Nonlinearities of Monetary Policy across States of Price Rigidity*

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April 2025

Abstract

This paper analyzes the nonlinear effects of monetary policy across states of price rigidity. In the United Kingdom from 1996 to 2023, consumer prices exhibit distinct cyclical and seasonal patterns: price changes occur more frequently during recessions than in expansions, rise with inflation, and are more common early in the year than later. Using these patterns to inform nonlinear local projection models of states of flexible and rigid price adjustment, I find that economic activity responds more strongly and prices more slowly to monetary policy shocks in periods of rigid compared to flexible prices. These patterns hold across both cyclical and seasonal periods of increased price rigidity and are further shaped by large differences in price adjustment across sectors. These findings provide microfounded evidence for the state dependence of monetary policy on the price-setting behavior of firms.

JEL Classification: E32, E52, C22

Keywords: Price rigidity, monetary policy, state dependence, nonlinear local projections, price setting

*For helpful comments and suggestions, I thank Benjamin Born, Luca Dedola, Hans Gersbach, Timo Haber, Òscar Jordà, Daniel Kaufmann, Oleksiy Kryvtsov, Sarah Lein, Andreas Müller, Damjan Pfajfar, Oliver Pfäuti, Alexander Rathke, Tiziano Ropele, Barbara Rudolf, Samad Sarferaz, Jan-Egbert Sturm, Fabrizio Venditti, as well as the participants at the ECB Conference on Monetary Policy 2024, Inflation: Drivers and Dynamics Conference 2024, 14th ifo Conference on Macroeconomics and Survey Data, VfS Annual Conference (Jobmarket Preparation Seminar), 2024 PhD Macro Workshop (University Basel) and KOF-ETH Zurich Seminar. I would also like to thank the Consumer Prices team of the Office for National Statistics (ONS) for their valuable help with the data.

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1 Introduction

There is a broad consensus in the literature on whether and to what extent monetary policy matters for the real economy. Monetary shocks have real effects on output, and the output response is persistent and occurs with a lag, peaking up to two years after the initial shock (Christiano et al., 1999, 2005). To explain why monetary policy matters, many theories attribute these real effects to nominal rigidities. Theoretical models typically assume some form of nominal price rigidity that is constant over time. For example, prices are assumed to be uniformly staggered (Taylor, 1980) or subject to change with a constant probability at any point in time (Calvo, 1983).

However, this simplification may not accurately reflect reality. In particular, price adjustments may occur more frequently at certain times than at others during different phases of the business cycle or during periods of higher and lower inflation. If prices are not uniformly staggered or change with varying probabilities, the effects of monetary policy on the real economy may differ over time. All else being equal, monetary policy should have a smaller impact in periods of lower price rigidity–that is, when the frequency of price changes is higher (e.g., Dotsey et al., 1999; Golosov and Lucas, 2007).

This paper examines the differential effects of monetary policy in periods of flexible and rigid price adjustment. To do so, I first estimate price rigidity using the frequency of consumer price changes and provide empirical evidence of the non-uniformity of price setting over time. I then use the frequency of price changes to identify states of flexible and rigid price adjustment and estimate nonlinear (i.e., state-dependent) impulse responses to monetary policy shocks through local projections with micro-founded regime dependence and a smooth transition technique between states. This allows me to separate the data into two regimes and estimate the response of economic activity and prices to monetary policy shocks when price adjustments are frequent and when they are not.

The data I use to estimate price rigidity are the monthly price quotes collected by the Office for National Statistics (ONS) to construct the Consumer Prices Index (CPI) for the United Kingdom (UK). The dataset spans about 27 years, from February 1996 to December 2023, and includes monthly price observations from nearly 20,000 outlets in 12 regions of the United Kingdom. These prices are categorized into narrowly defined expenditure items, such as flour, flat panel TVs (26”–42”), and restaurant main courses. After excluding invalid, duplicate, and imputed prices and applying other sampling decisions, the dataset contains 31 million price quotes for 1,306 expenditure items, covering over 60 percent of the CPI basket by expenditure weight.

