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Unraveling the Impact of Higher Uncertainty on Profits and Inflation

Abstract

This paper aims to explore the impact of rising uncertainty on prices using micro-data on prices and multi-sector new Keynesian models. We identify diverse price responses to increasing macroeconomic uncertainty: goods with relatively flexible prices experience a decline due to lower demand caused by the rising uncertainty, while those with sticky prices experience an increase. The model suggests that economic uncertainty creates strategic complementarity for firms with sticky prices, prompting them to raise markups and prices in anticipation of potentially higher future inflation. These findings establish a connection between heightened uncertainty, higher core inflation, and increased profits.

JEL-Codes: E520, E580.

Keywords: uncertainty, inflation, heterogeneity in price stickiness, micro-data on prices, New Keynesian.

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1 Introduction

Policymakers often cite higher uncertainty as a factor driving prices and inflation. Recently, researchers developed tools to help to understand the precise mechanisms through which increasing uncertainty affects the macroeconomy. Bloom (2009) makes a general point that uncertainty shocks play a quantitatively important role in driving business cycle fluctuations in the US economy. Others, using Structural Vector Autoregression (SVAR) models and the stock market volatility data to identify an uncertainty shock convincingly argue that higher uncertainty lowers both output and prices (see Fernandez-Villaverde et al. (2015), Leduc and Liu (2016) and Basu and Bundick (2017)). On the other hand, with plausible calibration, the new Keynesian model suggests that while output falls with increasing uncertainty, prices increase (see Born and Pfeifer (2014)). While substantial progress has been made in understanding the macroeconomic effects of higher uncertainty, further research is needed to explore the impact of heightened uncertainty on the economy, particularly in relation to prices at a more disaggregated level. Additionally, there is a need to reconcile the conflicting evidence from SVARs and the models.[1]

This paper contributes to the existing literature by utilising micro-data on prices to gain a deeper understanding of the mechanisms through which uncertainty impacts the economy and prices. Examining the effects of uncertainty shocks on prices at a disaggregated level and their broader implications for the supply side of the economy is crucial for comprehensively understanding the impact of such shocks. To achieve this objective, we

[1]To reconcile the model with empirical evidence, Basu and Bundick (2017) reformulate the standard one-sector new Keynesian model by allowing for recursive preferences, as in Epstein and Zin (1989). Alternatively, Leduc and Liu (2016) study the effect of uncertainty shocks in a new Keynesian model with search and matching frictions. Both studies strengthen the aggregate demand channel. So, aggregate demand falls more with increasing uncertainty, causing inflation to fall. Our approach differs as we shift our focus to the supply side, guided by the insights provided by the microdata on prices.

employ two disaggregated price datasets: one for the United States and another for the United Kingdom.

The US dataset, compiled by the Atlanta FED using US CPI data, categorises different CPI product categories based on how quickly prices adjust within those sectors. It offers two inflation series based on duration: one for products with flexible prices and another for products with sticky prices. We use this dataset to estimate an SVAR model, similar to those commonly used in the literature. However, it's important to acknowledge the limitations of this approach due to the level of data aggregation. While it can capture general patterns and trends between sectoral inflation rates and uncertainty, it may not fully account for the specific price dynamics within subgroups or individual goods.

Due to the unavailability of more detailed price data for the US, we complement our analysis by incorporating publicly available micro-data on prices from the UK. This dataset, compiled by the Office for National Statistics (ONS) for calculating the UK CPI, covers a substantial portion of the UK CPI basket, representing 60% of it. It spans from February 1988 to July 2022 and includes an extensive sample of 58 million price quotes.

For our theoretical analysis, we adopt a duration-based multi-sector model developed by Kara (2015). In this model, numerous sectors exist, each characterised by a distinct contract duration. Kara (2015) develops the multi-sector version of the Smets and Wouters (2007) model to account for heterogeneity in price stickiness across sectors. The reformulated model matches the macro data as well as the Smets and Wouters (2007) model but does so in a manner consistent with actual firm pricing, without necessitating significant markup shocks. The fact that the duration-based model matches the key macroeconomic data without relying on substantial exogenous price markups suggests that the mechanism employed in the model carries more empirical relevance compared to the widely used single-sector model.

The key insight of the model arises from the duration-based multi-sector model, which is further supported by the micro-data. The analysis yields two main results. First, goods with sticky prices, which can be seen as a proxy for core inflation and provide a better indication of medium-term trends, exhibit an increase in response to heightened uncertainty. Second, markups and profits demonstrate an upward trend in response to increasing uncertainty. To delve further into the results, all approaches we employ in the paper show that higher uncertainty affects prices differently, and there exists heterogeneity in firms' responses to increased uncertainty. Unlike sticky-price firms, firms with relatively flexible prices decrease their prices in response to heightened uncertainty. Since flexible prices tend to respond more strongly, headline inflation tends to fall in the face of increasing uncertainty. However, the fact that sticky prices increase after heightened uncertainty means that higher uncertainty has inflationary and persistent effects on prices. We test the robustness of our results with alternative specifications, including an extension of the baseline model to account for production networks as in Acemoglu et al. (2012) and Carvalho (2014 and 2018). Our results remain unchanged.

A key factor in understanding our results is that increasing uncertainty in our model leads to a decrease in the optimal flexible price. This is because the optimal flexible price is predominantly determined by demand and firms do not need to concern themselves with future uncertainties. Consequently, as uncertainty grows and precautionary savings increase, the demand falls, leading to a decline in relatively flexible prices. On the other hand, in the presence of heightened uncertainty, firms with sticky prices respond by attempting to protect their prices against the increased uncertainty, resulting in higher prices than they would otherwise set. This leads to an increase in price markups and profits. The extent of price stickiness within a sector determines the magnitude of the markup in that sector. The larger markups in sticky-price sectors then contribute to overall higher markups in the economy.

The reasoning behind higher markups lies in the concept of strategic complementarity in price setting, as suggested by Cooper and John (1988) (see also Blanchard and Kiyotaki (1987)). In contrast to the findings of Cooper and John (1988), our model suggests that in the presence of higher uncertainty, firms are motivated to raise their own prices due to the potential for higher future prices in the rest of the economy. The stickier the price, the more significant the price adjustments and precautionary price markups become. Ultimately, this strategic complementarity in price setting leads to higher profits.

To support the mechanism described in the model, our SVAR estimation incorporates Nekarda and Ramey's (2020) preferred measure of price markups. The estimation results confirm that price markups do indeed increase in response to heightened uncertainty, providing evidence for the mechanism operating in the model.

The rest of this paper is organised as follows. In section 2, we study both macro and micro data on prices to better understand the empirical effects of increasing uncertainty on prices and inflation. Section 3 outlines our model. Section 4 discusses the micro-evidence on prices and uses it to calibrate the model in this paper. Section 5 considers a simplier two-sector version of the model without production networks and explains the transmission mechanism in both the standard and the multi-sector model through which uncertainty shocks influence macroeconomic outcomes. Section 6 extends the analysis to a full-scale model with networks. Finally, section 7 presents the sensitivity analysis and section 8 concludes.

2 Uncertainty shocks and micro-data on prices

In this section, we proceed in two steps. First, we estimate an SVAR model using disaggregated price data for the US economy, along with other macro data, at a quarterly frequency for the period between 1990 and 2018. The disaggregated price data are constructed by Bryan and Meyer (2010), who classify goods in the CPI basket as flexible or sticky based on the average frequency of price changes. Goods with an average frequency of price change greater than 4.3 months are classified as flexible, while the remaining goods are considered sticky.

The macro data used in the analysis include inflation, the federal funds rate, 10-year inflation expectations data from the survey of professional forecasters, a measure for markups based on Nekarda and Ramey (2020), and a measure for uncertainty. The measure for markups is derived from a CES production function and considers utilisation-adjusted capital-output ratio, overhead labour, and variable capital utilisation based on Fernald (2014). In addition to the mentioned variables, we conducted additional estimations (not reported but available upon request) that included other variables such as investment growth and wage growth. However, the inclusion of these variables did not significantly change our results. The inclusion of long-run inflation expectations data is particularly relevant as the estimation period covers the period of unconventional monetary policy, as it helps to capture the effects of measures such as quantitative easing.

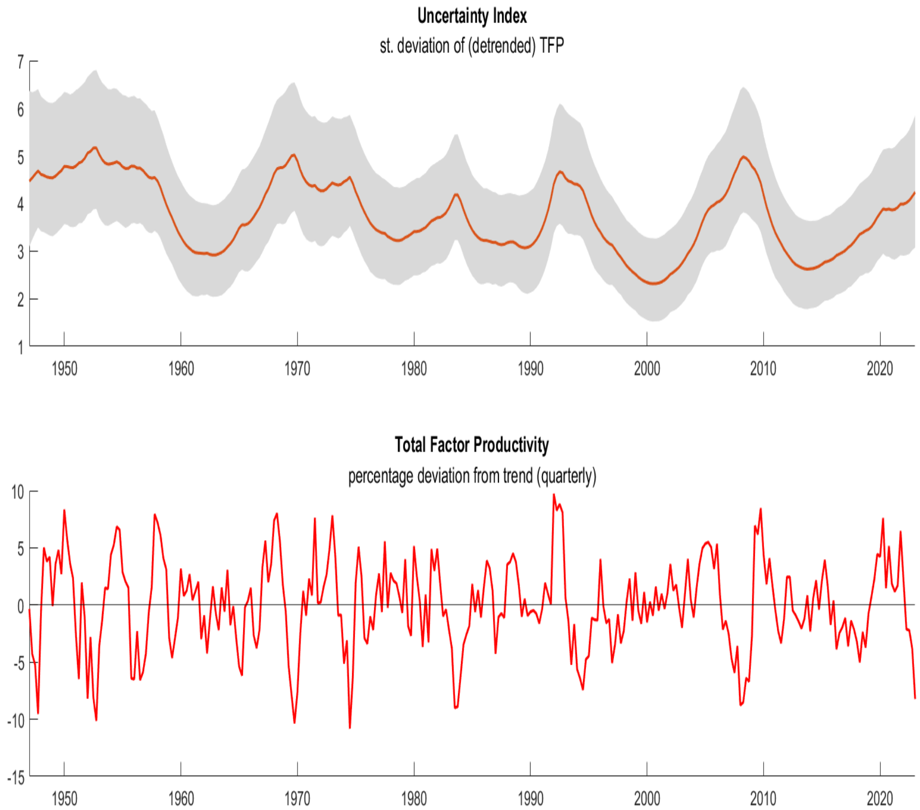
Second, we use microdata underlying the UK CPI to test if our results from the SVAR exercise hold at a more disaggregated level. The dataset is available at a monthly frequency and is compiled by Davies (2021). To conduct the analysis, we clean the data and convert it to a quarterly frequency.

