Time-varying Price Flexibility and Inflation Dynamics*

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August 2019

Abstract

We study how and to what extent inflation dynamics is shaped by time variation in the capacity of nominal demand to stimulate price adjustment. Using microdata underlying the UK consumer price index, we estimate a generalized Ss model of lumpy price adjustment, and condense large cross-sectional information on micro price changes into a measure of price flexibility. The latter displays sizable time variation, which maps into a marked non-linearity of inflation dynamics: the half-life of the rate of inflation is twice as large in periods of relatively low flexibility, along with appearing remarkably close to the one observed in a linear setting. Changes in firms' price-adjustment cost structure, as reflected in the adjustment hazard, are key to account for state dependence in price setting. Neglecting these facts may severely bias our understanding of inflation dynamics.

JEL codes: E30, E31, E37, C22.

Keywords: Inflation, Price flexibility, Ss models.

*We thank for comments Yoosoon Chang, Andrea Colciago, Luca Dedola, Federico Di Pace, Huw Dixon, Etienne Gagnon, Ana Galvao, Ricardo Nunes, Giorgio Primiceri, Omar Rachedi, Federico Ravenna, Søren Hove Ravn, Yad Selvakumar, Joseph Vavra, Daniel Villar, and seminar participants at the Bank of Finland, the ESCoE/ONS/BoE Conference on Economic Measurement, the National Institute of Economic and Social Research, the University of Surrey, the European Central Bank, De Nederlandsche Bank, the University of Warwick, the University of Padua, the Monetary Policy, Term Premia, and Macro Volatility SNDE session at the 2019 ASSA meetings, and the University of Lund. We also thank Rowan Kelsoe, Richard Campbell and Gareth Clews, from the Office of National Statistics, for their advice and help with the data.

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"(...) I hope that researchers will strive to improve our understanding of inflation dynamics and its interactions with monetary policy."
Janet Yellen, October 2016

1 Introduction

Over the last decade, the increased availability of disaggregated data on consumer prices has allowed economists to study in deep detail the role of price setting for the transmission of shocks and the conduct of monetary policy. Micro price data can be usefully employed to compute measures of aggregate *price flexibility*, which is broadly intended as the response of the aggregate price level to monetary shocks. This concept lies at the core of the monetary policy transmission mechanism, ultimately embodying Central Banks' capacity to affect output and inflation. Despite a large number of empirical contributions measuring the response of prices to nominal stimulus, little emphasis has been placed on the sources and the characteristics of time variation in price flexibility.[1] Most notably, the literature has been silent on how and to which extent time-varying price flexibility maps into inflation dynamics, and whether this information can be employed in the practice of monetary-policy making. We seek to fill this gap, using price microdata underlying the UK consumer price index (CPI).

Two novel facts stand out from our preliminary data analysis: *i*) the frequency of adjustment and the dispersion of price changes display negative comovement, at conventional business cycle frequencies; *ii*) while the dispersion of price changes has denoted a sustained increase after the Great Recession, the frequency of adjustment has dropped markedly over the same time span.[2] These facts are consistent with the occurrence of exogenous shifts in firms' price-adjustment cost structure, in a standard menu cost model. As such, they point to the need of disentangling movements in the *distribution of price gaps* (i.e., the wedge between the actual and the optimal reset price) from those in the *adjustment hazard* (i.e., the probability of a good's price changing as a function of its price gap), so as to unveil the underlying protocol of price adjustment and how this reflects into inflation dynamics.

To discipline our data, we estimate the generalized Ss model developed by Caballero and Engel (2007), fitting both the hazard function and the price gap distribution over the price quotes available in each month. Along with encompassing various price-setting protocols, this empirical framework is particularly well suited to examine time variation and comovements among various price-setting statistics. The estimation reveals that both functions vary substantially over time. In particular, when looking at the post-recession experience, changes in the price-adjustment cost structure—as reflected in the adjustment hazard—appear as key drivers of movements in the dispersion of price changes and the frequency of adjustment.

[1] In this respect, Caballero and Engel (1993b) and Berger and Vavra (2017) represent notable exceptions.

[2] These features stand in contrast with the behavior of US microdata, where the cross-sectional standard deviation of price changes typically displays positive comovement with the frequency of adjustment (see, e.g., Vavra, 2014).

To dig deeper into the microeconomic dimension of price setting we revisit a key, recurring, question, through the lens of time variation in the determinants of price adjustment: to what extent does price setting behave in accordance with time-dependent models, whereby the timing of all price changes is predetermined, as opposed to state-dependent protocols, according to which the timing of price changes can itself respond to shocks? To this end, we employ the Ss model to condense large cross-sectional information on micro price changes into a measure of price flexibility. Thus, we decompose the resulting series into predetermined price adjustments—the so-called *intensive margin*—and adjustments triggered or canceled by the shock—the *extensive margin*.[3] Two main insights are offered. First, the extensive margin appears quite important, and more so after the Great Recession, in correspondence with a marked increase in inflation volatility. This reflects a downward shift in the hazard function which, according to conventional menu cost models, may be rationalized—among other things—by a rise in market power. Incidentally, our results are consistent with DeLoecker and Eeckhout (2018) and Bell and Tomlinson (2018), who show that the mark-up in the UK has displayed only a modest increase in the 1996-2007 period, while rising substantially in the last decade. Second, movements in the hazard function that are orthogonal to shifts in the price gap distribution account for a large share of the variation in aggregate price flexibility and inflation. This result underscores the importance of accounting for exogenous variation in menu costs within structural models of price setting, which have typically posed greater emphasis on the role of first- or second-moment shocks to the distribution of price gaps.

We also highlight the importance of independent movements in the hazard function—and how they affect adjustment along the extensive margin—by exploiting changes in the value-added tax (VAT). As UK posted prices include the VAT, a key advantage of examining the transmission of large first-moment shocks of this type is that they are particularly suitable to understand whether price setting works in line with the predictions of menu cost models (Karadi and Reiff, 2014). In line with Gagnon et al. (2013), massive repricing occurring in the face of a VAT shock does not emerge as a mere shift of the distribution of price gaps, but reflects a major reallocation of probability mass over the price-gap support, thus confirming the importance of tracking changes in the hazard function. Many firms seize the opportunity to adjust their prices by more than the VAT change, which implies that inflationary/deflationary pressures from other sources are released in the process. In fact, movements in the hazard function, as compared with those in the distribution of price gaps, have most of the impact on adjustments along the extensive margin and account for the bulk of the adjustment in aggregate inflation. This fact, which has not been reported before, implies that price-setting units' incentives to adjust prices may vary markedly in the face of large first-moment shocks, even if the latter are largely foreseeable, as in the case of a VAT change. Acknowledging this property may be an important avenue to inform the design of structural models.

At the macroeconomic level, time variation in the frequency of adjustment and the dispersion of micro price changes are important in that they reflect shifts in the price-setting protocol

[3] Adjustments occurring over the intensive margin characterize both time- and state-dependent models. The extensive margin, instead, is a defining feature of state-dependent models.

that have the capacity to affect aggregate price stickiness. According to our estimates, the response of aggregate inflation to a nominal shock varies substantially, increasing by about 50% between the start of the Great Recession and 2011, thus reverting and attaining its minimum in the first quarter of 2016. As a result, the pass-through of aggregate nominal shocks to inflation has decreased markedly during this period, thus reverting after the Brexit referendum. More generally, changes in price flexibility tend to occur in correspondence with sizable departures of CPI inflation from the Bank of England's institutional target. In this respect, two facts stand out when examining inflation dynamics in the post-Great Recession sample: first, inflation has been outside the 1%-3% interval for a total of 22 out of 40 quarters, while this has only occurred for 11 quarters in the previous decade; second, over the same period, inflation has shot above and below the target, reaching both its maximum (+4.8%) and minimum (-0.1%) in the overall sample. In light of this, time variation in price flexibility may help us understand why hitting the inflation target may have proven to be rather arduous over the last decade, with relatively high flexibility exacerbating the impact of inflationary shocks (e.g., movements in the exchange rate and in commodity prices) during and straight after the recession, thus reaching its minimum in correspondence with inflation hitting its historical low in 2015.

Time variation in price flexibility is extremely important to understand inflation dynamics. The half-life of the rate of inflation is twice as large in periods of relatively low flexibility, along with appearing remarkably close to the one observed in a linear setting. In light of this, we posit that neglecting that inflationary shocks are propagated at different speeds depending on the overall degree of price flexibility may lead to overstating inflation persistence. We test this implication, and show that the Bank of England and market participants do not appear to take into account changes in price flexibility when computing their inflation expectations. In fact, price flexibility accounts for roughly 22% of the variability in the forecast error, at a four-quarter horizon. This reflects the fact that forecasters fail to incorporate the faster pass-through of inflationary shocks in periods of relatively high flexibility.

Related literature Our work relates to a number of studies that have examined the connection between micro price changes and aggregate inflation.[4] The paper that connects most closely to our analysis is that of Berger and Vavra (2017), who report that price flexibility is time-varying. We build on this, and show how accounting for time variation in price flexibility may improve our understanding of inflation dynamics. In line with what expected on theoretical grounds, we document that inflation is more persistent and less volatile in periods of relatively low price flexibility, and show that neglecting this fact can lead to a large prediction bias. Moreover, we employ the accounting framework of Caballero and Engel (2007) to build counterfactual experiments that highlight the prominence of state-dependent price setting, as well as the distinctive role of the adjustment hazard in the occurrence of large first-moment

[4]See, among others, Bils and Klenow (2004), Dotsey and King (2005), Alvarez et al. (2006), Gertler and Leahy (2008), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), Gagnon (2009), Costain and Nakov (2011), Midrigan (2011), Nakamura et al. (2011), Alvarez and Lippi (2014), Karadi and Reiff (2014), Berardi et al. (2015), Alvarez et al. (2016), Nakamura et al. (2018).

shocks. In this respect, we also connect to Luo and Villar (2017b) in that we highlight the importance of the aggregate hazard function for understanding aggregate inflation dynamics. Compared with them, however, we emphasize the need of allowing for time variation. In fact, movements in firms' incentives to price adjustment are shown to be prominent (see also Hobijn et al., 2006).

Our work also relates to a number of papers that devise and estimate specific structural models that connect movements in the distribution of price changes to price flexibility (see, e.g., Midrigan, 2011, Alvarez et al., 2016 and Vavra, 2014, among others). An empirical limitation of these models is to rely on specific shocks to the price-setting units, while the approach we follow is more agnostic. This represents a strategic advantage, and more so in the analysis of UK microdata, where the pattern of time variation in the distribution of price changes has been somewhat discontinuous, emerging at different points in time as the result of a different mix of first- and second-moment shocks, as well as changes in the endogenous incentives of firms to adjust their prices. We also relate to Gagnon et al. (2013) in that we focus on the distinction between price adjustments that are determined ahead of shocks, and those that are triggered or canceled by the shocks, using VAT changes to devise an event study. Compared with this paper, we employ the generalized Ss model to provide quantitative statements about the importance of both types of adjustment—examining the behavior of the distribution of price gaps in separation from that of the hazard function—and highlight important asymmetries over the two margins of price setting.

Some broad connection can be traced between our study and recent empirical contributions employing individual consumer prices from the UK. In this respect, Bunn and Ellis (2012) have been among the first to investigate the key characteristics of the frequency of price setting and the hazard functions implied by the microdata from the Office for National Statistics (ONS), while Dixon et al. (2014) have focused on the impact of the Great Recession on price setting. As compared with these papers, we place particular emphasis on state dependence in inflation dynamics, as well as on its role for the transmission of nominal demand shocks. Moreover, our application underlines the importance of the selection effect for aggregate inflation (see, on this, Carvalho and Kryvtsov, 2018 and references therein). Specifically, we highlight the versatility of the empirical approach of Caballero and Engel (2007), and show how this can be used to map price flexibility into changes in inflation persistence and volatility. Employing UK data, Chu et al. (2018) emphasize that information on the distribution of price changes can be exploited to forecast inflation. Our results are in line with this finding. In fact, we show that price flexibility—which condenses valuable information from key micro price statistics—contains valuable information for predicting inflation persistence.

With respect to the existing literature, we unveil three key results that have crucial implications for both modelling price-setting frictions and the practice of monetary policy: *i*) time-varying price flexibility is mostly driven by variation in the adjustment hazard, for a given price gap; *ii*) inflation is sensibly more volatile and less persistent in periods of relatively high price flexibility; *iii*) a sizable fraction of professional forecasters' prediction error is explained by time variation in the index of price flexibility, especially at medium-term forecast horizons.

Structure The rest of the paper is organized as follows. Section 2 discusses the key characteristics of the ONS microdata on consumer prices. Section 3 reviews a standard menu cost model we use to frame our empirical analysis. Section 4 reports the generalized Ss model and takes it to the data. Section 5 assesses time variation in price flexibility and discusses the relative contribution of adjustments along the intensive and the extensive margin. Section 6 discusses the implications of state dependence in price flexibility for inflation dynamics. Section 7 concludes.

2 Microdata on consumer prices

We use ONS microdata underpinning the UK CPI. Prices are collected on a monthly basis, for more than $1,100$ categories of goods and services, and published with a month lag. Our sample covers the 1996:M2-2017:M8 time window, thus resulting into about 27.5 million observations (see Table 1). Each month around $106,000$ prices are collected by a market research firm on behalf of the ONS. There are also about 140 items for which the corresponding price quotes are centrally collected. These are excluded from the publicly available dataset, as the structure of their market segment theoretically allows the identification of some price setters, or because of the need to frequently adjust for quality changes.[5] Price quotes are recorded on or around the second or third Tuesday of the month, with the exact date being kept secret to avoid abnormal prices that, among other things, may be due to the collection of prices during bank-holiday weeks, or to price manipulations by service providers and retailers. Furthermore, to make sure the collected price quotes are valid prices, the ONS has set various checks in place, both at the collection point and at later stages in the process. As a preliminary step in handling the dataset, we only employ price quotes that have been marked as being validated by the system or accepted by the ONS. Thus, any price quote that has been marked as missing, non-comparable, or temporarily out of stock is excluded from the sample. We refer to the remaining subset of prices—which make for approximately 60% of those included in the CPI—as *Classification Of Individual COnsumption by Purpose* (COICOP) price quotes.

Each price quote is classified by region, location, outlet and item. The region refers to the geographical entity within the UK from which a given price quote is recorded. The location is intended as a shopping district within a given region: on price-collection days, 146 different locations are visited.[6] For a given location, the shop code is a unique but anonymized *id* associated with the outlet from which the quote is recorded. In turn, each shop is classified

[5] This is typically the case for personal computers, whose frequent model upgrades impose the use of hedonic regressions, so as to enhance comparisons across time.

[6] Until August 1996, 180 different locations were being sampled. New locations are chosen every year, with about 20% of them being replaced. As a result, a location is expected to survive an average of about four years in the sample.

Table 1: SUMMARY STATISTICS

	Categories			
	COICOP	Unique	History	Regular
Price Quotes				
Total	27,479,532	27,314,761	23,258,171	19,954,005
Avg. per Month	106,099	105,462	89,800	77,042
Price Trajectories	4,333,302	4,314,903	3,196,697	2,880,332
Avg. CPI Weight	60.73%	60.37%	52.22%	46.48%
Sales and Recoveries				
Avg. per Month (Unweighted)	9.07%	9.10%	8.84%	
Avg. per Month (Weighted)	7.46%	7.49%	7.15%	
Product Substitutions				
Avg. per Month (Unweighted)	6.67%	6.67%	5.30%	
Avg. per Month (Weighted)	5.04%	5.05%	3.91%	

Notes: *COICOP* stands for the *Classification Of Individual COnsumption by Purpose* price quotes used to calculate the CPI index; *Unique* indicates the COICOP price quotes for which we uniquely identify a price trajectory; *History* refers to the subset of price quotes in the Unique category for which we can identify at least two consecutive price quotes; *Regular* refers to the price quotes in the History category that do not correspond to sales, product substitutions, or recovery prices. For each of these categories, we compute the total number of price trajectories, the weighted contribution of each category's price quotes to the CPI index, as well as the relative number of price quotes corresponding to sales, recovery prices, and product substitutions. Whenever weighted, these statistics are obtained by accounting for CPI, item-specific, stratum and shop (i.e., elementary aggregate) weights. Sample period: 1996:M2-2017:M8.

according to whether it is independent (i.e., part of a group comprising less than 10 outlets at the national level) or part of a chain (i.e., more than 10 outlets). Due to a confidentiality agreement between the ONS and the individual shops, for each price quote only the region, outlet and item classifications are published. In light of this, some of the price quotes may not be uniquely identified. This is typically the case when the ONS samples the same item, in the same outlet, but for multiple locations within the same region. As an example, in March 2013 we pick an item with the following characteristics: 'Women's Long Sleeves Top' (*id*: 510223) sold in multiple outlets (*shop type*: 1) within the region of London (*region*: 2). With these coordinates at hand we retrieve two different price quotes: one location sells the item for £22, and one for £26. In February 2013 the price quotes for the same type of good were recorded at £25 and £26, respectively. The price quotes are so close that telling the two price trajectories apart may be challenging. To make sure that price trajectories can be uniquely identified, we look at 'base prices', which are intended as the January's price for each of the items under scrutiny.[7] Given this information, the price trajectories can be identified. Even after conditioning on base prices, though, a small portion of price trajectories are still not uniquely identified (about 0.1%, on average): we opt for discarding them. In Table 1 the column labeled 'History' refers to the price quotes with an identifiable history that spans at

[7]The base price is typically relied upon to normalize price quotes and calculate price indices, or to adjust for changes in the quality and/or quantity of a given good.

least two consecutive periods. Following the criteria outlined above, we drop about 12,000 quotes per month.[8,9]

To aggregate the individual price quotes into a single price, we also make use of the following weights produced by the ONS:[10] the *shop* weights, which are employed to account for the fact that a single item's price is the same in different shops of the same chain (e.g., a pint of milk at a Tesco store);[11] the *stratification* weights, which reflect the fact that purchasing patterns may differ markedly by region or type of outlet;[12] finally, the *item* and *COICOP* weights reflect consumers' expenditure shares in the national accounts.

2.1 Variable definition

After deriving our price quotes in line with the criteria set out above, it is important to make a distinction between regular and temporary price changes such as sales, which tend to behave significantly differently from that of regular prices (see Eichenbaum et al., 2011 and Kehoe and Midrigan, 2015). To this end, we first exclude all the price quotes to which the ONS attaches a sales indicator.[13] As a second step, we implement a symmetric V-shaped filter, as defined by Nakamura and Steinsson (2010b), for the remaining price quotes. According to the filter, the sale price of item i at time t, $P^s_{i,t}$, is identified as follows: i) it is lower than last period's price (i.e., $P^s_{i,t} < P_{i,t-1}$) and ii) the next period's price is equal to last period's price (i.e., $P_{i,t+1} = P_{i,t-1}$). A recovery price $P^r_{i,t}$, instead, meets the following criteria: i) it is greater than last period's price (i.e., $P^r_{i,t} > P_{i,t-1}$) and ii) it is such that $P^r_{i,t} = P_{i,t-2}$. Once a price quote has been identified as being a sale or a recovery price, we discard it from the sample.[14]

Item substitutions are a further reason of concern when trying to identify price trajectories, as they require a certain degree of judgment to establish what portion of a price change is due to quality adjustment, and which component reflects a pure price adjustment. Product substitutions occur whenever an item in the sample has been discontinued from its outlet,

[8] Due to a particularly low coverage, Housing, Water, Electricity, Gas and Other Fuels (COICOP 4) and Education (COICOP 10) are excluded from the sample. We also exclude price changes larger than 300%, which we deem to be due to measurement errors. These take place rarely ($< 0.01\%$). Appendix A provides additional details on the construction of the dataset.

[9] The total number of available price quotes denotes a weak downward trend. However, it is important to stress that the composition in terms of categories accounted for by Table 1 is roughly stable over time. This implies the presence of no particular trends in the behavior of product substitutions and sales.

[10] See Chapter 7 of the ONS CPI Manual (ONS, 2014).

[11] In this case the ONS enters a single price for a pint of milk, but the weight attached to this is 'large', so as to reflect that all Tesco stores within the region have posted the same price.

[12] In this respect, four levels of sampling are considered for local price collection: locations, outlets within location, items within location-outlet section and individual product varieties. For each geographical region, locations and outlets are based on a probability-proportional-to-size systematic sampling, where size accounts for the number of employees in the retail sector (locations) and the net retail floor space (outlets).

[13] For a price to be marked as being associated with a sale, the ONS requires the latter to be available to all potential costumers—so as to exclude quantity discounts and membership deals—and that it only entails a temporary or an end-of-season price reduction. This definition excludes clearance sales of products that have reached the end of their life cycle.

[14] See also Nakamura and Steinsson (2008) and Vavra (2014). As an alternative approach, in place of the price associated with a sale, Klenow and Kryvtsov (2008) report the last regular price, until a new regular price is observed. Our results are robust to this approach.

and the ONS identifies a similar replacement item to the price going forward. Therefore, it is reasonable to expect that product turnovers are followed by price changes that either reflect uncaptured quality changes (Bils, 2009), or simply reflect a low-cost opportunity to reset prices that has nothing to do with the underlying sources of price rigidity, as argued by Nakamura and Steinsson (2008). In line with previous contributions, we interrupt a trajectory whenever it encounters a substitution flag, as indicated by the ONS (see, e.g., Berardi et al., 2015, Berger and Vavra, 2017, and Kryvtsov and Vincent, 2017).