I estimate price rigidity using the monthly frequency of price changes, which captures the share of prices that change in a given month. The data provide strong evidence that price rigidity is not uniform over time. For one, price rigidity shows distinct cyclical patterns. The frequency of price changes is strongly countercyclical, with price changes occurring more frequently when the economy is slowing down. For another, price rigidity is positively correlated with inflation. The frequency of price changes increases during periods of high inflation, most evidently in the post-pandemic inflation surge. In addition, price rigidity shows a distinct seasonal pattern. The frequency of price changes decreases monotonically over the four quarters and, within each quarter, over the months of a quarter, giving rise to a pattern of local peaks in January, April, July, and October. Both cyclical and seasonal patterns are more sensitive to price changes due to temporary sales than product substitution but robust to their exclusion.

Time variation in price rigidity may give rise to differential effects of monetary policy in periods when price adjustments are more frequent (e.g., in periods of economic slack or high inflation) and less frequent (e.g., in periods of economic tightness or low inflation). To test this hypothesis empirically, I estimate nonlinear impulse responses to monetary policy shocks using local projections (Jordà, 2005) with a microfounded regime dependence. In particular, I use the frequency of price changes to directly inform the model of states of flexible and rigid price adjustment in the data while modeling the transition between states using a smooth transition function (Granger and Teräsvirta, 1993). Otherwise, the specification of the model follows a parsimonious monetary VAR and employs monetary policy shocks as external instruments identified in the high-frequency asset price movements around monetary policy events in the UK (Braun et al., 2023).

The results provide microfounded evidence for the state dependence of monetary policy across states of price rigidity. Economic activity shows no significant response to a contractionary monetary policy shock when price adjustment is frequent, as identified by the low-frequency movements of price rigidity. At the same time, prices respond quickly and fall after just one year. Under rigid price adjustment, however, real gross domestic product (GDP) exhibits the usual hump-shaped dynamics: After an initial and only marginally significant increase, output declines significantly six to eight quarters after the initial shock. Moreover, prices react only sluggishly and fall after three years under the rigid price adjustment regime.

Three years after a monetary policy shock equivalent to a 100 basis point increase in the Bank Rate, real GDP declines by more than 5 percent under rigid price adjustment, compared with only 2 percent under flexible price adjustment. Similarly, the CPI declines by a maximum of 1.5 percent when price adjustment is flexible, compared with 0.6 percent when price adjustment is infrequent. Compared with linear local projections, the effect of a monetary policy shock is amplified by a factor of up to 3 for both variables: in the case of economic activity under rigid price adjustment in the long run, in the case of prices under flexible price adjustment in the short run. Thus, linear estimates run the risk of considerably underestimating the differential effects of monetary policy on changes in price flexibility.

Since the frequency of price adjustments is countercyclical, the rigid price adjustment regime corresponds to periods of economic expansion, in which monetary policy shocks thus prove to have a stronger real effect than in periods of recession. Similarly, since the frequency of price adjustments is positively correlated with inflation, states of rigid price adjustment correspond to periods of lower inflation, in which monetary policy shocks have stronger real effects than in periods of higher inflation.

The cross-sectional analysis further highlights the role of sectoral differences in price-setting behavior in shaping the transmission of monetary policy. In the goods sector, where price adjustment is more frequent, prices react swiftly to a monetary policy shock, while economic activity remains largely unaffected. By contrast, in the services sector, where price rigidity is more pronounced, output declines significantly under rigid price adjustment, while price responses are sluggish and materialize only after several years. These findings suggest that the aggregate real effects of monetary policy are primarily driven by the services sector, where infrequent price adjustment leads to stronger and more persistent output responses. At the same time, the delayed and protracted price response in rigid price adjustment regimes can be attributed to the slower price adjustment dynamics in the services sector.

Importantly, my analysis shows that these findings are not merely driven by asymmetric responses to expansionary and contractionary monetary policy shocks. The differential response of economic activity and prices across flexible and rigid price adjustment regimes holds regardless of the direction of the shock, confirming that state dependence, rather than asymmetries in policy transmission, drives the stronger real effects of monetary policy in periods of price rigidity. Furthermore, these results prove to be robust with respect to the identification of both the regimes and the monetary policy shocks used in estimating the nonlinear local projections, as well as to the model specification and data choices.