2.1 A measure for uncertainty

To maintain consistency throughout the paper, we construct a measure of uncertainty for both the US and the UK economies. For the US, we utilize the utilisation-adjusted total factor productivity (TFP) series, as constructed in Fernald (2014). To estimate a stochastic volatility model, we detrend the TFP series using the HP filter at a quarterly frequency. The time-varying standard deviation of the detrended utilisation-adjusted TFP process serves as our measure of uncertainty.[2] For the UK, we use the utilisation-adjusted multifactor productivity index provided by the Office for National Statistics (ONS) at a quarterly frequency, which is available for the period spanning from 1994 to 2021. Using this index, we estimate the stochastic volatility model.

[2]We employ the Matlab code provided by Joshua Chan on his website to estimate the stochastic volatility model (https://joshuachan.org/code.html).

Figure 1: **Uncertainty Index for the US**



Notes: The top panel reports time-varying standard deviation of the productivity index, estimated using the stochastic volatility model. The model is estimated using the utilisation-adjusted productivity index constructed in Fernald (2014) and detrended using HP filter at a quarterly frequency (bottom panel).

Figure 1 plots both the detrended TFP series and the measure for uncertainty obtained from estimations for the US.

2.2 Empirical evidence from VAR models

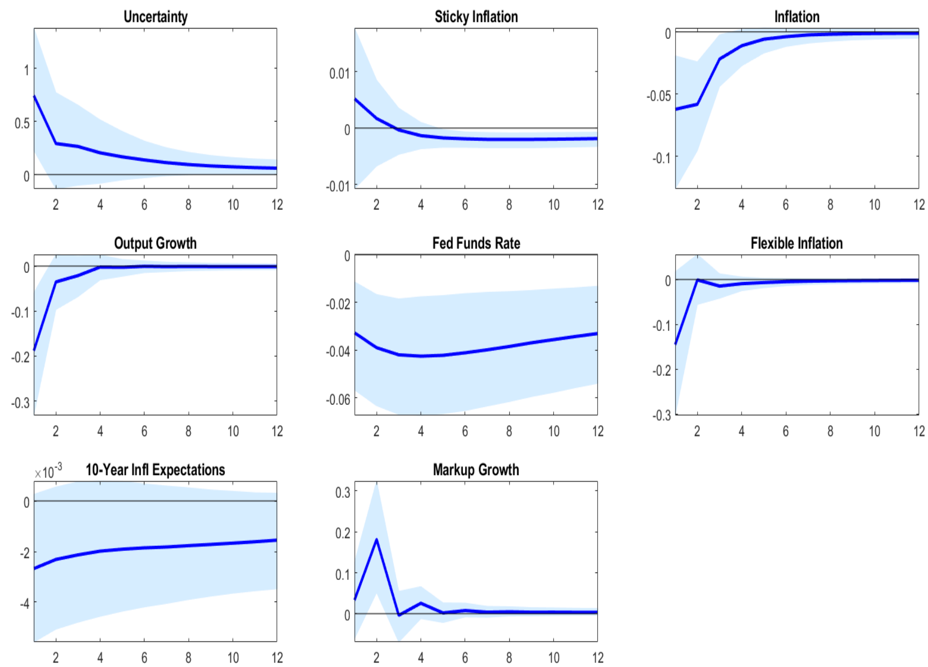
We estimate the effect of increasing uncertainty on key macroeconomic variables and sectoral inflation using a Bayesian vector-autoregression model. We take 10,000 draws and discard the initial 1000 draws when constructing the posterior distribution. Priors for the reduced-form model are specified as suggested in Litterman (1986). To identify shocks, we follow Faust (1998), Canova and De Nicholo (2002) and Uhlig (2005) and use sign restrictions. In particular, we identify the following structural shocks: an uncertainty shock, a monetary policy shock, a cost-push shock, and a demand shock. Table 1 shows short-run sign restrictions which each structural shock must satisfy. We identify uncertainty shock as a shock that increases uncertainty and decreases output and inflation. Since we are particularly interested in the response of sectoral inflation, we do not impose any restrictions on their response to the uncertainty shock. We also do not impose any restrictions on the response of markups to the uncertainty shock.

Table 1: **Sign Restrictions on Structural Shocks**

Variables	VIX	Mon-Policy	Cost-Push	Demand
Uncertainty	+	*	*	*
GDP Growth	-	-	-	+
Inflation	-	-	+	+
Interest Rate	-	+	+	+
Sticky-price Inflation	*	-	*	+
Flexible-price Inflation	*	-	+	+
Markups	*	*	*	*

Notes: This table presents sign restrictions on contemporaneous impact responses of model variables (rows) to structural shocks (columns) which must be satisfied.

Figure 2: **SVAR estimation results with disaggregated inflation data**



Notes: This figure plots simulated quantiles of impulse responses to an uncertainty shock. The subplots show point-wise median and 16% and 84% quantiles of the posterior distribution computed from 9,000 draws.

Figure 2 illustrates the impulse responses to a one standard deviation uncertainty shock. The figure presents a pointwise median response and 16% and 84% quantiles of the posterior distribution computed from 9,000 draws. The figure shows that higher uncertainty leads to a significant fall in output and inflation. This finding is consistent with previous literature that uncertainty shocks resemble demand shocks (Leduc and Liu, 2016; Basu and Bundick, 2017). However, there is heterogeneity in the way different sectors respond to higher uncertainty. In the median model, flexible-price inflation experiences a decrease of approximately 0.15 percentage points in response to the shock, followed by a full recovery by the end of the year. On the other hand, sticky-price inflation exhibits an initial increase upon impact. It takes around one year for sticky-price inflation to fall below its trend value before gradually returning to it over the course of several years. Furthermore, the magnitude of the response in sticky-price inflation is notably smaller compared to that of flexible-price inflation. This suggests that the initial impact on aggregate inflation is primarily dictated by the price-setting behaviour of firms in the flexible-price sector.

So far the key finding is the differential response of inflation in the sticky-price and flexible-price sectors. To further examine the finding that inflation should increase by more in the most sticky-price sectors, we replace the measure of sticky-price inflation with inflation for postal services. This choice is motivated by Nakamura and Steinsson (2008), who estimate that the average age of price contracts for postal mail services is approximately 9 quarters. Additionally, the data for postal services inflation is readily available on the FRED database for the relevant period of 1990-2018. By using inflation for postal services as a proxy for the most sticky prices, we can test whether inflation increases to a greater extent in this specific sector. The exact index used is the "Producer Price Index by Industry: U.S. Postal Service: Package Services Mail".

The results presented in Figure 3 provide further support for the finding that sectors facing greater nominal rigidities respond more to higher uncertainty. As is evident, inflation for the category of *postal services* exhibits a significantly larger increase compared to the increase observed in sticky-price inflation as shown in Figure 2. To extend this analysis, we repeat the exercise for several other categories that have stickier prices compared to the average goods in the sticky price index. These categories include printing and publishing, medical care services, and professional services. In all of these cases, the results indicate that inflation increases to a significantly greater extent than what is implied by the response observed in Figure 2.

These findings reinforce the notion that sectors with higher levels of price rigidity experience more pronounced increases in inflation, suggesting that firms operating in sectors with greater price stickiness tend to adjust their prices more aggressively in response to increased uncertainty.

These findings raise a natural question: Why does inflation increase in the sticky-price sector but fall in the flexible-price sector? This is one of the questions we address to provide an answer. As we will discuss in detail later in the text (Section 5), our model suggests that this is due to the disproportionate increase in markups in sticky-price sectors. Indeed, Figure 2 shows that markups increase in response to increased uncertainty.

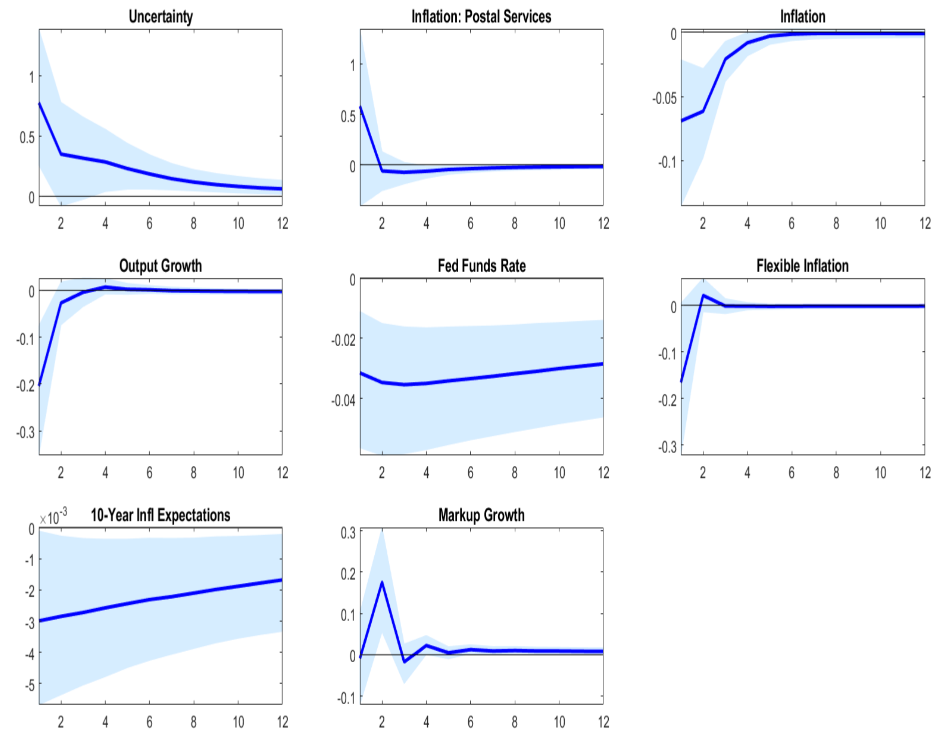
2.3 The UK CPI data

We now turn to microdata on prices underlying the UK CPI basket. Results based on microdata confirm the findings from the SVAR model. The dataset comprises 60% of the UK CPI basket and approximately 50% of the UK CPIH basket and does not include centrally collected prices. The centrally collected prices include 150 items whose prices are set at the national level, such as travel fares, electricity, imputed rents, university fees, computers, and other goods and services sold online or at chain shops with nationally determined prices. The dataset, compiled by Davies (2021), is available at a monthly frequency for the period between February 1988 and July 2022.[3]

Before proceeding with the analysis, we drop the price quotes which are identified as *sales* by the ONS. The uncertainty index we construct in section 2.4 is quarterly and is for the period from 1994 quarter 1 until 2021 quarter 3. Therefore, we restrict our dataset to

[3]We thank Richard Davies for sharing the dataset with us.