Table 1 shows that, after these preliminary steps, we are down to a monthly average of $79,000$ price quotes. Finally, we define the price change of item i at time t as $\Delta p_{i,t} = \log\left(P_{i,t}/P_{i,t-1}\right)$.[15]

2.2 Stylized facts

This section unveils key facts about the behavior of the ONS microdata.[16] The top panels of Figure 1 report the frequency of adjustment and the average magnitude of price changes: decomposing inflation as the product of these statistics carries important information about the relationship between the distribution of price changes and inflation itself (see, e.g., Gagnon, 2009). As expected, the average price change tends to display a high degree of positive co-movement with CPI inflation, at least until the end of the Great Recession. Thus, in the last part of 2015 the two series are back moving in tandem. As for the frequency of adjustment, this tracks very closely the contraction in the rate of inflation that starts in 2012—moving well below its sample average up to that point—while only displaying a weak reversion towards the end of 2015.[17]

In the middle panels of the figure, both statistics are split to account for positive and negative price changes. Throughout the entire sample, the frequency of positive price changes is greater than that associated with negative adjustments, while the opposite broadly holds true when comparing average price changes in either direction. Focusing on the post-recession sample, we appreciate two key aspects: i) the downward trend in the frequency, as depicted in the first panel of the figure, is mostly due to the component associated with positive price changes; ii) notwithstanding that the average of positive price changes displays a weak tendency to increase, the (mirror image of the) average of negative price changes denotes a more robust upward trend.[18] Both facts point to a certain degree of asymmetry in price adjustment.

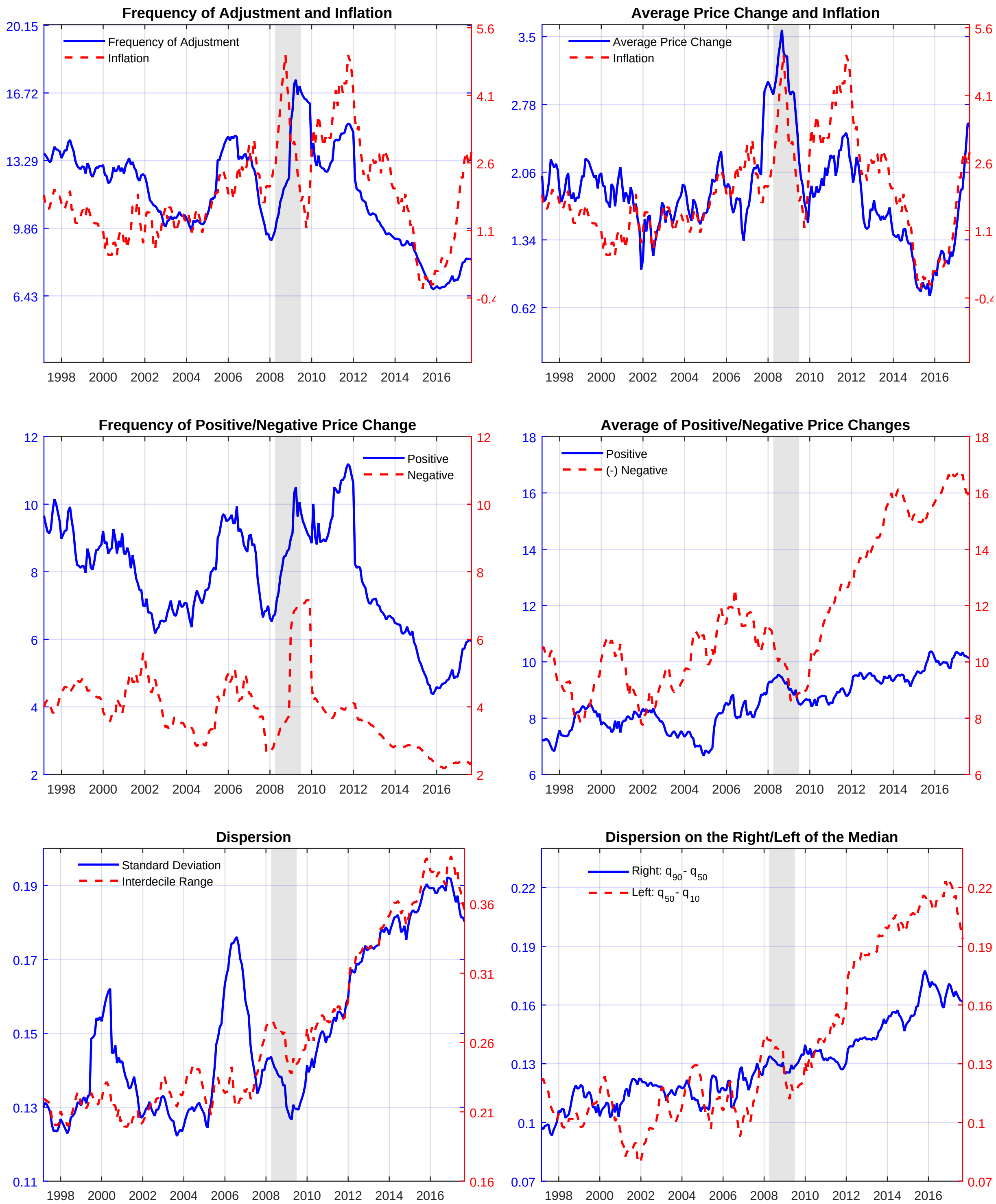
[15] We also compute price changes as $\Delta p_{i,t} = 2\frac{P_{i,t}-P_{i,t-1}}{P_{i,t}+P_{i,t-1}}$. This definition has the advantage of being bounded and less sensitive to outliers. The results—virtually unchanged with respect to the ones we report—are available from the authors, upon request.

[16] Throughout the paper all the statistics derived from microdata on prices are reported as a 12-month moving average, so as to get rid of seasonality.

[17] The average frequency of price adjustment prior to the fall is broadly in line with the figures reported by previous studies on UK micro price data. To see this, one has to account for the fact that we exclude both utility prices (COICOP 4) and sales. Bunn and Ellis (2012), instead, consider both categories, while Dixon and LeBihan (2012) and Dixon and Tian (2017) include sales, but exclude utility prices.

[18] Figure B.1 in Appendix B shows that composition effects have no role in generating the facts presented in this subsection. To this end, we compare the moments of the distribution of price changes with their counterparts obtained by averaging the corresponding moments of the price quotes, for each of the 25 COICOP

Figure 1: Frequency of Adjustment and Average Price Changes



Notes: The frequency of adjustment, fr_t , is computed as $\sum_i \omega_{i,t} \mathbb{1}_{\{\Delta p_{i,t} \neq 0\}}$, where $\omega_{i,t}$ denotes the CPI weight associated to good i at time t, and $\mathbb{1}_{\{\Delta p_{i,t} \neq 0\}} = 1$ if $\Delta p_{i,t} \neq 0$ and zero otherwise. The average price change, instead, is computed as $fr_t^{-1} \sum_i \omega_{i,t} \mathbb{1}_{\{\Delta p_{i,t} \neq 0\}} \Delta p_{i,t}$. The positive and negative counterparts of these statistics are obtained by conditioning them on positive and negative price changes, respectively. All series are in percentage terms. In the bottom-right panel we report the mirror image of the average of negative price changes. The inflation rate graphed in the upper panel of the figure is the official CPI inflation rate published by the ONS. Price dispersion on the right (left) side of the median price quote is computed as $q_{50} - q_{10}$ $(q_{90} - q_{50})$. The shaded vertical band indicates the duration of the Great Recession.

group categories.

Table 2: Pairwise Correlations: Pricing Moments and Macroeconomic Variables

Rotemberg Filter				
	fr_t	σ_t	$q_{75,t} - q_{25,t}$	$q_{90,t} - q_{10,t}$
y_t	-0.569	0.264	0.334	0.422
π_t	0.169	0.000	-0.016	-0.147
fr_t	–	0.162	-0.510^{***}	-0.737^{***}

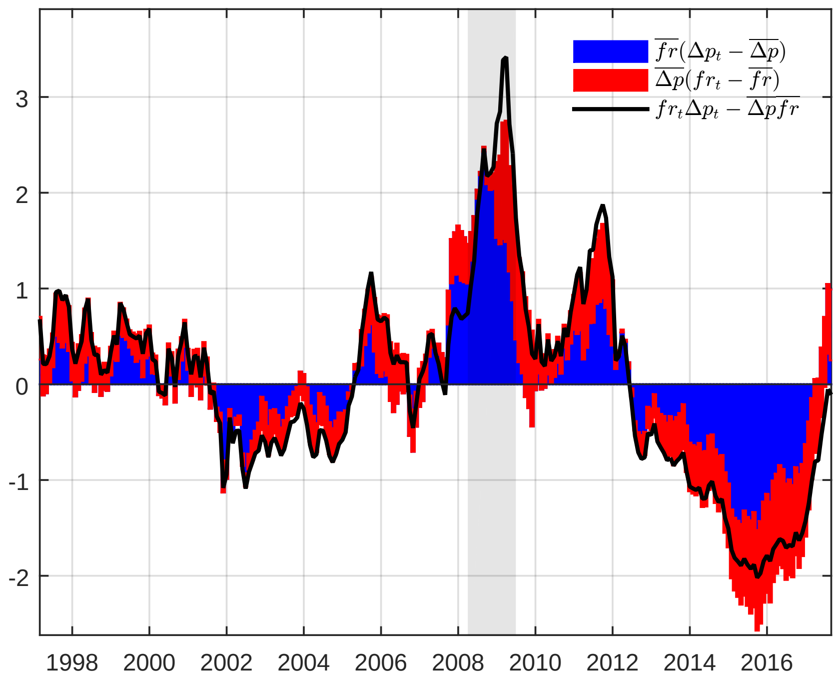
Hamilton Filter				
	fr_t	σ_t	$q_{75,t} - q_{25,t}$	$q_{90,t} - q_{10,t}$
y_t	-0.428	0.232	-0.085	-0.064
π_t	0.125	0.031	0.239	0.199
fr_t	–	0.129	-0.413^{***}	-0.652^{***}

Notes: fr_t denotes the frequency of adjustment; σ_t stands for the volatility of the distribution of price changes; $q_{n,t}$ measures the $n-$th quantile of the distribution of price changes; π_t indicates aggregate CPI inflation. Aside of the inflation rate, all series are obtained by detrending their raw counterparts by means of: i) Rotemberg's (1999) version of the HP filter, which sets the smoothing coefficient so as to minimize the correlation between the cycle and the first difference of the trend estimate (top panel); ii) two-years difference as suggested in Hamilton (2018) (bottom panel). $^{***}/^{**}/^{*}$ indicates statistical significance at the 1/5/10% level, respectively. The standard errors are computed using a moving block bootstrap (with blocks size of 2 years), so as to account for serial dependence in the underlying data.

The bottom panels of the figure plot different measures of dispersion of the distribution of (non-zero) price changes. Both the cross-sectional standard deviation and the interdecile range display a very large increase in the aftermath of the Great Recession. In fact, as displayed by the right panel of the figure, dispersion increases on either side of the median, though negative price changes become more dispersed than positive price changes. In light of this, it should be stressed that the fall in CPI inflation occurred in the post-2010 sample is to a large extent a manifestation of the trend in the dispersion of negative price changes—relative to that of positive ones—rather than reflecting a mere shift in the mode of the density.

To contextualize the joint behavior of the frequency of adjustment and the trend in the dispersion of price changes, Figure 2 reports the contribution of the variation in the average price change and that of the frequency to the deviation of inflation from its sample mean. Only about half of the variability of inflation is explained by the variability of the average price change, whereas the remaining half is due to variation in the frequency (either directly or indirectly, through its positive comovement with the average price change). Most importantly, a large fraction of the observed deviation of inflation from its mean can be attributed to the deviation of the frequency from its mean. This is particularly evident in the post-recession period, when we appreciate diverging movements in fr_t and σ_t. Specifically, if one considers the 2011 inflation spike, or the period of weak inflation in the last part of the sample, about half of the overall inflation deviation from the mean is explained by a relatively high or a relatively low frequency of price adjustment, respectively.

Figure 2: Inflation Decomposition



Note: We decompose the deviation of inflation from its sample average between the contribution of the variation in the average price change (holding the frequency fixed) and that of the variation in the frequency of adjustment (holding the average price change fixed). Specifically, since $\pi_t = fr_t \Delta p_t$, one can take the following decomposition: $\pi_t - \overline{fr\Delta p} = \overline{fr}(\Delta p_t - \overline{\Delta p}) + \overline{\Delta p}(fr_t - \overline{fr}) + (\Delta p_t - \overline{\Delta p})(fr_t - \overline{fr})$. The shaded vertical band denotes the duration of the Great Recession.

A key fact emerging from this graphical analysis is that the dispersion of price changes and the frequency of adjustment tend to comove negatively, and more so after the Great Recession. As stressed by Vavra (2014), the joint dynamics of these statistics and their cyclical properties are key to understand the endogenous and exogenous determinants of price adjustment. To confirm our visual impression, Table 2 reports the pairwise correlation between both moments, as well as with CPI inflation and a business cycle indicator.[19] We set aside potential spurious correlation emanating from the low-frequency behavior of these series, and detrend all of them—using different filters—apart from the inflation rate. The frequency of adjustment and the dispersion of price changes consistently display negative correlation.[20] Otherwise, none of these statistics shows significant business-cycle comovement.[21,22]

[19]Appendix C contains more details on the derivation of the monthly coincident indicator of economic activity.

[20]As displayed by the left-bottom panel of Figure 1, σ_t is often influenced by outliers, a feature that might severely affect its pairwise correlations. This problem is not shared by the interquantile and the interdecile range, which are also reported in the table.

[21]The emergence of no statistical significance of this pairwise correlation is at least in part due to the fact that, over the sample we examine, only one large recession has occurred. This is also likely to explain the cyclical discrepancies between the UK data and the US data employed by Berger and Vavra (2017), which comprise three recessionary episodes.

[22]Notably, we also detect a certain tendency for the skewness to behave countercyclically, while kurtosis

The next section introduces a stylized menu cost model that stresses how changes in the incentives firms face when deciding to change prices can provide us with a rationale for time variation in the distribution of price changes and, more specifically, negative comovement between the dispersion of price changes and the frequency of adjustment.

3 A simple analytical setting to frame the stylized facts

We consider the menu cost model popularized by Barro (1972) and Dixit (1991). As illustrated by Vavra (2014), the advantage of this framework is to provide us with a simple analytical setting to keep track of the determinants of the frequency and the dispersion of price changes, as well as the dispersion of price gaps, intended as the difference between the actual price of a given good and its reset price (i.e., the price that would have prevailed in the absence of price-setting frictions). For the sake of our analysis, we will use this model as a prism through which interpreting distinctive time-varying phenomena behind price setting.

Firms face a dynamic control problem where x—the deviation of the current price from the optimal price—is a state variable. A wedge between the state variable and zero entails an out-of-equilibrium cost αx^2, where α can be inversely related to market power. When not adjusting, x follows a Brownian motion $dx = \phi dW$, where W is the increment to the Wiener process. It is possible to change the value of x by applying an instantly effective control at a lump-sum cost λ. From this environment, a simple Ss rule emerges, according to which the optimal policy is 'do not adjust' when $|x| < \sigma$ and 'adjust to zero' when $|x| \geq \sigma$, where $\sigma = (6\lambda\phi^2/\alpha)^{1/4}$ denotes the standard deviation of price changes. Moreover, $fr = (\alpha/6\lambda)^{1/4}\,\phi$ is the frequency of adjustment.[23]

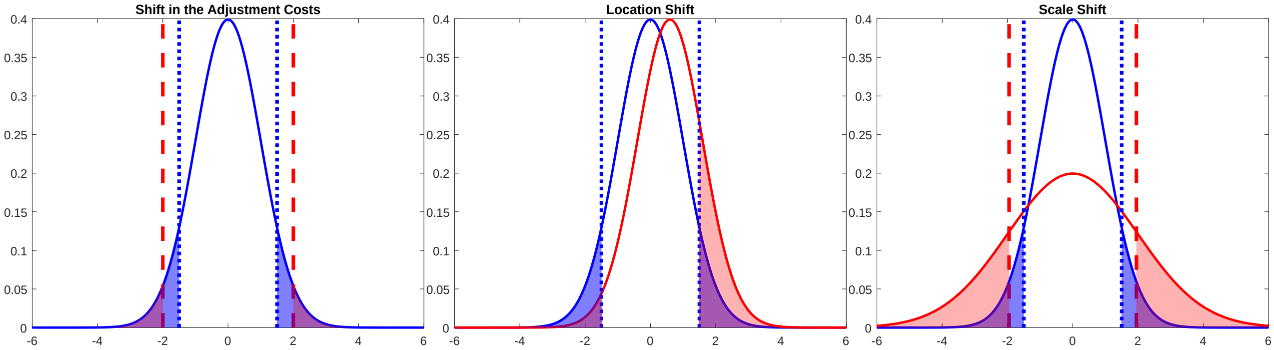
To provide an overview of different determinants of the distribution of price gaps and the associated distribution of price changes, Figure 3 considers three possible scenarios: i) a positive shift in the cost of adjustment λ (or, equivalently, a negative shift in α) that affects the inaction region, while leaving the distribution of price gaps unaffected; ii) a first-moment shock that causes a shift in the distribution of price gaps, affecting all x's in the same manner; iii) an increase in the dispersion of the distribution of price gaps (i.e., a rise in ϕ).

As for i), a positive change in λ widens the inaction region, translating automatically into a reduction in the frequency of adjustment and an increase in the dispersion of price changes, which is in line with the behavior of the two statistics in the post-recession sample. As for ii), the immediate effect of a shift in the distribution of price gaps is to push more firms out of the inaction region, thus inducing an increase in the frequency of adjustment. Importantly, this result does not depend on the specific sign of the shock, as all firms' desired price changes will be affected in the same way. Thus, all firms pushed out of the inaction region will denote

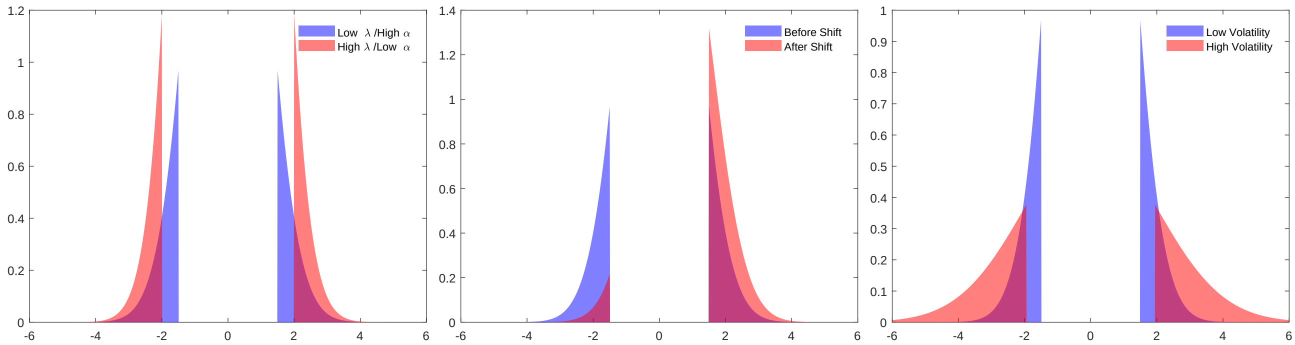
appears acyclical. Most importantly, the skewness displays no correlation with the rate of inflation. This is somewhat puzzling, given that a wide range of structural models tend to produce non-zero inflation-skewness comovement (see, e.g., Luo and Villar, 2017a). However, we should stress that the correlation turns positive and significant in the post-recession period, thus emphasizing the role of the extensive margin of price adjustment and, therefore, state dependence.

[23] For analytical details and proofs, see Barro (1972) and Vavra (2014).

Figure 3: ANALYTICAL FRAMEWORK



(a) Price Gap Distribution



(b) Price Change Distribution

Note: The first column considers a positive shift in λ (or a negative shift in α) that affects the inaction region, while leaving the distribution of price gaps unaffected. The second column considers the effects of a first-moment shock that affects all x's in the same direction. The last column depicts the effects of an increase in ϕ. The upper panels report the ex-ante distribution of price gaps and the corresponding bands delimiting the inaction region (dotted-blue lines), together with their ex-post counterparts (dashed-red lines). The bottom panels report the corresponding distributions of price changes.-

price changes of the same sign, implying a decrease in their dispersion.[24] Thus, while negative comovement would emerge in this case, it is important to recognize that first-moment shocks would not be suitable to characterize the (diverging) movements in the frequency and the dispersion that have occurred over the post-recession sample.[25] Finally, a rise in ϕ, as sketched in the last column of the figure (iii), induces increased dispersion in the price gap distribution and an expansion in the inaction region. As a result, both fr and σ increase.

Vavra (2014) points to second-moment shocks as potential drivers of the positive comovement between the frequency of adjustment and price-change dispersion in U.S. CPI data. It is clear how this type of shock would not be suitable to rationalize negative comovement. In fact, only an increase in the fixed cost of adjustment and/or a drop in the cost of deviating from the optimal price may account for a concurrent drop (increase) in the frequency of adjustment

[24] In fact, Vavra (2014) shows that, while in environments with zero inflation small shocks to x do not produce any effect on the frequency of adjustment and the dispersion of price changes, in the presence of positive trend inflation the frequency (dispersion) increases (decreases).