In addition, I obtain similar results for states identified by the seasonal component of the price adjustment frequency, which captures high-frequency movements in price rigidity. Economic activity contracts more rapidly in the second half of the year, the period identified by the seasonal component as a period of rigid price adjustment, than in the first half of the year, when price changes are more frequent. As a result, monetary policy shocks that occur early in the year have larger real effects than shocks that occur later in the year.

This paper contributes to the literature by combining two different strands. The first strand highlights the variability of price rigidity over time, which I complement with evidence from consumer prices in the United Kingdom. Non-uniformity over time has been documented in the context of both cyclical patterns and comovement with inflation. CPI microdata from the United States (Vavra, 2014) and the euro area (Gautier et al., 2024) indicate that the frequency of price changes increases during recessions. Kryvtsov and Vincent (2021) extend this evidence of countercyclicality to the frequency of sales in both the United States and the United Kingdom, showing that it increases with the unemployment rate. Using German business survey data, Bachmann et al. (2019) show that the frequency of price adjustments increases with idiosyncratic firm-level volatility, especially during recessions. Regarding inflation, there is widespread evidence that the frequency of price changes increases during periods of high inflation, for example, in Mexico (Gagnon, 2009), the United States (Nakamura et al., 2018), Hungary (Karadi and Reiff, 2019), or Argentina (Alvarez et al., 2019). In the context of the post-pandemic inflation surge starting in 2021, several studies document an increase in the frequency of price adjustments using CPI microdata (Montag and Villar, 2022; Rudolf and Seiler, 2022), online prices (Cavallo et al., 2024), and survey data (Dedola et al., 2023).

The second strand concerns the effects of monetary policy shocks on economic aggregates in general and the state dependence of monetary policy in particular. While the potential for asymmetries and their policy implications was not the focus of the traditional literature (Christiano et al., 2005; Galí, 2008; Woodford, 2011), a recent and growing body of empirical research considers state-dependent reactions in the impulse responses to monetary policy shocks. Among the states considered are interest rate cycles (Alpanda et al., 2021; Berger et al., 2021; Eichenbaum et al., 2022), credit cycles (Alpanda and Zubairy, 2019; Alpanda et al., 2021; Aikman et al., 2016; Harding and Klein, 2019; Jordà et al., 2020), financial frictions (Ottonello and Winberry, 2020), and–particularly relevant to this paper–business cycles, inflation, and nominal rigidities.

There is conflicting evidence as to whether monetary policy is more effective in expansions than in recessions (e.g., Thoma, 1994; Tenreyro and Thwaites, 2016; Jordà et al., 2020; Alpanda et al., 2021) or vice versa (e.g., Weise, 1999; Garcia and Schaller, 2002; Lo and Piger, 2005; Burgard et al., 2019; Bruns and Piffer, 2021; De Santis and Tornese, 2024). Using a closely related empirical approach, Tenreyro and Thwaites (2016) employ nonlinear local projections and find that the response of the US economy to a monetary policy shock is smaller in recessions. Vavra (2014) provides a theoretical explanation based on the underlying price-setting mechanism: recessions, characterized by high realized volatility and frequent price adjustments, exhibit a steeper Phillips curve, which makes monetary policy less effective. While Vavra

(2014) relies on model simulations, my results empirically validate his hypothesis regarding the differential effects of monetary policy in states of flexible and rigid price adjustment, and they are consistent with the evidence that stimulating a weak economy is more difficult than stimulating a strong one.

Inflation presents another dimension in which the effects of monetary policy are nonlinear. Jordà et al. (2020) find that monetary policy tends to be ineffective in low inflation environments, attributing this to nominal interest rates approaching the zero lower bound, which limits the action radius of central banks. Similarly, Ascari and Haber (2022) find that the response of inflation to monetary policy shocks is larger and the real effects smaller in high trend-inflation regimes. They rationalize their results using state-dependent pricing models in which average inflation affects the frequency of price adjustments (e.g., Dotsey et al., 1999; Costain and Nakov, 2011) but do not explicitly account for price rigidity in their empirical estimations. My results fill this gap.