Figure 3: **SVAR estimation with disaggregated inflation data**



Notes: This figure plots simulated quantiles of impulse responses to an uncertainty shock. The subplots show point-wise median and 16% and 84% quantiles of the posterior distribution computed from 9,000 draws.

the same time period and further transform it to quarterly frequency by selecting the first observed price-quote within a quarter for a given quote-line. We use the transformed data to calculate the quarterly inflation series for each quote-line. The transformed dataset contains outliers with absolute inflation exceeding 1000%. We winsorize the dataset by dropping the top and bottom percentile of observations on inflation. This results in a minimum and maximum inflation of -59% and 59%, respectively. Finally, we drop quote-lines for which we only observe inflation for a year or less.

The transformed dataset has 555,619 quote-lines with 10.7 million observations for price changes. The median quote-line has observations for 23 quarters, while 5% of the quote lines have observations for 7 quarters or less. The quote-lines include price-quotes for 1,164 items collected from 3,875 shops spread across the 13 regions.[4] The average quarterly inflation (excluding sales) over the sample period equals 0.47% with a standard deviation of 10.79. The median quarterly inflation equals 0%.

2.3.1 Heterogeneity in the frequency of price adjustment

To study whether price rigidities matter for how firms adjust their prices in response to increased uncertainty, we categorise quote-lines according to the degree of nominal rigidities they face. To do so, we follow Nakamura and Steinsson (2008) and calculate the frequency of price change, f, for each of the quote-line. This is calculated by identifying price changes over the period for which price change data is available for each quote-line. We report results for *regular prices* which exclude sales.

The median frequency of price change in our sample is 28%. This implies a median duration of a price contract of 3.1 quarters.[5] There is, however, considerable heterogeneity in the frequency of price change both across and within different categories. To make this clear, table 2 reports summary statistics for the frequency of price adjustment across all the divisions of *Classification of Individual Consumption According to Purpose*

[4]There were 2.6 million price quotes which were duplicates in the original dataset. As a hypothetical example, a loaf of bread sold at Sainsbury's in South West had multiple price quotes for a particular month. We deleted duplicate entries in such cases before proceeding with the rest of the analysis in this paper.

[5]As in Nakamura and Steinsson (2008), we define the corresponding median implied duration to be $d = -1/ln(1-f)$, where f is the median frequency.

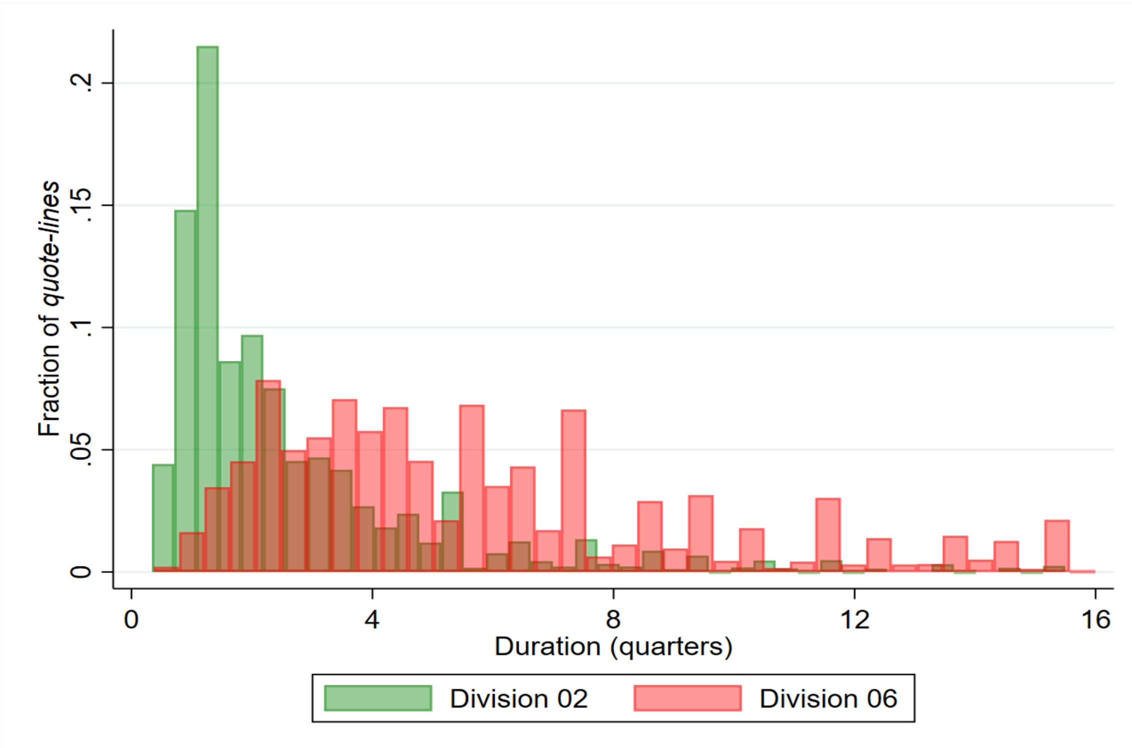
(i.e. COICOP).[6] The frequency of price change is the highest for Division 02 (*Alcoholic beverages, tobacco and narcotics*) and the lowest for Division 06 (*Health*).

[6] There are 336 *items* comprising of 115,221 *quote-lines* which are not mapped to the COICOP classification in the dataset. Almost all of these *items* and *quote-lines* are for the period before the 2008 crisis.

Table 2: **Frequency of price adjustment across COICOP divisions**

COICOP Divisions	Mean	Median	25 Percentile	75 Percentile	N
Food and drinks					
01 - Food and non-alcoholic beverages	34.6	30.0	17.4	48.6	114,972
02 - Alcoholic beverages, tobacco and ...	40.4	40	25	57.1	15,403
Manufacturing					
03 - Clothing and footwear	31.8	30	16.7	44.4	75,783
04 - Housing, water, electricity, gas and ...	26.8	22.2	11.8	37.5	14,470
05 - Furnishings, household equipment and ...	27.2	23.8	12.9	37.5	55,496
Services					
06 - Health	16.9	14.3	6.3	25.0	8,023
07 - Transport	32.6	25	12.5	46.5	19,598
08 - Information and communication	26.3	25	13.0	38.3	1,056
09 - Recreation, sport and culture	30.0	25	12.5	42.9	48,015
11 - Restaurants and accommodation services	24.9	22.9	12.5	35	52,648
12 - Insurance and financial services	22.7	20	10.9	33.3	34,934
All	30.1	26.1	14.3	42	440,398

Figure 4: **Duration of price contracts within COICOP divisions**



Notes: The figure plots the distribtuion of average contract length for quote-lines within the two COICOP divisions, division 02 (green) and division 06 (red).

Figure 4 shows the distribution of the implied age of price contracts at the level of *quote-lines* within the two divisions of the COICOP. The median implied age of the price contract for Division 02 is almost 2 quarters, whereas the same for Division 06 is 6.5 quarters. Only 2% of the *quote-lines* within Division 02 have implied age of more than 12 quarters. In contrast, for Division 06, this number is as high as 15%. Nonetheless, the figure makes clear that there is a heterogeneity in price stickiness within a product sector.

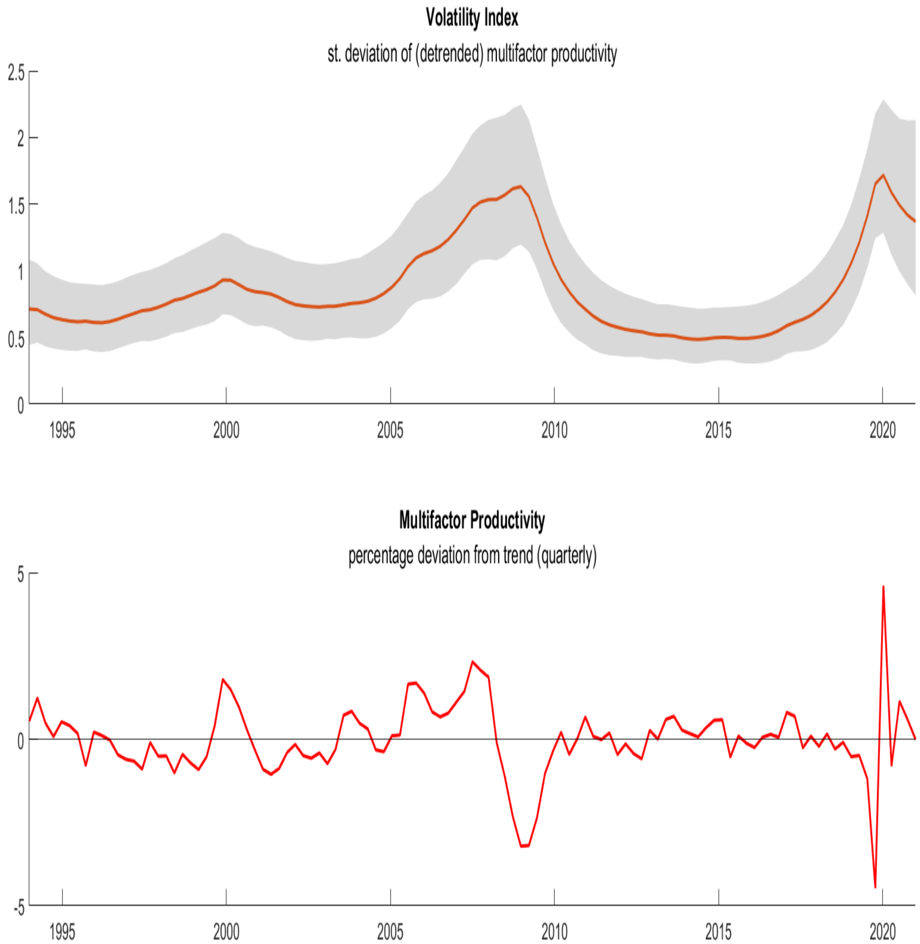
2.4 Uncertainty and the frequency of price adjustment

We now turn to study how the price of a *quote-line* responds to changes in aggregate uncertainty. We particularly focus on the responsiveness of quote-lines which adjust their prices less or more frequently. Equation 1 specifies the fixed effect model we estimate:

$$\pi_{isr,t} = \alpha + \mu_{isr} + \beta_u vol_t + \delta t + \epsilon_{isr,t} \tag{1}$$

where $\pi_{isr,t}$ is the quarter-on-quarter inflation for *item* i at shop s in region r at time t (a quote-line). To capture aggregate uncertainty, we estimate a stochastic volatility model using quarterly data for multifactor productivity provided by the ONS. Figure 5 plots both the (detrended) multifactor productivity index used to estimate the stochastic volatility model and the estimates for the corresponding volatility measure, vol_t. The estimates show a sharp increase in volatility leading up to the 2008 financial crisis and during COVID-19. We further control for quote-line fixed effects, μ_{isr}, and allow for a time trend, t.

Figure 5: **Volatility Index**



Notes: The top panel reports time-varying standard deviation of the multifactor productivity index, estimated using the stochastic volatility model. The model is estimated using the multifactor productivity index provided by the ONS for the UK and detrended using hp filter for quarterly frequency (bottom panel).