[25] One should note that such movements could be rationalized, in the occurrence of a first-moment shock, whenever the latter hits outside the steady state and shifts the distribution towards its ergodic counterpart. However, in Section 5.1 we present evidence in support of the explanation based on changes in the price-adjustment cost structure, as opposed to first- or second-moment shocks. In fact, first-moment shocks seem to account only for a small part of the increase in the dispersion of price changes, and mainly when aggregate inflation has come close to zero, towards the end of the sample.

(dispersion of price changes), as observed after the Great Recession.

For the continuation of the analysis, it is important to stress that shifts in λ and α would immediately reflect into the shape of adjustment hazard, while leaving the price gap distribution unaffected.[26] To account for movements in both functions, the next section introduces an accounting framework that is particularly suitable to quantify the link between changes in the timing of individual price adjustments, money non-neutrality, and inflation dynamics.

4 The generalized Ss model

The generalized Ss model developed by Caballero and Engel (2007) has two clear advantages that make it particularly indicated to discipline our data. First, it is consistent with lumpy and infrequent price adjustments—which are typically seen as distinctive traits of price setting—along with encompassing several pricing protocols.[27] In this respect, Berger and Vavra (2017) show that this empirical setting provides a good fit to the data generated by different structural models (e.g., Golosov and Lucas, 2007 and Nakamura and Steinsson, 2010a). Second, as we allow for time variation in the determinants of price adjustment, we can estimate the model over each cross section of price microdata, matching different price-setting statistics. More details on the estimation are reported in Section 4.1. In the remainder of this section, instead, we discuss the analytical details of the accounting framework.

Assume that, due to price rigidities, the log of firm i's actual price may deviate from the log of the target or reset price, which is denoted by p^*_{it}. Thus, we define the price gap as $x_{it} \equiv p_{it-1} - p^*_{it}$, implying that a positive (negative) price gap is associated with a falling (increasing) price when the adjustment is actually made. In a simple Ss model as the one detailed in the previous section, a price is adjusted when the associated price gap is large enough, and $p_{it} = p^*_{it}$ after the adjustment has taken place. Assuming l_{it} periods since the last price change, the adjustment reflects the cumulated shocks: $\Delta p_{it} = \sum_{j=0}^{l_{it}} \Delta p^*_{it-j}$, with $\Delta p^*_{it} = \mu_t + \upsilon_{it}$, where μ_t is a shock to nominal demand and υ_{it} is an idiosyncratic shock.

As discussed by Caballero and Engel (2007), the basic Ss setting of the previous section can be generalized by assuming *iid* idiosyncratic shocks to the adjustment costs. Thus, by integrating over their possible realizations, we obtain an adjustment hazard, $\Lambda_t(x)$. This is defined as the (time t) probability of adjusting—prior to knowing the current adjustment cost draw—by a firm that would adjust by x in the absence of adjustment costs (i.e., as if the adjustment cost draw was equal to zero). Caballero and Engel (1993a) prove that the probability of adjusting is non-decreasing in the absolute size of a firm's price gap (i.e., the so-called 'increasing hazard property'). Denoting with $f_t(x)$ the cross-sectional distribution of

[26] In this respect, Appendix D shows how large diverging movements in the dispersion of price changes and the frequency of adjustment in the post-recession period can be rationalized by an expansion of the inaction region that dominates the effects of positive shifts in the dispersion of price gaps.

[27] To mention two extreme examples, the generalized Ss model can account for both price setting à la Calvo (1983)—where firms are selected to adjust prices at random and price flexibility is fully determined by the frequency of adjustment—as well as for schemes à la Caplin and Spulber (1987)—where adjusting firms change prices by such large amounts that the aggregate price is fully flexible, regardless of the frequency of adjustment.

price gaps immediately before an adjustment takes place at time t, aggregate inflation can be recovered as

$$\pi_t = -\int x\Lambda_t(x)\, f_t(x)\, dx. \tag{1}$$

Notice that the Calvo pricing protocol implies the same hazard across x's (i.e., $\Lambda_t(x) = \Lambda_t > 0,\ \forall x$).

4.1 Taking the model to the data

To take the model to the data we need to specify generic functional forms for the distribution of price gaps and the hazard function. Specifically, we postulate that the distribution of price gaps at time t, $f_t(x)$, can be accounted for by the Asymmetric Power Distribution (APD henceforth; see Komunjer, 2007). The probability density function of an APD random variable is defined as

$$f_t(x) = \begin{cases} \frac{\delta(\varrho_t,\nu_t)^{1/\nu_t}}{\psi_t \Gamma(1+1/\nu_t)} \exp\left[-\frac{\delta(\varrho_t,\nu_t)}{\varrho_t^{\nu_t}} \left|\frac{x-\theta_t}{\psi_t}\right|^{\nu_t}\right] & \text{if } x \leq \theta_t \\ \frac{\delta(\varrho_t,\nu_t)^{1/\nu_t}}{\psi_t \Gamma(1+1/\nu_t)} \exp\left[-\frac{\delta(\varrho_t,\nu_t)}{(1-\varrho_t)^{\nu_t}} \left|\frac{x-\theta_t}{\psi_t}\right|^{\nu_t}\right] & \text{if } x > \theta_t \end{cases}, \tag{2}$$

with $\delta(\varrho_t, \nu_t) = \frac{2\varrho_t^{\nu_t}(1-\varrho_t)^{\nu_t}}{\varrho_t^{\nu_t}+(1-\varrho_t)^{\nu_t}}$. The parameters θ_t and $\psi_t > 0$ capture the location and the scale of the distribution, whereas $0 < \varrho_t < 1$ accounts for its degree of asymmetry. Last, the parameter $\nu_t > 0$ measures the degree of tail decay: for $\infty > \nu_t \geq 2$ the distribution is characterized by short tails, whereas it features fat tails when $2 > \nu_t > 0$. This functional form nests a number of standard specifications, such as the Normal ($\nu_t = 2$), the Laplace ($\nu_t = 1$) and the Uniform ($\nu_t \to \infty$). Most importantly, it can capture intermediate cases between the Normal and the Laplace distribution, which is consistent with the steady-state distribution of price changes according to Alvarez et al. (2016).

We then assume that the hazard function can be characterized by an asymmetric quadratic function:

$$\Lambda_t(x) = \min\left\{a_t + b_t x^2 \mathbb{1}_{\{x>0\}} + c_t x^2 \mathbb{1}_{\{x<0\}}, 1\right\}, \tag{3}$$

where $\mathbb{1}_{\{z\}}$ is an indicator function taking value 1 when condition z is verified, and zero otherwise. This parsimonious specification nests the Calvo pricing protocol for $b_t = c_t = 0$, while potentially allowing for asymmetric costs of adjustment, which has recently been supported by Luo and Villar (2017b).[28]

Given the parametric specifications of $f_t(x)$ and $\Lambda_t(x)$, we estimate seven parameters for each cross section of micro price data, so as to match the following moments of the distribution of price changes: mean, median, standard deviation, interquartile range, difference between the 90th and 10th quantile of the distribution, as well as (quantile-based) skewness and kurtosis.[29]

[28] We have also checked that our results are robust to plausible variations to the specification of these functional forms. Using a mixture of two Normal distributions for the price gap and/or the asymmetric inverted normal function for the hazard function delivers results that are qualitatively similar to those reported in the next section.

[29] We match quantilic moments, as the 3rd and 4th moments of the cross-sectional distribution are quite sensitive to outliers. Figure E.1 graphs the dynamics of both $f_t(x)$ and $\Lambda_t(x)$, while Figures E.2 and E.3 report the estimated parameters. Finally, Figure E.4 reports the fit of selected data moments, and shows that

We also match the frequency and the average size of prices movements, after distinguishing between positive and negative price changes. Last, we match the observed rate of inflation. The estimates are obtained by simulated minimum distance, using the identity matrix to weight different moments.[30]

4.2 Identification

Appendix F reports a series of exercises that highlight how the indirect inference approach we follow is able to identify the shape of the price gap distribution and the hazard function. As a first exercise, we aim at evaluating the systematic impact of each of the estimated parameters on the moments that we are matching. To this end, we vary the parameters of $f_t(x)$ and $\Lambda_t(x)$—one at the time, while keeping the other coefficients at their baseline estimates—and examine their impact on key moments of the price change distribution, as well as on the resulting rate of inflation (see Figure F.1 and Figure F.2). All in all, marginal changes in the parameters typically correspond to a large variation in the moments we match, indicating that the latter carry valuable information to identify the parameter of interest.

Having established that all the parameters have an impact on the moments we attempt to match, a fair question is whether moment matching allows us to appropriately identify/distinguish the shape of the price gap distribution from that of the hazard function. In fact, one might question whether the specific model we choose is able to identify a fatter price gap distribution from a steeper hazard function, or a skewed price gap distribution from an asymmetric hazard function. To see this, we simulate price-change data from the model, under different parameterizations, and then contrast the true price gap distribution and the hazard function to their estimated counterparts. According to Figure F.3, discrepancy is minimal, and the model does a good job at separately identifying the parameters of $f_t(x)$ and $\Lambda_t(x)$.

It is also important to stress that Berger and Vavra (2017) produce a battery of exercises in support of the indirect inference approach. Most importantly, they address how well the resulting measure of price flexibility —which, as we will highlight in the next section, only captures the impact response of prices to a nominal shock— reflects overall non-neutrality. To this end, they estimate simulated data from the CalvoPlus model of Nakamura and Steinsson (2008), and report close comovement between the impact response from the structural model and the estimated index of price flexibility from the accounting framework.

Notably, this exercise also addresses the criticism towards estimating the generalized Ss model in every period, as if observations were independent across time. In this respect, we should stress that standard structural frameworks tend to impose a rather tight relationship between distributions at a given point in time and how they evolve. In line with our predeces-

the empirical model is able summarize the main stylized facts in the data.

[30] Altonji and Segal (1996) highlight that matching the unweighted distance between moments often performs better in small samples, as compared with using optimal weights. The moments of the simulated distribution are estimated by drawing $100,000$ price quotes. We use the Genetic Algorithm to minimize the quadratic distance between data moments and simulated moments, so as avoid ending up in local minima (see, e.g., Dorsey and Mayer, 1995).

sors, we claim that imposing flexible functional forms within a period—in a way that represents an intermediate step between a fully structural approach and a non parametric one—allows us to exploit valuable information, in the perspective of studying time variation in aggregate price flexibility.

5 On the importance of state dependence in price adjustment

The estimation of the generalized Ss model highlights the importance of tracking changes in the distribution of price gaps and the hazard function. To dig deeper into the connection between individual price adjustment and the response of aggregate inflation to nominal demand, Caballero and Engel (2007) show that, within their accounting framework, one can derive a measure of aggregate price flexibility that captures the impact response of realized inflation to a one-off aggregate nominal shock:

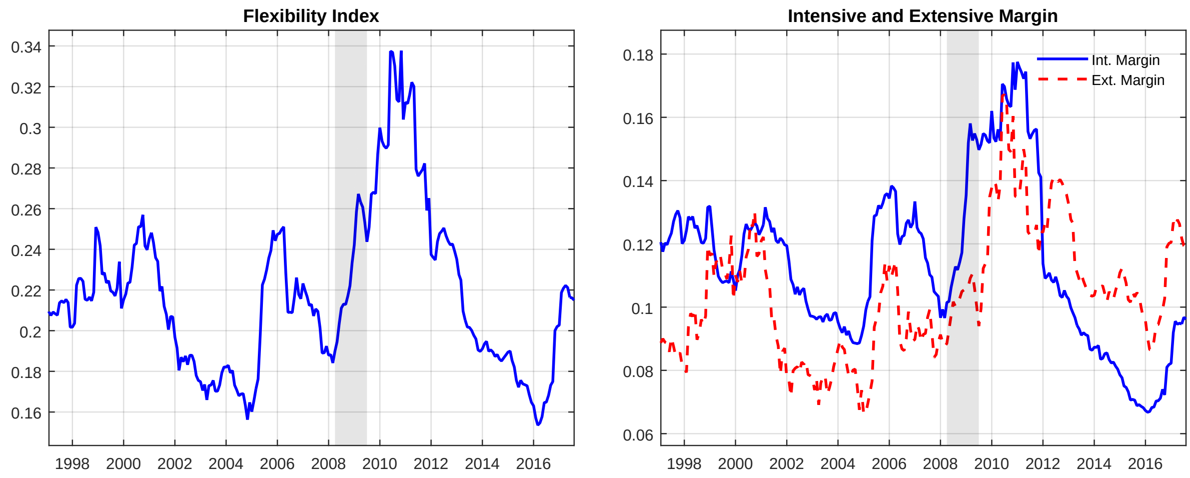
$$\mathcal{F}_t = \lim_{\mu_t \to 0} \frac{\partial \pi_t}{\partial \mu_t} = \underbrace{\int \Lambda_t(x) f_t(x)\, dx}_{\text{Intensive Margin}} + \underbrace{\int x \Lambda_t'(x) f_t(x)\, dx}_{\text{Extensive Margin}}. \tag{4}$$

Since this flexibility index is simply derived from the accounting identity (1), its validity as a measure of aggregate flexibility does not require that we take a stand on a specific model of price setting.

The flexibility index can be naturally decomposed into an intensive and an extensive margin component. On one hand, the intensive margin (Int) measures the average frequency of adjustment, and accounts for the part of inflation that reflects price adjustments that would have happened even in the absence of the nominal shock. On the other hand, the extensive margin (Ext) accounts for the additional inflation contribution of firms whose decision to adjust is either triggered or canceled by the nominal shock. Therefore, it comprises both firms that would have kept their price constant and instead change it, as well as firms that would have adjusted their price but choose not to do it. In this respect, it is useful to recall that, being characterized by a constant hazard function, Calvo price setting implicitly assumes that the extensive margin is null.

Figure 4 reports the estimated index of price flexibility and its decomposition into the intensive and the extensive margin of price adjustment. Price flexibility displays sizable variation over time, and more so in the last part of the sample, rising substantially during the Great Recession, and declining thereafter. This is consistent with our analysis of the distribution of price gaps. In fact, after the Great Recession both the intensive and the extensive margin of price adjustment contract, though the fall in the former is much more abrupt, in line with the sustained drop in the frequency of adjustment. As for the extensive margin, the expansion in the inaction region implies that fewer firms are pushed near the adjustment boundaries. It should be stressed that, over most of the decline, the extensive margin tends to contribute

Figure 4: Price Flexibility and Different Margins of Price Adjustment



Notes: The left panel reports the estimated index of price flexibility, which is decomposed in the right panel between the intensive and the extensive margin of price adjustment. The shaded vertical band indicates the duration of the Great Recession.

more to price flexibility, as compared with the intensive one, even after they both revert in 2016. Otherwise, the relative importance of the frequency of adjustment has generally been higher prior to 2012, with few and short-lived exceptions.

To see why we observe such a switch in the relative contribution of the two margins, it is useful to recall Caballero and Engel (2007) and their transformation of (4):

$$\mathcal{F}_t = \int \Lambda_t(x) \, f_t(x) \left[1 + \eta_t(x)\right] dx \tag{5}$$

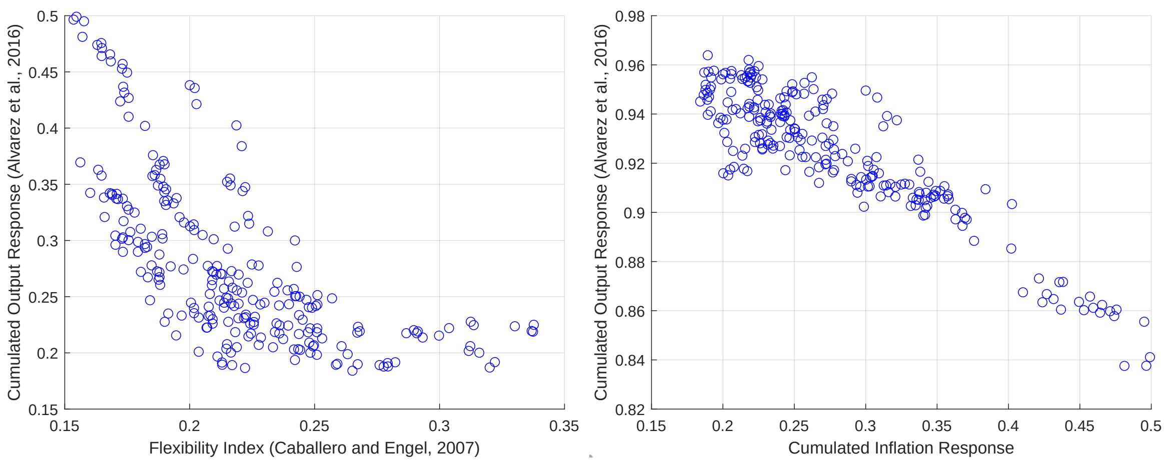
where $\eta_t(x) = x\Lambda_t'(x)/\Lambda_t(x)$ is the elasticity of the hazard function with respect to the price gap. A downward shift in the hazard function magnifies $\eta_t(x)$ and, as a result, the importance of the extensive margin relative to the intensive one. This is exactly what happens in the period under examination, as it can be appreciated by inspecting the estimated constant of the hazard function (see Figure E.3 in Appendix E). Alternatively, the same point can be made by approximating the flexibility index as $F_t \cong Int_t + 2\left[Int_t - \Lambda_t(0)\right]$:[31] from this expression it is clear how a downward shift in a_t—which is equivalent to lowering $\Lambda_t(0)$—translates into an increase in the importance of the extensive margin relative to the intensive one, *ceteris paribus*. It is important to recognize that such a shift in the hazard function is in line with the mechanics of the analytical framework of Section 3, as it would be the case following an increase in market power that determines a drop in the cost of being away from the optimal price. In fact, this view is consistent with the sizable increase in the mark-up that has been observed during the post-recession period, as recently documented by De Loecker and Eeckhout (2019) and Bell and Tomlinson (2018) for the UK economy.[32]

[31] For a formal proof, please refer to Caballero and Engel (2007).

[32] Both papers show that the mark-up has displayed only a modest increase in the 1996-2007 period, while

From a cyclical perspective, movements in price flexibility do not seem to occur at random: in fact, $\mathcal{F}_t$ goes from being positively correlated with output growth in the first part of the sample (0.456), to comoving negatively during the last decade (-0.577). As for the correlation with the rate of inflation, this is generally positive, and more so in the post-recession sample (0.380), while it is not statistically different from zero in the previous decade. On a more general note, it is worth emphasizing how changes in the correlation structure over the two subsamples are consistent with a shift from an environment where the intensive margin dominates the extensive one, to one where the extensive margin assumes a prominent role and inflation volatility is particularly marked (see Figure 4). The remainder of this section will be largely devoted to providing a rationale for this type of state dependence.

Figure 5: Comparison with Alvarez et al. (2016)



Note: The left panel of the figure reports a scatter plot of the cumulated output response to a monetary policy shock, as computed by Alvarez et al. (2016), against the index of price flexibility, as computed by Caballero and Engel (2007). The right panel, instead, features a scatter plot of the cumulated output response to a monetary policy shock against the cumulated inflation response to a one-off 1% nominal shock, where we cumulate the inflation response over a 18 month period.

It should also be noted that alternative measures of money non-neutrality could be computed to track price flexibility. In fact, Alvarez et al. (2016) show that the steady-state ratio of kurtosis to the frequency of adjustment is a sufficient statistic of money non-neutrality, in a wide variety of frameworks. However, as highlighted by Berger and Vavra (2017), while their characterization provides us with a measure of cumulative output response, it does not apply to settings that allow for large shocks to the price gap distribution. Despite this fundamental difference, the left panel of Figure 5 shows that the measure proposed by Alvarez et al. (2016) features a strong negative correlation with the one we compute, as expected on theoretical grounds. The degree of comovement is even stronger when looking at the medium-term pass-through of nominal shocks, as displayed by the right panel of the figure.[33]

increasing substantially afterwards.

[33]The strikingly high correlation between Alvarez et al. (2016)'s statistics of money non-neutrality and our proxy of the pass-through of norminal shocks to inflation reinforces our confidence in the ability of the model to identify shifts in the price gap distribution and in the hazard function.

5.1 The hazard function and price adjustment

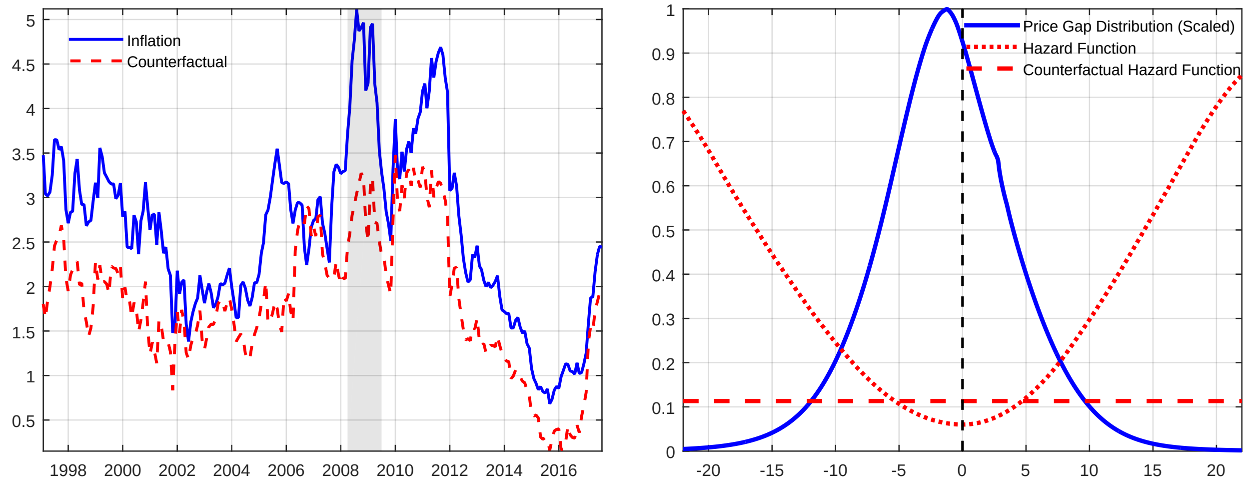
The analysis so far has established that the extensive margin of price adjustment may be quantitatively important to money non-neutrality. This is confirmed by the left panel of Figure 6, which compares inflation with a counterfactual obtained by setting the period hazard function to a constant equal to the intensive margin. As pointed out by Gagnon et al. (2013), this is equivalent to calibrating the Calvo model to match the intensive margin by assuming that the probability of price adjustment, while exogenous to the firm, can vary with the state of the economy (i.e., $\pi_t^{Calvo} = -fr_t^{Calvo} \int x f_t(x)\, dx$, where $fr_t^{Calvo} = \int \Lambda_t(x) f_t(x)\, dx$). To facilitate the understanding of the counterfactual exercise, the right panel of Figure 6 reports the average hazard function estimated over the entire sample, together with the flat adjustment hazard implied by Calvo price setting, and the average distribution of price gaps (scaled to be equal to 1 at the mode).

