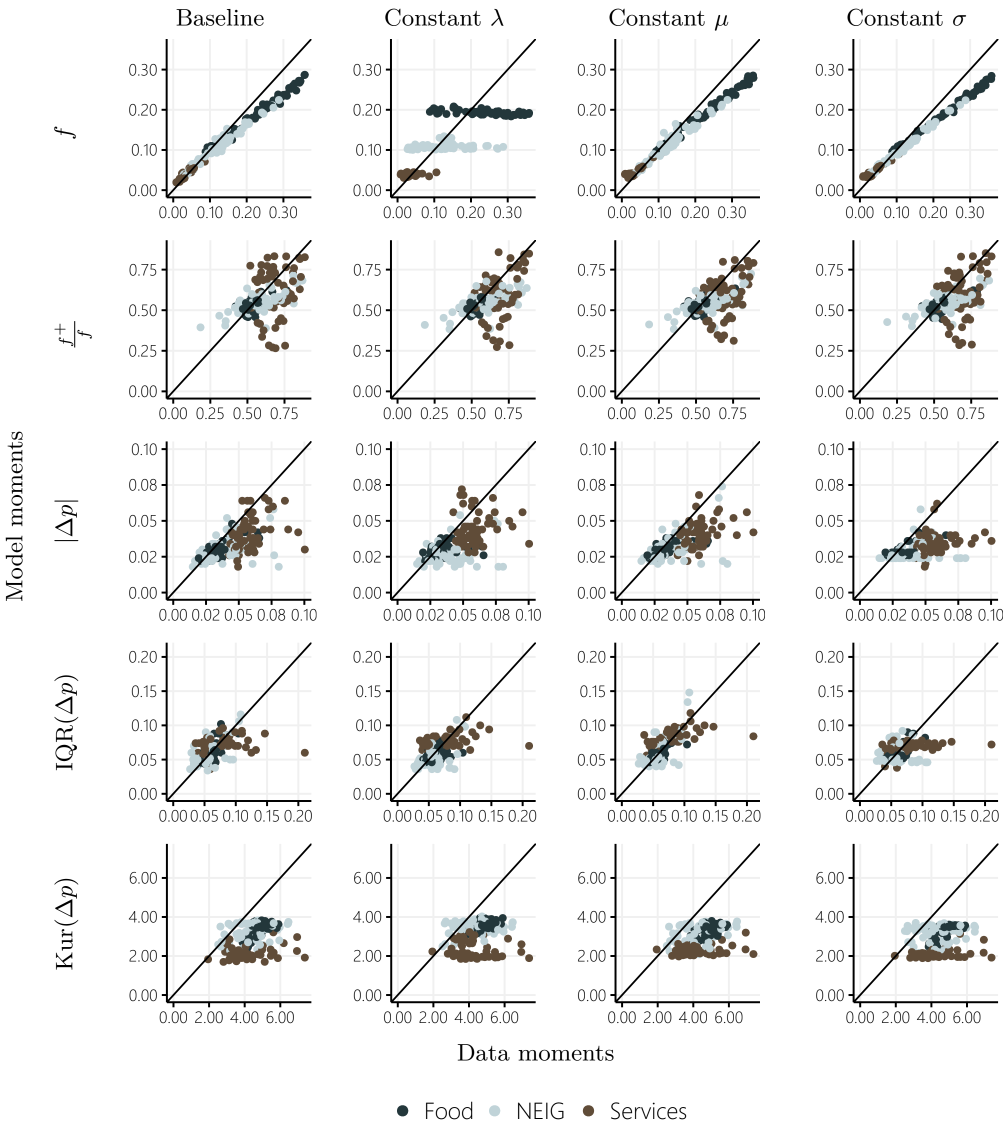
Figure 3: Cross-period relationship between the price-setting moments and the parameters estimated using the four-sector model



Notes: The figure relates the variations in the empirical price-setting moments over time to the structural parameters estimated from the CalvoPlus model. Each point in the scatter plots represents one moment-parameter combination for a given sector and quarter. Values on the y-axis are the price-setting moments in the data. Values on the x-axis are the parameter values. The parameters are estimated with the four-sector model using the sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution.

from our baseline model that estimates all three parameters. Columns 2–4 report scatter plots of the counterfactual experiments, each holding λ, μ, and σ constant at their sector-specific average, respectively.

Figure 4: Comparison between the empirical data moments and counterfactual model moments simulated from the four-sector model



Notes: The figure relates data moments to (counterfactual) model moments simulated by the CalvoPlus model. Each point in the scatterplots represents a data-model moment combination for a given sector and quarter. The values on the y-axis are the price-setting moments simulated with the four-sector model. The values on the x-axis are the price-setting moments in the data. The first column reports the results from the baseline, which estimates all three parameters. Columns 2–4 report scatterplots of the counterfactuals, where λ, μ, and σ are held constant at their sector-specific averages, respectively. The sample of Swiss CPI microdata spans from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution.

First, we examine the frequency of price changes (in the top row of Figure 4). In the baseline model (first column), all points in the scatterplot lie along the 45-degree line, indicating a close fit between the empirical data moments and the simulated model moments. When considering the counterfactuals where μ (third column) and σ (fourth column) are set to their sector-specific averages over time, the scatterplots appear almost unchanged from the baseline. This suggests that variation in these parameters contributes little to the observed time variation in the frequency of price changes. In stark contrast, the counterfactual assuming constant λ shows that the resulting simulated moments remain at sector-specific levels throughout the estimation period, and the share of explained variance drops from nearly 100% to 20% (Table B.2). Thus, the variation in λ is a major contributor to the variation in the frequency of price changes over time.

Another key finding pertains to the absolute size of price changes (in the third row of Figure 4). In this case, the price-setting parameters λ and μ play a minimal role in explaining the variations in the size of price adjustments over time. Instead, the productivity volatility σ is an important determinant. In the counterfactual where σ is held constant (fourth column), the simulated moments deviate more from the empirical data moments than the baseline.

The patterns for the remaining price-setting moments are less obvious. The share of price increases appears to be slightly influenced by λ and, to a lesser extent, by σ, as indicated by the smaller slope coefficients (Table B.2). Additionally, the interquartile range of price changes is mainly driven by time variation in σ. Finally, no distinct pattern is evident for the kurtosis of the price change distribution, and all three parameters appear to contribute to its time variation.

In summary, time variation in the extensive margin of price adjustment (the frequency of price changes and the share of price increases) is mostly explained by variation in the probability of price adjustment, λ. Meanwhile, variation in the standard deviation of idiosyncratic productivity shocks, σ, tends to explain time variation in the intensive margin of price adjustment (especially the size of price changes, but also their interquartile ranges and kurtosis). Conversely, the menu cost parameter, μ, plays a relatively minor role in explaining the time variation in any of the price-setting moments.

5 Time variation in monetary non-neutrality

Building on our previous analysis of the observed changes in price-setting moments in CPI microdata and their impact on the price-setting parameters in the multi-sector menu cost model, we now examine how time variation in price setting influences the real response of the economy to a monetary policy shock.

We assess the degree of monetary non-neutrality on a quarterly basis using our estimated multi-sector menu cost models and generate impulse response functions (IRFs) of output to a monetary policy shock. Specifically, for each quarter, we simulate the IRFs of output to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) and cumulate the responses over a forty-quarter horizon. This process generates a time-series measure of monetary non-neutrality from 2008:I to 2022:IV.

We complement this model-implied monetary non-neutrality with an additional measure of monetary non-neutrality that can be derived directly from the price-setting moments. In particular, we use the "sufficient statistic" proposed by Alvarez et al. (2016a), according to which the cumulated response of output to a monetary policy shock is proportional to the ratio of the kurtosis of the distribution of non-zero price changes to the frequency of price changes.[22] Using the empirical data moments, we compute the sufficient statistic for each quarter t in our sample as the weighted average of the item-level kurtosis-frequency ratios:

$$R_t \propto \sum_{k=1}^{K} w_{k,t} \frac{\text{Kur}(\Delta p_{k,t})}{f_{k,t}}, \tag{5.1}$$

where $w_{k,t}$, $\text{Kur}(\Delta p_{k,t})$, and $f_{k,t}$ are the CPI weights, the kurtosis of the price change distribution, and the frequency of price changes for item k in quarter t. We compute the sufficient statistic at the item level ($K = 120$) as well as using the moments aggregated to our four sectors ($K = 4$) and a single sector economy ($K = 1$).

Section 5.1 presents the results for the average values of the two measures of monetary non-neutrality, focusing on the effects of heterogeneity. Section 5.2 shows the variation of monetary non-neutrality over time.

5.1 Average monetary non-neutrality

Table 3 reports averages of our measures of monetary non-neutrality over the sample from 2008:I to 2022:IV.[23] Column 2 presents model-based cumulated IRFs for the one-sector model estimated based on mean and median moments, respectively, and

[22] Alvarez et al. (2016a) establish the result for the sticky price model of Nakamura and Steinsson (2010), which nests the time-dependent pricing model of Calvo (1983) and the state-dependent pricing model of Golosov and Lucas (2007). The sufficient-statistic proposition also holds in a broader class of state-dependent models using the generalized hazard function setup of Caballero and Engel (1993, 1999), as shown by Alvarez et al. (2022), or in models where firms are rationally inattentive and follow time-dependent pricing rules as in Reis (2006), as shown by Alvarez et al. (2016b).

[23] The results in Table 3 are based on the sample of CPI microdata that excludes price changes due to temporary sales and product substitution. Table C.1 provides the averages of our measures of monetary non-neutrality based on the sample that includes price changes due to temporary sales and product substitution.

the cumulated IRFs for the four-sector model. Columns 4 and 6 present the sufficient statistic for varying levels of sectoral disaggregation based on either data moments or model moments. Columns 3, 5, and 7 report the amplification factors of the measures in a given row relative to the corresponding value shown in the first row (mean moments).

Table 3: Average estimates of monetary non-neutrality

	Impulse responses		Sufficient statistic			
			Data moments		Model moments	
	Cum. IRFs	Ampli.	R	Ampli.	R	Ampli.
One-sector model						
Mean moments	0.76	1.00	17.73	1.00	11.47	1.00
Median moments	2.23	2.93	29.41	1.66	24.40	2.13
Four-sector model						
Average	3.84	5.04	78.19	4.41	38.74	3.38
Average (excl. Energy)			86.46	4.88	42.34	3.69
Food			22.99	1.30	18.58	1.62
NEIG			45.23	2.55	32.45	2.83
Energy			3.61	0.20	6.22	0.54
Services			172.45	9.73	70.75	6.17
120 sectors (item level)						
Median moments			72.36	4.08	–	–

Notes: The table reports averages of our measures of monetary non-neutrality from 2008:I to 2022:IV. Column 2 presents averages of the model-based cumulated IRFs to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) for the one-sector model estimated using mean and median moments as well as for the four-sector model using median moments. To obtain average estimates of monetary non-neutrality, the responses are cumulated each quarter over a forty-quarter horizon and averaged over the sample period. Columns 4 and 6 present the sufficient statistics as in Equation (5.1) for varying levels of aggregation based on either data moments or model moments. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat. The sufficient statistics are calculated using the sample of CPI microdata that excludes price changes due to temporary sales and product substitution. Columns 3, 5, and 7 report the amplification factors of the measures in a given row relative to the corresponding value shown in the first row of the table (mean moments).

We highlight three results. First, the cumulated response of output to a monetary policy shock, as measured by both the cumulated IRFs and the sufficient statistic, is lower in the one-sector model using mean moments than in the one using median moments. Additionally, the IRFs in the one-sector model based on mean moments show considerably less persistence than those based on median moments (Figure C.2). The amplification factor of the IRFs is 2.9, and the amplification factor of the sufficient statistics is 1.7 (using data moments) and 2.1 (using model moments). This is consistent with previous studies which find that the degree of monetary non-neutrality generated by a one-sector model based on median moments is higher than that generated by a model based on mean moments. Estimates of the amplification factor range from 2.6 in French data (Gautier and Le Bihan, 2022) to three to four in US data (Nakamura and Steinsson, 2010).