Table 3 reports results from estimating equation 1. The first and the second columns split the sample into *quote-lines* which face an implied duration of price contract of less than 1 quarter (flexible) and more than 1 quarter, respectively. The median implied contract length in the sticky sector is 3.3 quarters.

Table 3: **Inflation: Regression results**

	Sectors	
	Flexible	Sticky
β_u	-0.231**	0.163***
	(-2.84)	(18.12)
δ	-0.010***	-0.002***
	(-7.02)	(-13.52)
Cons.	1.487***	0.491***
	(12.81)	(33.46)
Fixed effects	Yes	Yes
Median duration (quarters)	0.7	3.1
No. of *quote-lines*	36605	519014
Observations	553026	10130939

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our main conclusion, which is consistent with the insights from the previous section for the US, is apparent from the table. On average, inflation in the flexible sector decreases, while inflation in the sticky sector increases in the face of heightened uncertainty. More generally, firms facing a higher degree of nominal rigidities tend to raise their prices in response to increased uncertainty.

2.5 Intensive vs Extensive margins

Inflation can be attributed to two factors: (1) firms making larger price adjustments when resetting their prices in response to shocks (intensive margin), and (2) a higher frequency of price adjustments, indicating more firms adjusting their prices (extensive margin). If our classification of prices into relatively flexible and relatively sticky holds true in the data, we would expect to observe larger price changes in sticky-price goods. In this section, we put this prediction to the test. We demonstrate that while the frequency of price change remains relatively stable, sticky-price goods experience substantial price adjustments.

Given the significant heterogeneity observed within and across different categories regarding the degree of nominal rigidities faced by individual quote-lines, selecting an appropriate level of aggregation becomes a challenge. To address this, we divide all quote-lines into ten sectors based on the frequency of price change they exhibit. For instance, the first sector includes quote-lines with an average frequency of price change of 87% or higher, while the last sector comprises quote-lines with an average frequency of price change below 7%.

Next, we calculate the average size of price changes within a sector by averaging all price changes within a given quarter across all quote-lines for an item. To be consistent with the results presented earlier, we classify sectors with an implied duration of the price contract of less than 1 quarter as flexible (sectors 1, 2, and 3), and those with an implied duration greater than 1 quarter as sticky (sectors 4 to 10). Finally, we estimate the following model:

$$\pi^*_{is,t} = \alpha + \mu_{is} + \beta_u vol_t + \delta t + \epsilon_{is,t} \tag{2}$$

where $\pi^*_{is,t}$ is reset inflation for item i in sector s at time t. Table 4 reports the results. The first and the second columns report results for reset inflation in the flexible and sticky sectors, respectively.

As indicated in the table, there is a clear relationship between the degree of price sticki-

Table 4: **Reset Inflation: Regression results**

	Sectors	
	Flexible	Sticky
β_u	-0.125	0.429***
	(-0.71)	(6.89)
δ	-0.000	-0.001
	(-0.14)	(-1.35)
Cons.	0.746***	1.325***
	(3.73)	(15.54)
Fixed effects	Yes	Yes
No. of aggregated *quote-lines*	2328	7690
Observations	58239	317630

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ness and the magnitude of price changes. Sticky-price goods show considerably larger price adjustments when confronted with heightened uncertainty. Specifically, a one standard deviation increase in uncertainty leads to a 42 basis points rise in the magnitude of price change for the sticky sector, exceeding the 16 basis points increase in overall inflation in the sector. Consistent with our previous results, relatively flexible prices tend to decline in response to increased uncertainty.

Next, we proceed to assess the significance of the extensive margin. To achieve this, we estimate the model presented in Equation 3, which captures the relationship between uncertainty and the fraction of price changes,

$$n_{is,t} = \alpha + \mu_{is} + \beta_u^n vol_t + \delta t + \epsilon_{is,t} \tag{3}$$

where $n_{is,t}$ is the fraction of quote-lines seeing a price change at an *item* level within sector s at time t, and μ_{is} are fixed effects at item-sector level.

Table 5: **Extensive Margin: Regression results**

	All price changes			Price increases			Price decreases		
	Full sample	Flexible	Sticky	Full sample	Flexible	Sticky	Full sample	Flexible	Sticky
β_u^d	0.033***	0.012**	0.036***	0.013***	-0.012**	0.016***	0.020***	0.025***	0.020***
	(26.40)	(2.89)	(27.67)	(13.62)	(-3.03)	(17.65)	(22.06)	(5.79)	(22.48)
δ	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***	-0.000*	-0.000***
	(-21.02)	(-4.48)	(-20.63)	(-18.00)	(-2.22)	(-19.07)	(-10.76)	(-2.25)	(-11.19)
Constant	0.379***	0.791***	0.311***	0.227***	0.448***	0.191***	0.152***	0.343***	0.120***
	(245.69)	(166.89)	(191.48)	(185.02)	(94.01)	(157.72)	(130.38)	(70.83)	(107.08)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of items	10266	2328	7938	10266	2328	7938	10266	2328	7938
Observations	455480	64407	391073	455480	64407	391073	455480	64407	391073

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 presents the results obtained from estimating Equation 3. The first three columns provide the findings for all price changes at both the aggregate and sectoral levels. The subsequent three columns focus exclusively on price increases, while the final three columns focus solely on price decreases.

Across all sectors, the median fraction of all price changes is 30%. For the flexible-price sector, this fraction is 100%, whereas for the sticky sector, it is 25%. Additionally, the median fraction of price increases is 12.5% (with corresponding values of 37% for the flexible-price sector and 11% for the sticky-price sector), while the median fraction of price decreases is 5.9% (with corresponding values of 25% for the flexible-price sector and 4.6% for the sticky-price sector).

Regarding the results for all price changes, there is evidence of more quote-lines undergoing price adjustments in response to shocks, with a stronger effect observed in the sticky-price sector. However, the quantitative impact is relatively small. Furthermore, when examining data specifically for price increases and price decreases, the implications for inflation dynamics become even less apparent. In the case of sticky sectors, an increase in uncertainty leads to an increase in both price increases and price decreases.

Based on these findings, we conclude that the role of the extensive margin in shaping inflation dynamics appears to be limited.

3 Model

The model is the Multiple Calvo model presented in Kara (2015). Specifically, we add heterogeneity in price stickiness suggested by micro-data on price changes to an otherwise standard NK model.

To model heterogeneity in price stickiness, first, as in the standard model, we allow for a continuum of firms $f \in [0,1]$ and assume that each firm f produces a differentiated good in an imperfectly competitive market. Next, we split firms into N segments according to how frequently firms adjust their prices. We refer these segments as sectors. The share of each sector i (where $i = 1...N$) is given by α_i. Finally, we assume that firms face nominal rigidities within each sector i when setting their prices. Under Calvo pricing, the sector-specific Calvo hazard rate is $1 - \zeta_i$.

We define the cumulative share of sectors as $\hat{\alpha}$, where $\hat{\alpha}_N = 1$ and the interval for sector i is $[\hat{\alpha}_{i-1}, \hat{\alpha}_i]$. With these assumptions, consumption aggregate (C_t) and the corresponding general price index (P_t) can be rewritten in terms of sectors as follows.

$$C_t = \left[\sum_{i=1}^{N} \int_{\hat{\alpha}_{i-1}}^{\hat{\alpha}_i} Y_{ft}^{\frac{\epsilon-1}{\epsilon}} df \right]^{\frac{\epsilon}{1-\epsilon}} \tag{4}$$

$$P_t = \left[\sum_{i=1}^{N} \int_{\hat{\alpha}_{i-1}}^{\hat{\alpha}_i} P_{ft}^{1-\epsilon} df \right]^{\frac{1}{1-\epsilon}} \tag{5}$$

3.1 Firms

We assume that firms only need labour to produce output. The production function for firm f in sector i is given by:

$$Y_{it}(f) = A_t N_{it}(f) \tag{6}$$

where $Y_{it}(f)$ is output produced by firm f in sector i and $N_{it}(f)$ is labour used by firm f is sector i. A_t is aggregate technology shock and is given by:

$$lnA_t = (1 - \rho_a) ln\bar{A} + \rho_a lnA_{t-1} + \sigma_t^a \hat{a}_t \tag{7}$$

where ρ_a is the persistence parameter and $\hat{a}_t \sim IID(0, \sigma_t^a)$. The uncertainty shock is characterised by σ_t^a which is time-varying standard deviation of the productivity shock. σ_t^a follows:

$$ln\sigma_t^a = (1 - \rho_\sigma)\bar{\sigma}^a + \rho_\sigma ln\sigma_{t-1}^a + \sigma_\sigma \hat{\sigma}_t^a \tag{8}$$

where ρ_σ is the persistence parameter and $\exp(\bar{\sigma}^a)$ is standard deviation of the productivity shock in steady-state. $\hat{\sigma}_t^a$ is the i.i.d. shock with mean zero and standard deviation σ_σ.

Marginal cost is sector i (MC_{it}) is given by:

$$MC_{it} = \frac{W_{i,t}}{A_t} \tag{9}$$

where W_{it} is the nominal wage in sector i. Since we assume a perfectly competitive labour market, firms across all sectors face a similar wage rate, W_t.

3.1.1 Multiple Calvo Pricing

Under multiple Calvo pricing, within each sector, there is a Calvo process and only a faction of firms can reset their prices in any given period. Moreover, whether a firm can readjust its price in any given period does not depend on how far its prevailing price is from what is optimal. As a result, when setting its prices, firm f sets a price which maximises the expected discounted value of her profits over the expected duration when the firm cannot change her price. Firms' profit maximisation problem gives the following expression for the reset price in sector i:

$$X_{it}^* = \left(\frac{\epsilon}{\epsilon - 1}\right) \frac{E_t \sum_{\tau=0}^{\infty} (\beta\zeta_i)^\tau \lambda_{t+\tau} (\prod_{s=1}^{\tau} \pi_{t+s}^{\epsilon}) \frac{MC_{it+\tau}}{P_{it+\tau}} Y_{it+\tau}^d}{E_t \sum_{\tau=0}^{\infty} (\beta\zeta_i)^\tau \lambda_{t+\tau} (\prod_{s=1}^{\tau} \pi_{t+s}^{\epsilon-1}) Y_{it+\tau}^d} \tag{10}$$

where β is the discount factor and ζ_i is the probability that a firm in sector i cannot change her price in a given period. X_{it}^* is reset price and π_{it} is inflation in sector i. This equation shows that the reset price in sector i is a markup over marginal cost during the expected duration of the contract. Since there is a distribution of contracts, there is a distribution of reset prices in the multi-sector model.

Finally, P_{it} is the sector-specific price index which evolves according to:

$$P_{it}{}^{1-\epsilon} = \zeta_i P_{it-1}{}^{1-\epsilon} + (1-\zeta_i) X_{it}^{*\,1-\epsilon} \tag{11}$$

We discuss the calibration of ζ_i across N sectors in Section 4.