Finally, several studies examine the impact of nominal rigidities on the effectiveness of monetary policy, leveraging differences in wage-setting patterns over time. Drawing on narrative and survey evidence on wage bargaining, which is more frequent at the beginning of the year, Olivei and Tenreyro (2007, 2010) estimate quarter-dependent vector autoregression (VAR) models and find smaller effects in the early compared to the late quarters. While their evidence addresses the role of seasonal wage-setting patterns in the monetary policy transmission mechanism, Björklund et al. (2019) find similar results using microdata on Swedish wage negotiations, which show no deterministic seasonal pattern. By isolating periods when the labor market operates under fixed-wage contracts, they demonstrate that monetary policy shocks have a larger impact during fixed-wage episodes relative to the average response. While these papers examine the role of wage rigidities, this paper investigates the state dependence of monetary policy on price rigidities, using rich microfoundations to model states of flexible and rigid price adjustment.

Overall, my approach combines the strand of research that analyzes empirical patterns of price rigidity with the strand that studies state dependence of monetary policy, bringing the latter closer to the underlying economic mechanism determined by the timing of actual price adjustments and disciplined by micro price data. In doing so, it provides empirical support for theoretical predictions (e.g., Vavra, 2014) and offers an explanation, in terms of the underlying price-setting mechanism, for the differential effects of monetary policy that have been documented over business cycles (e.g., Tenreyro and Thwaites, 2016; Alpanda et al., 2021) and inflation (e.g., Jordà et al., 2020; Ascari and Haber, 2022).

The remainder of the paper is organized as follows. Section 2 introduces the micro price data and uses the frequency of consumer price changes to document the non-uniformity of price rigidity over business cycles and periods of varying inflation in the United Kingdom from 1996 to 2023. Section 3 outlines the econometric methodology used to study the differential effects of monetary policy in periods of flexible and rigid price adjustment, including the nonlinear local projection model, the microfounded state variable, the estimation data, and the external instrument for monetary policy shocks. Section 4 presents the main results on the differential effects of monetary policy in periods of flexible and rigid price adjustment, based on the nonlinear model that uses the frequency of price changes as a state variable. Section 5 provides a comprehensive set of robustness exercises. Section 6 concludes.

2 Empirical evidence on the non-uniformity of price rigidity over time

This section introduces the micro price data[1] (Section 2.1) and uses the frequency of consumer price changes (Section 2.2) to document the non-uniformity of price rigidity over business cycles and periods of varying inflation (Section 2.3) in the United Kingdom from 1996 to 2023.

The dataset is uniquely suited for this purpose for several reasons. First, it has broad coverage of the consumption basket, which is essential for analyzing the effects of monetary policy on the broader economy. In particular, the coverage is much broader than with (supermarket or household) scanner data or web-scraped prices. Second, the data contain granular information on price observations, including information on temporary sales and product substitution, which are important factors to consider when estimating price rigidity. Third, the Office for National Statistics (ONS) publishes some of the microdata underlying the UK CPI on its website, making the data available to the public and for research purposes. Furthermore, the United Kingdom represents a geography for which key data are available at a monthly frequency (e.g., monthly estimates of GDP, see Section 3.3) and for which monetary policy shocks have been identified in multiple ways using high-frequency identification schemes (see Section 3.4), all of which are essential to the empirical strategy and contribute to the quality of the analysis.

[1]Several studies have previously analyzed these data. In particular, Bunn and Ellis (2012) document stylized facts about price-setting behavior in consumer prices in the United Kingdom from 1996 to 2006. More recently, Davies (2021a) examines price setting during the COVID-19 pandemic. Other studies include Hahn and Marenčák (2020), Kryvtsov and Vincent (2021), Blanco (2021), Davies (2021b), or Adam and Weber (2023).

2.1 UK CPI microdata

The data I use to estimate price rigidity are the monthly price quotes collected by the Office for National Statistics (ONS) to construct the Consumer Prices Index (CPI) for the United Kingdom.[2] The data span the period from February 1996 to December 2023 and cover the economic territory of the United Kingdom, excluding the offshore islands. The raw data consist of over 40 million individual price quotes[3], all sampled on a monthly basis from nearly 20,000 outlets and 12 regions (plus central collection) across the UK. For any given sales outlet[4], data collectors find the most popular and regularly available goods and services and record the prices as well as the information to identify the products uniquely. At the most granular level of product disaggregation, there are 1,396 so-called expenditure items[5] categorized in the Classification of Individual Consumption by Purpose (COICOP). Using the available product and outlet characteristics, I identify 2.4 million unique price spells.[6]

The publicly available micro price data do not contain all the price information underlying the UK CPI. In particular, they do not include administered prices and prices of central items[7]. In addition, the imputed prices of seasonal items[8] are excluded in their off-season.