The extensive margin confirms to be rather important, accounting for a large gap between price flexibility and its 'Calvo-counterfactual', where the latter matches (by construction) the intensive margin (see Figure 4), and is generated by a flat hazard function over the entire spectrum of price gaps. In this case, the absence of a selection effect is key to explain the positive gap between actual inflation and its Calvo-counterfactual. Within the sample under analysis, we observe positive inflation in the presence of a price gap distribution that is typically slightly skewed on the left and centered around a negative value. This implies that positive large price changes are more likely than large negative price changes. Therefore, the selection effect implied by an increasing hazard function returns an average price change that is necessarily larger than the average (negative) price gap. By contrast, with a flat hazard function, the price change distribution resembles the price gap distribution, so that inflation is aligned with the average price change. As a result, the Calvo-counterfactual rate of inflation always lies below the actual one.

The selection effect matters even more in periods of particularly volatile inflation, when the difference between the latter and the countefactual is sizable. For instance, in the aftermath of the Great Recession, changes in the shape of the price gap distribution—as implied by our estimates—interact with the selection effect, so that large positive price changes reflect into major spikes in inflation dynamics. In this respect, the presence of an increasing hazard function tends to exacerbate the impact of large shocks (Caballero and Engel, 1991).

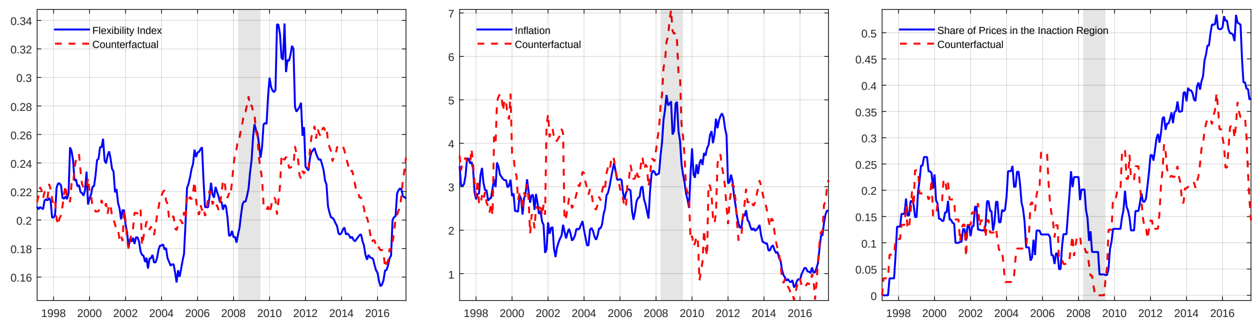
A number of studies have considered empirical specifications of the Caballero and Engel (2007) framework with a fixed hazard function (see, e.g., Caballero and Engel, 2006, and Luo and Villar, 2017b and references therein). However, Section 3 has emphasized how changes in the incentives that firms face when deciding to change their prices—which, in the accounting framework, reflect into the shape of the hazard function—may be crucial for capturing the comovement between the frequency of adjustment and the dispersion of price changes. Figure 7 reports the results of a counterfactual exercise that highlights the importance of shifts in the hazard function for the behavior of price flexibility, inflation, and the inaction region of price adjustment.

Figure 6: A Calvo Counterfactual: Shutting Down the Extensive Margin



Notes: The left panel reports the rate of inflation obtained from our sample of ONS price quotes (blue-solid line) and its counterfactual (red-dashed line), obtained by setting the period hazard function to a constant equal to the intensive margin. The shaded vertical band indicates the duration of the Great Recession. The right panel reports the average *pdf* of the price gap (blue-solid line)—scaled to be equal to 1 at the mode—the average estimated hazard function (red-dotted line), and the counterfactual hazard function implied by Calvo price setting (red-dashed line).

Figure 7: Counterfactual Analysis: No Independent Movements in the Hazard Function



Notes: The left panel reports the flexibility index estimated from the data (blue-solid line) against its counterfactual (red-dashed line), obtained by assuming no independent movements in the hazard function parameters. The central panel reports the corresponding rate of inflation and its counterfactual. The last panel reports the share of prices in the estimated inaction region associated with an hazard probability of 5%, both in the actual and in the counterfactual scenario. The shaded vertical band indicates the duration of the Great Recession.

In principle, the hazard function may change both in the face of shocks that also affect the price gap distribution, as well as in reaction to changes in the cost firms face when deciding to adjust prices. In this counterfactual we aim at capturing what would have been price flexibility and inflation, had the hazard function only reflected shocks affecting the price gap distribution. To this end, we regress the hazard function parameters up to the fourth lag of the parameters of the price gap distribution. Thus, we compute the index of price flexibility and the corresponding rate of inflation based on the predicted values from this regression.[34]

Inspecting Figure 7 clearly shows how price flexibility is largely driven by autonomous movements in the adjustment hazard, in the absence of which it would have displayed much less variability throughout the sample. In principle, inflation may be attenuated or amplified by exogenous movements in the hazard function. Notably, exogenous changes in $\Lambda_t(x)$ reduce inflation volatility before the Great Recession. For instance, in the 2002-2005 time span they reduced price flexibility, thus attenuating the impact of inflationary shocks. By the same token, in the absence of independent movements in the hazard function we would have appreciated a much higher peak during the Great Recession, followed by a much stronger reversal. In this respect, the exogenous increase in price flexibility occurred in the aftermath of the recession (2010-12) has been a key determinant of the fast pass-through of inflationary shocks over the period.

To conclude, the last panel of Figure 7 reports the share of prices in the estimated inaction region associated with an hazard probability of 5%, both in the actual and in the counterfactual scenario. Periods in which price flexibility lies above its counterfactual are associated with a lower proportion of prices that are not adjusted. Notably, the counterfactual share of prices within the inaction region does not feature an upward trend over the 2012-2016 time span, when the counterfactual flexibility index persistently lies above the actual one. Consistent with the prediction of the stylized model in Section 3, an (exogenous) persistent shift in the incentives firms face when deciding whether to adjust prices is responsible for the rise in the dispersion of price changes, and the concurrent fall in the frequency of price adjustment.[35]

5.2 On the impact of large first-moment shocks: a VAT event study

We have highlighted the importance of independent movements in the hazard function for adjustments along the extensive margin. An alternative way to corroborate this point is to exploit the occurrence of events that imply a major shift in the price gap distribution. To this end, we can usefully exploit episodes of major repricing activity triggered by changes in the VAT.

VAT shocks are typically useful for three reasons. First, they are relatively simple to study, because their timing and size are directly observable. Second, changes in the VAT are particularly suitable to understand whether price setting works in line with the predictions of menu cost models (Karadi and Reiff, 2014): as in the UK posted prices include the VAT, price-setting units need to post new prices—and, thus, bear a menu cost—if they choose to incorporate the tax change into their prices. Third—and most importantly for the evidence produced so far—large first-moment shock are particularly well-suited to disentangle movements in the price gap distribution from those in the adjustment hazard. Otherwise, as shown in Section 3, both $f_t(x)$ and $\Lambda_t(x)$ would vary—albeit to different extents—in the face of second-moment shocks.

[34]We have also considered including quadratic transformation of the price gap parameters, so as to capture possible nonlinearities. The results were qualitatively similar to the ones reported in Figure 7.

[35]Concurrently, this shift is compatible with the reversal in the cyclicality of the flexibility index we detect around the recessionary episode.

Gagnon et al. (2013) suggest that, if the timing of all price changes was predetermined, following a nominal shock we should observe a shift in the gap distribution, with the shape of the distribution being preserved (see, e.g., the middle panel of Figure 3). Thus, one can measure the importance of adjustment along the extensive margin by comparing the observed distribution of price changes to a counterfactual distribution that obtains in the absence of the shock. Any evidence that the two distributions differ by more than a shift can be attributed to the extensive margin.

The recent UK history has been characterized by three episodes of changes in the VAT: a reduction, from 17.5% to 15%, on December 1, 2008, followed by two hikes: one, up to 17.5%, on January 1, 2010, and one, further up to 20%, on January 4, 2011. To examine the contribution of VAT changes to the overall degree of price flexibility, Figure 8 reports the distribution of price gaps and that of price changes, together with the corresponding hazard function. Moreover, we report counterfactuals which depict the environment that would have prevailed in absence of the VAT change, those are obtained by averaging the the price gap distribution and the hazard function, for the same month of the year, in the previous six years.[36]

Looking at the inflation rate in the month corresponding to a VAT change, we note that shifts in the distribution of price changes are such that many firms seize the opportunity to adjust prices by more than the VAT change, thus implying that inflationary/deflationary pressures from other sources have been released in the process. In support of the view that episodes of massive repricing cannot be seen as mere translations of the distribution of price gaps, we appreciate both a major upward shift and a steepening of the hazard function across all the three episodes of VAT change: in fact, these are associated with a large rise in the frequency of adjustment. Moreover, Table 3 shows that the intensive margin is much higher in correspondence with a VAT hike, as compared with a negative VAT change. In this respect, our evidence is consistent with Karadi and Reiff (2014).

To dig deeper into the role of state-dependent pricing, Table 3 also reports some statistics in coincidence with the three VAT changes, as well as two counterfactual scenarios.[37] In the *no* $\Lambda(x)$ *change* scenario, we keep the hazard function as that computed in the counterfactual exercise of Figure 8, but let the price gap distribution vary as a result of the VAT change. Thus, we abstract from any amplification that could be induced by state-dependent pricing through upward shifts of the hazard function. The *no VAT change* scenario, instead, considers a situation in which neither the price gap distribution nor the hazard function are affected by the VAT change.[38]

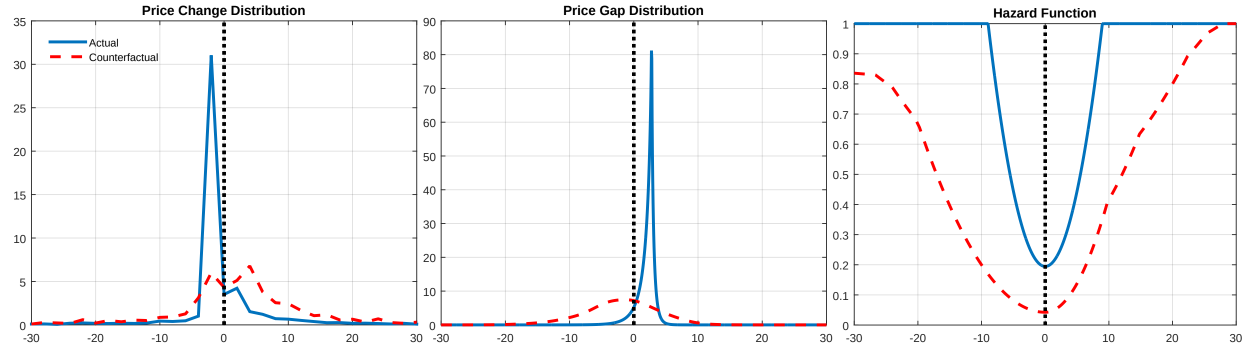
From the comparison between inflation in the occurrence of a VAT change and its counterfactuals, two features are worth emphasizing. First, state-dependent pricing accounts for most

[36]January 2010 has not been included when computing the counterfactual distribution for January 2011, so as to avoid that the second VAT change affects the counterfactual distribution corresponding to the last episode.

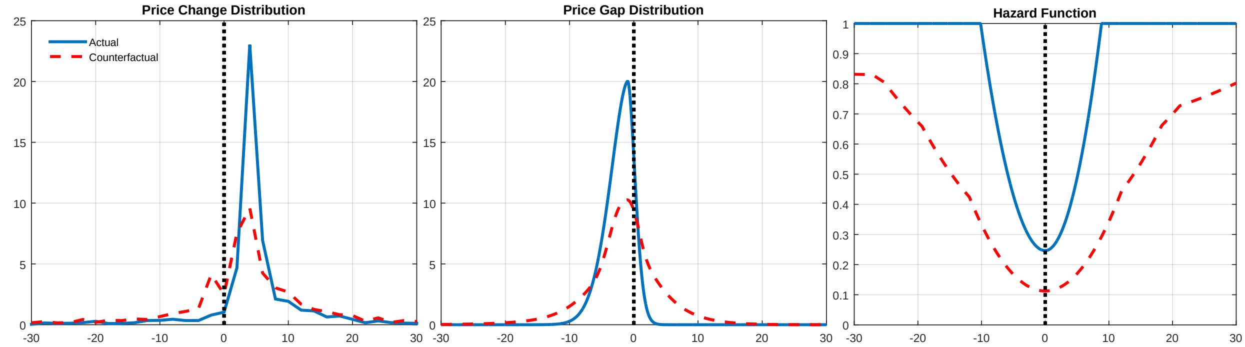
[37]More details on the computation of two alternative scenarios are provided in Appendix G.

[38]This amounts to keeping both the price gap distribution and the hazard function to their counterfactuals in Figure 8.

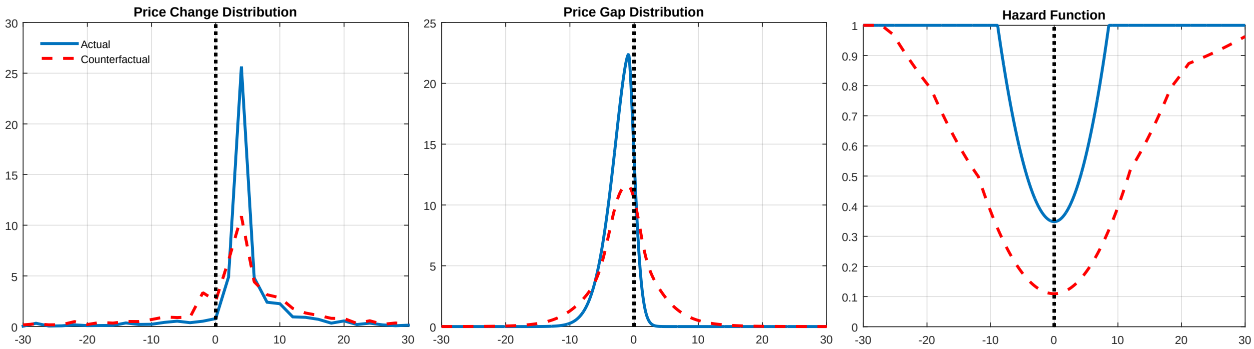
Figure 8: Event Study: VAT Changes



(a) VAT Decrease: Dec. 2008



(b) VAT Increase: Jan. 2010



(c) VAT Increase: Jan. 2011

Notes: Each line of the figure reports the distribution of price changes, the distribution of price gaps, and the hazard function in the month corresponding to a VAT change. The distribution of price changes is computed by grouping observations into bins of 2% (excluding zeros), and weighting them by their relative importance in the CPI. In all cases, the counterfactuals are computed by averaging the same function, for the same month of the year in the previous 6 years. Three recent episodes of changes in the VAT are considered: a reduction, from 17.5% to 15%, on December 1, 2008, followed by two hikes, one up to 17.5% on January 1, 2010, and further up to 20% on January 4, 2011.

of the change in the rate of inflation in the presence of a VAT change. Otherwise, inflation would have been not very different from its counterfactual in the *no VAT change* scenario. This is particularly evident when the VAT is raised. Second, movements in the hazard function, as compared with those in the distribution of price gaps, have most of the impact on adjustments along the extensive margin. This implies that price-setting units' incentives to adjust prices—as embodied by their adjustment costs structure—may display substantial variation in the face of large first-moment shocks, even if the latter are largely foreseeable, as in the case of VAT changes. In this respect, the price-setting behavior we portray bears close resemblance to price

Table 3: VAT Changes: Actual and Counterfactual Statistics

	VAT 1							
	π	$\mathcal{F}$	*Int*	*Ext*	Int^{+}	Int^{-}	Ext^{+}	Ext^{-}
Actual	-5.941	0.346	0.235	0.111	0.211	0.023	0.105	0.006
No $\Lambda(x)$ change	-1.604	0.101	0.060	0.041	0.055	0.005	0.040	0.001
No VAT change	1.863	0.200	0.096	0.104	0.038	0.058	0.048	0.056
	VAT 2							
	π	$\mathcal{F}$	*Int*	*Ext*	Int^{+}	Int^{-}	Ext^{+}	Ext^{-}
Actual	11.631	0.471	0.322	0.149	0.019	0.304	0.003	0.146
No $\Lambda(x)$ change	4.580	0.181	0.135	0.045	0.008	0.127	0.001	0.045
No VAT change	4.111	0.218	0.148	0.070	0.043	0.105	0.016	0.054
	VAT 3							
	π	$\mathcal{F}$	*Int*	*Ext*	Int^{+}	Int^{-}	Ext^{+}	Ext^{-}
Actual	14.487	0.573	0.428	0.145	0.019	0.409	0.002	0.143
No $\Lambda(x)$ change	4.708	0.190	0.136	0.053	0.006	0.130	0.001	0.053
No VAT change	4.258	0.239	0.154	0.086	0.041	0.113	0.020	0.066

Notes: The table reports the inflation rate, the inflation rate that would have been observed had there not been any extensive margin, the flexibility index, the intensive and extensive margins of price adjustment (as well as their counterparts computed for positive and negative price gaps), all in the month of a VAT change. Three recent episodes of changes in the VAT are considered: a reduction from 17.5% to 15% on December 1, 2008 (indicated by VAT 1), followed by two hikes, on up to 17.5% on January 1, 2010 and then up to 20% on January 4, 2011 (indicated by VAT 2 and VAT 3, respectively). The the extensive margin associated with positive and negative price gaps are computed by decomposing the extensive margin as $Ext_t{=}\int_{-\infty}^{0^-} x\Lambda_t'(x)\, f_t(x)\, dx + \int_0^{\infty} x\Lambda_t'(x)\, f_t(x)\, dx$, where Ext_t^- (Ext_t^+) is the first (second) term on the right side of the equality. For every VAT change episode, we contrast the actual numbers with two alternative scenarios. In the *no* $\Lambda(x)$ *change* scenario, the VAT change only impacts on the distribution of price gaps, while the hazard function is kept at the counterfactual (see Figure 8). The *no VAT change* scenario, instead, considers an alternative case in which neither the hazard function nor the price gap distribution change.

adjustment as described by Hobijn et al. (2006) in the occurrence of the Euro changeover. As in this case, the VAT-adjustment decision could result from the interplay between a *churning effect*—whereby price-setting units concentrate otherwise staggered price increases around the VAT change—and a *horizon effect*, which depends on the fact that prices adjusted before the VAT change do not reflect the marginal cost increases expected to occur afterwards.

When comparing the two margins of adjustment, the intensive one is typically much larger than its counterparts in the alternative scenarios—indicating that upward shifts in $\Lambda_t(0)$ are the most prominent feature in the occurrence of a VAT change—while movements along the extensive margin appear less dramatic. However, such a conclusion is not warranted after conditioning both margins to positive and negative price changes. In this case, substantial variation also takes place along the extensive margin coherent with the sign of the underlying price change. For instance, in the occurrence of the VAT drop, Ext^{+} is more than twice as large as its counterfactuals. The same order of magnitude can be observed when comparing the two VAT hikes (in this case, we need to focus on Ext^{-}). Movements in the extensive margin are a reflection of the interplay between the hazard function and the distribution of price gaps. In this respect, Figure 8 shows that all three episodes are associated with a close-to-symmetric increase in the steepness of the hazard function, as well as with a shift in the distribution of price gaps in the direction opposite to the VAT change. On one hand, this necessarily implies that the extensive margin associated with price gaps coherent with the sign of the adjustment is large. On the other hand, the extensive margin associated with price gaps of the opposite sign is very low, in light of the hazard function being weighed by a very small probability mass, after a shift in the distribution of price gaps has occurred.

All in all, these experiments support the predictions for the response to large nominal shocks in models with a prominent role for the extensive margin, such as Golosov and Lucas (2007) and Nakamura and Steinsson (2010a). More specifically, they imply that VAT changes cannot fully be assimilated to first-moment shocks, for they do not just affect the location of the price gap distribution, but also the adjustment hazard, implying they modify the incentives firms face when deciding whether to adjust their prices or not. Notably, the ultimate effect on the cost structure depends both on the size and the sign of the VAT shock.