3.2 Households

There is also a continuum of households $h \in [0,1]$. Households choose consumption and labour supply to maximise their expected lifetime utility. We assume a CRRA utility function of the form:

$$\max_{C_{ht},N_{ht}} E_t \sum_{t=0}^{\infty} \beta^t \left(\frac{(C_{ht} - \chi C_{ht-1})^{1-\sigma}}{1-\sigma} - \psi \frac{N_{ht}^{1+\varphi}}{1+\varphi} \right) \tag{12}$$

where σ and φ are the inverse of the intertemporal elasticity of substitution and inverse Frisch labour supply elasticity, respectively. χ determines habits in the household's consumption decision. C_{ht} is the final consumption good consumed by household h and N_{ht} is hours worked by household h.[7] Households maximise (12) subject to the following budget constraint:

$$P_t C_{ht} + \sum_{s_{t+1}} Q(s^{t+1}|s^t) B_h(s^{t+1}) \leq W_t N_{ht} + B_{ht} + T_{ht} + \Pi_{ht} \tag{13}$$

where $E\big[\sum_{s_{t+1}} Q(s^{t+1}|s^t)\big] = 1/R_t$. s^t denotes the state of economy in period $'t'$ and $Q(s^{t+1}|s^t)$ is the price of one period bond portfolio in state s^{t+1} as expected in current state, s^t. $B_h(s^{t+1})$ represents bond portfolio in s^{t+1} held by household $'h'$. Finally, T_{ht} is lump-sum taxes and Π_{ht} is lump-sum profits from firms.

3.3 Monetary Authority

The central bank conducts policy according to a Taylor-type rule. The central bank reacts to changes in aggregate inflation and the growth rate of output:

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\rho_r} \left[\left(\frac{\pi_t}{\bar{\pi}}\right)^{r_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{r_y}\right]^{1-\rho_r} \tag{14}$$

where $\bar{R}$ and $\bar{\pi}$ are steady-state interest rate and inflation, respectively. ρ_r, r_π and r_y are coefficients in front of the targeting variables.

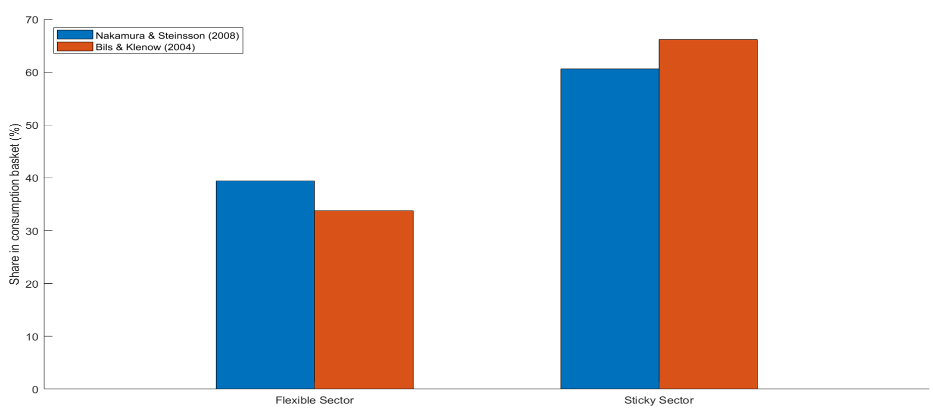
4 Calibration

We start with restricting our focus to the two sector model without production networks. This simplified model helps clarify key transmission mechanisms. Later we also consider the full model with ten sectors and show that results from the two-sector model

[7] Note that throughout the paper we drop the index h from consumption. This reflects the standard new Keynesian assumption that there exist complete contingent claims markets for consumption, implying that consumption is identical across all households in each period ($C_{ht} = C_t$).

appear robust. We use Nakamura and Steinsson (2008) (NS) dataset to calibrate the probability of price change in the two sectors $(1-\zeta_i)$ and the share of each sector in the economy (α_i). Nakamura and Steinsson report the frequency of price adjustment for 272 non-shelter product categories, which cover 70% of the US CPI. We define the flexible-price sector as one including product categories for which the average frequency of price change is 100%. The rest of the product categories form the sticky-price sector. The average frequency of price change for the sticky-price sector is 33%.

Figure 6: **Sectors' Weights & Frequency of Price Changes**



Notes: The figure plots consumption shares for each of the two sectors. Firms in the flexible sector face an average frequency of price change of 100%, whereas those in the sticky sector face an average frequency of price change of 33%.

Figure 6 plots the distribution. An important point to note is that the US economy has plenty of flexible prices. The share of flexible prices is around 40%. Figure 6 also plots the corresponding distribution implied by the Bils and Klenow (2004) (BK) dataset. As is evident from the figure, the distribution implied by the BK dataset is similar to that suggested by the NS dataset. The average age of price spells is 3 quarters in the NS dataset and 2.5 quarters in the BK dataset. While we use the NS distribution throughout this paper, using the BK distribution does not change our results. The share of flexible prices in the BK dataset is slightly lower at 33%.

Table 6: **Other Parameters**

Parameters	Values	Parameters	Values
β	0.99	ϵ	10
σ	3	$1/\varphi$	0.5
ψ	8.5	χ	0.65
$\bar{\pi}$	2.5% (annual)	ρ_r	0.5
r_π	1.5	r_y	0.2
ρ_a	0.9	σ_a^2	0.0025
ρ_σ	0.79	σ_σ^2	0.038

Note: *This table provides calibrated values for structural parameters which are similar across sectors.*

Table 6 reports values for the rest of the parameters, which are common in the literature. We calibrate trend inflation ($\bar{\pi}$) to 2.5% which is the average inflation rate over the last three decades. The value of the persistence parameter of productivity shock (ρ_a) equals 0.9, whereas its standard deviation (σ_a) equals 0.05. Values for parameters governing the uncertainty shock process, ρ_σ and σ_σ, are 0.79 and 0.038, respectively.

5 Results

Given the second-moment nature of uncertainty shocks, we employ a third-order Taylor approximation of the equilibrium conditions around the steady-state when solving the model. In this section, we perform model simulations and analyse the impulse responses to an uncertainty shock relative to the stochastic steady-state. We first focus on examining the discrepancies in the response of aggregate variables between the Calvo and MC models, as shown in Figure 7.

In the MC model, we observe that inflation declines in response to an increase in uncertainty, while in the Calvo model, inflation increases. The inflation response in the MC model is consistent with the empirical literature and the empirical findings we have reported. These results clearly demonstrate how incorporating micro-evidence on prices into an otherwise standard New Keynesian model can significantly alter its predictions. To gain further insight into the differences in responses, it is helpful to consider sectoral inflation responses within the MC model, which are presented in Figure 8.

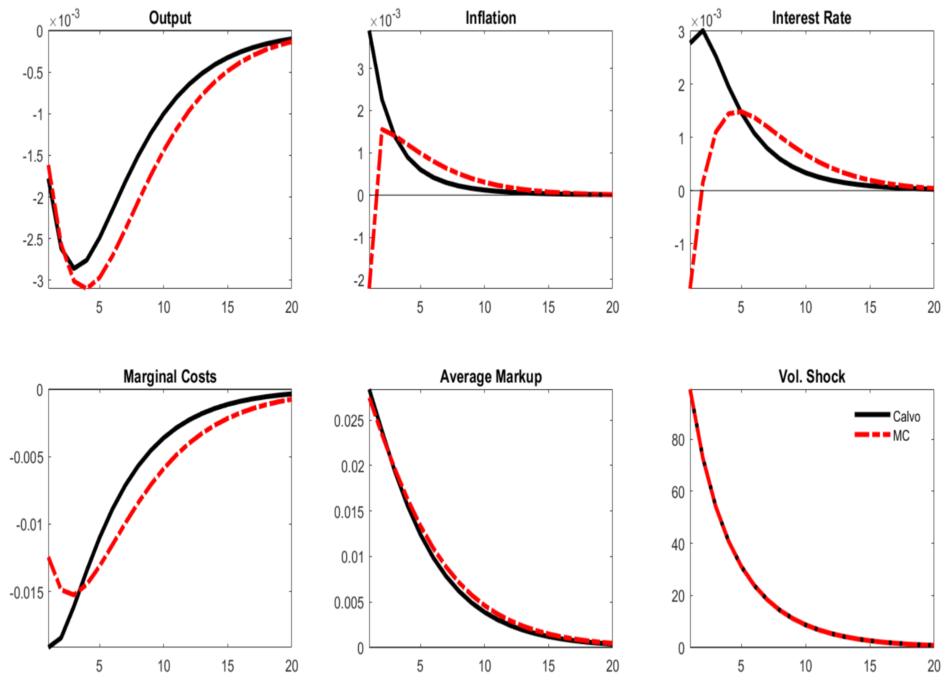
As depicted in Figure 8, there exists heterogeneity in the inflation responses across sectors. Inflation decreases in the flexible-price sector, while it increases in the sticky-price sector. This pattern is consistent with the empirical evidence discussed in section 2. What can explain this disparity in inflation responses across sectors? The answer lies in differences in markups.

The discrepancy in inflation responses can be attributed to variations in markups. Specifically, the increase in inflation observed in the sticky-price sector can be linked to a disproportionate rise in markups within that sector. This finding suggests that changes in markups play a crucial role in shaping the differential inflation dynamics across sectors.

Figure 8 also illustrates the response of marginal markups to an increase in uncertainty across sectors. As shown in the figure, markups in the sticky-price sector exhibit an increase that is more than twice as large as the increase observed in the flexible-price sector. Consequently, despite facing a similar decline in marginal costs, the two sectors display contrasting inflation responses.