To improve the informativeness of the data, I exclude several types of observations

[2]The ONS publishes some of the microdata underlying the UK CPI on its website (Office for National Statistics, 2024). Price quote data and item indices are published monthly for the most recent month.

[3]Price quotes reflect transaction prices. The CPI measures consumption expenditure mostly by the acquisition of goods and services, i.e., "the total value of all goods and services delivered during a given period is considered, whether or not they are wholly paid for during the period" (Office for National Statistics, 2019).

[4]The UK is divided into twelve regions, and in each region, a number of locations is determined from which outlets are selected for the local price collection. Outlets are divided into two types of stores: multiples (retailers with ten or more outlets) and independents (retailers with fewer than ten outlets).

[5]While the ONS tracks the prices of products at the barcode level, the true identity of the products is masked by narrowly defined product categories called "expenditure items" (e.g., women's cardigan, flat panel TV 26"–42", or restaurant main course). These items come from the basket of goods and services, which contains all the products that represent household consumption expenditure in the United Kingdom. They represent the lowest level of the survey scheme and determine the categories for which the ONS collects prices of goods and services.

[6]I define a "price spell" as the sequence of price quotes corresponding to a specific product (identified at item level) collected in a specific outlet (identified at shop code, shop type, region, and stratum levels) over time. In addition, I split price spells if there are missing price quotes for more than one month to ensure that products are not inadvertently grouped because no prices were recorded in the month prior to the price collection month.

[7]There are around 150 items for which prices are centrally collected, and the index calculation is separate from the main index construction method (Office for National Statistics, 2019). Examples are most items related to housing, travel fares, or computer games.

[8]In a few areas covered by the CPI, there are distinct seasonal patterns of purchasing or consumption, for example, for some clothing or garden products. In the past, some fresh fruits and vegetables were also seasonal, although this has become less apparent with the importation of products from around the world. The prices of seasonal items are usually imputed during their off-season.

a priori. First, I discard duplicate price quotes for a given item, shop, and region for the same month. For reasons of confidentiality, the ONS does not always publish all available local information, resulting in product identifiers in the data containing duplicate price quotes. Second, I remove price quotes that do not pass ONS cross-checking procedures (so-called "invalid" price quotes, see Office for National Statistics (2019) for details) and do not enter the calculation of the official CPI. Third, whenever possible[9], I exclude imputed prices from the sample.

Because measurement errors raise concerns beyond these restrictions, I further remove outliers by excluding monthly price changes larger than the 99th percentile of absolute log price changes and smaller than the 1st percentile of absolute log price changes for each expenditure item.[10] I also exclude price changes that coincide with changes in the weight or volume of the product, ensuring that price changes due solely to changes in the package size or volume are not counted as price changes. Finally, price changes in months when the UK value-added tax (VAT) rate has changed are excluded[11] when measuring price rigidity.[12] VAT rate changes often occur at the beginning of the year, which could bias the estimation of price rigidity. Table A.1 in the appendix illustrates the effect of all sample restrictions on the sample size. The resulting baseline sample consists of 30.8 million price quotes and 777,000 products across 1,306 expenditure items and averages more than 60 percent of the CPI basket by expenditure weights.

In measuring price rigidity, the treatment of temporary sales and product substitution poses two challenges. On the one hand, temporary sales involve price discounts for a limited period, after which the original price is usually restored, leading to high-frequency price fluctuations. On the other hand, product substitutions replace (temporarily) unavailable or discontinued products, which can lead to price changes that result from comparing close substitutes rather than identical products.

The baseline sample includes price changes due to both temporary sales and product substitution to capture all price changes relevant to the CPI when analyzing the differential effects of monetary policy in periods of flexible and rigid price adjustment. However, since both temporary sales and product substitution can exhibit cyclical or seasonal patterns (see Figure B.1 and Figure B.2 in the appendix), I complement the analysis of the non-uniformity of price rigidity over time net of these two effects.

[9]The ONS flags products that are missing or temporarily out of stock in a store and imputes the prices of these products.