Second, the real effects of a monetary policy shock are about five times larger in the estimated four-sector model than in the one-sector model using mean moments. The amplification factors are similar for the sufficient statistics based on four sectors: 3.7 and 4.9 (excluding energy) and 3.4 and 4.4 (including energy). When the sufficient statistic is computed from item-level moments, the amplification factor of the cumulated real response to a monetary policy shock remains in the same range as that observed when only four sectors are considered. This finding is consistent with Carvalho (2006), Nakamura and Steinsson (2010), and Gautier and Le Bihan (2022), which suggest that a model with only a few sectors can produce the same level of monetary non-neutrality as a multi-sector model with many more products.

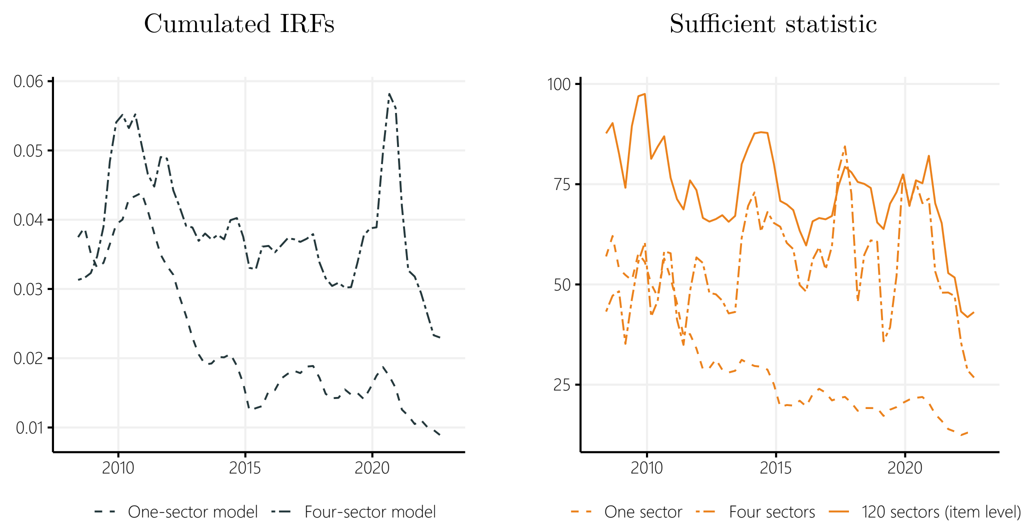
Third, there is considerable cross-sectional heterogeneity in the kurtosis-frequency ratios. The energy sector, where prices are almost fully flexible, has the lowest ratio, suggesting that a monetary shock has negligible real effects in this sector. By contrast, the service sector has the highest sufficient statistic, indicating a high degree of monetary non-neutrality. Food and NEIG are in the middle, with the NEIG sector having a sufficient statistic twice as high as the food sector. These findings highlight the varying degrees of monetary non-neutrality across sectors.

Overall, both measures of monetary non-neutrality, the cumulated real effects obtained from the impulse responses of model simulations and the sufficient statistics computed from price-setting moments, are quite similar and yield consistent results on the amplification factors. These confirm that the real effects of a monetary shock are larger and more persistent when price rigidity is assumed to be heterogeneous rather than identical across sectors.

5.2 Monetary non-neutrality over time

Figure 5 shows the evolution of our two measures of monetary non-neutrality each quarter from 2008:I to 2022:IV.[24] The left panel compares the cumulated IRFs obtained from the estimated one-sector and four-sector models. The right panel shows the sufficient statistics computed from the item-level price-setting moments as well as from the moments aggregated to one and four sectors.

Figure 5: Evolution of monetary non-neutrality over time



Notes: The figure shows the evolution of monetary non-neutrality from 2008:I to 2022:IV. The left panel compares the cumulated real effects of output to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) obtained from the one-sector and four-sector models. The responses are cumulated over forty quarters. The right panel compares the sufficient statistics computed as in Equation (5.1) from the item-level mean moments as well as from the moments aggregated to one and four sectors using median moments. All calculations are based on Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution. All series are depicted as three-quarter centered moving averages.

Comparing the cumulated IRFs with the sufficient statistics reveals that both approaches produce similar time series. The correlation between the measures based on one sector is 0.94, while the correlation between the measures based on four sectors is 0.56. Both measures suggest that monetary non-neutrality is not uniform over time. A closer examination of the low-frequency movements of these measures of monetary non-neutrality reveals the following results:

First, when we ignore the effects of heterogeneity in price-setting behavior and con-

[24] The results in Figure 5 are based on the sample of CPI microdata that excludes price changes due to temporary sales and product substitution. Figure C.1 shows the evolution of our two measures of monetary non-neutrality based on the sample including price changes due to temporary sales and product substitution.

sider the results based on one sector, both the cumulated IRFs and the sufficient statistics indicate a significant decline in monetary non-neutrality from 2008 to 2022. These results reflect the effect of the increase in the median frequency of price changes observed over the sample period.

Second, when we account for the cross-sectional heterogeneity in price rigidity and consider the results based on four sectors, the downward trend in both measures of monetary non-neutrality is much flatter, and the gap between the one-sector and four-sector results becomes larger over time. Although increases in price adjustment frequencies generally reduce the size and persistence of the output response to a monetary shock, the observed increase in the heterogeneity of price adjustment frequencies has the opposite effect, increasing the size and persistence of the output response to a monetary shock, as demonstrated by Nakamura and Steinsson (2010) and Gautier and Le Bihan (2022). The two effects offset each other to some extent between 2008 and 2022. This suggests that the decline in monetary non-neutrality derived from four sectors is less pronounced than the decline derived from one sector, which does not account for heterogeneity in price rigidity.

Third, when we compare the sufficient statistic based on four sectors with the sufficient statistic based on item-level moments, we detect only small differences, at least after 2013, again suggesting that a model with a limited number of sectors can achieve a similar degree of monetary non-neutrality as a more detailed multi-sector model with many products, as pointed out by Carvalho (2006), Nakamura and Steinsson (2010) and Gautier and Le Bihan (2022).

So far, we have discussed the low-frequency movements that explain the overall trend in monetary non-neutrality over the sample period. Beyond these low-frequency movements, both the cumulated IRFs and the sufficient statistics also show variation at higher frequencies, suggesting that monetary non-neutrality may exhibit cyclical or seasonal patterns. To examine these patterns more formally, we run OLS time-series regressions, regressing both measures of monetary non-neutrality separately on CPI inflation, real GDP growth, and quarter dummies. Table 4 shows the OLS coefficients for the cumulated IRFs based on the four-sector model in Columns 1 to 5 and the sufficient statistic computed from the item-level price-setting moments in Columns 6 to 10.

For both measures in all specifications, the coefficients on CPI inflation are negative and statistically significant at the 5% level or below. This indicates that periods of higher inflation are associated with lower IRFs and sufficient statistic. Similarly, the coefficients on GDP growth are also negative, although not significant in all specifications. This suggests a countercyclical tendency of both the IRFs and the sufficient statistic, which increase when the economy slows down. Taken together, these re-

Table 4: Cyclical and seasonal properties of the cumulated IRFs and the sufficient statistic

	Cumulated IRFs					Sufficient statistic R				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CPI inflation	−0.4***		−0.4***	−0.4***	−0.6**	−7.6***		−6.9***	−7.1***	−7.7**
	(0.1)		(0.1)	(0.1)	(0.2)	(1.8)		(2.0)	(1.9)	(3.5)
GDP growth		−0.1*	−0.0	−0.0	0.0**		−2.0**	−0.7	−0.7	−0.1
		(0.1)	(0.1)	(0.1)	(0.1)		(0.9)	(0.8)	(0.8)	(0.9)
Dummy 2nd quarter				0.1	0.1				3.0	2.9
				(0.3)	(0.2)				(4.9)	(3.3)
Dummy 3rd quarter				0.8**	0.8***				14.8***	14.9***
				(0.3)	(0.2)				(4.9)	(3.3)
Dummy 4th quarter				0.7*	0.6***				7.3	7.2**
				(0.3)	(0.2)				(4.9)	(3.3)
Constant	4.0***	4.0***	4.0***	3.6***	4.1***	75.7***	77.6***	76.8***	70.5***	78.5***
	(0.1)	(0.2)	(0.2)	(0.3)	(0.3)	(1.9)	(2.4)	(2.2)	(3.6)	(5.3)
Linear time trend	N	N	N	N	Y	N	N	N	N	Y
Observations	60	60	60	60	60	60	60	60	60	60
R^2	0.17	0.05	0.17	0.28	0.80	0.25	0.09	0.26	0.39	0.79
Adjusted R^2	0.15	0.04	0.14	0.21	0.70	0.23	0.07	0.22	0.32	0.69

Notes: The table shows the OLS coefficients from estimating the cumulated IRFs (in the first five columns) and the sufficient statistic (in the last five columns) on CPI inflation, real GDP growth, and quarter dummies. The cumulated IRFs are the cumulated real effects of output to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) obtained from the four-sector model. The responses are cumulated over forty quarters. The sufficient statistic is computed as in Equation (5.1) from the item-level price-setting moments based on the quarterly sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution. CPI inflation is the year-on-year change in the consumer price index from the Federal Statistical Office. GDP growth is the year-on-year change in the real gross domestic product from the State Secretariat for Economic Affairs. *p<0.1; **p<0.05; ***p<0.01.

sults imply a higher degree of monetary non-neutrality during recessions compared to expansions and during periods of lower inflation compared to higher inflation, consistent with empirical evidence on the state-dependent effects of monetary policy (e.g., Tenreyro and Thwaites, 2016; Jordà et al., 2020; Ascari and Haber, 2022; Seiler, 2024).

Apart from these cyclical patterns, both measures of monetary non-neutrality also exhibit seasonal variations. The coefficients on the quarterly dummies are all positive and statistically significant for the third and fourth quarters of the year. This suggests that the cumulated IRFs and the sufficient statistic are higher in the second half of the year than in the first quarter, implying that the degree of monetary non-neutrality tends to be lower at the beginning of the year. This is consistent with empirical evidence of seasonal differences in the impulse responses of output to monetary policy shocks, depending on the timing of these shocks over the year (Olivei and Tenreyro, 2007, 2010).

6 Empirical validation of the measures of monetary non-neutrality

The results in the previous section have revealed time variation in monetary non-neutrality, as measured by both the cumulated IRFs and the sufficient statistic. If monetary non-neutrality varies over time, the transmission of monetary policy is nonlinear: the real effects of a monetary shock are larger in states with higher degrees of non-neutrality than in states with lower degrees of non-neutrality.

To test this prediction empirically, we use the local projection methodology of Jordà (2005) and estimate nonlinear local projections that allow for state-dependent impulse response functions of macroeconomic variables to an identified monetary policy shock. To identify the states, we use our measures of monetary non-neutrality.

In particular, we estimate

$$\begin{aligned} y_{t+h} = F(z_{t-1})\left(\alpha_h^L + \beta_h^L e_t + \sum_{k=1}^{K} \gamma_{h,k}^L w_{t,k}\right) + \\ (1 - F(z_{t-1}))\left(\alpha_h^H + \beta_h^H e_t + \sum_{k=1}^{K} \gamma_{h,k}^H w_{t,k}\right) + \varepsilon_{t+h}, \end{aligned} \tag{6.1}$$

where the impulse response of the variable of interest y_t at horizon $h \in [0, \bar{H}]$ in state $s = \{L, H\}$ to a unitary monetary policy shock e_t is the estimated coefficient

β_h^s. The states[25] are determined by the state variable z_t, which we choose to be the cumulated IRFs obtained from the four-sector model or the sufficient statistic computed from item-level price-setting moments as in Equation (5.1). To model the transitions between states, we follow Granger and Teräsvirta (1993) and use the logistic function, which casts the state variable[26] into the unit interval and smooths[27] the transitions between states:

$$F(z_t) = \frac{e^{-\gamma(z_t-\mu_z)/\sigma_z}}{1+e^{-\gamma(z_t-\mu_z)/\sigma_z}} \in [0,1], \quad \gamma > 0. \tag{6.2}$$

Since the logistic function $F(z_t)$ is decreasing in z_t, values of $F(z_t)$ close to zero indicate states with high degrees of monetary non-neutrality. Figure 6 displays the smooth transition functions, $F(z_t)$, resulting from the cumulated IRFs (in the left panel) and the sufficient statistic (in the right panel).