The reason behind this difference lies in how firms with longer-term contracts handle uncertainty. In the face of potential future inflation, firms with sticky prices may find themselves locked into lower prices for an extended period. This situation can lead to reduced profits. To avoid this scenario, firms with longer-term contracts opt to set higher prices

Figure 7: **Impulse responses to an uncertainty shock in Calvo and MC models**

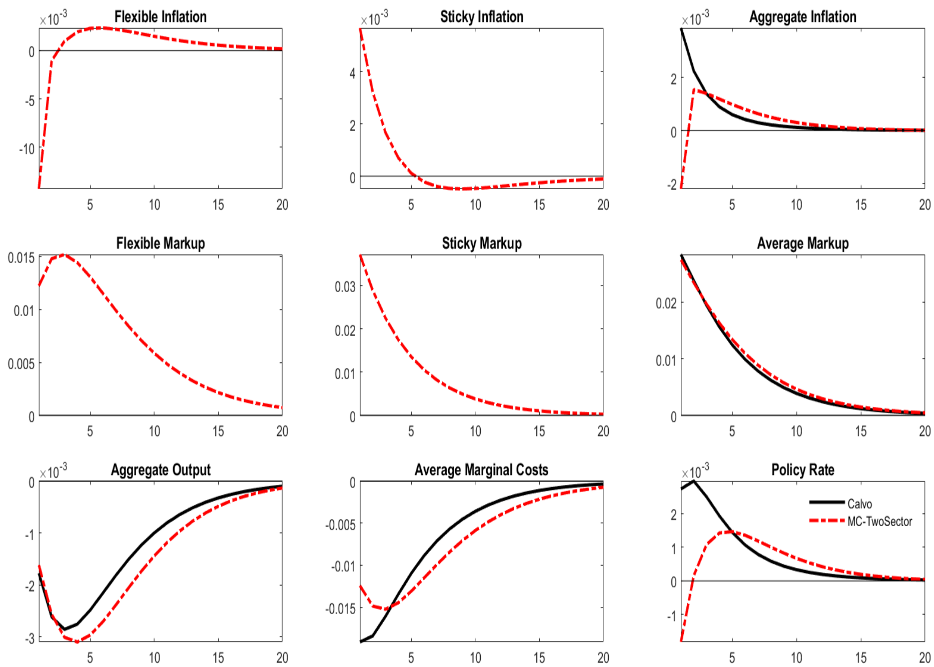


Notes: The figure plots impulse responses to a 100% increase in uncertainty. The black line represents responses from the Calvo model. The dashed red line represents responses from the multi-calvo model. The IRFs for inflation and interest rate are plotted in terms of percentage points whereas for all other variables, these are in terms of percentage deviation from the steady-state.

now, thereby increasing their markups. The introduction of economic uncertainty creates a strategic complementarity where the anticipation of higher future inflation prompts firms in the sticky-price sectors to raise prices. This decision, in turn, contributes to an increase in markups and profits.

Moving on to examine the impulse response functions (IRFs) of other variables, we observe that output declines in response to an increase in uncertainty. This is due to

Figure 8: **Sectoral Inflation: IRFs to an uncertainty shock**



Notes: The black-solid line plots responses from the standard Calvo model. The red-dash line plots responses from the two sector version of the multi Calvo model. The figure includes responses for both sectoral inflation and markups, and aggregate variables.

households' precautionary motives, which lead to a decrease in demand for consumption goods, resulting in reduced consumption and output. The decline in output leads to a drop in marginal costs in both the MC and Calvo models.

Interestingly, the initial impact of the shock on marginal costs is smaller in the MC model compared to the Calvo model. However, in the later stages of the adjustment process, marginal costs are relatively lower in the MC model. This can be explained by the dynamics of different sectors. Firms with sticky prices put downward pressure on marginal costs as they raise their prices in response to the shock, while those with flexible prices put upward pressure as they lower their prices. The increase in prices in sticky-price sectors has a contractionary effect on output and, subsequently, on marginal costs. On the other hand, the decrease in prices in the flexible-price sector has a positive effect on marginal costs, as demand for factor inputs is higher in this sector. Since prices in the flexible-price sector respond more to the shock initially, they play a more significant role than sticky prices, resulting in a smaller initial decline in marginal costs in the MC model. However, as time passes and firms with flexible prices have adjusted their prices, the adjustment process is dominated by sticky-price firms. As a result, in the later period, marginal costs become relatively lower in the MC model compared to the Calvo model.

Considering the behaviour of the nominal interest rate, which is set by the central bank following a Taylor-type rule, its response reflects the behaviour of inflation in each model. In the MC model, the nominal interest rate decreases as both inflation and output decline in response to the shock. Conversely, in the Calvo model, the increased uncertainty leads to an initial increase in inflation, causing the nominal interest rate to rise before gradually returning to its steady-state value.

6 Full model: 10 sectors with production networks

To add more realism, we now increase the number of sectors to ten and further include production networks as in Acemoglu et al. (2012) and Carvalho (2014 and 2018). To model production networks, we assume a production function of the form:

$$Y_{it}(f) = \Big[A_t N_{it}(f)\Big]^{1-\mu} \Big[M_{it}(f)\Big]^{\mu} \tag{15}$$

where μ is the output elasticity of intermediate inputs and M_{it} denotes the CES aggregate of sector-specific intermediate inputs that is used by firms in sector i to produce gross output, $Y_{it}(f)$. We denote the share of intermediate input from sector m used by firm f in sector i as α_{im}. With these assumptions, M_{it} can be expressed as:

$$M_{it} = \left[\sum_{m=1}^{N} \alpha_{im}^{\frac{1}{\theta}} Y_{mt}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{1-\theta}} \tag{16}$$

Under the assumption that $\theta = 1$, firms' cost minimisation problem gives the following expression for marginal costs in sector i:

$$MC_{it} = \hat{\mu} \left(\frac{W_{it}}{A_t} \right)^{1-\mu} {P_{It}}^{\mu} \tag{17}$$

where $P_{It} = \prod_{m=1}^{N} {P_{mt}}^{\alpha_{im}}$ is the input price index specific to sector i, P_{mt} is the sector-specific price index, and $\hat{\mu} = \mu^{-\mu}(1-\mu)^{-(1-\mu)} \prod_{m=1}^{N} \left(\frac{1}{\alpha_{im}}\right)^{\alpha_{im}\mu}$. To facilitate explanation, the log-linearised version of equation (17) is:

$$\hat{MC}_{it} = (1-\mu)(\hat{W}_{it} - \hat{P}_t - a_t) + \mu(\hat{P}_{It} - \hat{P}_t) + P_t \tag{18}$$

where P_t is the aggregate price index.

The production network can influence firms' pricing decisions through both having a *direct* and *indirect effect* on firms' marginal costs. As long as $\alpha_{im} \neq \alpha_m$, an increase in sector $m's$ price will have a *direct effect* on sector $i's$ marginal costs. α_m is the share of sector m in households' consumption basket. When $\alpha_{im} > \alpha_m$, an increase in sector $m's$ price will increase sector $i's$ marginal costs. In contrast, when $\alpha_{im} < \alpha_m$, the effect is opposite. This is due to the wedge between $\hat{P}_{It}$ and $\hat{P}_t$ seen in equation 18.

In our context, firms for which the share of flexible sectors in the corresponding input-price index outweighs the share of these in the consumption basket, the *direct effect* will result in a drop in their marginal costs. This is because the flexible sector firms decrease their prices in response to an uncertainty shock. In contrast, firms for which the sticky sectors are relatively more important than implied by the consumption basket, the *direct effect* will result in an increase in marginal costs.

The *indirect effect* comes from the effect of input prices on wages. After some straightforward algebra, the log linearised expression for the nominal wage in sector i is:

$$\hat{W}_{it} = \frac{1}{1+\varphi\mu}\left[\varphi\hat{y}_{it} + \sigma\hat{c}_t - \varphi(1-\mu)a_t + \varphi\mu(\hat{P}_{It} - \hat{P}_t)\right] + \hat{P}_t \qquad (19)$$

Equation 19 shows that the wedge between the input price index and the aggregate price index, $\hat{P}_{It} - \hat{P}_t$, also has an effect on the nominal wage. This is due the substitution between labour and intermediate inputs. For example, when the wedge is positive, firms in such a sector substitute intermediate inputs for labour thus causing wages to increase. Moreover, the existence of production networks also dampens the effect of sectoral output, aggregate consumption, and productivity shock on wages.

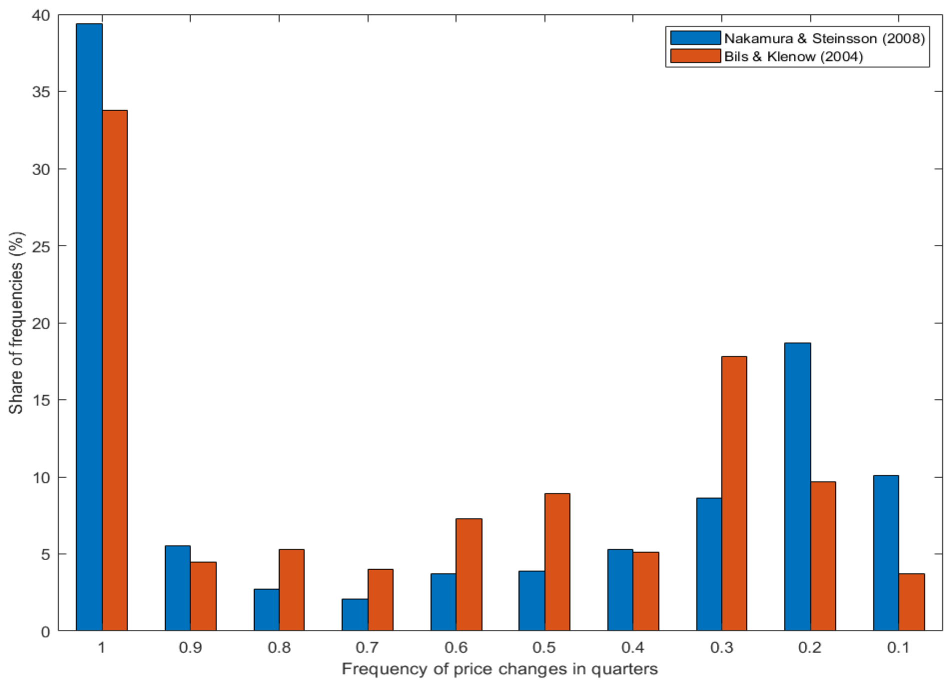
6.1 Calibration

We use Nakamura & Steinsson dataset and the BEA Input-Output tables to calibrated the model. First, we aggregate the 272 product categories in Nakamura & Steinsson dataset into 10 groups with distinct price reset probabilities. The aggregation is performed by forming probability focal points in increments of 0.1 percentage points [thus: 0.1; 0.2; 0.3 ... 1]. We then round the reset probabilities to 0.1 percentage points and allocate the 272 product categories to these 10 focal points. The groups are scaled by the share that is allocated to each focal point. We use this information to calibrate a 10-sector model. The distribution of the frequency of price change in each sector i and the corresponding shares is plotted in Figure 9.

Second, we use 2007 input-output tables provided by the BEA to calibrate parameters governing the network structure, α_{im}. In absense of information on the mapping between NAICS industries in the input-output tables and the ELI categories underlying CPI data, we map individual NAICS industries to each of the 10 sectors as closely as possible.[8] The resulting calibration is reported in table 7.

[8] The challenge is to map 405 NAICS industries to 272 ELI categories in absense of official correspondance tables between NAICS and ELI. It is not always straightforward to map individual NAICS industries to each of the 10 sectors when different sectors include ELI categories which seemingly belong to similar industry clusters. When this is the case, we include NAICS industries to the sector which includes most ELI items of similar types.

Figure 9: **Distribution of Price Changes**



Notes: The figure plots the distribution of price changes. The horizontal axis represents sectors, each with a fixed average frequency of price change. The vertical axis represents the share of each sector in the consumption basket. The distribution based on Bils & Klenow (2004) is taken from Kara (2015).