[10]Eichenbaum et al. (2014) raise various concerns regarding mismeasurement in the context of CPI microdata. The treatment chosen to deal with these measurement errors is in line with several contributions in the literature, for example, Gautier et al. (2024) or Rudolf and Seiler (2022).

[11]In regression analyses, I control for VAT rate changes by including dummies in the corresponding months instead of excluding these months altogether.

[12]Over the sample period, the standard VAT rate decreased from 17.5% to 15.0% on 1 December 2008, increased to 17.5% on 1 January 2010, and to 20.0% on 4 January 2011.

To do this, I identify temporary sales and product substitution using flags provided by the ONS.[13] To exclude temporary sales, I replace each sales price with the last observed non-sales price and refer to prices excluding temporary sales as "regular prices." To exclude product substitutions, I start a new price spell with each product substitution.

2.2 Frequency of price changes as a measure of price rigidity

To measure price rigidity, I use the monthly frequency of price changes, which captures the share of prices that change in a given month. Formally, the frequency of price changes for item i in month t is calculated as

$$f_{i,t} = \frac{\sum_{p,s} \omega_{p,s,t} I_{p,s,t}}{\sum_{p,s} \omega_{p,s,t}}, \tag{1}$$

where $I_{p,s,t}$ is an indicator that takes the value one if the price of product p of item i in outlet s has changed from the previous month $t-1$, otherwise it takes the value zero.[14]

The weight $\omega_{p,s,t}$ is calculated as the CPI share of item i divided by the number of prices collected for that item in month t. To compute aggregate statistics, I use average weights over the sample period to minimize the impact of compositional changes in the basket of goods and services and aggregate item-level moments using weighted medians. Hence, the aggregate frequency of price changes, f_t, is the weighted median frequency across items using average CPI expenditure weights.

2.3 Non-uniformity of price rigidity over business cycles and periods of varying inflation

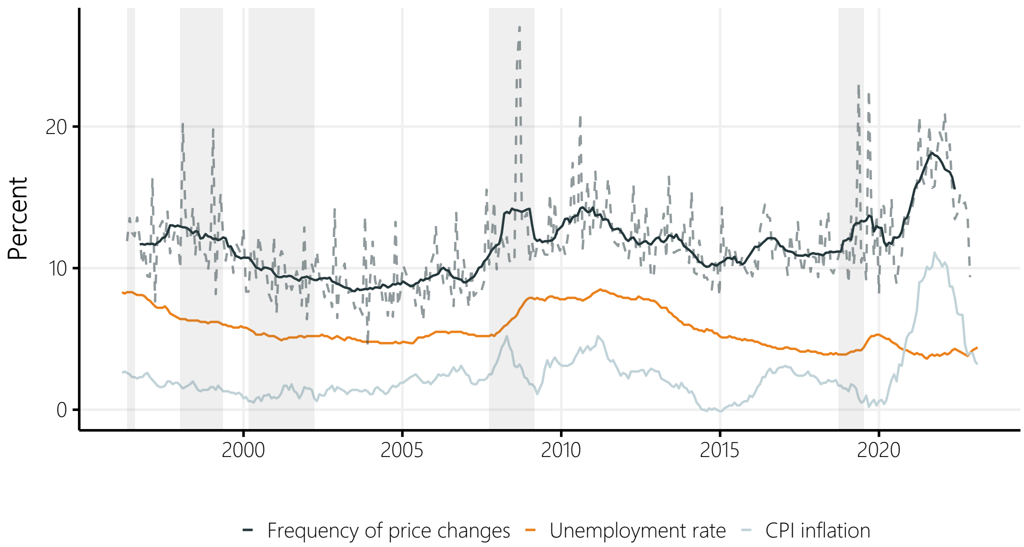
This section presents empirical evidence on the non-uniformity of price rigidity over business cycles and periods of varying inflation. Figure 1 shows the evolution of the frequency of consumer price changes, including price changes due to temporary

[13] For temporary sales, the ONS price collectors flag a price observation as a sales price if the discount is temporary and granted to all consumers without restriction. For product substitution, the ONS has established rules to account for quality adjustments when products are substituted (Office for National Statistics, 2019).