The baseline specification of the model in Equation (6.1) follows a standard monetary VAR model, which we choose to be as parsimonious as possible to capture the main transmission channel of monetary policy (e.g., Christiano et al., 2005). We let the vector of endogenous variables, y, include the real gross domestic product (GDP), the consumer price index (CPI), and the Swiss Average Rate Overnight (SARON), a short-term nominal interest rate reflecting the policy rate of the Swiss National Bank.[28] To avoid estimating a negative inflation response to policy rate cuts, i.e., the "price puzzle" (Eichenbaum, 1992; Sims, 1992), we further include an index of commodity prices (in dollars) as an exogenous forward-looking variable and the nominal exchange rate between the Swiss franc and the US dollar. Our measure of monetary policy shocks is the series provided by Nitschka and Oktay (2023), applying the identification approach of Bu et al. (2021) and Ciminelli et al. (2022) for Switzerland. A detailed overview of the data and their sources can be found in Appendix A.4.

We estimate the model using quarterly Swiss data from 2008:I to 2022:IV. The SARON is expressed in percent and the exchange rate in Swiss francs per US dollar, and all other variables are expressed in natural logs multiplied by 100. Figure D.1

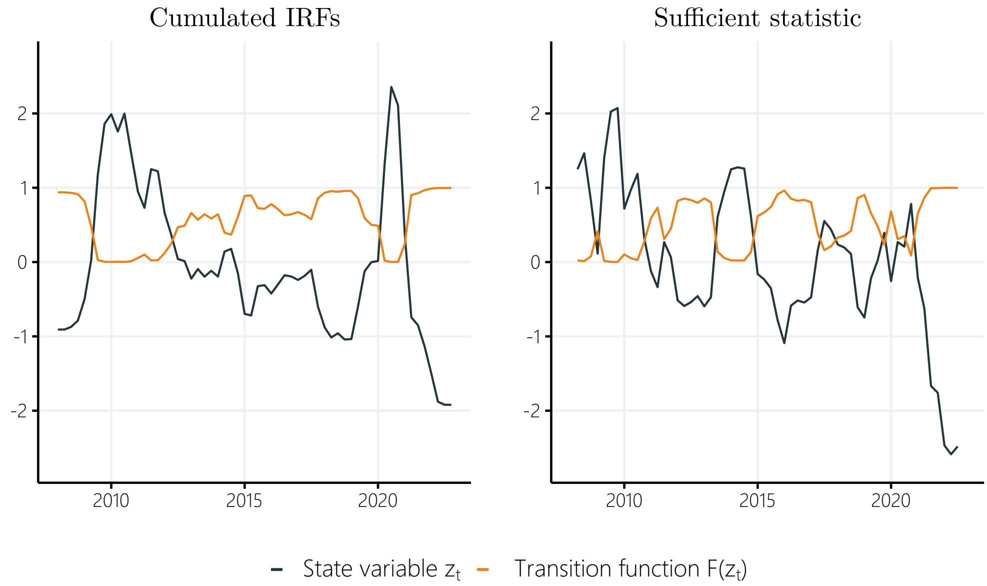
[25] The state L corresponds to periods with a low degree of monetary non-neutrality, the state H corresponds to periods with a high degree of monetary non-neutrality.

[26] The transition function standardizes the state variable z_t by subtracting its mean μ_z and dividing it by its variance σ_z. This splits the estimates roughly equally between the two states over the estimation period.

[27] The parameter γ determines the intensity of the switching between states as z_t changes. Higher values of γ mean that $F(z_t)$ spends more time near the bounds of the unit interval, bringing the model closer to a discrete regime switching setup. We set $\gamma = 3$, which gives an intermediate level of regime switching intensity.

[28] Before January 2022, the short-term nominal interest rate corresponds to the 3-month London Interbank Offered Rate (LIBOR).

Figure 6: State variables and smooth transition functions

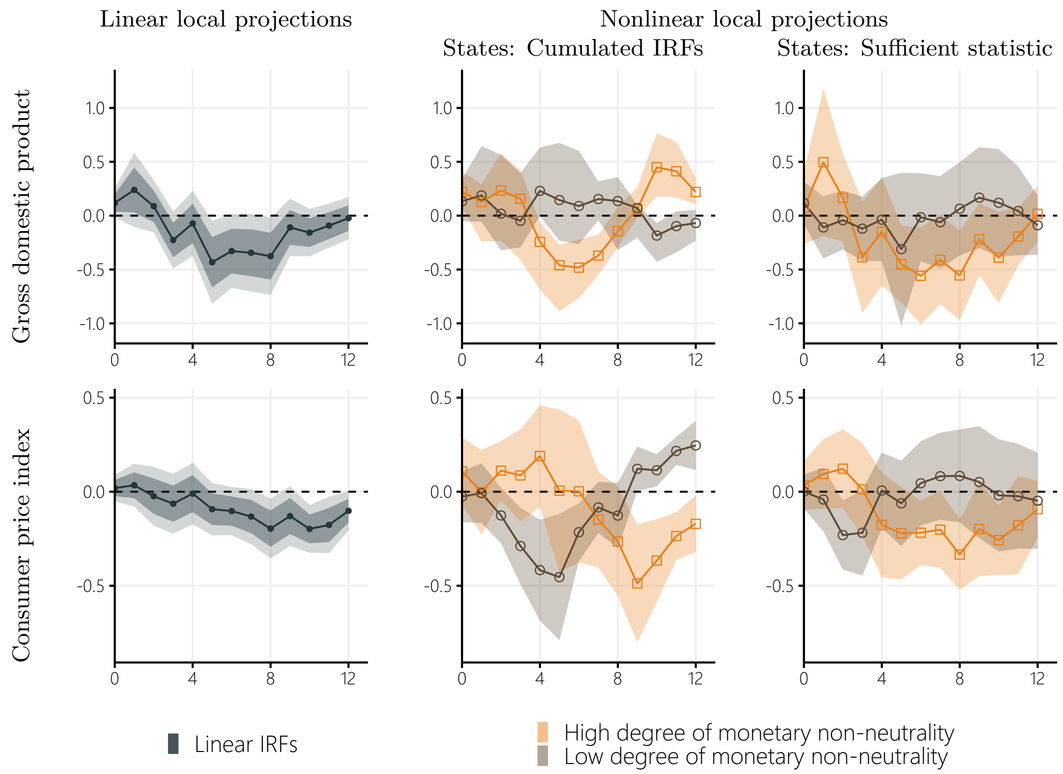


Notes: The figure shows the smooth transition functions resulting from the cumulated IRFs (in the left panel) and the sufficient statistic (in the right panel). The cumulated IRFs are the three-quarter centered moving averages obtained from the four-sector model and standardized. The sufficient statistic is the three-quarter centered moving average calculated from the CPI microdata and standardized. The sample spans from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution. The parameterization of the transition function $F(z_t)$ follows the baseline specification (i.e., $\gamma = 3$).

shows the data used to estimate the baseline model over the sample period from 2008:I to 2022:IV. We set $H = 12$, corresponding to an impulse response horizon over three years. The lag order is set to 2. In terms of deterministic variables, only a constant term is included.

Figure 7 shows the impulse responses. We first consider a linear version of the local projection model in Equation (6.1) that does not discriminate between states when the sufficient statistic is high and low. This serves as a benchmark and validates the overall empirical specification. The impulse responses obtained from the linear local projections (in the first column) display typical and well-documented characteristics. The contractionary monetary policy shock, transformed to raise the SARON by 25 basis points on impact, induces a hump-shaped contraction in output. GDP (in the top row) declines significantly five to eight quarters after the initial shock, contracting by about 0.4 percentage points. The initial response of consumer prices (in the bottom row) is muted, but inflation subsequently falls significantly and persistently, in line with the decline in economic activity. After two years, the CPI declines by as much as 0.1 percentage points.

Figure 7: Linear and nonlinear local projection coefficients across states of monetary non-neutrality



Notes: The figure shows the impulse responses following a contractionary monetary policy shock, which is transformed to raise the SARON by 25 basis points on impact. The rows show the impulse responses by response variable: real GDP (in the top row) and the consumer price index (in the bottom row). The first column shows the linear local projection coefficients. The light-shaded and dark-shaded areas represent the 68% and 90% confidence intervals, respectively. The second column shows the impulse responses across states identified using the cumulated IRFs obtained from the four-sector model. The third column shows the impulse responses across states identified using the sufficient statistic calculated from CPI microdata. The shaded areas in the second and third columns represent the 90% confidence intervals. Confidence bands are based on the Newey and West (1987) heteroscedasticity- and autocorrelation-consistent standard errors to account for serial correlation. The data used for the estimation span from 2008:I to 2022:IV. The impulse responses are plotted over a three-year horizon (twelve quarters).

The remaining columns show the nonlinear local projection coefficients across states of monetary non-neutrality. The second column presents impulse responses using the cumulated IRFs as the state variable. The third column shows impulse responses using the sufficient statistic as the state variable.

The results are similar for both measures of monetary non-neutrality and suggest that the effects of monetary policy on economic activity and prices differ across states of non-neutrality. When the degree of monetary non-neutrality is low (i.e., the cumulated IRFs are small or the sufficient statistic is low), the coefficients associated with the output response are not significantly different from zero. Moreover, consumer prices fall quickly and significantly three to four quarters after the shock before rebounding.

By contrast, monetary policy has substantial real effects when the degree of monetary non-neutrality is high (i.e., the cumulated IRFs are large or the sufficient statistic is high). Five quarters after the initial shock, GDP contracts significantly by more than 0.5 percentage points in both identifications of states using the cumulated IRFs and the sufficient statistic. Moreover, prices respond sluggishly. After a year and a half, they fall by up to 0.5 percentage points when states are identified using the cumulated IRFs, and by more than 0.2 percentage points when states are identified using the sufficient statistic.

Our measures of monetary non-neutrality provide a clear explanation for the state-dependent transmission of a monetary shock and give an indication of the time variation in the slope of the Phillips curve (in terms of the output gap-inflation trade-off). Periods of low monetary non-neutrality correspond to periods with more frequent price adjustments, more price selection (i.e., smaller kurtosis), or both, implying more flexibility in the aggregate price level. As a result, the pass-through of a monetary shock to consumer prices is faster but more temporary, leading to a quicker but more short-lived response in prices. The flexibility in the aggregate price level decouples the nominal and real sides of the economy, thereby reducing the impact of a monetary shock on output. Consequently, the Phillips curve is steep.

By contrast, periods of high monetary non-neutrality correspond to periods with less frequent price adjustments and less flexibility in the aggregate price level. With higher price rigidity, an increase in nominal interest rates translates into an increase in real interest rates, thereby reducing output. At the same time, the response of consumer prices to a monetary shock is slower but more persistent, reflecting the less flexible aggregate price level. This results in a relatively flat Phillips curve.

Overall, our estimation results in Figure 7 confirm that the transmission of monetary policy is nonlinear and varies significantly depending on our two measures of monetary non-neutrality. In particular, the impact of monetary policy on output is substantially larger in periods when our measures indicate high monetary non-neutrality and smaller when they indicate low monetary non-neutrality. In addition, our results provide empirical evidence for the sufficient statistic proposed by Alvarez et al. (2016a). This indicator of monetary non-neutrality relies solely on the ratio of the kurtosis of the distribution of price changes to the frequency of price changes without depending on specific modeling assumptions. Unlike Alvarez et al. (forthcoming), who tested its empirical relevance by examining price-setting moments and responses to monetary policy shocks across sectors, our approach offers novel insights from a time-series perspective. This perspective confirms the potential of the sufficient statistic as a real-time indicator of monetary non-neutrality, as it can be directly evaluated using relevant price-setting moments from microdata.

7 Conclusion

This paper examined the sources of time variation in price-setting behavior and its implications for monetary non-neutrality using Swiss CPI microdata from 2008 to 2022. The frequency of price changes has increased in the decade leading up to the pandemic and accelerated during the post-pandemic inflation surge. Over the same period, heterogeneity in the frequency of price adjustments increased across sectors. Meanwhile, the absolute size of price changes declined slightly while the dispersion of price changes became more pronounced.