Table 7: **Parameters for Production Networks**

α_{11}	0.542	α_{12}	0.014	α_{13}	0.002	α_{14}	0.046	α_{15}	0.104	α_{16}	0.024	α_{17}	0.037	α_{18}	0.100	α_{19}	0.105	α_{110}	0.025
α_{21}	0.305	α_{22}	0.127	α_{23}	0.002	α_{24}	0.038	α_{25}	0.080	α_{26}	0.041	α_{27}	0.024	α_{28}	0.180	α_{29}	0.115	α_{210}	0.088
α_{31}	0.457	α_{32}	0.032	α_{33}	0.037	α_{34}	0.066	α_{35}	0.085	α_{36}	0.025	α_{37}	0.040	α_{38}	0.127	α_{39}	0.102	α_{310}	0.029
α_{41}	0.263	α_{42}	0.010	α_{43}	0.001	α_{44}	0.120	α_{45}	0.071	α_{46}	0.024	α_{47}	0.102	α_{48}	0.204	α_{49}	0.170	α_{410}	0.035
α_{51}	0.225	α_{52}	0.017	α_{53}	0.002	α_{54}	0.024	α_{55}	0.270	α_{56}	0.015	α_{57}	0.025	α_{58}	0.154	α_{59}	0.217	α_{510}	0.051
α_{61}	0.315	α_{62}	0.018	α_{63}	0.003	α_{64}	0.024	α_{65}	0.089	α_{66}	0.138	α_{67}	0.023	α_{68}	0.154	α_{69}	0.179	α_{610}	0.056
α_{71}	0.334	α_{72}	0.017	α_{73}	0.006	α_{74}	0.049	α_{75}	0.097	α_{76}	0.022	α_{77}	0.126	α_{78}	0.142	α_{79}	0.153	α_{710}	0.053
α_{81}	0.243	α_{82}	0.031	α_{83}	0.011	α_{84}	0.030	α_{85}	0.109	α_{86}	0.033	α_{87}	0.050	α_{88}	0.263	α_{89}	0.173	α_{810}	0.057
α_{91}	0.172	α_{92}	0.016	α_{93}	0.002	α_{94}	0.019	α_{95}	0.157	α_{96}	0.034	α_{97}	0.040	α_{98}	0.151	α_{99}	0.290	α_{910}	0.118
α_{101}	0.195	α_{102}	0.015	α_{103}	0.002	α_{104}	0.020	α_{105}	0.135	α_{106}	0.034	α_{107}	0.051	α_{108}	0.144	α_{109}	0.207	α_{1010}	0.196

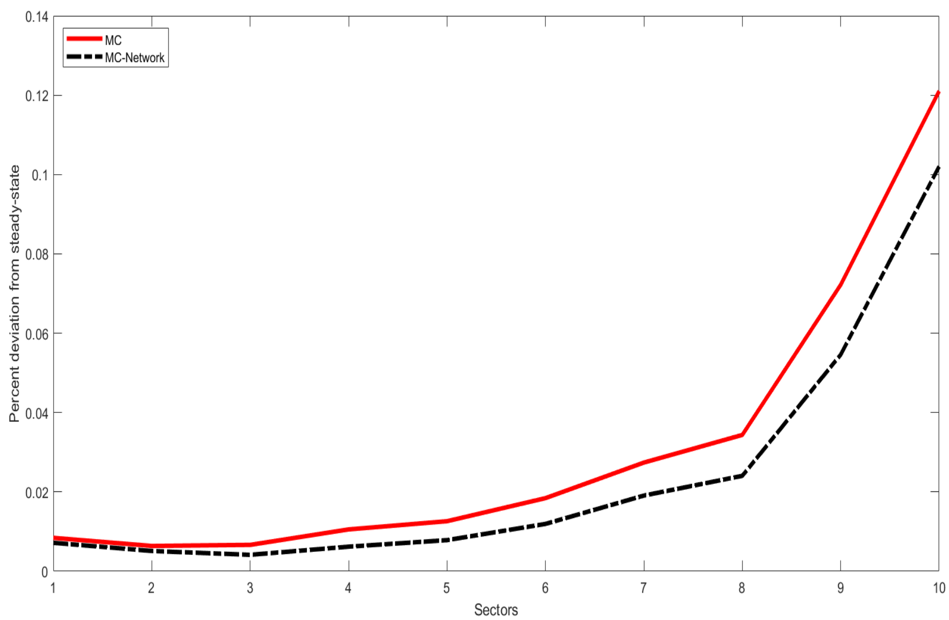
Note: *This table provides calibrated values for parameters defining production networks.*

6.2 Results

Figure 10 plots the increase in markups on impact of the shock across all sectors in our model economy. Several things stand out. First, markups increase by more as we move from sectors with flexible prices to sectors with sticky prices (i.e. left to right). Second, incorporating production networks results in slighly lower markups. The difference is greater for sticky-price sectors than for flexible-price sectors.

The relatively smaller increase in markups in the presence of production networks is due to the difference in how the wedge between input-price index and aggregate price

Figure 10: **Impact Price Markups across sectors with and without Production Networks**

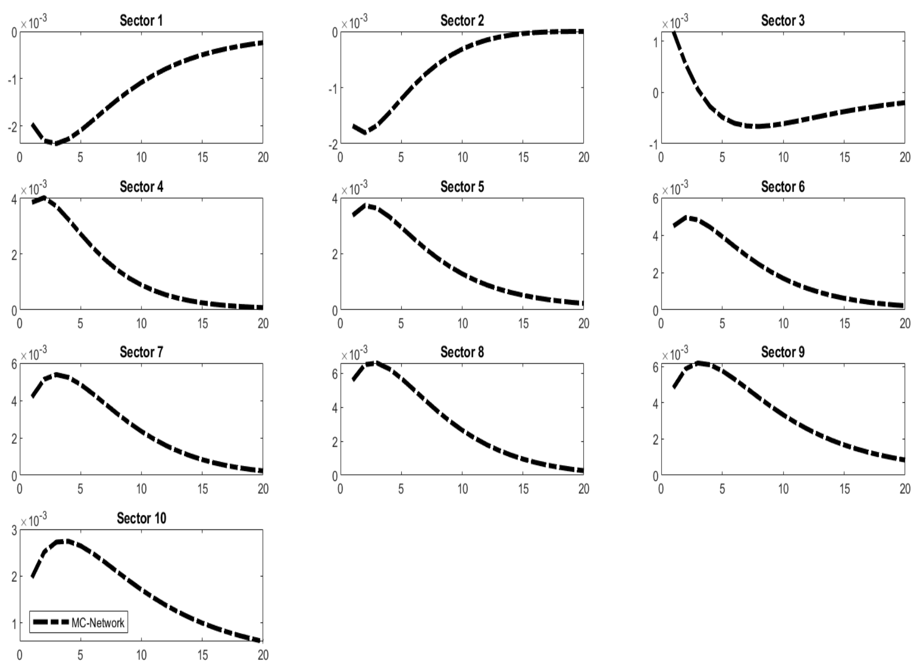


Notes: The figure plots the increase in average marginal markup across sectors on impact of the shock. The solid red line are the impact responses from the MC model, whereas the dash-black line are the impact-responses from the MC model with production networks. These are in terms of percentage deviation from the stochastic steady-state.

index responds to the shock. This affects firms' marginal costs differently across sectors (see equation 18). Figure 11 shows that, for our network structure, the wedge increases in the sticky sectors, thus causing marginal costs to decrease by less compared to the case with no production networks. This results in lower markups in sticky-price sectors.

Finally, we consider how aggregate variables respond in our ten-sector model with production networks. Figure 12 plots impulse responses for aggregate variables. Aggregate inflation continues to fall on impact, followed by an overshooting. Nonetheless, the mag-

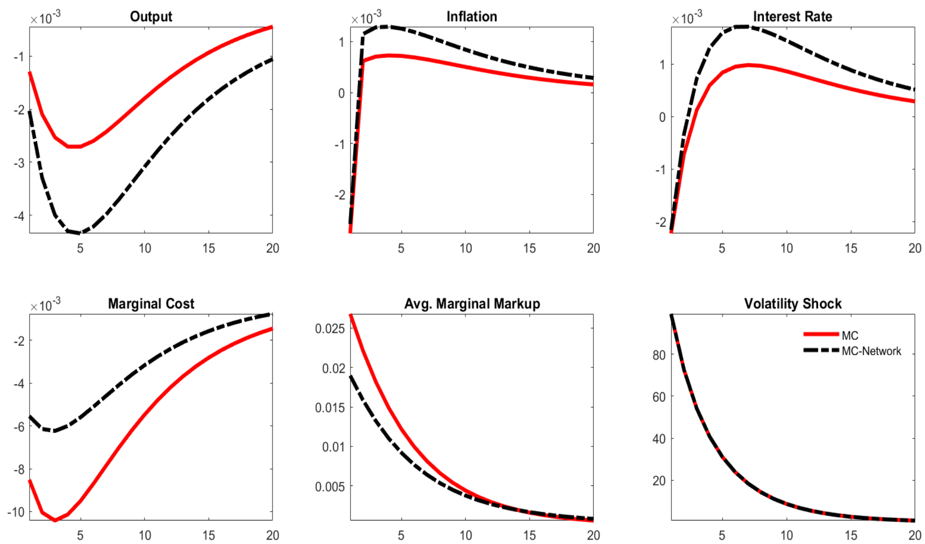
Figure 11: **IRFs: Wedge between Input-Price Index and Aggregate Price Index**



Notes: The figure plots impulse responses for input-price wedge across sectors to a 100% increase in uncertainty (see equation 18). The IRFs are in terms of percentage deviation from the stochastic steady-state.

initude of overshooting is considerably less compared to the two-sector model in section 5. There are also other important differences. In the model with production networks, average marginal costs fall by less. This is despite the relatively bigger drop in real wages (not reported). The reason for relatively higher average marginal costs is the increase in input-price wedge in the sticky-price sectors explained above. This also results in output decreasing by considerably more in the model with production networks.

Figure 12: **Impulse responses to an uncertainty shock in the presence of production networks**



Notes: The figure plots impulse responses to a 100% increase in uncertainty. The solid red line represent responses from the model without production networks but with heterogeneity in degree of price rigidities under Calvo pricing. The dash black line respresents responses from the model with production networks under Calvo pricing, respectively. The IRFs for inflation and interest rate are plotted in terms of percentage points whereas for all other variables these are in terms of percentage deviation from the stochastic steady-state.

7 Sensitivity Analysis

In this section, we consider the two-sector model from section 5 and show that the qualitative response of aggregate inflation and inflation in the flexible and sticky sector is robust to changes in the structure of the economy. In what follows we consider how results change when we allow for a more persistent uncertainty shock, a central bank which does not allow for interest rate smoothing or cares more about stabilising output, and a low Frisch elasticity of labour supply.