6 Price flexibility and inflation dynamics

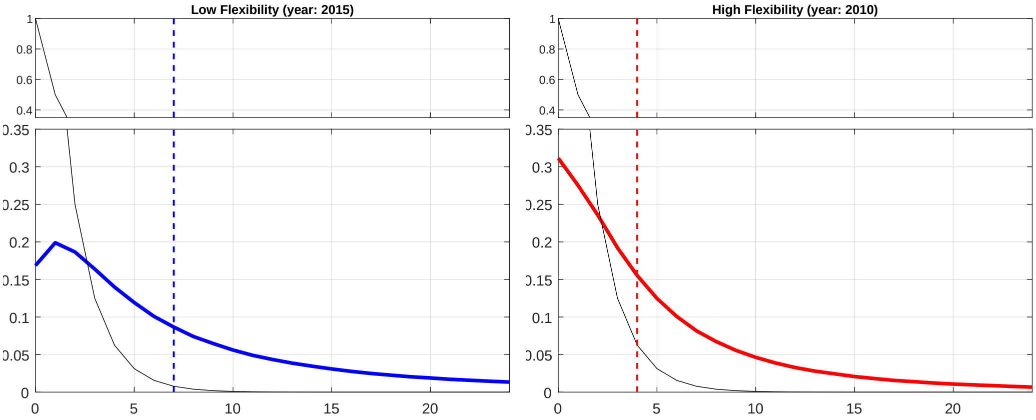
The estimation of Caballero and Engel's model of lumpy price adjustment shows that the pass-through of nominal shocks to inflation can vary substantially. We also report that—while not hinging on a specific margin of adjustment—flexibility is higher in connection with positive price changes. These properties bear major implications for evaluating the transmission of shocks to nominal demand. Using the estimated Ss model, we are able to examine the response of inflation to an aggregate nominal shock in two different periods, characterized by relatively high and low price flexibility, respectively.[39] As expected, Figure 9 shows that inflation is more responsive and less persistent in a period of relatively high price flexibility. In light of this simple exercise, one would expect price flexibility to contain valuable information for the analysis of inflation dynamics. This section aims at substantiating this claim.

We seek to examine how inflation behaves in periods of relatively high and low flexibility, and to contrast its inherent non-linear dynamics to its behavior in a linear setting. To this end, we employ a regime-switching autoregressive moving average model, where the transition across regimes is a smooth function of the degree of price flexibility. The STARMA(p,q) model is a generalization of the smooth transition autoregression model proposed by Granger and Terasvirta (1993).[40] Estimating a traditional ARMA(p,q) for each regime separately entails a certain disadvantage in that we may end up with relatively few observations in a given regime, which typically renders the estimates unstable and imprecise. By contrast, we can effectively

[39] As we only identify the price gap distribution at each point in time, we are not able to disentangle the contribution of the aggregate shock from that of idiosyncratic shocks. Therefore, for purely illustrative purposes, we choose an autoregressive specification for the first-moment shock. More details are available in Appendix H.

[40] In this respect, the STARMA(p,q) model also generalizes the threshold ARMA(p,q) model (DeGooijer, 2017).

Figure 9: Impulse Responses from the Ss Model



Note: The graphs display the average inflation response to a 1% aggregate nominal shock, μ_t, in two periods of relatively low and high price flexibility. The shock is assumed to die out with a persistence component of 0.5 and is depicted by the thin black line (with a negative sign). The left panel (low price flexibility) plots the average inflation response in 2010, while the right panel (high price flexibility) plots the average inflation response in 2015. In each of the two panels the vertical line delineates the half-life of the shock.

rely upon more information by exploiting variation in the probability of being in a particular regime, so that estimation and inference for each regime are based on a larger set of observations (Auerbach and Gorodnichenko, 2012).[41]

We assume that inflation can be described by the following model:

$$\begin{aligned}\pi_t &= G\left(\widetilde{\mathcal{F}}_{t-1},\gamma\right)\left(\phi_0^H+\sum_{j=1}^{p}\phi_j^H\pi_{t-j}+\varepsilon_t^H+\sum_{i=1}^{q}\theta_i^H\varepsilon_{t-i}^H\right)\\ &\quad+\left[1-G\left(\widetilde{\mathcal{F}}_{t-1},\gamma\right)\right]\left(\phi_0^L+\sum_{j=1}^{p}\phi_j^L\pi_{t-j}+\varepsilon_t^L+\sum_{i=1}^{q}\theta_i^L\varepsilon_{t-i}^L\right),\end{aligned} \tag{6}$$

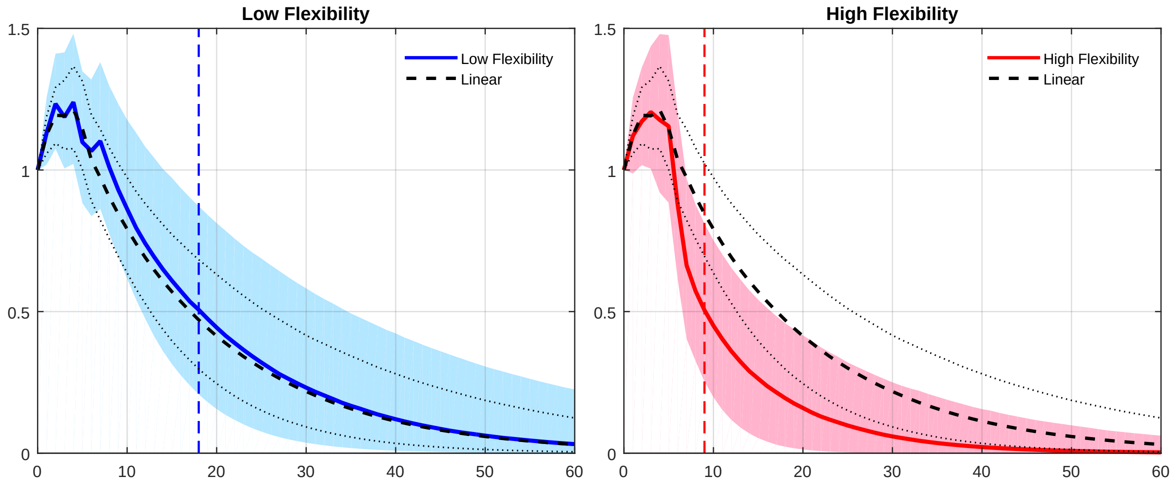
with $\varepsilon_t^i \sim N(0,\sigma_i^2)$ for $i=\{L,H\}$. Moreover, we set $G\left(\widetilde{\mathcal{F}},\gamma\right)=(1+e^{-\gamma\widetilde{\mathcal{F}}})^{-1}$, where $\widetilde{\mathcal{F}}$ denotes the normalized flexibility index and γ is the speed of transition across regimes.[42] We allow for different degrees of inflation persistence across the two regimes, as captured by the regime-specific autoregressive and moving average coefficients, as well as for different volatilities of the innovations in either regime. The likelihood of the model can be easily computed by recasting the system in state space (see, e.g., Harvey, 1990). We use Monte Carlo Markov-chain methods developed in Chernozhukov and Hong (2003) for estimation and inference. The parameter estimates, as well as their standard errors, are directly computed from the generated chains.[43]

[41]Estimating the properties of a given regime by relying on the dynamics of inflation in a different regime would bias our results towards not finding any evidence of non-linearity. In light of this, the asymmetries we will be reporting in the remainder of this section acquire even more statistical relevance.

[42]We employ a backward-looking MA(12) of the flexibility index to get rid of seasonality in the data. Moreover, we lag the index by one month, in order to avoid potential endogeneity with respect to CPI inflation.

[43]See Appendix I for further details.

Figure 10: Price Flexibility and Inflation Persistence



Note: This figure reports the responses of inflation to a 1% shock in the STARMA(1,7) model. The left (right) panel graphs the response in the low (high) price flexibility regime. In both cases we also report the the response from a (linear) ARMA(1,7) model. 68% confidence intervals are built based on the Markov Chain Monte Carlo (MCMC) method developed in Chernozhukov and Hong (2003). In each of the two charts the vertical line delineates the half-life of the shock.

As we focus on the post-1996 sample, we estimate the model by imposing that, in both regimes, the long-run inflation forecast is 2%, consistent with the mandate of the Bank of England. Whereas one can potentially estimate the speed of transition between regimes, the identification of γ relies on nonlinear moments. Moreover, in short samples the estimates may be sensitive to a handful of observations. Therefore, we decide to calibrate γ so that roughly 25% of the observations are classified to be in the high-flexibility (low-flexibility) regime, where this is defined by $G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right) > 0.8$ ($G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right) < 0.2$).[44] Thus, based on the Akaike criterion, we choose $p = 1$ and $q = 7$.[45]

Figure 10 reports the impulse-response functions to a 1% shock to inflation in each of the two regimes, and compares them to the response from an equivalent linear model. Inflation is much more persistent in periods characterized by a relatively low price flexibility, with the half-life of the shock being almost twice as large, as compared with periods of high flexibility. In fact, the estimated inflation volatility is 1.44 in the high-flexibility regime and 0.91 in the low-flexibility regime. These results are broadly supportive of the basic insights of the Ss model illustrated in the previous sections, and highlight the importance of keeping track of the degree of price flexibility.

Notably, the impulse-response function from the linear model is consistent with the behavior of inflation in the low-flexibility regime. A direct implication of this is that neglecting that

[44]Figure J.2 in Appendix J reports the dynamics of $G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right)$. Clearly, this specification identifies the 2009-2012 period as being characterized by a high-flexibility regime, whereas the 2002-2005 and 2015-2016 periods are marked by low price flexibility. The qualitative results are robust to variations in γ.

[45]Note that the modified AIC information criterion indicates a STARMA(1,3). Figures J.3 and J.4 in Appendix J report the results for this alternative setting. Our key insights are not affected by the exact specification of the STARMA(p,q) model.

Table 4: INFLATION FORECAST ERRORS AND PRICE FLEXIBILITY

(a) BoE MPC RPIX/CPI Forecast Errors

Horizon	Slope at $G = 0.2$		Slope at $G = 0.8$		F$-stat$	$\tilde{R}^2$
1	-0.195	[0.695]	0.797	[0.172]	0.168	2.61
2	-0.920	[0.261]	2.059	[0.031]	0.004	12.88
3	-1.341	[0.241]	2.927	[0.041]	0.000	18.33
4	-0.925	[0.563]	3.919	[0.025]	0.000	21.98
5	-0.493	[0.796]	4.067	[0.016]	0.000	22.86
6	-0.249	[0.901]	3.596	[0.033]	0.000	21.59
7	-0.275	[0.895]	3.555	[0.016]	0.000	19.96
8	-0.903	[0.621]	3.543	[0.003]	0.001	16.33

(b) Market Participants' Forecast Errors

Horizon	Slope at $G = 0.2$		Slope at $G = 0.8$		F$-stat$	$\tilde{R}^2$
1	0.317	[0.706]	0.636	[0.305]	0.468	-0.60
2	-1.117	[0.213]	2.097	[0.030]	0.003	13.50
3	-1.567	[0.224]	2.950	[0.041]	0.000	18.69
4	-1.045	[0.569]	3.860	[0.028]	0.000	21.03
5	-0.504	[0.815]	3.866	[0.022]	0.000	21.36
6	-0.085	[0.970]	3.161	[0.055]	0.000	19.45
7	-0.005	[0.998]	2.808	[0.045]	0.002	15.74
8	-0.665	[0.745]	2.431	[0.030]	0.022	9.27

Notes: The table reports the results of a quadratic spline regression of the forecast errors $e_{t+h|t}$ (for different forecast horizons, h, measured in quarters) on a quarterly average of an indicator of the normalized price flexibility index, $G_{t-1} = G(\widetilde{\mathcal{F}}_{t-1}; \gamma) = (1 + e^{-\gamma \widetilde{\mathcal{F}}_{t-1}})^{-1}$, where $\widetilde{\mathcal{F}}$ denotes the normalized flexibility index. The regression takes the form: $e_{t+h|t} = a_0 + a_1 G_{t-1} + a_2 G_{t-1}^2 + a_3 \mathbb{1}_{\{G_{t-1}>0.5\}} G_{t-1}^2$, where $\mathbb{1}_{\{G_{t-1}>0.5\}}$ is an indicator function taking value 1 when $G_{t-1} > 0.5$ and zero otherwise. The upper panel refers to the Bank of England MPC's RPIX/CPI forecast errors, while the bottom panel considers market participants' forecast errors. In each panel, the first two pairs of columns report the slope of the relationship evaluated at different levels of the indicator, together the p-value associated with the null hypothesis that the slope is equal to 0 (this is calculated using Newey-West standard errors). The penultimate column (F-$stat$) reports the p-value of the null hypothesis that all the coefficients associated to the flexibility regime are equal to 0 (i.e., $H_0 : a_1 = a_2 = a_3 = 0$). The last column reports the adjusted R-squared, denoted by $\tilde{R}^2$.

shocks are propagated at different speeds—depending on the overall degree of price flexibility—would entail an overestimation of their inflationary impact during windows of relatively high price flexibility. This should be particularly evident at medium-term forecast horizons, i.e. when the difference between the responses from the linear and the nonlinear model is somewhat larger. This begs the following question: do the Bank of England and/or market participants take price flexibility into account when computing their inflation expectations? In the remainder of this section we turn our attention to addressing this issue. In this respect, our premise delivers a key testable implication: if state dependence in price flexibility is accounted for by the forecaster, the resulting inflation forecast errors should be orthogonal to the flexibility regime.

In every quarter, the Inflation Report of the Bank of England publishes (year-on-year) Monetary Policy Committee's inflation forecasts, along with market participants' forecasts.

Both types of forecasts refer to the Bank of England's inflation target, which has switched from RPIX inflation to CPI inflation in December 2003. Thus, we construct quarterly forecast errors as the difference between realized inflation and the appropriate (mean) forecast at a given horizon.[46] These are then regressed on a nonlinear function of the flexibility regime indicator, $G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right)$: specifically, we use a quadratic spline function with a knot at 0.5. This function is a rather flexible tool, as it allows us to capture a number of potential shapes characterizing the relationship between the flexibility regime and the forecast errors.

Table 4 provides a summary of the results from our regression exercise. The first four columns report the slope coefficients and the associated p-values at relatively low and high levels of flexibility (i.e., $G = 0.2$ vs. $G = 0.8$). We recover an inclined L-shaped relationship between the forecast errors and price flexibility, which confirms that inflation tends to be overpredicted when prices are relatively flexible. The last two columns of the table also report the p-value associated with the null that no relationship between the forecast error and the flexibility regime exists, as well as the R-squared (adjusted for the number of regressors), so as to get an idea of the strength of the relationship. The results are consistent with the idea that information about the degree of price flexibility is not fully exploited by the Central Bank or by market participants. In line with Figure 10, the relationship tends to be stronger at medium-term horizons, while weakening at both short-term and long-term horizons. Specifically, around a four-quarter horizon, price flexibility accounts for roughly 22% of the variability in the absolute forecast error. The relationship is not statistically significant in periods of relatively low flexibility, whereas it is typically positive and statistically significant when flexibility is relatively high, with the slope displaying larger values at medium-term forecast horizons. The results are roughly the same, no matter which source of forecasts we consider.

Pronounced time variation in price flexibility after the Great Recession helps us to get a better understanding of the concurrent dynamics of the inflation rate. Inflation peaks twice between 2008 and 2011, while reaching its sample minimum in 2016, partially reflecting sharp movements in the value of the GBP and commodity prices.The Bank of England has generally underestimated the speed and impact of shocks to inflation in the 2008-2011 period. In light of our evidence, this points to a potential failure in appreciating that price flexibility was itself at the historical peak, possibly as a reflection of the three VAT adjustments taking place over a rather short time window. Conversely, the low-flexibility regime can explain the protracted period of low inflation towards the end of the sample, during which the Bank of England has displayed greater predictive accuracy. This regime of low price flexibility has then reversed in the summer of 2016, in coincidence with the sharp movements of the GBP in the aftermath of the Brexit referendum.

[46]Table J.1 in Appendix J returns similar evidence when we use absolute and squared forecast errors. The results are also virtually unchanged if we use median in place of mean forecasts.

7 Concluding remarks

We document some distinctive patterns in the evolution of the distribution of micro price changes in the UK, and discuss their implications for the transmission of nominal stimulus to output and inflation. By estimating the generalized Ss model of Caballero and Engel (2007), we are able to report that price flexibility displays pronounced time variation, especially during the last decade. Despite the marked non-linearity in the price response to inflationary shocks—which is crucially dictated by the degree of price flexibility—neither the Bank of England nor professional forecasters appear to account for this type of state dependence when forecasting CPI inflation. In fact, both of them tend to overestimate the impact of inflationary shocks in periods of relatively high price flexibility, especially at medium-term forecast horizons. In light of this, we point to price flexibility as a state variable that both practitioners and policy makers should carefully account for in their forecasting routine. In this respect, we show that a reliable proxy of aggregate price flexibility can easily be constructed from timely available micro prices, and it can successufully be employed to improve medium-term inflation projections.

A final note on the implications of our results for modeling price setting: by imposing a Calvo price-setting protocol to match the frequency of adjustment one could understate time variation in price flexibility, which is heavily influenced by the extensive margin of price setting, especially during periods of high volatility in inflation dynamics. Our work does not just emphasize the importance of time variation in higher moments of the distribution of price changes and their connection with price flexibility, but also assigns a prominent role to state-dependent price setting for the study of inflation dynamics, which is what Central Banks and practitioners are ultimately concerned with. In doing so, we point to the importance of allowing for time variation in menu costs. In this respect, more research should be devoted to understanding the sources of such time variation, and to what extent this is connected with firm dynamics, the degree of market concentration, and other relevant microeconomic and macroeconomic features.

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Time-varying Price Flexibility and Inflation Dynamics

Supplementary Material

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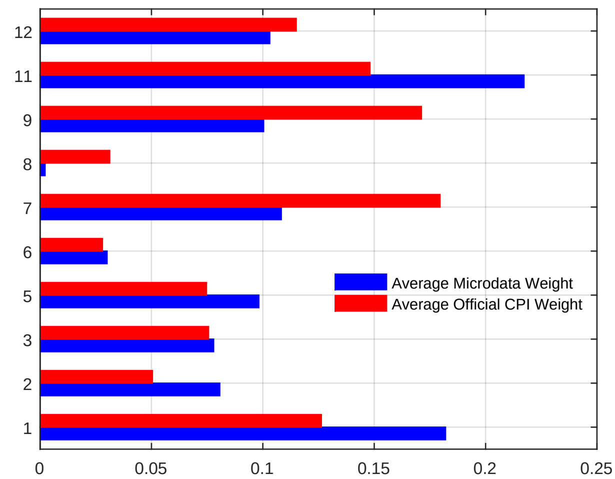
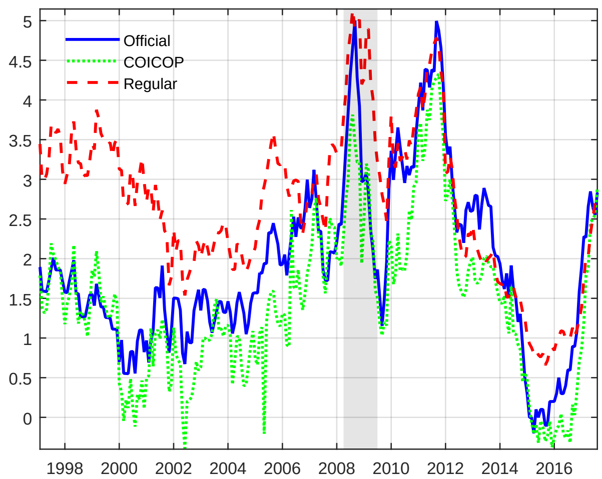
A On the representativeness of the data

This section provides additional details on the construction of the dataset used in the empirical analysis. The ONS data have a good coverage of all COICOP sectors, with the exception of Housing, Water, Electricity, Gas And Other Fuels (COICOP 4), Communication (COICOP 8) and Education (COICOP 10), whose coverage are less than 15%, 4%, and 3%, respectively. Given the extremely low coverage, we exclude COICOP 4 and 10. We keep COICOP 8, as the available price quotes are clustered in a small subset of items, such as Flower Delivery, Telephone for home use and Phone Accessories.[1]

The left panel of Figure A.1 contrasts the weights assigned to each of the COICOP sectors to those employed to build the CPI (re-normalized to exclude COICOP 4 and 10). Overall, we observe that using the available price quotes results into relatively larger weights for COICOP 1 and 11, whereas sectors 7 and 9 are underweighed. The right panel of Figure A.1 reports the official CPI inflation together with the inflation series retrieved from all the available price quotes (labeled *COICOP*) and the inflation obtained once all filters described in Section 2 are applied (labeled *Regular*). Unfiltered data track quite closely the official numbers, whereas the 'regular' series displays a robust correlation with the official data (roughly 0.7), and shows a positive bias. The latter mainly emerges from the exclusion of sales from the sample.