We interpreted these changes in price-setting behavior through the lens of a multi-sector menu cost model (Nakamura and Steinsson, 2010). The estimation results suggest that changes in the time-dependent Calvo parameter primarily account for variations in the extensive margin of price adjustments over time, while fluctuations in the standard deviation of idiosyncratic productivity shocks mainly explain variations in the intensive margin of price adjustments. The menu cost parameter, on the other hand, plays a minor role in explaining temporal changes in any of the price-setting moments.

To assess the implications of our findings for monetary non-neutrality, we used the cumulated output responses to a monetary policy shock obtained from our multi-sector menu cost models and, additionally, the sufficient-statistic proposition of Alvarez et al. (2016a) computed from the microdata. Our results showed that the changes in price adjustment patterns have slightly reduced the real effects of monetary policy. These findings imply nonlinearities in the transmission of monetary policy to output and inflation, which we confirmed in empirical tests using nonlinear local projections. The estimation results revealed differential effects of monetary shocks between states with higher and lower degrees of monetary non-neutrality. This analysis empirically validates our two measures of monetary non-neutrality and confirms the usefulness of the sufficient statistic as a real-time indicator of monetary non-neutrality. It can be calculated directly using the relevant price-setting moments from microdata without relying on a specific model.

The results of the nonlinear local projections also have implications for the slope of the Phillips curve. In periods of high monetary non-neutrality, the Phillips curve is relatively flat because price rigidity amplifies the impact of monetary policy on output. Conversely, in periods of low monetary non-neutrality, the Phillips curve is relatively steep because faster and more transitory price responses reduce the impact of monetary policy on output.

Our analysis builds on the examination of heterogeneity in cost processes and pricing across sectors by Gautier and Le Bihan (2022). Using the same model and estimation method, we explored time variation in price-setting behavior through estimating the multi-sector menu cost model of Nakamura and Steinsson (2010) sequentially over time. This approach focused solely on heterogeneity in cost processes and price-setting characteristics. Future research could benefit from incorporating other types of heterogeneity into the model, such as cross-sector linkages (Pastén et al., 2024). In addition, moving from a sequential to a dynamic estimation approach could be a valuable extension beyond the scope of this analysis, enhancing our understanding of the role of time variation in price-setting behavior on monetary policy transmission.

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Appendix

A Data and stylized price-setting facts

This appendix refers to Section 2 and provides additional information on the data and stylized facts about the temporal dynamics of price-setting moments from 2008 to 2022. It provides figures and tables not included in the main body of the paper.

A.1 Data treatment and sampling decisions

Our data cover 15 years, from January 2008 to December 2022. The start of this period is determined by the point at which the Swiss Federal Statistical Office (FSO) switched from quarterly to monthly price collection for most products and services in January 2008.

To minimize the impact of compositional shifts over time, we restrict the sample to expenditure items (which correspond to the five-digit COICOP level) available throughout the sample period and whose prices are collected at a quarterly or higher frequency. To improve the informativeness of the data and to control for measurement errors, we further restrict the basket as follows. First, we exclude items for which the FSO constructs auxiliary indices to track price movements rather than actual price quotes. Examples are rental prices or books. Second, we exclude items of administered and semi-administered prices because they are set by government authorities and collected centrally. Examples include electricity, public transport services, and medicines. Third, we exclude clothing items because a significant share of their price changes are due to temporary sales or product substitution, which we exclude from the analysis, as explained in more detail below. The remaining sample consists of 120 expenditure items, representing up to 40 percent of the CPI basket by expenditure weights.

Our baseline dataset is the sample that excludes price changes due to temporary sales and product substitution. Excluding price changes due to temporary sales allows us to capture more persistent price changes and filter out much of the high-frequency variation since temporary sales are often completely reversed within months. Excluding price changes due to product substitution discards potentially spurious price changes when items are replaced. We identify sales prices using the FSO sales flag and exclude them by replacing each sales price with the last observed non-sales price. Similarly, we identify product substitutions using the FSO replacement flag and exclude them by starting a new price spell with each product replacement. Beyond, the sample excludes the imputed prices of seasonal products in their off-season.[29]

We calculate price changes as monthly log differences in the unit prices of products. We use unit prices to ensure that price changes due solely to changes in the package size or volume are not counted as price changes. Because changes in the unit of measurement affect the unit price of items, we correct quantities for measurement errors when quantity changes are greater than a factor of 10 (or less than a factor of 1/10) and use a carry-forward procedure to replace errors. Because measurement errors in price changes raise concerns beyond these restrictions (Eichenbaum et al.,

[29]Other imputed prices, such as those of temporarily unavailable products, cannot be identified in the Swiss CPI microdata (Rudolf and Seiler, 2022).

2014), we drop price changes greater than the 99th percentile of absolute log price changes and less than 1% in absolute values for each variety. As a result, we drop less than 2 percent of all price changes.

We present stylized facts about price setting using five conventional moments of price rigidity: the frequency of price adjustments, the share of price increases in all price changes, the median size of absolute price adjustments, the interquartile range, and the kurtosis of the distribution of price changes. We compute these moments at the disaggregated level by pooling price changes per expenditure item over the months of a quarter, converting monthly data to quarterly data. Because heterogeneity at the lowest level of product identification in the CPI microdata can bias the measurement of the kurtosis of price changes (Alvarez et al., 2016a), we calculate the kurtosis based on standardized price changes. We standardize price changes at the ten-digit COICOP level by subtracting their mean (for all non-zero price changes) and dividing them by their standard deviation.

To compute aggregate statistics, we use constant basket weights (average weights over the entire sample period) and take weighted median moments across items. Aside from aggregating the moments to a single sector of the economy, we consider four sectors: food, non-energy industrial goods (NEIG), energy, and services. These sectors correspond to the COICOP-HICP special aggregates defined by Eurostat.

A.2 Stylized price-setting facts based on the sample including price changes due to temporary sales and product substitution

Table A.1 shows the average price-setting moments for all products and the four sectors for the sample that includes price changes due to temporary sales and product substitution.

Table A.1: Average price-setting moments in Swiss CPI microdata based on the sample including price changes due to temporary sales and product substitution

	Weight	Frequency		Size		
		f	$\frac{f^+}{f}$	$\lvert\Delta p\rvert$	IQR(Δp)	Kur(Δp)
All products						
Mean	0.363	0.278	0.602	0.064	0.108	4.705
Median		0.184	0.576	0.048	0.070	4.186
Standard deviation		0.285	0.197	0.060	0.114	2.650
By sector (median moments)						
Food	0.115	0.248	0.530	0.040	0.074	4.874
NEIG	0.086	0.140	0.568	0.043	0.069	4.290
Energy	0.036	0.843	0.543	0.027	0.037	2.909
Services	0.126	0.029	0.729	0.062	0.078	4.261

Notes: The table shows average price-setting moments in Swiss CPI microdata. The sample ranges from 2008:I to 2022:IV and includes price changes due to temporary sales and product substitution. Moments are calculated at the disaggregated item level (corresponding to the five-digit COICOP level) and aggregated across items as weighted medians using average CPI expenditure weights. Over time, the aggregate moments are simple time averages. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat.

Figure A.1 shows the distribution of the price-setting moments across expenditure items over time for the sample that includes price changes due to temporary sales and product substitution. For each quarter, the figures show the median, the interquartile range (dark-shaded area), and the 15th to 85th percentile range (light-shaded area) of the moments calculated across expenditure items.

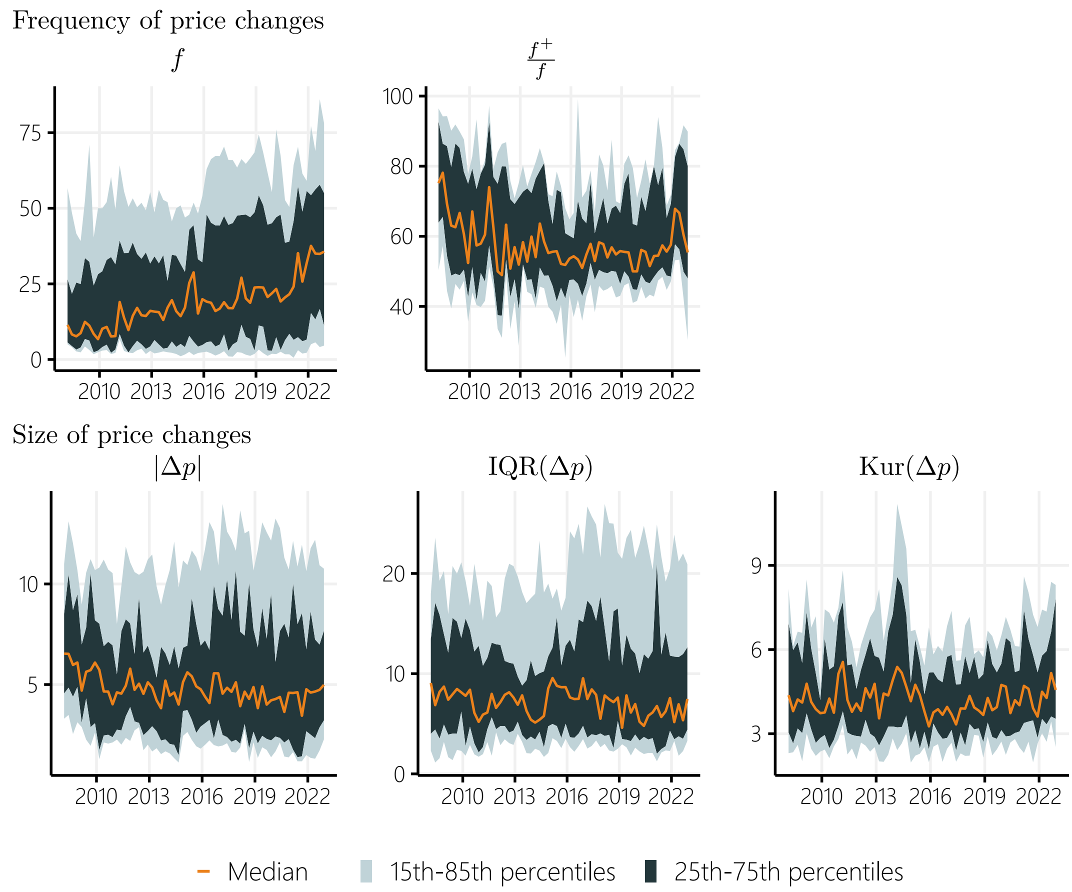
Including sales and substitutions increases our estimates of both the frequency of price changes and the moments of the distribution of price changes. Nevertheless, the five stylized facts presented in the main body of the paper prove robust to the treatment of temporary sales and product substitution.

A.3 Additional price-setting moments

Figure A.2 shows the distributions of the frequency and size of price increases and decreases across expenditure items over time. It highlights that the slight but steady increase in the frequency of price adjustments from 2008 to 2022 is driven by both more frequent price increases and decreases. At the same time, the smaller size of absolute price adjustments is due to both smaller price increases and absolute price decreases.