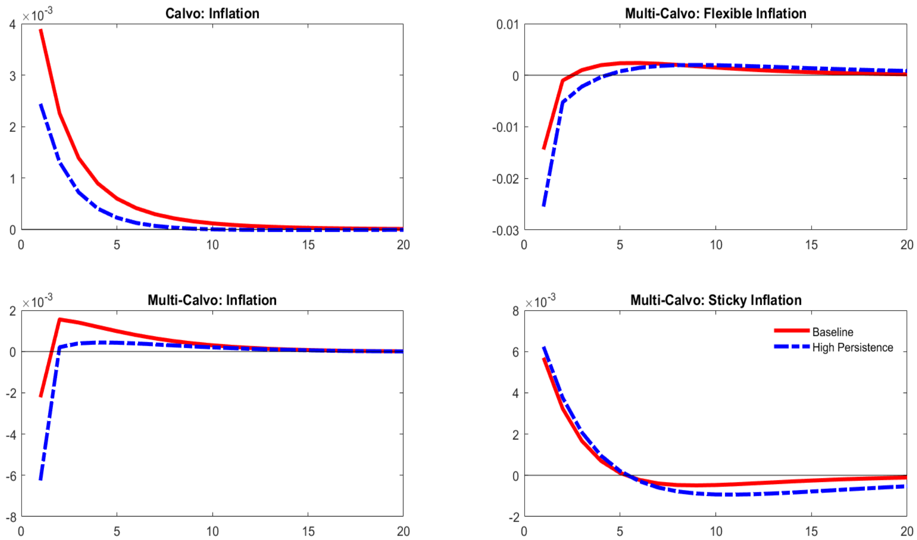
7.1 The shock process

Figure 13 plots the impulse response for inflation and sectoral inflation both under baseline calibration and also when the uncertainty shock process is highly persistent, $\rho_\sigma = 0.9$. While inflation increases by less, a persistent shock process still leads to an increase in inflation in the Calvo model. In contrast, in the multi-calvo model, aggregate inflation falls by significantly more. Moreover, unlike under baseline calibration, the strength of overshooting decreases considerably.

The response of sectoral inflation in the multi-calvo model remains qualitatively similar. However, the magnitude of response for flexible sector inflation is almost twice as much. The greater decline in flexible sector inflation also explains why aggregate inflation falls by significantly more in the multi-Calvo model.

The increase in persistence of the shock process results in firms' setting even higher markups when setting their prices. However, this also results in output falling my more. Together with the increase in precautionary savings on part of the households, the decrease in output is significant such that inflation in the flexible sector falls by considerably more despite the increase in markups.

Figure 13: **Inflation response when the uncertainty shock is persistent**



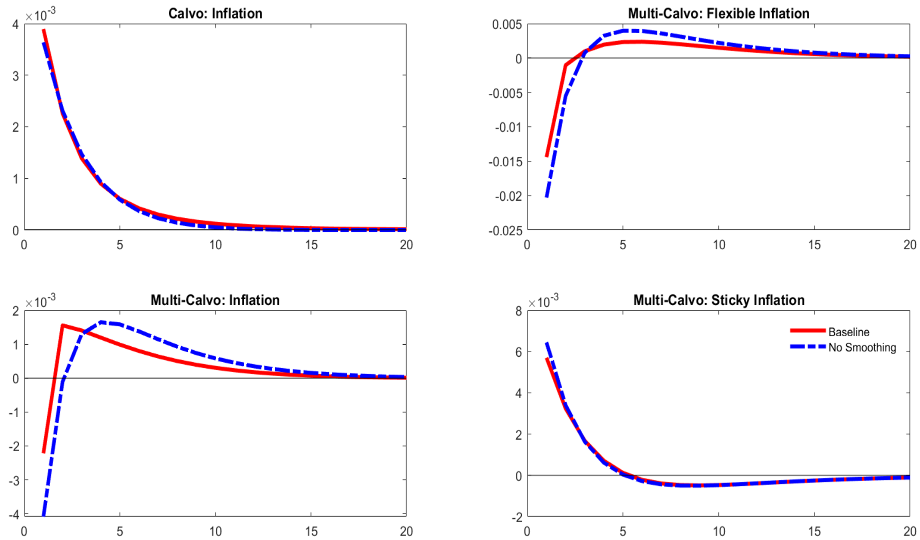
Notes: The figure plots impulse response for inflation to a 100% increase in uncertainty. The first column plots responses for aggregate inflation from the Calvo and the Multi-Calvo model, whereas the second column plots responses for sectoral inflation from the Multi-Calvo model. The red-solid line plots responses under baseline calibration. The blue-dash line plots responses when the uncertainty shock is highly persistent, $\rho_\sigma = 0.9$.

7.2 Policy rule

How policymakers respond to the shock also has important implications for firms price-setting behaviour in the model. Figure 14 plots the response of inflation both under the baseline calibration and also when there is no interest-rate smoothing i.e. $\rho_r = 0$. The results are qualitatively comparable to those when the uncertainty shock is more persistent in the case of multi-Calvo model. The absence of interest-rate smoothing amplifies the disinflationary effect of uncertainty shock. However, the response of aggregate inflation remains almost similar in the Calvo model.

Finally, we also consider what happens when the central bank cares more about stabil-

Figure 14: **Inflation response in absence of interest-rate smoothing**



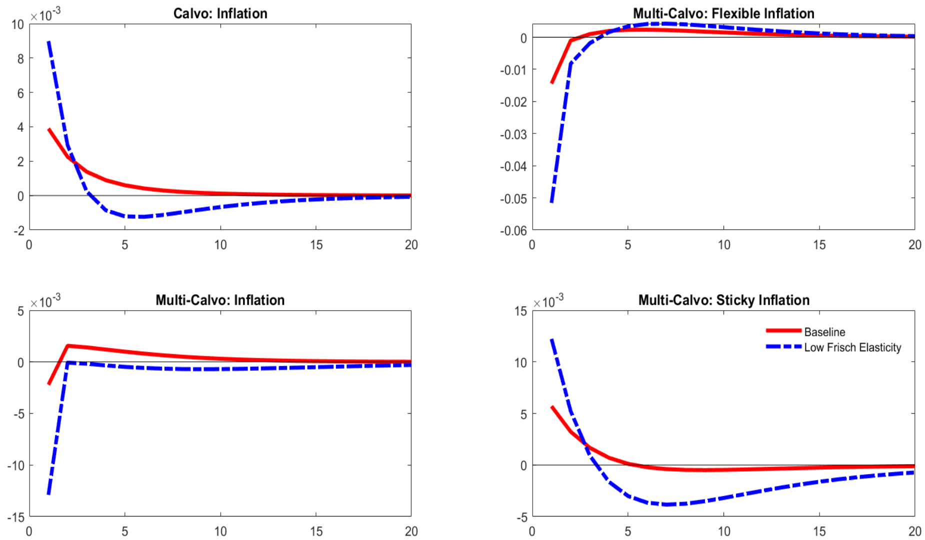
Notes: The figure plots impulse response for inflation to a 100% increase in uncertainty. The first column plots responses for aggregate inflation from the Calvo and the Multi-Calvo model, whereas the second column plots responses for sectoral inflation from the Multi-Calvo model. The red-solid line plots responses under baseline calibration. The blue-dash line plots responses when there is no interest rate smoothing, $\rho_r = 0$.

ising output than under benchmark calibration i.e. we increase r_y from 0.2 to 0.75. While the results do not change qualitatively, inflation increases more in the standard model. In the case of the multi-Calvo model, inflation falls less on impact before overshooting soon after.

7.3 Frisch elasticity

A lower Frisch elasticity of labour supply also plays an important role in how firms respond to uncertainty shocks. Figure 15 plots inflation responses under baseline calibration and when Frisch elasticity of labour supply is calibrated at a lower value of 0.2. While,

Figure 15: **Inflation response under low Frisch elasticity**



Notes: The figure plots impulse response for inflation to a 100% increase in uncertainty. The first column plots responses for aggregate inflation from the Calvo and the Multi-Calvo model, whereas the second column plots responses for sectoral inflation from the Multi-Calvo model. The red-solid line plots responses under baseline calibration. The blue-dash line plots responses when Frisch elasticity of labour supply is calibrated at 0.2, instead of 0.5 in the baseline case.

in the Calvo model, inflation increases by even more on the impact of the shock, it moves below its trend level after a few periods. In contrast, a lower value for Frisch elasticity implies that inflation falls several times more in the model incorporating heterogeneity in firms' price-setting behaviour even on the impact of the shock.

8 Conclusions

This paper has focussed on understanding how firms respond to increasing economic uncertainty. To this end, we have used micro-data on prices as well as new Keynesian models that account for the main features of the micro-data on prices. On the empirical side of the paper, we use two datasets. The first dataset is the duration-based inflation data complied by Atlanta FED. Atlanta FED uses the US CPI data and groups goods according to the frequency of price adjustment. In particular, they provide two inflation series: one for flexible prices and one for sticky prices. The second dataset is compiled by the ONS and is used to calculate UK CPI. The dataset has around 60 million price quotes.

Our main finding suggests that in the face of higher uncertainty, goods with sticky prices tend to increase while those with flexible prices tend to decrease. This implies that during the initial phase of the price adjustment process, flexible prices play a dominant role, leading to a decline in headline inflation in response to increased uncertainty. However, the observed increase in sticky-price inflation, which serves as a proxy for core inflation, indicates that uncertainty has persistent and inflationary effects on inflation.

To gain a deeper understanding of this result, we employ our duration-based multi-sector model. Our model suggests that the increase in sticky prices can be attributed to a rise in markups. When firms are confronted with higher uncertainty, they choose to raise their markups as a means to safeguard their prices during periods when they are expected to remain constant. This finding is supported by the use of data on markups compiled by Nekarda and Ramey (2020).

Finally, although Nekarda and Ramey's (2020) preferred measure of price markups provides support for the finding that markups increase in response to an increase in uncertainty, further research is needed in this field. Born and Pfeifer (2021) employ industry-level price markup data to investigate the influence of heightened uncertainty on markups. Their findings present a more pessimistic perspective on the markup channel. Notably, the price markup data based on a CES production function and production-worker compensation lend support to the channel, while those based on a Cobb-Douglas production function do not. Additionally, they utilise price markups compiled by Bils, Klenow, and Malin (2018), which are derived from the share of intermediate inputs and the KLEMS database. These data cover 60 sectors and span from 1987 to 2012 on an annual basis. The results from the BKM dataset appear to be consistent with our findings, indicating heterogeneity in price markups. Following the shock, price markups decrease, but shortly thereafter, they increase. The increase in markups in the latter phase is consistent with our results, as it corresponds to relatively sticky prices that experience an increase in markups. In light of our approach, exploring the connection between duration sectors and price markups may provide a clearer understanding of the relationship between price stickiness and price markups. This is important because, as we have discussed, there is also heterogeneity within a product sector. We leave this issue as a matter of further research.

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