Figure A.1: Representativeness



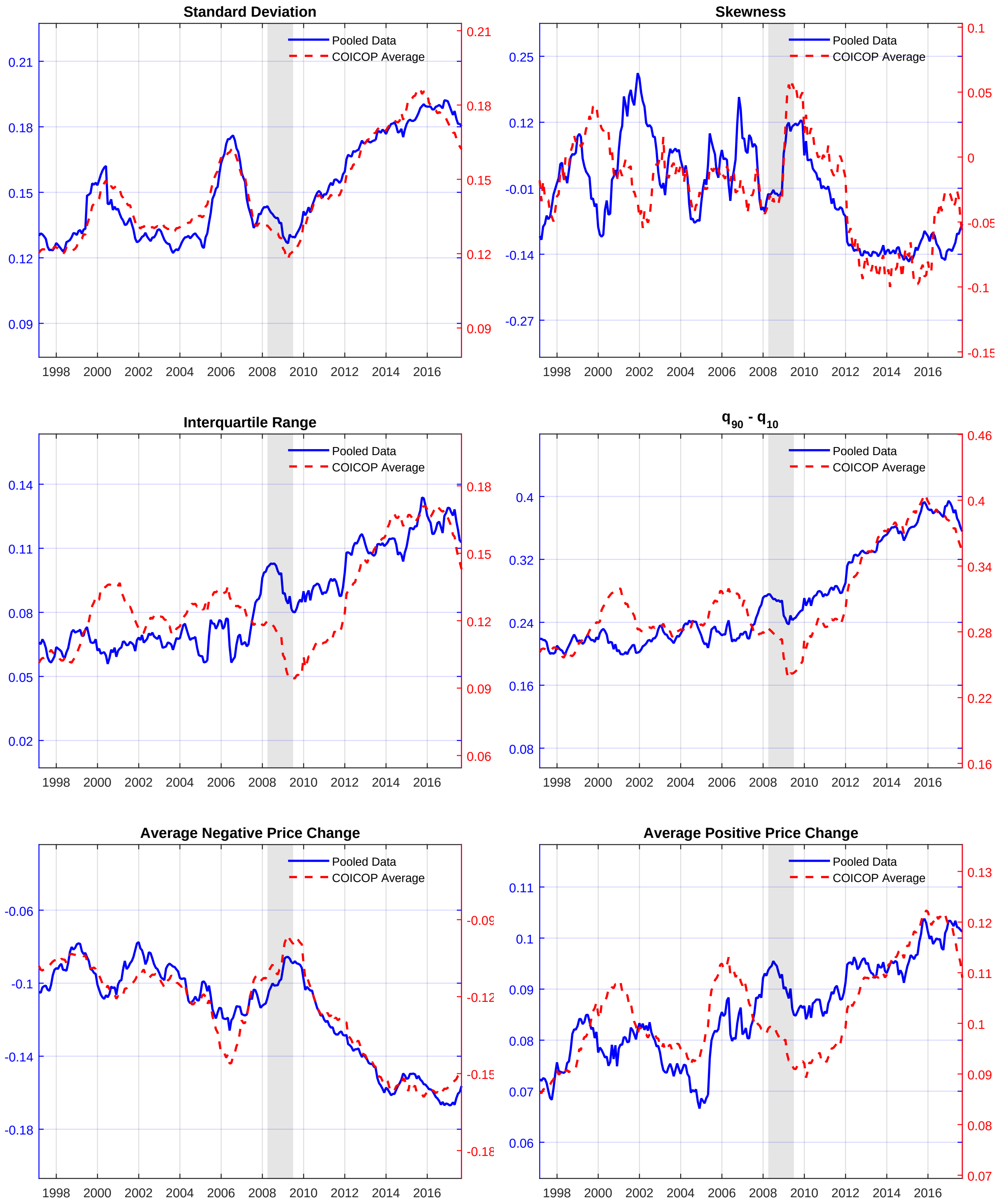


Notes: The left panel contrasts the weights assigned to each of the COICOP sectors to those assigned to build the CPI (re-normalized to exclude COICOP 4 and 10). The right panel reports the official CPI inflation, together with the inflation series retrieved from all the available price quotes (labeled *COICOP*) and the inflation obtained once all filters described in Section 2 are applied (labeled *Regular*). The COICOP codes are (1) Food And Non-Alcoholic Beverages, (2) Alcoholic Beverages, Tobacco And Narcotics, Clothing And Footwear (3), Furnishings, Household Equipment And Routine Household Maintenance (5), Health (6), Transport (7), Communication (8), Recreation And Culture (9), Hotels, Cafes And Restaurants (11), Miscellaneous Goods And Services (12).

[1]Due to the small number of price quotes in this sector, the results would be little affected by its exclusion from the analysis.

B On the role of aggregation and composition effects

Figure B.1: Aggregate vs Disaggregated Moments



Notes: The figure compares various moments of the distribution of price changes with their counterparts obtained by averaging the corresponding moments of the price quotes obtained for each of the 25 COICOP group categories. The shaded vertical band indicates the duration of the Great Recession.

C A monthly coincident indicator of economic activity

We use monthly information on a number of macroeconomic indicators of economic activity to infer the underlying movements of GDP at the monthly frequency. Following Mariano and Murasawa (2003), we approximate the (normalized) quarterly growth of real GDP, Δy_t^q, as a moving average of an unobserved month-on-month GDP growth rate, Δy_t^*:

$$\Delta y_t^q = \frac{1}{3}\Delta y_t^* + \frac{2}{3}\Delta y_{t-1}^* + \Delta y_{t-2}^* + \frac{2}{3}\Delta y_{t-3}^* + \frac{1}{3}\Delta y_{t-4}^*.$$

We then assume that Δy_t^* can be decomposed into an aggregate component, α_t, which is common across a number of other macroeconomic indicators, and an idiosyncratic component, ε_t:

$$\Delta y_t^* = \alpha_t + \varepsilon_t.$$

We assume that the idiosyncratic component follows an autoregressive process of order one:

$$\varepsilon_t = \psi \varepsilon_{t-1} + \eta_t.$$

The other macroeconomic indicators are available at a monthly frequency. We specify (the standardized value of) each of them as the sum of two mutually orthogonal components, a common and an idiosyncratic one. The former is captured by the current and lagged values of the aggregate common factor (see, e.g., D'Agostino et al., 2016). Specifically, denoting with Δx_{it} the generic i-th macroeconomic indicator, we have that

$$\Delta x_{it} = \sum_{j=1}^{l} \lambda_{ij} \alpha_{t-j} + e_{it},$$

where e_{it} follows an autoregressive process of order one:

$$e_{it} = \rho_i e_{it-1} + \upsilon_{it},$$

where the innovations to the idiosyncratic process are *iid* and uncorrelated across the indicators (i.e., $E(\upsilon_{it}\upsilon_{jt}) = 0, \forall i \neq j$, and $E(\upsilon_{it}\eta_t) = 0, \forall i$).

We let the aggregate factor follow an autoregressive process of order two:

$$\alpha_t = \phi_1 \alpha_{t-1} + \phi_2 \alpha_{t-2} + u_t.$$

In our specific application, we set $l = 3$ and all autoregressive processes are restricted to be stationary. The model can be cast in state space. Therefore, the likelihood can be easily computed through the Kalman filter and the factor is retrieved by using the Kalman smoother (see Harvey, 1990).

Together with the GDP data, we use following short term (monthly) macroeconomic indicators: (1) the index of manufacturing, (2) the index of services, (3) retail sales (excl. Auto Fuel), (4) Employment and (5) unemployment (claimants count). We use data starting on January 1990: we rely on a sample that is longer than the one employed in our analysis, so as to include two recessionary episodes. The dataset is unbalanced, as some of the indicators are not available form the starting date (and GDP is observed only once in the quarter). This is not an issue, as the Kalman filter can easily deal with an arbitrary pattern of missing observations in the sample.

Table C.1 reports the fit of the aggregate components for the quarter-on-quarter growth rates of each of the variables being employed. Clearly, the single-factor specification is able to capture a large fraction of the variation in the set of indicators considered here. Figure C.1 reports quarter-on-quarter variations in the aggregate factor ($\alpha_t^q = \frac{1}{3}\alpha_t + \frac{2}{3}\alpha_{t-1} + \alpha_{t-2} + \frac{2}{3}\alpha_{t-3} + \frac{1}{3}\alpha_{t-4}$), together with the GDP growth. The level of the business cycle indicator is then computed by cumulating the common factor over time, and assuming that trend growth equals the mean of GDP growth over the sample (this is denoted by μ):

$$z_t = \sum_{\tau=1}^{t} (\widehat{\mu} + \widehat{\alpha}_\tau),$$

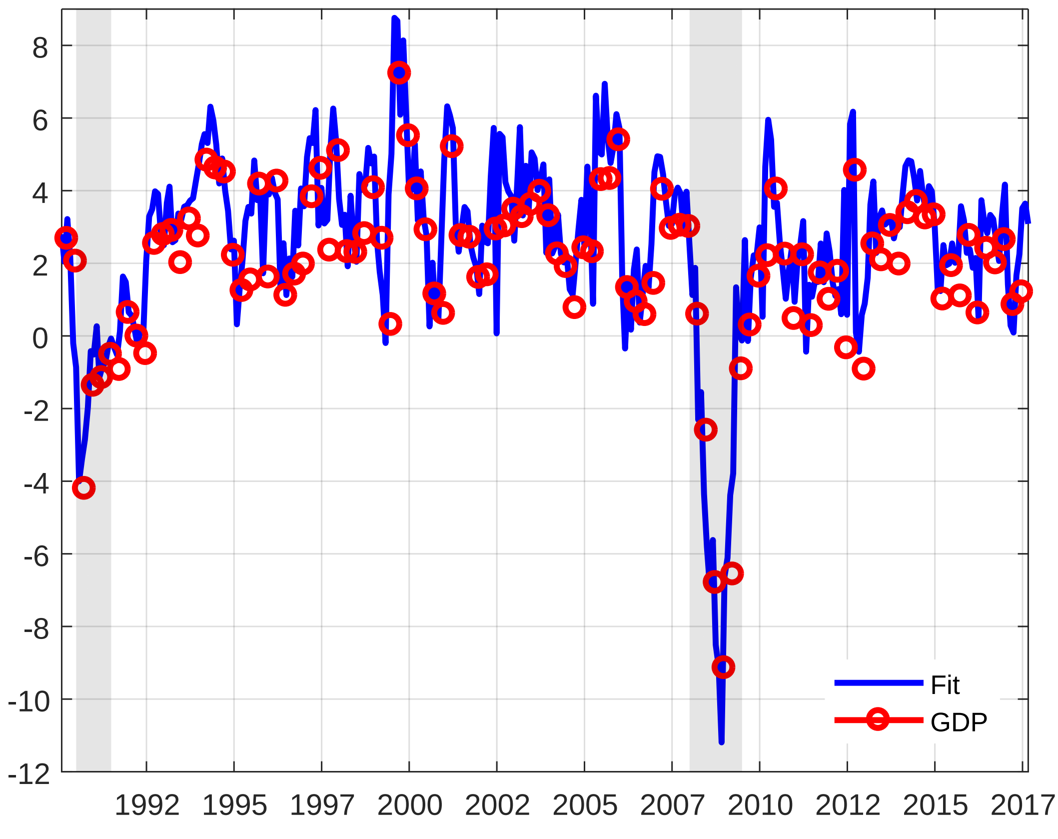
where $\widehat{\alpha}_\tau$ is retrieved by using the Kalman smoother. The business cycle indicator is then computed by applying a simple filter to z_t. For the baseline results in the paper we use the Rotemberg (1999) version of the HP filter, which chooses the smoothing coefficient of the HP filter to minimize the correlation between the cycle and the first difference of the trend estimate.

Table C.1: Coincident Indicator - Model Fit

	$R^2(\%)$
GDP	87.9
Index of Manufacturing	39.6
Index of Services	82.4
Retail Sales	14.7
Employment	23.3
Unemployment	22.4

Notes: The table reports the fit of the coincident business cycle indicator on the quarter-on-quarter growth rate of the underlying variables.

Figure C.1: Monthly (QoQ) GDP

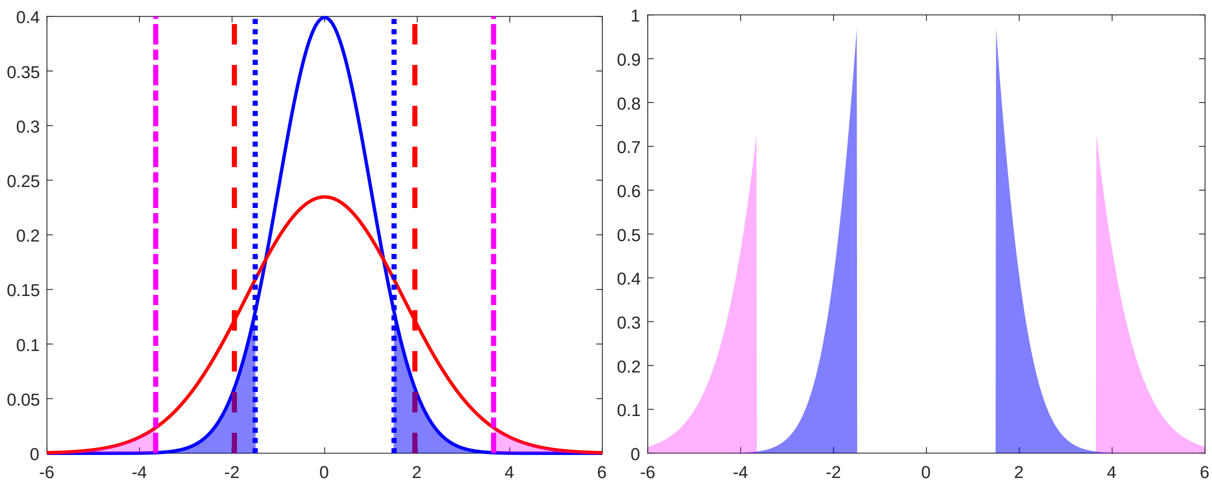


Note: The figure shows the fit of the (monthly) coincident indicator on the (annualized) quarter-on-quarter growth of real GDP.

D The combined effect of second-moment shocks and changes the incentives to adjust prices

Figure D.1 considers a situation in which both ϕ and λ increase.[2] The rise in the dispersion of price changes determines an expansion in the inaction region, thus increasing the density outside the adjustment bands and, in turn, the frequency of adjustment. This effect is counteracted by the rise in λ, which widens the inaction region further and restricts the density outside the adjustment bands beyond the initial situation. If the expansion in the inaction region is large enough to overcome the increase in dispersion, we observe opposite movements in the cross-sectional dispersion of prices and the frequency of adjustment. This is in line with what we observe in the post-recession period. The next subsection confirms this intuition through the estimation of the generalized Ss model of Caballero and Engel (2007).

Figure D.1: A COMBINED INCREASE IN ϕ AND λ



(a) Price Gap Distribution (b) Price Change Distribution

Note: We consider a positive shift in λ that affects the inaction region (while leaving the distribution of price gaps unaffected), combined with an increase in the dispersion of the distribution of price gaps, ϕ. The left panel reports the transformations occurring to the distribution of price gaps and the corresponding bands delimiting the inaction region: the dotted (blue) line refers to the ex-ante situation, the dashed (red) line denotes the effects of the volatility shift, while the dashed-dotted (magenta) line refers to the effects produced by the joint increase in ϕ and λ. The right panel reports the distributions of price changes, both in the ex-ante situation and in the case of a combined increase in ϕ and λ.

D.1 Making sense of changing comovement between the frequency and dispersion of price changes

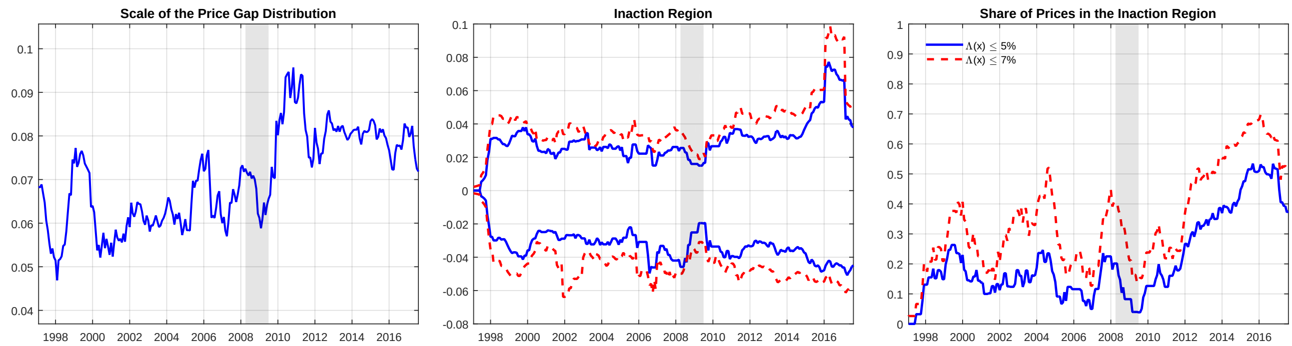
The first two panels of Figure D.2 report the estimated scale parameter of $f_t(x)$ and the inaction region associated with two hazard probabilities (namely, 5% and 7%). Both statistics are time-varying, and increase markedly in the second decade of the sample. According to our comparative statics analysis in Section 3, a prolonged decline in the frequency of adjustment, coupled with a surge in its dispersion, may be rationalized by an expansion in the inaction region—as triggered by an increase in the fixed cost of adjustment and/or a drop in the cost of deviating from the optimal price, for instance—that overcomes the effects of a positive shift in the dispersion of price gaps. To verify this is indeed the case, the last panel of Figure D.2 reports the share of prices in the inaction region, defined as the proportion of prices whose $\Lambda_t(x)$ is lower than a given hazard rate.

[2]Once again, a drop in α would lead to qualitatively similar results.

Notably, by the end of the sample about five times as many firms are inactive, as compared with the pre-2010 time window. This stands as indirect evidence that the expansion in the inaction region, as captured by the downward shift in the hazard function, dominates the increase in the dispersion of $f_t(x)$. Note also that greater inactivity appears more evident in correspondence with positive price gaps, as compared with the negative ones, thus implying an increased degree of downward price stickiness.

On a more general note, changes in the shape of the distribution of price gaps, coupled with the expansion of the inaction region, imply that non-predetermined price adjustments—which are more likely to occur for large price gaps—have played an increasingly important role in the recent past, as confirmed in the analysis reported in the main body of the paper.

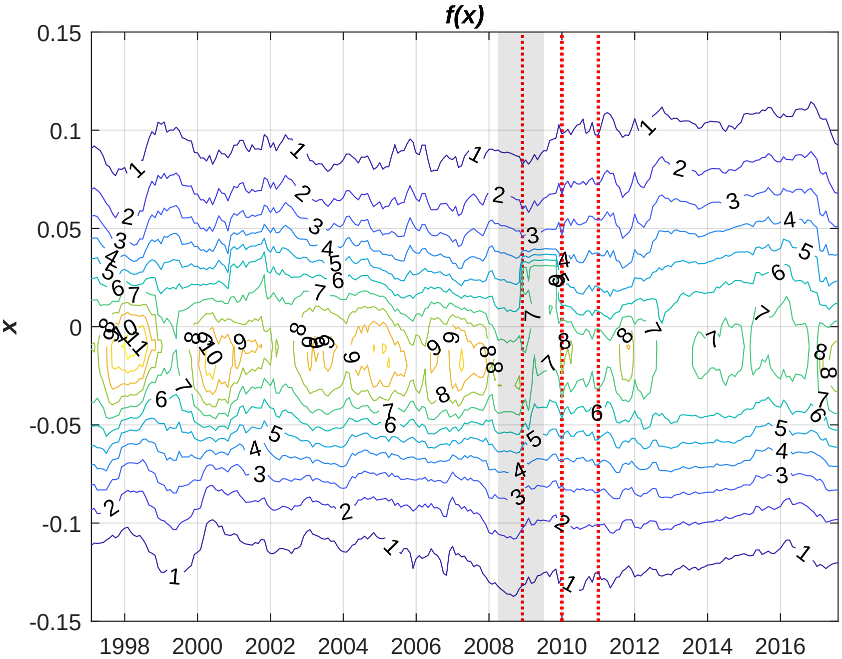
Figure D.2: Dispersion of Price Gaps and the Inaction Region



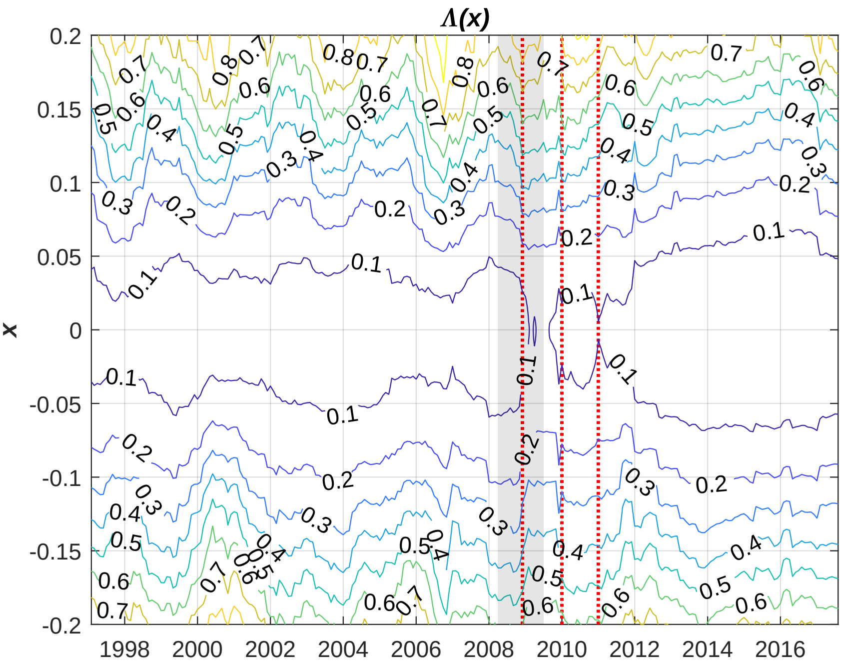
Note: The three panels of the figure report the estimated scale parameter of $f(x)$, the inaction region (for two different hazard rates), and the corresponding share of prices within the inaction region, respectively. The shaded vertical band indicates the duration of the Great Recession.