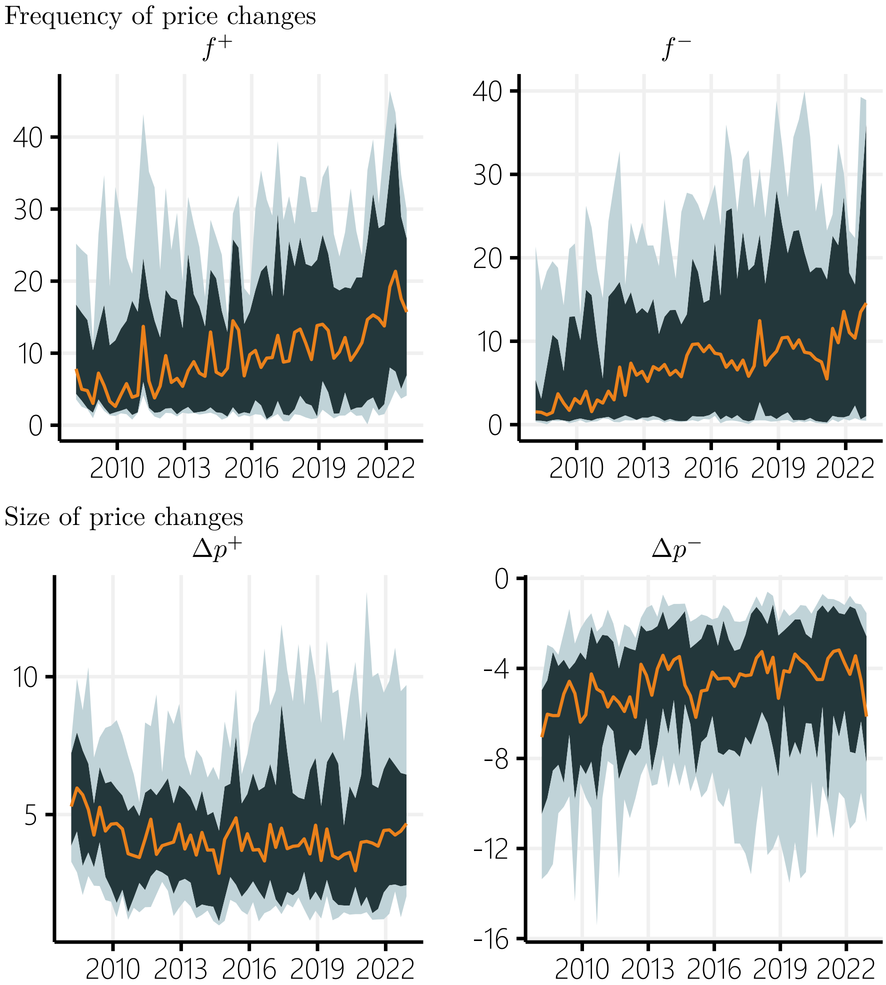
Figure A.3 shows the median price-setting moments per sector in Swiss CPI microdata and the weighted average across sectors over time. The sectors are food, NEIG, energy, and services, corresponding to the COICOP-HICP special aggregates defined by Eurostat.

Figure A.1: Distribution of price-setting moments across expenditure items over time based on the sample including price changes due to temporary sales and product substitution



Notes: The figure shows the distribution of price-setting moments across expenditure items in Swiss CPI microdata and their evolution over time. The sample ranges from 2008:I to 2022:IV and includes price changes due to temporary sales and product substitution. The panels show the frequency of price changes and the share of price increases in all price changes (in the top row), the median absolute size of price adjustments, the interquartile range, and the kurtosis of the price change distribution (in the bottom row). For each quarter, the panels depict the median, the interquartile range (dark-shaded areas), and the 15th to 85th percentile range (light-shaded areas). The frequency and size of price changes are reported in percent.

Figure A.2: Price-setting moments on the frequency and size of price increases and decreases across expenditure items over time

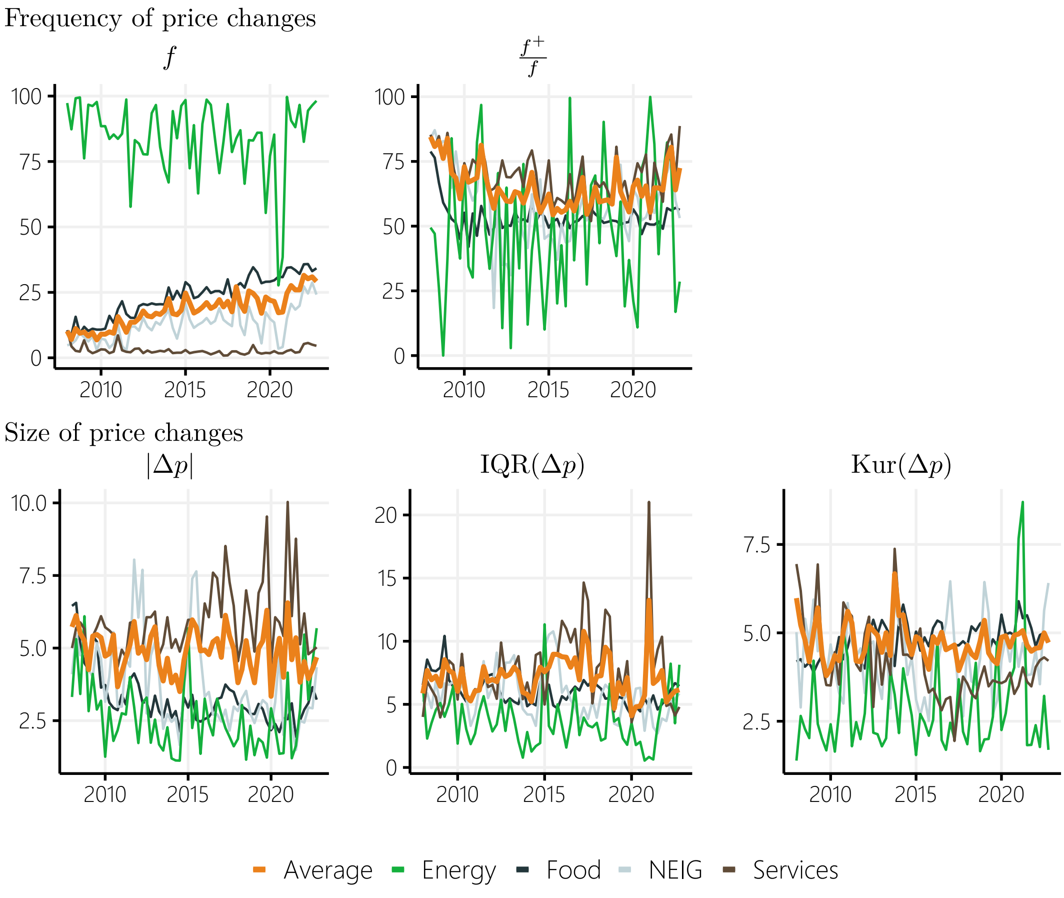


Notes: The figure shows the distribution of price-setting moments across expenditure items in Swiss CPI microdata and their evolution over time. The sample ranges from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution. The panels show the frequency (in the top row) and the size (in the bottom row) of price increases and decreases. For each quarter, the panels depict the median, the interquartile range (dark-shaded areas), and the 15th to 85th percentile range (light-shaded areas). The frequency and size of price changes are reported in percent.

A.4 Data sources

Table A.2 gives details on the data used in the paper, including information on the coverage and data sources.

Figure A.3: Price-setting moments per sector over time



Notes: The figure shows the evolution of the median price-setting moments per sector and their average across sectors from 2008:I to 2022:IV. The moments are calculated per expenditure item using Swiss CPI microdata excluding price changes due to temporary sales and product substitution and aggregated using CPI expenditure weights. The panels show the frequency of price changes and the share of price increases in all price changes (in the top row), the median absolute size of price adjustments, the interquartile range, and the kurtosis of the price change distribution (in the bottom row). The frequency and size of price changes are reported in percent.

Table A.2: Data description, sources, and coverage

Variable	Description	Source	Sample
Microdata			
CPI price quotes	Price quote data that underpin consumer price inflation statistics in Switzerland	FSO	2008:01–2022:12

CPI item indices	Item index data that underpin consumer price inflation statistics in Switzerland	FSO	2008:01–2022:12
Model calibration			
1170_302	Consumer price index (CPI), core inflation 2 (2015=100)	FSO	1982:01–2022:12
Monetary policy shocks			
moposhocks	Monetary policy shocks identified with the approach of Bu et al. (2021) and Ciminelli et al. (2022) for Switzerland	Nitschka and Oktay (2023)	2000-01-20–2022-12-15
Baseline variables			
GDP	Real gross domestic product (GDP), quarterly estimates	SECO	1980:I–2022:IV
100_100	Consumer price index (CPI), all items (2015=100)	FSO	1982:01–2022:12
SARON	SARON (CHF Libor - 3 months until 2021:12; SARON 1 day from 2022:01 onward), monthly averages	SNB	1983:01–2022:12
DEXSZUS	Swiss Francs to U.S. Dollar Spot Exchange Rate	FRED	1971-01-04–2022-12-31
iOVERALL	Commodity Price Data (The Pink Sheet), overall index, monthly, US dollars, 2010=100	World Bank	1960:01–2022:12

Notes: The table provides details of the data used in the study, including information on coverage and data sources. Unless otherwise stated, the geographical scope of the variables refers to Switzerland.

B Time variation in price setting

This appendix refers to Section 4 and provides additional information on the sources of the variation in price-setting behavior over time as identified by the multi-sector menu cost model. It provides figures and tables not included in the main body of the paper.

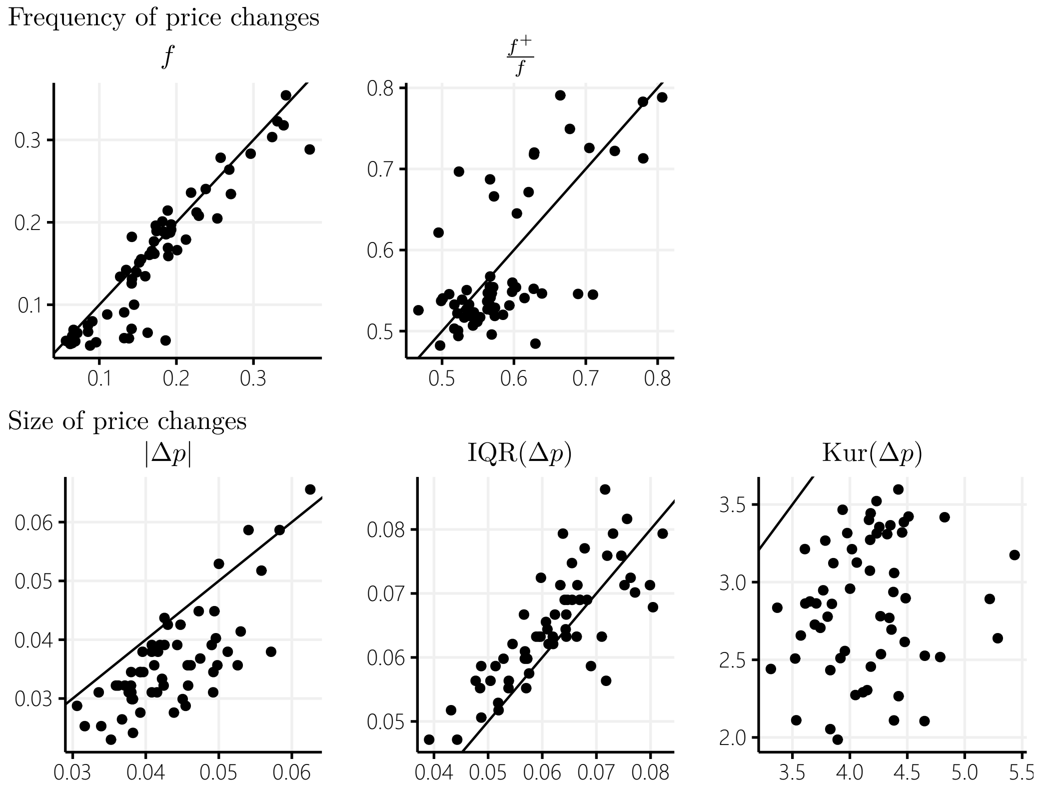
B.1 Fit of the one-sector model

To assess the fit of the one-sector model, we compare the empirical data moments on firms' price-setting behavior with the simulated price-setting moments.

For each of the five targeted price-setting moments, Figure B.1 relates the empirical moments from the data to the corresponding simulated moments from the model for each quarter. Thus, each point in the scatterplots represents one combination of data and model moments in a given quarter. The values on the y-axis are the price-setting moments simulated with the four-sector model. The values on the x-axis are the price-setting moments in the data.

The one-sector model fits most of the targeted moments relatively well. The simulated frequency of price changes is particularly close to the data moments, except for a few periods with a low median frequency of price adjustments. The size of absolute price adjustments tends to be slightly underestimated, while the interquartile range of price adjustments is slightly overestimated. A remaining difficulty is to reproduce the large kurtosis values observed in the data.

Figure B.1: Comparison of empirical data moments and simulated model moments obtained from the one-sector model



Notes: The figure relates the empirical moments from the data to the corresponding simulated moments from the one-sector CalvoPlus model. Each point in the scatterplots represents a data-model moment combination in a given quarter. The values on the y-axis are the price-setting moments simulated with the four-sector model. The values on the x-axis are the price-setting moments in the data. The figure shows the fit for the five targeted price-setting moments: the frequency of price changes and the share of price increases (in the top row), the size of absolute price changes, the interquartile range, and the kurtosis of the price change distribution (in the bottom row). The sample of Swiss CPI microdata used for estimation spans from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution.

B.2 Fit of the four-sector model

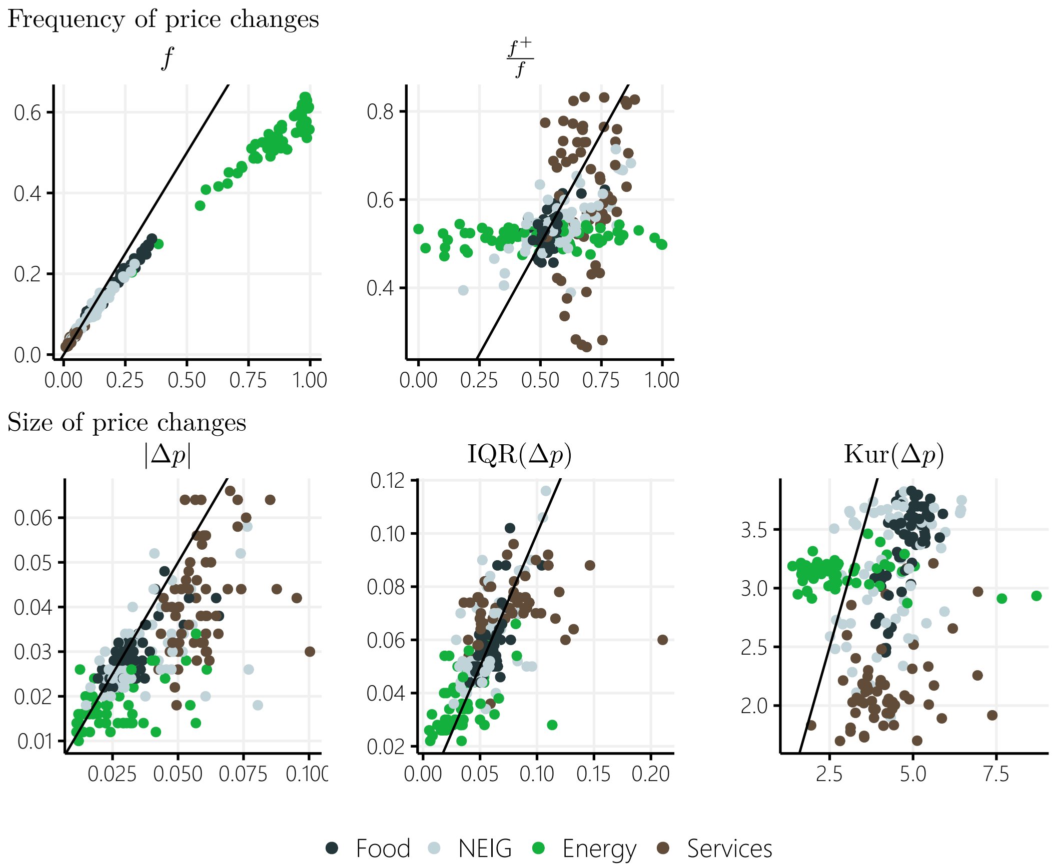
To assess the fit of the four-sector model, Figure B.2 relates the empirical moments from the data to the corresponding simulated moments from the model for each sector and quarter for each of the five targeted price-setting moments. Thus, each point in the scatterplots represents one combination of data and model moments for a given sector and quarter. The values on the y-axis are the price-setting moments simulated with the four-sector model. The values on the x-axis are the price-setting moments in the data.

The four-sector model fits most of the targeted moments well across sectors, except the energy sector. Specifically, it struggles to reproduce the price-setting characteristics of the energy sector at the extensive margins of price adjustment, such as the almost fully flexible prices and the varying share of price increases. In addition, the model overestimates the kurtosis of the price change distribution in the energy sector while underestimating it in the other sectors, similar to the one-sector model. Otherwise, the model fit is comparable across the remaining sectors.

B.3 Results based on the sample including price changes due to temporary sales and product substitution

Table B.1 provides estimation results for the parameters of the multi-sector menu cost model at the aggregate level of the economy based on the sample of CPI microdata including price changes due to temporary sales and product substitution. In the top panel, the parameters are obtained from the one-sector model, which we estimate in two versions using the median and mean moments of the data. In the bottom panel, the parameters are obtained from the four-sector model and averaged across sectors using CPI expenditure weights.

Figure B.2: Comparison of empirical data moments and simulated model moments obtained from the four-sector model



Notes: The figure relates the empirical moments from the data to the corresponding simulated moments from the four-sector CalvoPlus model. Each point in the scatterplots represents a data-model moment combination for a given sector and quarter. The values on the y-axis are the price-setting moments simulated with the four-sector model. The values on the x-axis are the price-setting moments in the data. The figure shows the fit for the five targeted price-setting moments: the frequency of price changes and the share of price increases (in the top row), the size of absolute price changes, the interquartile range, and the kurtosis of the price change distribution (in the bottom row). The sample of Swiss CPI microdata used for estimation spans from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution.

Table B.1: Average estimates of price rigidity parameters based on the sample including price changes due to temporary sales and product substitution

	Pricing frictions		Volatility	Calvo share
	λ	μ	σ	$\frac{\lambda}{f}$
One-sector model				
Mean moments	0.254	0.190	0.073	0.893
Median moments	0.156	0.110	0.055	0.800
Four-sector model				
Average	0.167	0.084	0.037	0.801
Food	0.202	0.074	0.049	0.813
NEIG	0.113	0.068	0.044	0.803
Energy	0.685	0.110	0.022	0.812
Services	0.023	0.096	0.025	0.787
Coefficient of variation	0.190	0.158	0.085	-

Notes: The table shows the estimated parameters obtained using the method of simulated moments. For the one-sector model, it reports two different versions: a model estimated using the median moments of the data and a model estimated using the mean moments of the data. The four-sector model uses median moments. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat. Moments are calculated at the disaggregated item level (corresponding to the five-digit COICOP level) and aggregated across items as weighted medians using average CPI expenditure weights. Over time, the average results are simple arithmetic means. Estimations are based on the sample of CPI microdata including price changes due to temporary sales and product substitution.

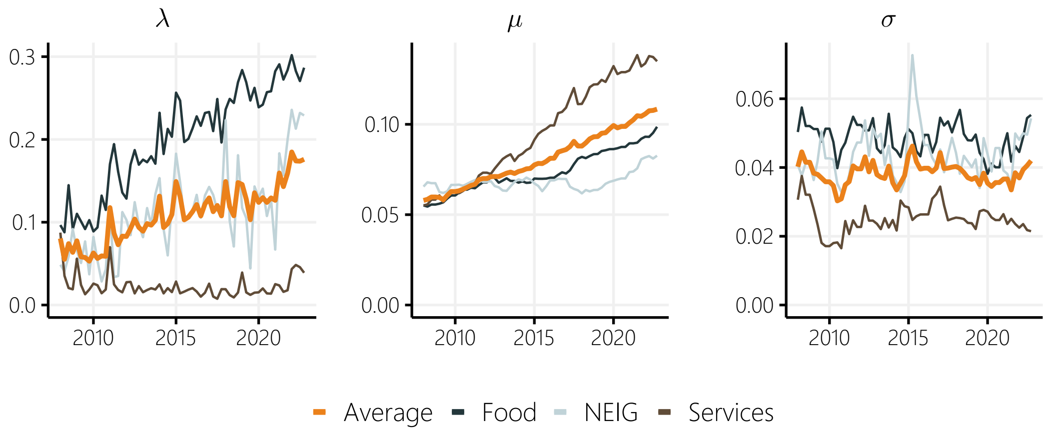
Figure B.3 plots the parameters estimated from the four-sector model over time, using the sample of CPI microdata that includes price changes due to temporary sales and product substitution. It shows the estimates for each sector and the weighted average across sectors.

B.4 Results over time

Figure B.4 shows the estimated parameters from the one-sector model. Our conclusions about the evolution of the parameters estimated with the four-sector model are broadly consistent with those obtained from the one-sector model.

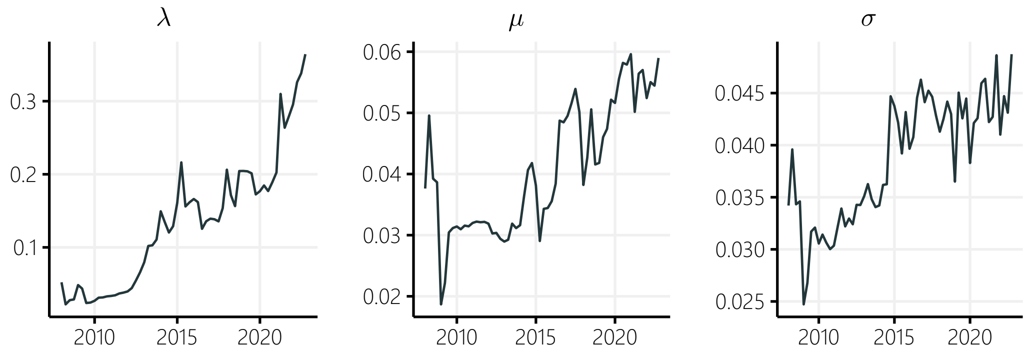
Figure B.5 plots the estimated parameters from the four-sector model over time. It shows the estimates for each sector (including energy) and the weighted average across sectors.

Figure B.3: Evolution of the parameters estimated using the four-sector model based on the sample including price changes due to temporary sales and product substitution



Notes: The figure shows the evolution of each parameter estimated with the four-sector model using the median moments of the sample of Swiss CPI microdata from 2008:I to 2022:IV, including price changes due to temporary sales and product substitution. It shows the estimates for each sector and the weighted average across sectors using CPI expenditure weights, where the sectors correspond to the COICOP-HICP special aggregates defined by Eurostat.

Figure B.4: Evolution of the parameters estimated using the one-sector model over time



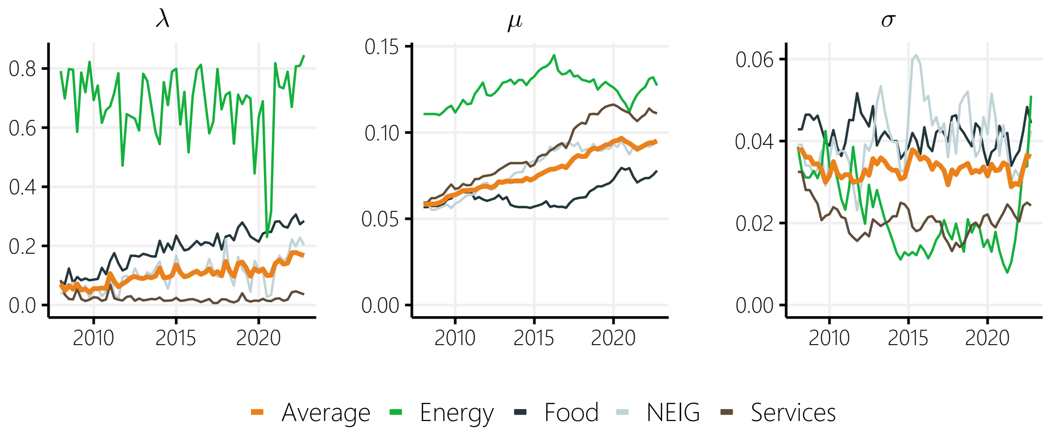
Notes: The figure shows the evolution of each parameter estimated with the one-sector model using the median moments of the sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution.

B.5 Cross-period relationship between price-setting moments and parameters

Figure B.6 illustrates the cross-period relationship between the price-setting moments and the parameters estimated using the four-sector model and aggregated across sectors using CPI expenditure weights. Our conclusions from the disaggregated four-sector model are broadly consistent with this alternative estimation.

Figure B.7 illustrates the cross-period relationship between the price-setting moments

Figure B.5: Evolution of the parameters estimated using the four-sector model over time, including the energy sector



Notes: The figure shows the evolution of each parameter estimated with the four-sector model using the median moments of the sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution. It shows the estimates for each sector and the weighted average across sectors using CPI expenditure weights, where the sectors correspond to the COICOP-HICP special aggregates defined by Eurostat.