E Model estimates

Figure E.1: Estimated Price Gap Distributions and Hazard Functions



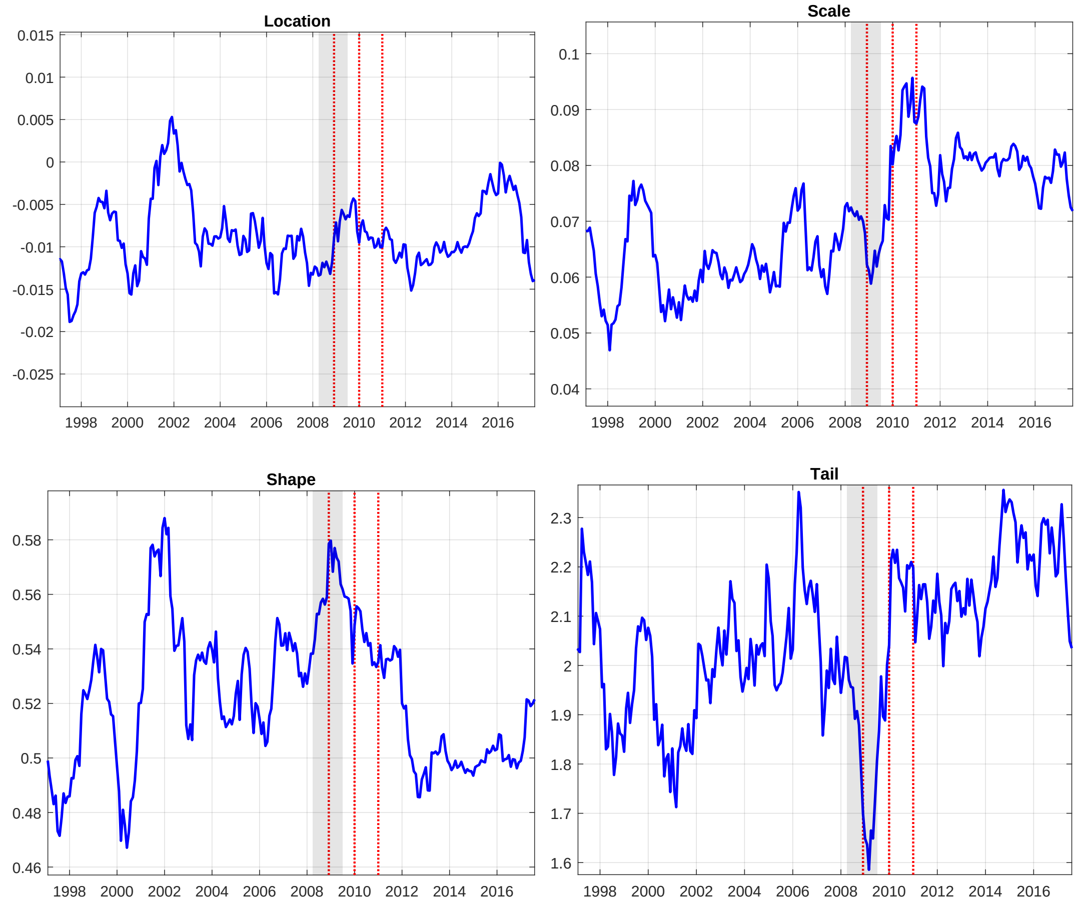
(a) Price Gap Distributions



(b) Hazard Functions

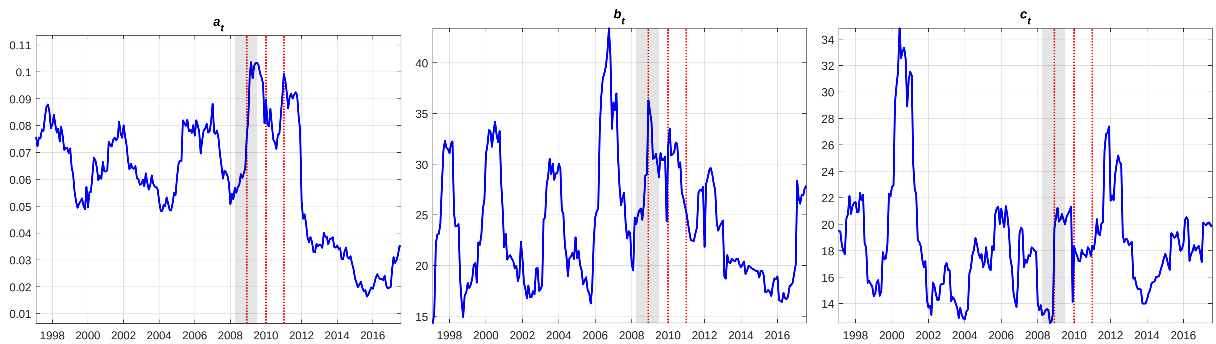
Note: The red lines denote the three VAT changes in the sample. The shaded vertical band indicates the duration of the Great Recession.

Figure E.2: Parameters of the Price Gap Distribution



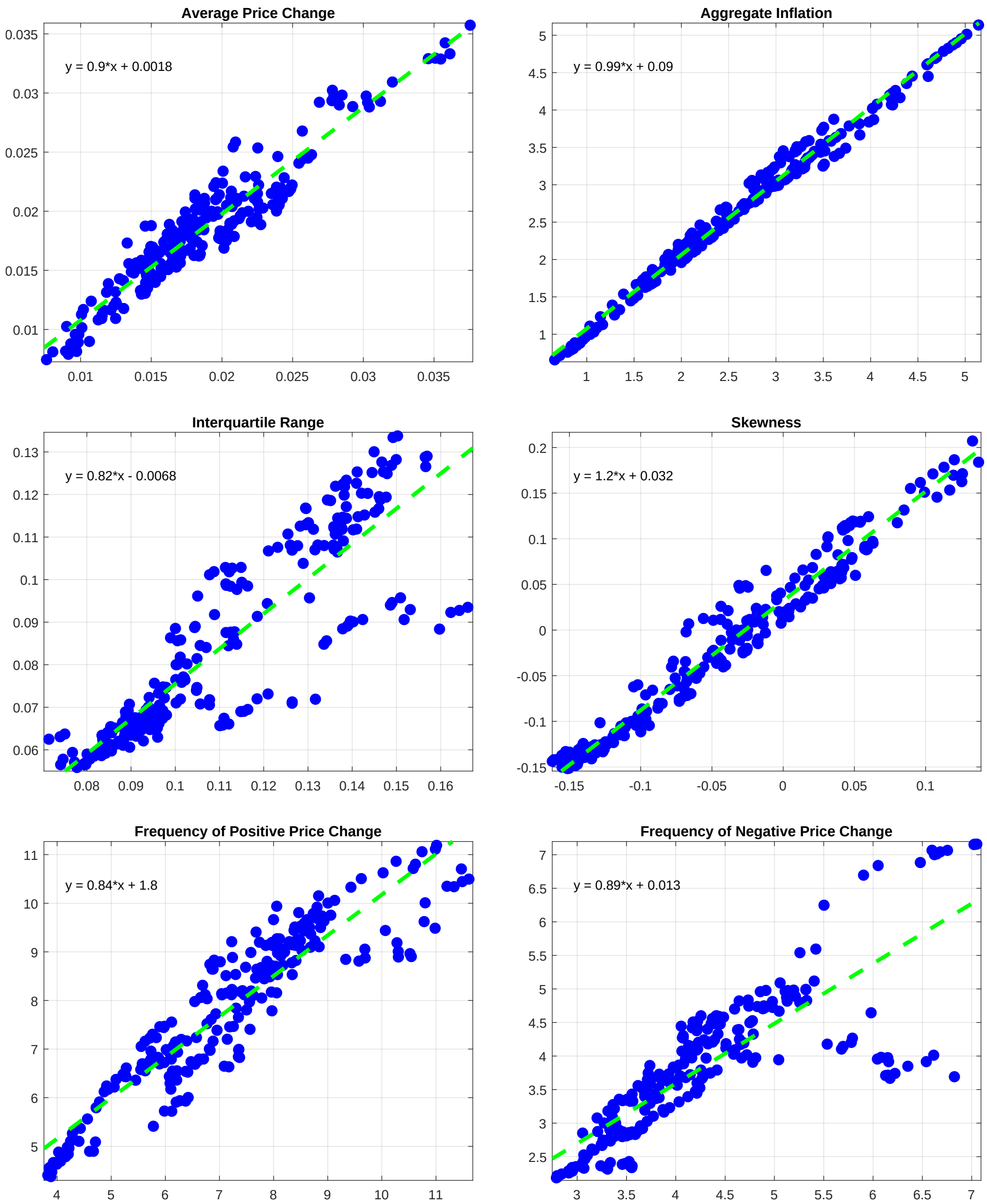
Note: The red lines denote the three VAT changes in the sample. The shaded vertical band indicates the duration of the Great Recession.

Figure E.3: Parameters of the Hazard Function



Note: The red lines denote the three VAT changes in the sample. The shaded vertical band indicates the duration of the Great Recession.

Figure E.4: Fit of the Ss Model (Selected Moments)



Notes: The figure compares the estimated moments from the Ss model in Section 4 (x-axis) to the moments estimated from the raw data (y-axis). Each chart also reports the linear fit (green/broken) line.

F Model identification

In this appendix we check whether the SMM estimation strategy we employ for the estimation of the generalized Ss model is able to separately identify the shape of the price gap distribution and the hazard function.

The parameters of the model are identified through their ability to match the selected moments. As noted in Section 4.1, we match the following moments of the distribution of price changes: mean, median, standard deviation, interquartile range, difference between the 90th and 10th quantile of the distribution, as well as (quantile-based) skewness and kurtosis. We also match the frequency and the average size of prices movements, after distinguishing between positive and negative price changes, as well as the observed rate of inflation.

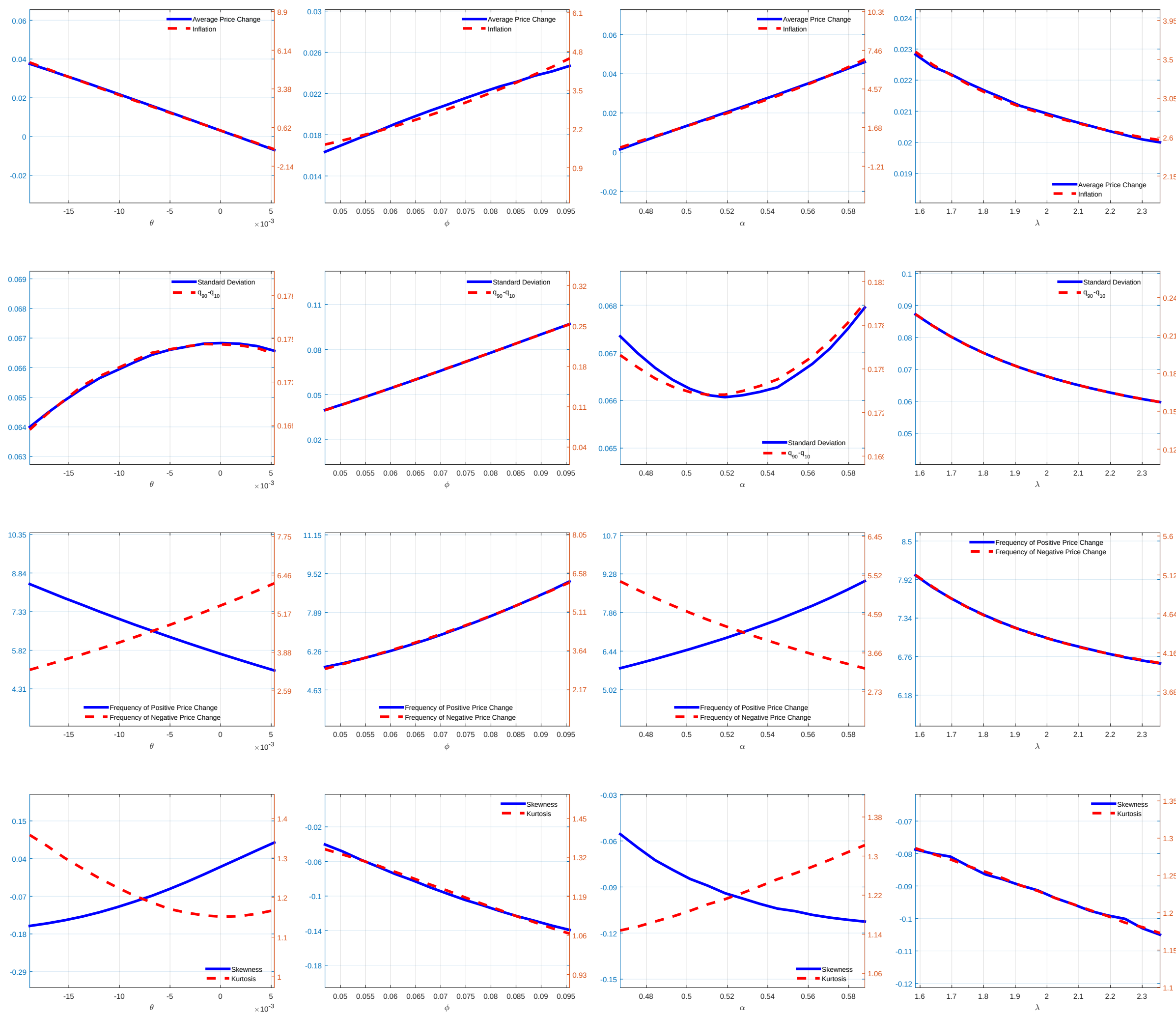
We evaluate the systematic impact of each parameter on the moments that we are matching. To this end, the first exercise we perform consists of investigating whether marginal variation in each of the parameters of the model affects the moments that we are matching. Figure F.1 and Figure F.2 reports the results of this exercise. We fix all the parameters at their median estimates, and for each column we vary one of of them at the time (within the range of values that the parameters assume in our estimation) and report the impact of these changes for some selected moments.

All parameters have an impact on a number of moments, and in the expected direction. For instance, increasing the scale (tail) parameter of the price gap distribution increases (decreases) monotonically the implied dispersion of the distribution of (non-zero) price changes, and in both cases decreases the skewness and the kurtosis. Instead, changing the location or the shape parameter has an opposite impact on skewness and kurtosis, and affects non-monotonically the dispersion (with higher dispersion obtained for a more skewed distribution, regardless of the sign of the skewness). As for the parameters of the hazard function, changing the constant term affects equally the frequency of price adjustment, whereas changes in the slope for positive (negative) price gaps impacts the frequency of negative (positive) price changes and the average negative (positive) price changes, leaving invariate the positive (negative) side. These results confirm the observation of Berger and Vavra (2017) for the specific functional forms of the price gap distribution and the hazard function we employ.

Having established that all the parameters have an impact on the moments we attempt to match, a fair question is whether moment matching allows us to appropriately identify/distinguish the shape of the price gap distribution from the shape of the hazard function. In fact, one might question whether the specific model we choose is able to identify a fatter price gap distribution from a steeper hazard function, or a skewed price gap distribution from an asymmetric hazard function. To this end, we simulate samples of 100,000 price changes from the model, and then fit the model on each of these synthetic samples by SMM, matching the same moments we use in the baseline estimation (see Section 4.1). Figure F.3 contrasts the true price gap distribution (upper panel) and hazard function (lower panel) to the estimated counterparts. We look at three possible different parameterizations of the model, and report the 'fan charts' of the estimated functions. The specific parameterizations are merely meant to serve for illustrative purposes: we would obtain very similar evidence by imposing alternative specifications. Finally, for each set of calibrations, we simulate and estimate the model over 200 different samples.

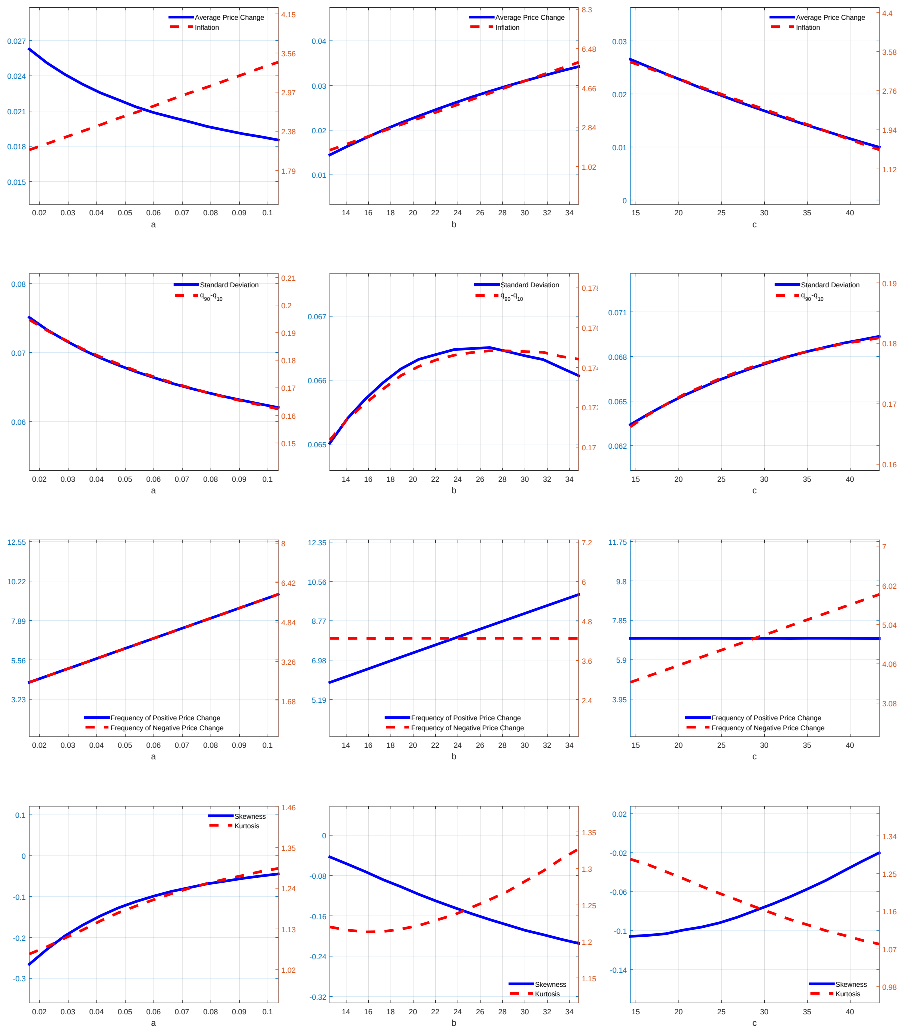
The charts highlight that the model is able to separately identify the shape of the price gap and hazard function in all the settings we consider. The discrepancy between the true parametrization and the estimate is minimal, and the resulting match of the flexibility index and its decomposition is very close to the true one.

Figure F.1: Identification and the parameters of $f_t(x)$



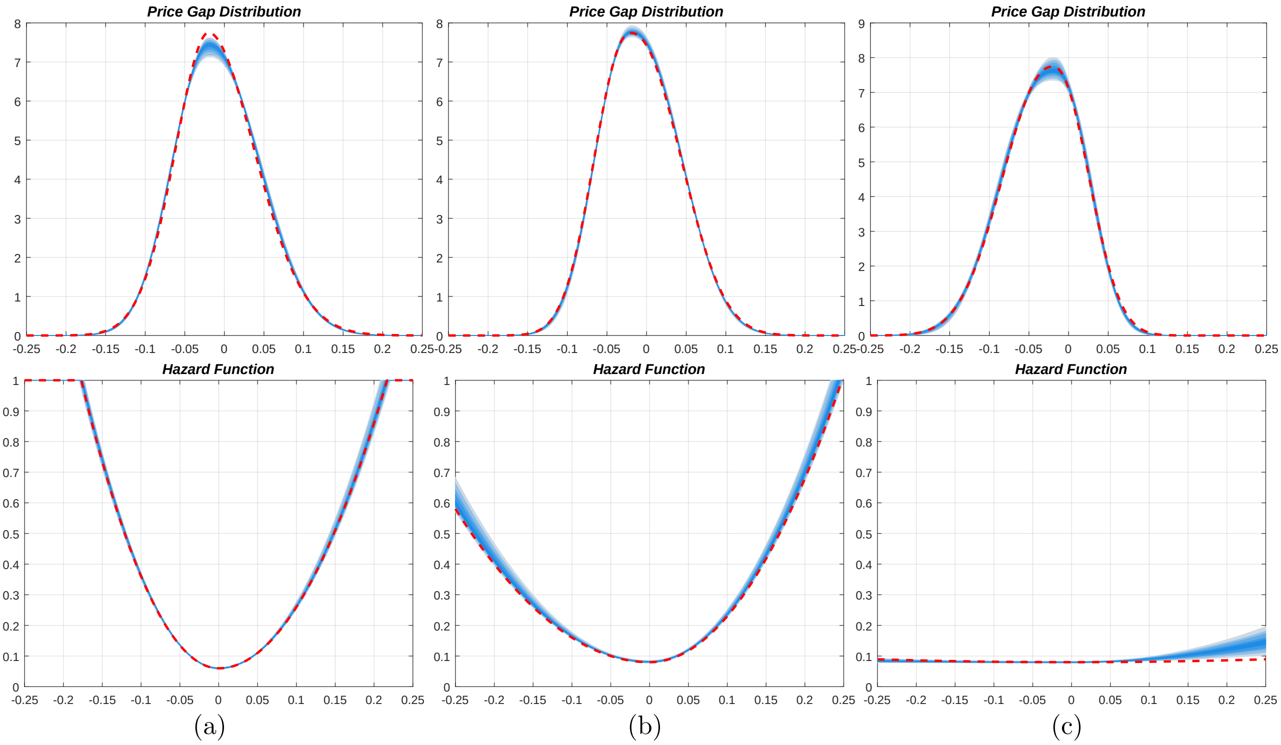
Notes: In each panel, we vary one of the parameters of $f_t(x)$ at the time—while keeping the other coefficients at their baseline estimate—and report its effect on key moments of the price change distribution, as well as the resulting rate of inflation.