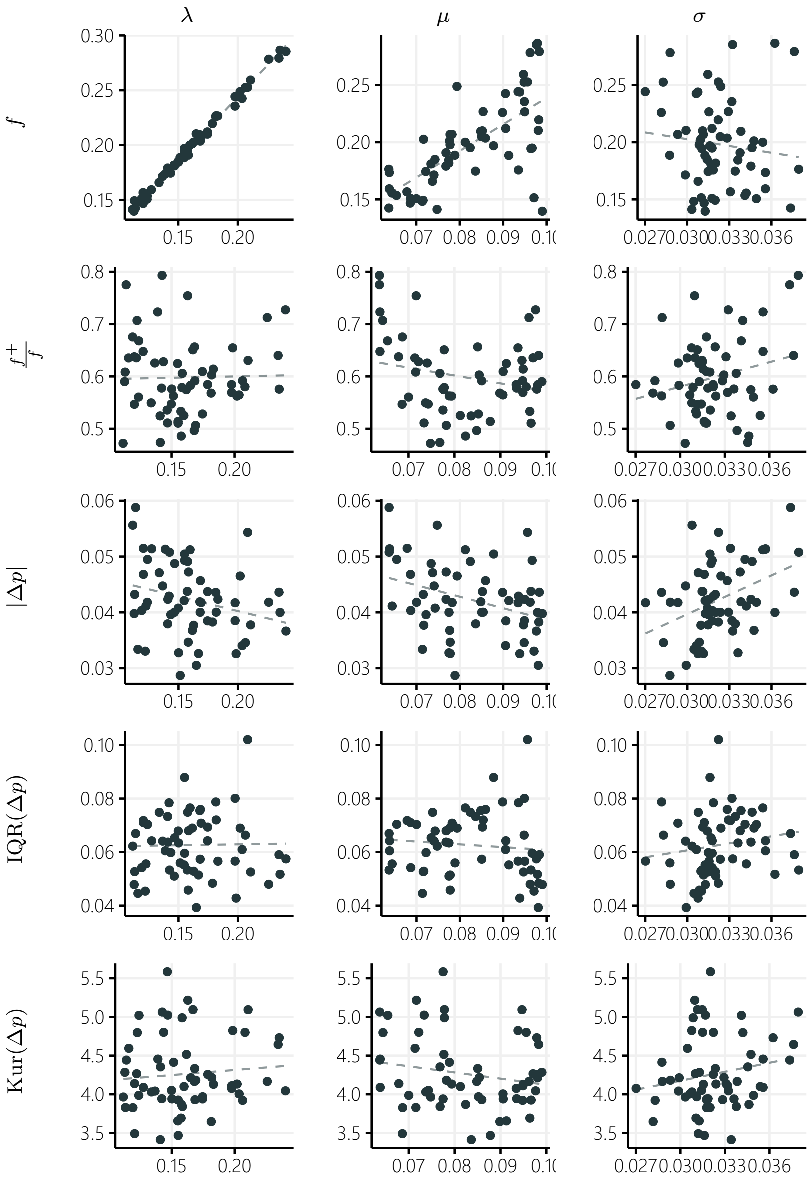
and the parameters estimated using the one-sector model. Our conclusions from the disaggregated four-sector model are broadly consistent with this alternative estimation.

B.6 Counterfactual experiments

Figure B.8 reports the results of the counterfactual experiments from Section 4.3.2 for each price-setting moment estimated with the one-sector model. Each panel relates the data moment on the x-axis against the (counterfactual) model moment on the y-axis for each quarter.

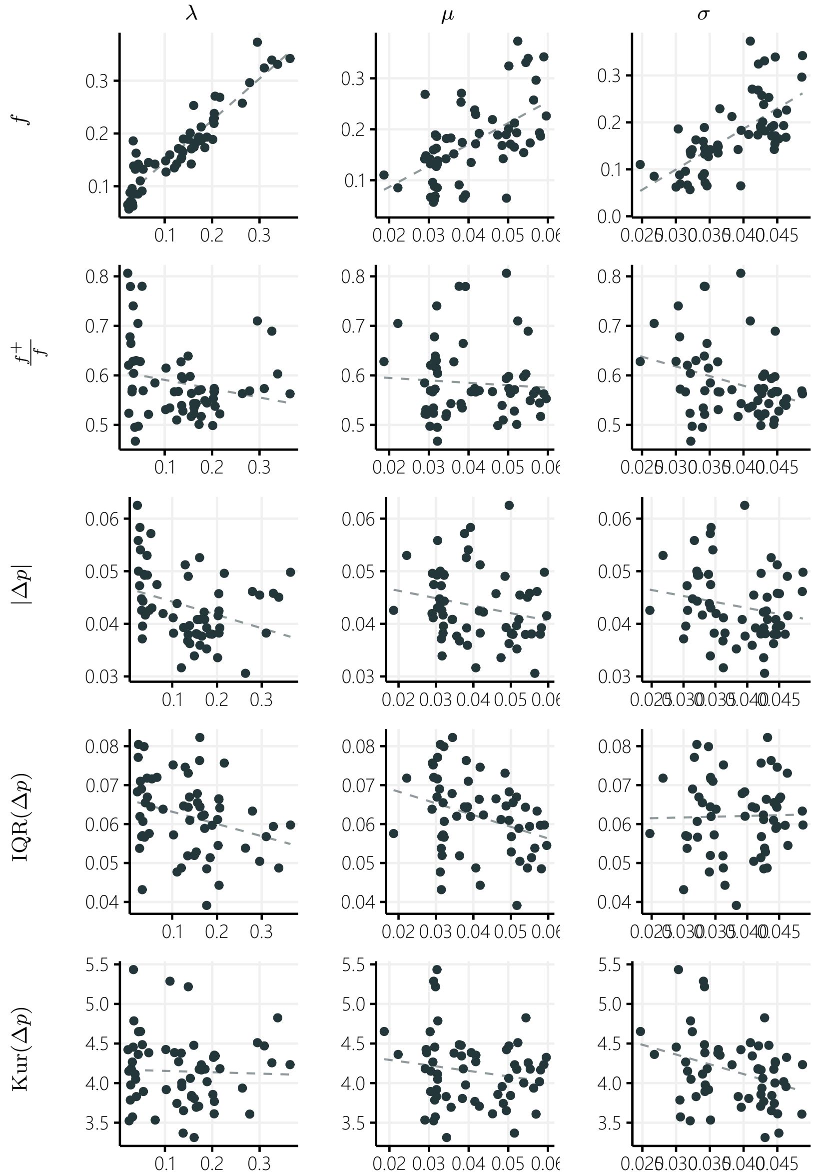
Table B.2 supplements the evidence shown in Figure 4 by reporting the slope coefficients and adjusted R-squared values for each scatterplot obtained from OLS regressions, where we regress the model moments for each sector onto the corresponding data moments.

Figure B.6: Cross-period relationship between the price-setting moments and the parameters estimated using the four-sector model, aggregated across sectors



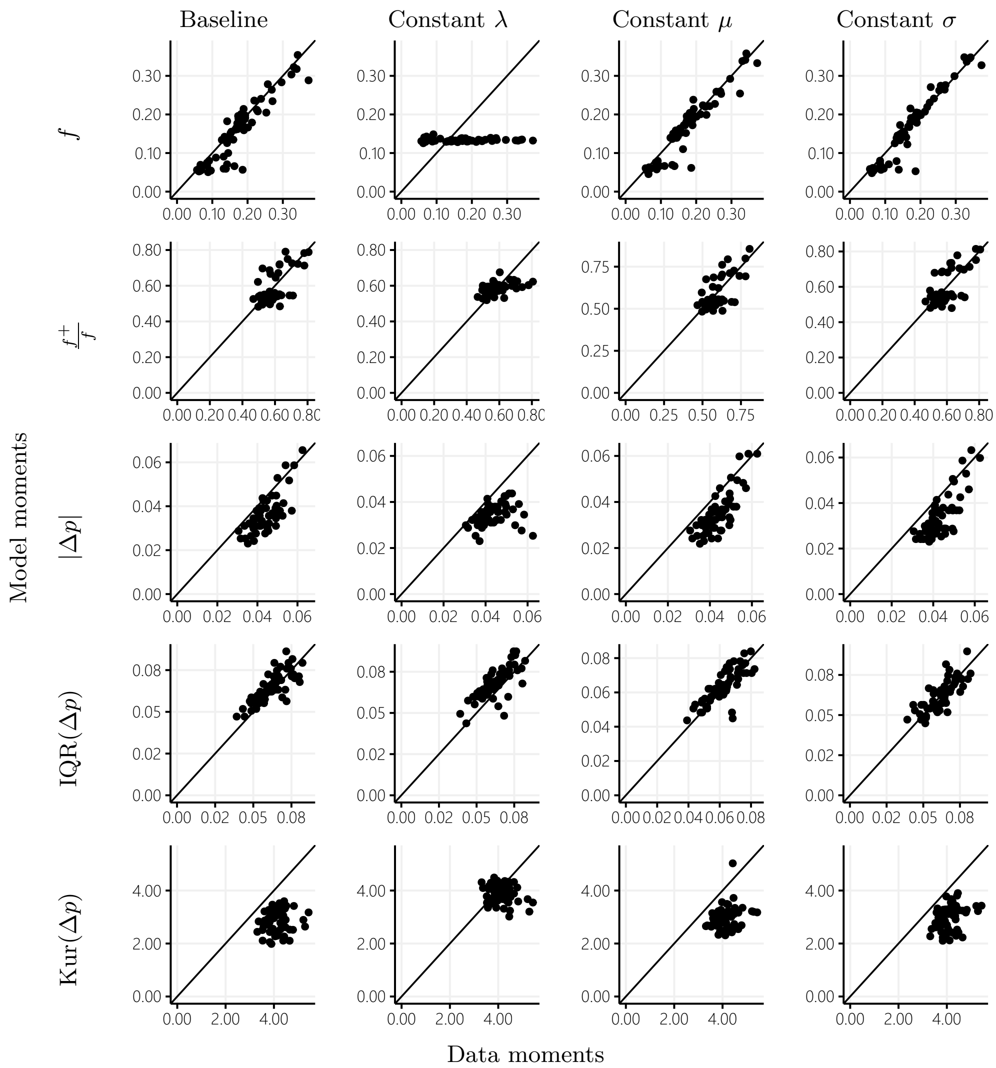
Notes: The figure relates the variations in the empirical price-setting moments over time to the structural parameters estimated from the CalvoPlus model. Each point in the scatter plots represents one moment-parameter combination in a given quarter. The values on the y-axis are the price-setting moments in the data. The values on the x-axis are the parameter values. The parameters are estimated with the four-sector model and aggregated across sectors using CPI expenditure weights. The sample of Swiss CPI microdata ranges from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution.

Figure B.7: Cross-period relationship between the price-setting moments and the parameters estimated using the one-sector model



Notes: The figure relates the variations in the empirical price-setting moments over time to the structural parameters estimated from the CalvoPlus model. Each point in the scatter plots represents one moment-parameter combination in a given quarter. The values on the y-axis are the price-setting moments in the data. The values on the x-axis are the parameter values. The parameters are estimated with the one-sector model using the sample of Swiss CPI microdata from 2008:I to 2022:IV, excluding price changes due to temporary sales and product substitution.

Figure B.8: Comparison between the empirical data moments and counterfactual model moments simulated from the one-sector model



Notes: The figure relates data moments to (counterfactual) model moments simulated by the Calvo-Plus model. Each point in the scatterplots represents a data-model moment combination in a given quarter. The values on the y-axis are the price-setting moments simulated with the one-sector model. The values on the x-axis are the price-setting moments in the data. The first column reports the results from the baseline, which estimates all three parameters. Columns 2–4 report scatterplots of the counterfactuals, where λ, μ, and σ are held constant at their sector-specific averages, respectively. The sample of Swiss CPI microdata spans from 2008:I to 2022:IV and excludes price changes due to temporary sales and product substitution.