Figure F.2: IDENTIFICATION AND THE PARAMETERS OF $\Lambda_t(x)$



Notes: In each panel, we vary one of the parameters of $\Lambda_t(x)$ at the time—while keeping the other coefficients at their baseline estimate—and report its effect on key moments of the price change distribution, as well as the resulting rate of inflation.

Figure F.3: Model Simulations and Empirical Fit



Note: The red line corresponds to the 'true' DGP, while the blue shades correspond to the [5,10,20,. . . 90,95]-th quantile of the estimated price gap distribution (upper panel) and hazard function (lower panel). The following parameterizations are considered: Panel (a): $\theta = -0.02, \psi = 0.07, \varrho = 0.42, \nu = 1.9, a = 0.06, b = 20, c = 30$; Panel (b): $\theta = -0.02, \psi = 0.07, \varrho = 0.42, \nu = 2.2, a = 0.08, b = 15, c = 8$; Panel (c): $\theta = -0.02, \psi = 0.07, \varrho = 0.58, \nu = 2.2, a = 0.08, b = 0.15, c = 0.15$.

G Alternative scenarios in the occurrence of a VAT change

Recall that inflation in the occurrence of a VAT change is computed as

$$\pi_t^{VAT\ change} = -\int x\Lambda_t^{VAT\ change}(x)\, f_t^{VAT\ change}(x)\, dx,$$

implying that the observed inflation results from both changes in the distribution of price gaps, as well as from shifts in the hazard function. Based on this benchmark, one can envisage two relevant scenarios:

- *No $\Lambda(x)$ change*: What rate of inflation would have been observed, had the VAT change only been associated with a change in the price gap distribution, while keeping the incentives of changing prices fixed? To address this question, we compute the following counterfactual rate of inflation

$$\pi_t^{No\ \Lambda(x)\ change} = -\int x\Lambda_t^{No\ VAT\ change}(x)\, f_t^{VAT\ change}(x)\, dx$$

- *No VAT change*: What inflation would have been observed in absence of changes in the price gap distribution and the hazard function? This can be retrieved as

$$\pi_t^{No\ VAT\ change} = -\int x\Lambda_t^{No\ VAT\ change}(x)\, f_t^{No\ VAT\ change}(x)\, dx$$

The *No VAT change* counterfactual is computed by averaging the same function, for the same month of the year in the 6 years before the VAT change.

Comparing $\pi_t^{No\ VAT\ change}$ with the actual rate of inflation highlights the overall effects of the VAT, whereas the comparison between $\pi_t^{No\ \Lambda(x)\ change}$ and observed inflation quantifies the relevance of the state dependence in price setting (i.e., the fact that incentives to change prices are themselves a function of the underlying environment).

H Details on the computation of the impulse response function from the Ss model

This appendix gives a brief account of how we compute the impulse response functions from the generalized Ss model presented in Section 4. We start by specifying a process for the exogenous (first-moment) shock.[3] Specifically, we assume that:

$$\mu_t = \rho\mu_{t-1} + \eta_t.$$

Thus, we fix $\rho = 0.5$ and select a shock $\eta_0 = -1\%$. In light of this, should prices be fully flexible, we would observe a 1% increase of inflation that dies out relatively quickly.

The impulse responses are then calculated as:

$$\begin{aligned} IRF_j &= \mathtt{E}(\pi_{t+j}|\mu_{t+j} = \hat{\mu}_{t+j}) - \mathtt{E}(\pi_{t+j}|\mu_{t+j} = 0) \\ &= -\int z_j\Lambda_t(z)\, f_t(z)\, dz + \int x_j\Lambda_t(x)\, f_t(x)\, dx, \end{aligned}$$

where $z_j = x_j + \hat{\mu}_{t+j}$. Note that, by definition, the cumulative impact of the shock equals the sum of the μ_t's.

I Estimation of the STARMA (p,q) model

Recall the smooth transition ARMA model, STARMA(p,q), in Section 6:

[3] Since we assume that the shock has the same impact on all price quotes, the shock acts as a location shifter of the price gap distribution.

$$
\begin{aligned}
\pi_t \quad = \quad & G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right)\left(\phi_0^H+\sum_{j=1}^{p}\phi_i^H\pi_{t-j}+\varepsilon_t^H+\sum_{i=1}^{q}\theta_i^H\varepsilon_{t-i}^H\right) \\
& +\left[1-G\left(\widetilde{\mathcal{F}}_{t-1};\gamma\right)\right]\left(\phi_0^L+\sum_{j=1}^{p}\phi_i^L\pi_{t-j}+\varepsilon_t^L+\sum_{i=1}^{q}\theta_i^L\varepsilon_{t-i}^L\right). \qquad \text{(I.1)}
\end{aligned}
$$

This can be easily casted in state space. Therefore the likelihood can be calculated recursively using the Kalman filter (see Harvey, 1990). Since the model is highly non-linear in the parameters, it is possible to have several local optima and one must try different starting values of the parameters. Furthermore, given the non-linearity of the problem, it may be difficult to construct confidence intervals for parameter estimates, as well as impulse responses. To address these issues, we use a Markov Chain Monte Carlo (MCMC) method developed in Chernozhukov and Hong (2003; henceforth CH). This method delivers not only a global optimum but also distributions of parameter estimates.

Denote with θ the vector of parameters. We employ the Hastings-Metropolis algorithm to implement CH's estimation method. Specifically, our procedure to construct chains of length N can be summarized as follows:

- *Step 1*: Draw $\vartheta^{(n+1)}$, a candidate vector of parameter values for the chain's $n+1$ state, as $\vartheta^{(n+1)}=\theta^{(n)}+\mathbf{u}_n$ where $\mathbf{u}_n$ is a vector of *iid* shocks taken from a student-t distribution with zero mean, $\nu=5$ degrees of freedom and variance Ω.
- *Step 2*: Take the $n+1$ state of the chain as

$$
\theta^{(n+1)}=\begin{cases}\vartheta^{(n+1)} & \text{with probability } \min\left\{1,\frac{L\left(\vartheta^{(n+1)}\right)}{L\left(\theta^{(n)}\right)}\right\}\\ \theta^{(n)} & \text{otherwise}\end{cases}
$$

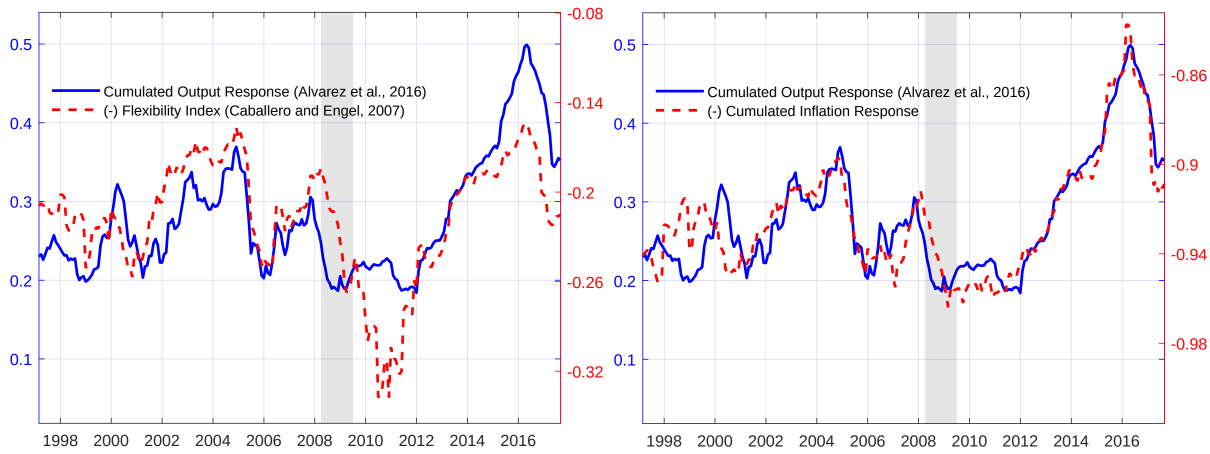
where $L(\theta)$ denotes the value of the likelihood of the model evaluated at the parameters values θ.

Specifically, we use an adaptive step for the value of Ω, i.e. this is recalibrated using the accepted draws in the initial part of the chain and then adjusted on the fly to generate $25-35\%$ acceptance rates of candidate draws, as proposed in Gelman et al. (2004). We use a total of 50,000 draws, and drop the first 25,000 draws (i.e., the 'burn-in' period). We then pick the 1-every-5 accepted draws to mitigate the possible autocorrelations in the draws. We run a series of diagnostics to check the properties of the resulting distributions from the generated chains. We find that the simulated chains converge to stationary distributions and that simulated parameter values are consistent with good identification of parameters.

CH show that $\overline{\theta}=\frac{1}{N}\sum_{i=1}^{N}\theta^{(i)}$ is a consistent estimate of θ under standard regularity assumptions of maximum likelihood estimators. CH also prove that the covariance matrix of the estimate of θ is given by the variance of the estimates in the generated chain. Furthermore, we can use the generated chain of parameter values $\theta^{(i)}$ to construct confidence intervals for the impulse responses.

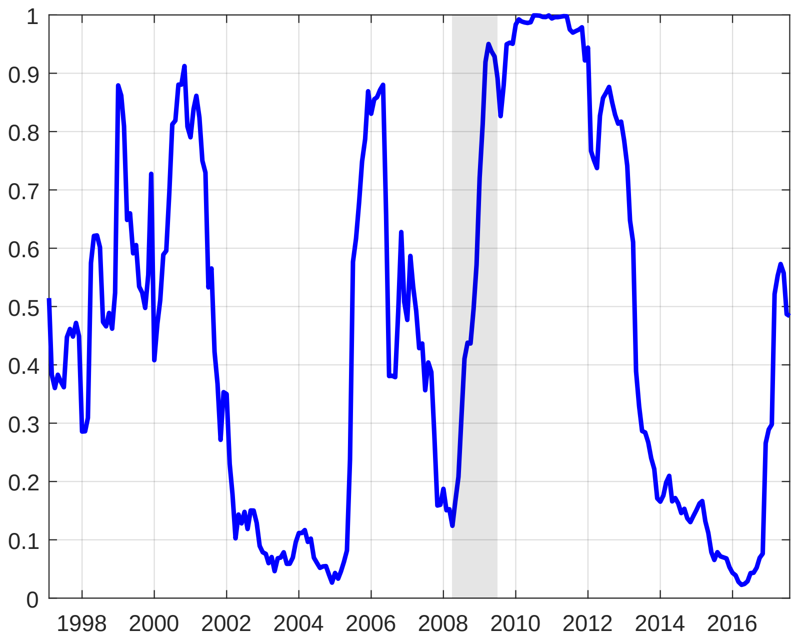
J Additional figures and tables

Figure J.1: Comparison with Alvarez et al. (2016)



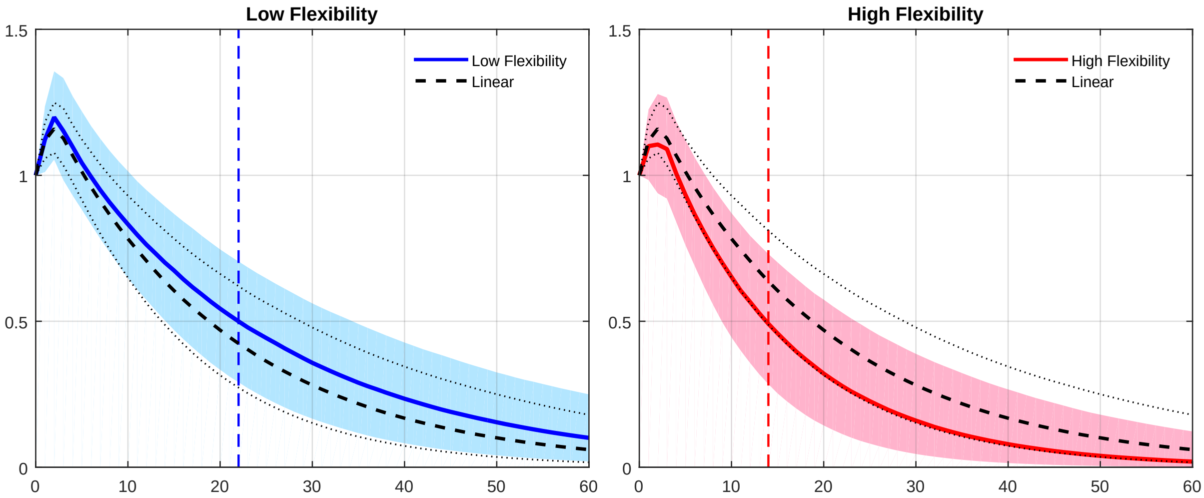
Note: The left panel of the figure reports a the cumulated output response to a monetary policy shock (solid-blue line), as computed by Alvarez et al. (2016), and the (negative of the) index of price flexibility, as computed by Caballero and Engel (2007) with inverted sign (dashed-red line). The right panel, instead, features a scatter plot of the cumulated output response to a monetary policy shock (solid-blue line) against the (negative of the) cumulated inflation response, where we cumulate the inflation response over a 18 month period again with inverted sign (dashed-red line).

Figure J.2: Probability of a High-flexibility Regime



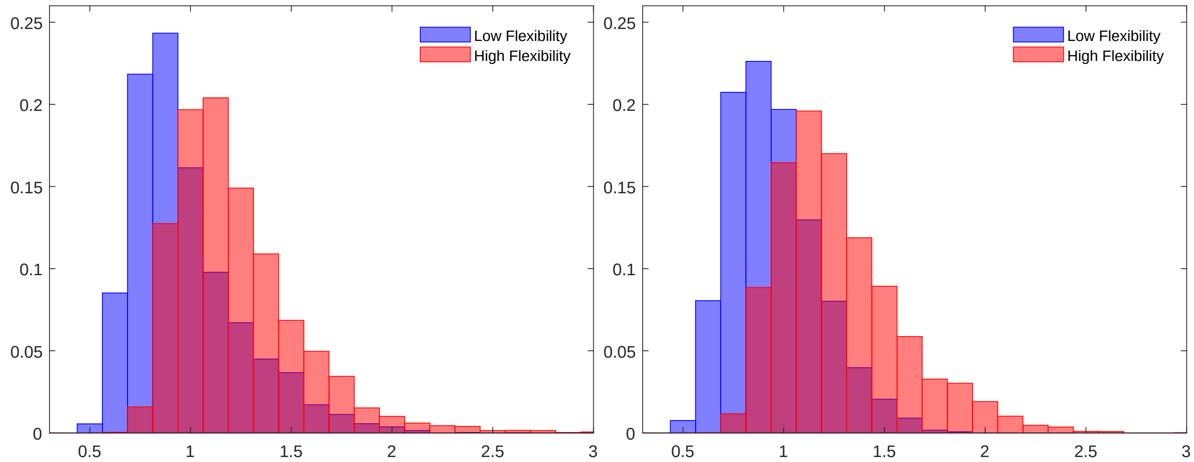
Note: The figure reports the probability of ending up in a high-flexibility regime used in the STARMA model of Section 6. The shaded vertical band indicates the duration of the Great Recession.

Figure J.3: Price Flexibility and Inflation Persistence



Note: Figure J.3 reports the responses of inflation to a 1% shock in the STARMA(1,3) model. The left (right) panel graphs the response in the low (high) price flexibility regime. In both cases we also report the the response from a (linear) ARMA(1,3) model. 68% confidence intervals are built based on the Markov Chain Monte Carlo (MCMC) method developed in Chernozhukov and Hong (2003). In each of the two charts the vertical line delineates the half-life of the shock.

Figure J.4: Price Flexibility and Inflation Volatility



(a) STARMA(1,7) (b) STARMA(1,3)

Notes: Each panel reports the distribution of the estimated inflation volatility in the two regimes. The left panel refers to the STARMA(1,7), while the right panel refers to the STARMA(1,3).

Table J.1: Forecast Errors and Price Flexibility: Robustness (Absolute and Squared Forecast Errors)

(a) BoE MPC RPIX/CPI (Absolute) Forecast Errors						
Horizon	Slope at $G = 0.3$		Slope at $G = 0.9$		F-*stat*	$\tilde{R}^2$
1	0.093	[0.628]	0.840	[0.092]	0.229	1.69
2	-0.330	[0.279]	2.319	[0.011]	0.045	6.41
3	-0.484	[0.145]	4.117	[0.010]	0.003	13.82
4	-0.344	[0.437]	6.161	[0.003]	0.000	26.45
5	-0.144	[0.811]	5.945	[0.011]	0.000	20.10
6	0.309	[0.603]	4.858	[0.032]	0.003	13.70
7	0.634	[0.236]	4.402	[0.021]	0.006	12.32
8	0.691	[0.182]	3.029	[0.055]	0.063	5.93

(b) BoE MPC RPIX/CPI (Squared) Forecast Errors						
Horizon	Slope at $G = 0.3$		Slope at $G = 0.9$		F-*stat*	$\tilde{R}^2$
1	0.078	[0.679]	0.606	[0.183]	0.507	-0.87
2	-0.317	[0.490]	3.242	[0.008]	0.124	3.55
3	-0.588	[0.303]	8.723	[0.011]	0.003	13.16
4	-0.485	[0.584]	15.984	[0.014]	0.000	26.28
5	-0.010	[0.994]	17.957	[0.022]	0.000	23.22
6	0.800	[0.554]	15.398	[0.050]	0.001	16.92
7	1.551	[0.225]	12.104	[0.078]	0.006	12.18
8	2.123	[0.143]	7.055	[0.244]	0.094	4.71

(c) Market Participants' (Absolute) Forecast Errors						
Horizon	Slope at $G = 0.3$		Slope at $G = 0.9$		F-*stat*	$\tilde{R}^2$
1	0.265	[0.361]	0.826	[0.122]	0.278	1.11
2	-0.383	[0.264]	2.448	[0.010]	0.053	6.12
3	-0.561	[0.150]	4.293	[0.008]	0.004	13.10
4	-0.382	[0.418]	6.398	[0.002]	0.000	25.60
5	-0.103	[0.862]	6.042	[0.009]	0.000	18.74
6	0.453	[0.412]	4.516	[0.049]	0.013	10.48
7	0.903	[0.052]	3.631	[0.052]	0.019	9.47
8	0.883	[0.099]	1.935	[0.221]	0.211	2.19

(d) Market Participants' (Squared) Forecast Errors						
Horizon	Slope at $G = 0.3$		Slope at $G = 0.9$		F-*stat*	$\tilde{R}^2$
1	0.713	[0.291]	0.426	[0.497]	0.363	0.25
2	-0.396	[0.464]	3.491	[0.007]	0.123	3.65
3	-0.763	[0.287]	9.235	[0.008]	0.007	11.63
4	-0.608	[0.517]	16.589	[0.010]	0.000	24.46
5	-0.063	[0.960]	18.043	[0.016]	0.000	20.81
6	0.923	[0.465]	14.287	[0.045]	0.005	13.17
7	1.789	[0.129]	9.562	[0.099]	0.043	7.16
8	2.315	[0.091]	3.916	[0.431]	0.390	0.02

Notes: The table reports the results of a quadratic spline regression of the absolute (LHS) and squared (RHS) forecast errors (for different forecast horizons, h, measured in quarters) on a quarterly average of an indicator of the normalized price flexibility index, $G_{t-1} = G(\widetilde{\mathcal{F}}_{t-1}; \gamma) = (1+e^{-\gamma \widetilde{\mathcal{F}}_{t-1}})^{-1}$, where $\widetilde{\mathcal{F}}$ denotes the normalized flexibility index. The regression takes the form: $z_t = a_0 + a_1 G_{t-1} + a_2 G_{t-1}^2 + a_3 \mathbb{1}_{\{G_{t-1}>0.5\}} G_{t-1}^2$, where $\mathbb{1}_{\{G_{t-1}>0.5\}}$ is an indicator function taking value 1 when $G_{t-1} > 0.5$ and zero otherwise, $z_t = |e_{t+h|t}|$ (tables (a) and (c)) and $z_t = e_{t+h|t}^2$ (tables (b) and (d)). The upper panels refer to the Bank of England MPC's RPIX/CPI forecast errors, while the bottom panels consider market participants' forecast errors. In each panel, the first two pairs of columns report the slope of the relationship evaluated at different levels of the indicator, together the p-value associated with the null hypothesis that the slope is equal to 0 (this is calculated using Newey-West standard errors). Since the fitted function tends to reach a minimum at about $G = 0.6$, for most forecast horizons, we report the slope of the function at values of the indicator equal to 0.3 and 0.9 (so as to consider an equal distance from the minimum point). The penultimate column (F-*stat*) reports the p-value of the null hypothesis that all the coefficients associated to the flexibility regime are equal to 0 (i.e., $H_0 : a_1 = a_2 = a_3 = 0$). The last column reports the adjusted R-squared, denoted by $\tilde{R}^2$.