Table B.2: Slope coefficients and adjusted R-squared values comparing empirical data moments with counterfactual model moments simulated from the four-sector model

	Slope coefficients				Adj. R-squared			
	Baseline	λ	μ	σ	Baseline	λ	μ	σ
Frequency of price changes								
Food	0.688	-0.038	0.699	0.676	0.982	0.286	0.985	0.993
NEIG	0.704	0.007	0.726	0.723	0.965	0.003	0.945	0.992
Energy	0.521	0.035	0.545	0.516	0.915	0.172	0.966	0.975
Services	0.773	0.068	0.570	0.595	0.940	0.121	0.846	0.895
Share of price increases								
Food	0.356	0.224	0.368	0.385	0.335	0.206	0.337	0.340
NEIG	0.344	0.310	0.347	0.326	0.527	0.451	0.523	0.522
Energy	0.005	0.003	0.003	-0.001	0.005	0.003	-0.014	-0.017
Services	0.287	0.606	0.448	0.450	0.027	0.143	0.091	0.064
Size of absolute price changes								
Food	0.439	0.123	0.347	0.293	0.517	0.092	0.475	0.548
NEIG	0.277	0.097	0.350	0.084	0.227	0.037	0.241	0.026
Energy	0.210	0.233	0.245	0.005	0.218	0.346	0.426	0.003
Services	0.311	0.088	0.298	0.116	0.098	0.009	0.142	0.025
Interquartile range of price changes								
Food	0.832	0.333	0.656	0.483	0.559	0.236	0.501	0.373
NEIG	0.565	0.438	0.773	0.015	0.381	0.294	0.468	-0.017
Energy	0.261	0.317	0.302	0.020	0.218	0.432	0.435	0.090
Services	0.076	0.121	0.261	0.096	0.049	0.148	0.374	0.137
Kurtosis of price changes								
Food	0.499	0.264	0.438	0.498	0.428	0.342	0.418	0.441
NEIG	0.152	0.063	0.188	0.042	0.092	0.039	0.150	-0.007
Energy	-0.012	-0.017	-0.002	0.009	0.023	0.291	-0.016	0.011
Services	0.090	-0.041	0.064	0.067	0.080	0.011	0.043	0.103

Notes: The table reports slope coefficients (in the first four columns) and adjusted R-squared values (in the last four columns) from comparing empirical data moments with counterfactual model moments simulated from the four-sector model using sector-specific OLS regressions. "Baseline" corresponds to the baseline estimation. The remaining columns correspond to the counterfactual experiments, where λ, μ, and σ are held constant at their sector-specific average, respectively. A slope coefficient of 1 indicates a high correlation between the simulated and data moments. A high R-squared value indicates that the simulated moments are far from the data moments.

C Time variation in monetary non-neutrality

This appendix refers to Section 5 and provides additional information on the variation in monetary non-neutrality over time. It provides figures and tables not included in the main body of the paper.

C.1 Results based on the sample including price changes due to temporary sales and product substitution

Table C.1 reports averages of our measures of monetary non-neutrality using the sample that includes price changes due to temporary sales and product substitution.

Table C.1: Average estimates of monetary non-neutrality based on the sample including price changes due to temporary sales and product substitution

	Impulse responses		Sufficient statistic			
			Data moments		Model moments	
	Cum. IRFs	Ampli.	R	Ampli.	R	Ampli.
One-sector model						
Mean moments	1.05	1.00	17.37	1.00	11.33	1.00
Median moments	2.26	2.16	26.97	1.55	24.27	2.14
Four-sector model						
Average	3.26	3.12	75.80	4.36	35.52	3.14
Average (excl. Energy)			83.80	4.82	38.76	3.42
Food			21.39	1.23	15.78	1.39
NEIG			38.65	2.22	26.93	2.38
Energy			3.67	0.21	6.25	0.55
Services			171.52	9.87	67.80	5.98
120 sectors (item level)						
Median moments			65.89	3.79	–	–

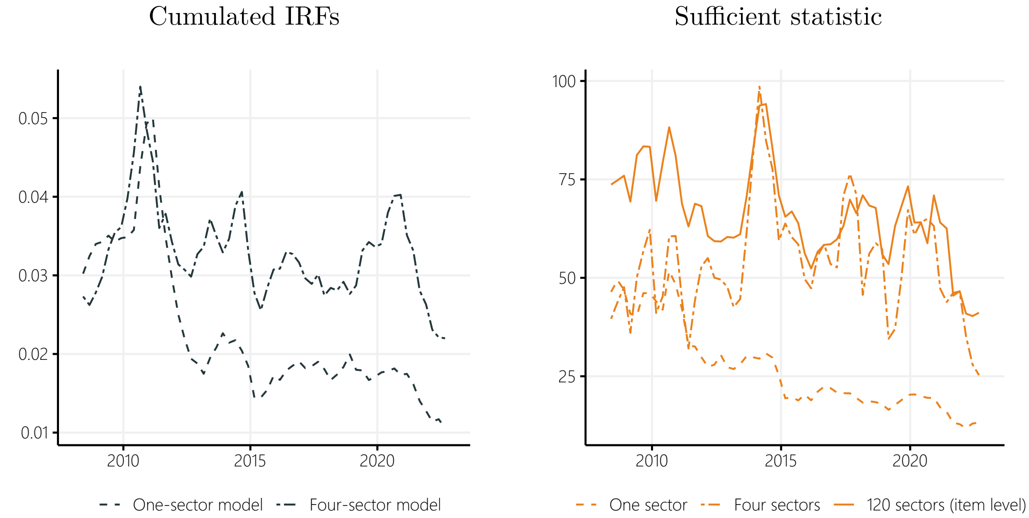
Notes: The table reports averages of our measures of monetary non-neutrality from 2008:I to 2022:IV. Column 2 presents averages of the model-based cumulated IRFs to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) for the one-sector model estimated using mean and median moments as well as for the four-sector model using median moments. To obtain average estimates of monetary non-neutrality, the responses are cumulated each quarter over a forty-quarter horizon and averaged over the sample period. Columns 4 and 6 present the sufficient statistics as in Equation (5.1) for varying levels of aggregation based on either data moments or model moments. The sectors (food, NEIG, energy, and services) correspond to the COICOP-HICP special aggregates defined by Eurostat. The sufficient statistics are calculated using the sample of CPI microdata that includes price changes due to temporary sales and product substitution. Columns 3, 5, and 7 report the amplification factors of the measures in a given row relative to the corresponding value shown in the first row of the table (mean moments).

Figure C.1 shows the degree of monetary non-neutrality as measured by the sufficient statistic over time using the sample of Swiss CPI microdata that includes price changes due to temporary sales and product substitution. It shows the kurtosis-frequency ratios for each sector and the weighted average across sectors.

C.2 Persistence of the impulse response functions of output

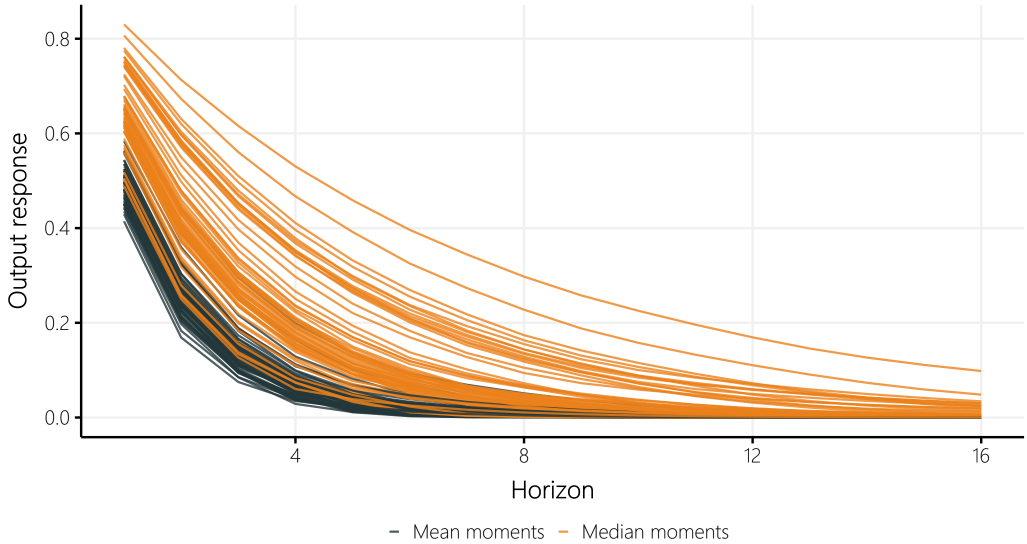
Figure C.2 shows impulse response functions of output to a one-standard-deviation monetary shock over a horizon of 16 quarters generated each quarter of our data sample from 2008:I to 2022:IV in the one-sector model based on mean price-setting moments (blue lines) and based on median price-setting moments (orange lines). Most IRFs based on mean moments are below those of the model based on median moments, suggesting they are considerably less persistent.

Figure C.1: Evolution of monetary non-neutrality over time based on the sample including price changes due to temporary sales and product substitution



Notes: The figure shows the evolution of monetary non-neutrality from 2008:I to 2022:IV. The left panel compares the cumulated real effects of output to a one-standard-deviation monetary policy shock ($\sigma_\eta = 0.97\%$) obtained from the one-sector and four-sector models. The responses are cumulated over forty quarters. The right panel compares the sufficient statistics computed as in Equation (5.1) from the item-level mean moments as well as from the moments aggregated to one and four sectors using median moments. All calculations are based on Swiss CPI microdata from 2008:I to 2022:IV, including price changes due to temporary sales and product substitution. All series are depicted as three-quarter centered moving averages.

Figure C.2: Persistence in the IRFs of output to a monetary shock generated based on mean versus median moments



Notes: The figure shows impulse response functions of output to a one-standard-deviation monetary shock over a horizon of 16 quarters generated for each quarter of our data sample from 2008:I to 2022:IV in the one-sector model based on mean price-setting moments (dark lines) and based on median price-setting moments (orange lines). The sample of Swiss CPI microdata excludes price changes due to temporary sales and product substitution.

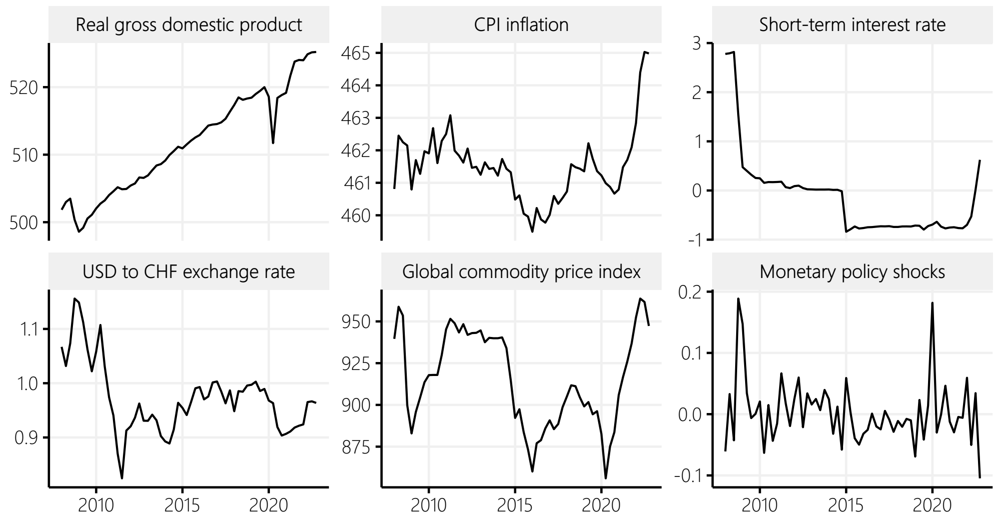
D Empirical validation of the measures of monetary non-neutrality

This appendix refers to Section 6 and provides additional information on the empirical validation of the measures of monetary non-neutrality.

D.1 Nonlinear local projections

Figure D.1 shows the series included in the baseline local projection model over the 2008–2022 sample period

Figure D.1: Data series in the baseline local projection model



Notes: The figure shows the series included in the baseline local projection model over the 2008–2022 sample period. Real GDP, the consumer price index, and the commodity price index are in log levels multiplied by 100. The exchange rate is in Swiss francs per US dollar. The SARON is in percent.