[14] By analogy, I calculate the frequency of price increases, $f^+_{i,t}$, by considering only price increases in the price change indicator, $I^+_{p,s,t}$, and the frequency of price decreases, $f^-_{i,t}$, by considering only price decreases in the price change indicator, $I^-_{p,s,t}$.

sales and product substitution[15], together with the UK unemployment rate and CPI inflation from February 1996 to December 2023.

Figure 1: Cyclicality of the frequency of price changes



Notes: Average frequency of consumer price changes in the United Kingdom from February 1996 to December 2023 using the sample including price changes due to temporary sales and product substitution. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the raw series (in dashed lines) and the 12-month moving average centered on each month (in solid lines). Outliers related to VAT rate changes are excluded. The unemployment rate is the monthly unemployment rate for civilians aged 15 and over, according to the infra-annual labor statistics. CPI inflation is the year-on-year change in the consumer price index excluding owner-occupier housing costs from the ONS. Recessions (shaded areas) are dated by the Organisation for Economic Co-operation and Development (OECD). All values are in percent.

Four observations emerge. First, the raw series of the frequency of price changes (in dashed lines) shows strong high-frequency movements. Many of these are attributable to seasonal patterns, which are examined separately in Appendix B.6. To focus on the low-frequency movements, the figure also reports the 12-month moving average centered on each month (solid lines). Second, the frequency[16] of price changes is far from constant over time. It was around 12 percent at the beginning of the sample in

[15] Figure B.3 in the appendix shows the frequency of price changes (as a 12-month moving average) across sample combinations, distinguished by the inclusion and exclusion of price changes due to temporary sales and product substitution. The treatment of temporary sales and product substitution affects the levels but not so much the time variation of the series.

[16] Figure B.4 in the appendix shows the absolute size of price changes across samples including and excluding price changes due to temporary sales and product substitution over time. Starting in 2010, the absolute size of price changes increased over the sample period. It averages about 12 percent before 2010 and almost 16 percent after.

1996, then fell to a low of 8.6 percent in 2003, before rising again to over 14 percent in 2009 and 2011. In the last decade, it declined again to 10.3 percent in 2015, before rising above 17 percent in 2022 after the pandemic. Third, the frequency of price changes is strongly countercyclical. The share of consumer price changes moves closely with the unemployment rate and rises when the economy slows down. Fourth, the frequency of price changes also moves together with inflation. In the 2000s, the frequency of price changes increased with inflation, and in the last decade, it decreased as inflation declined. Even more striking is the increase in the frequency of price changes during the recent surge in inflation from 2021 to 2023.

The degree of price rigidity varies significantly across sectors, as illustrated in Appendix B.7. In the goods sector, the frequency of price changes is relatively high, averaging 16.3 percent over the sample period, and exhibits pronounced cyclical and seasonal fluctuations. In contrast, the services sector is characterized by a much lower frequency of price changes, averaging only 5.9 percent, with weaker cyclical and seasonal patterns.

To verify that the graphical evidence presented in Figure 1 is statistically significant and robust, I formally examine the relationship between the frequency of price changes and the unemployment rate and CPI inflation in regression analyses. In particular, I run OLS time-series regressions, regressing the monthly frequency of price changes on CPI inflation and aggregate business cycle indicators, namely the unemployment rate and recession dummies, controlling for seasonal effects by including calendar month dummies and dummies for VAT rate changes. I run these regressions for frequency estimates using all sample combinations, including and excluding price changes due to temporary sales and product substitution.

In each regression in Table 1, the coefficients on CPI inflation and the business cycle indicators are statistically significant at the 1% level, even when a linear time trend or one lag of the dependent variable is included. The elasticity of the frequency of price adjustments to fluctuations in inflation is higher than to fluctuations in the unemployment rate across all frequency estimates. Nevertheless, both effects are economically large. A 1-percentage-point increase in inflation is associated with a 0.8 percentage point (pp) higher probability of observing a price change. A 1-percentage-point increase in the unemployment rate is associated with a 0.4 pp higher frequency of price changes. During recessions, the frequency of price changes is significantly higher than in normal times, increasing by 0.7 pp on average.

Excluding price changes due to product substitution reduces the unconditional estimates of the frequency of price changes by 20 to 40 percent while excluding price changes due to temporary sales reduces the frequency by more than half. Moreover, the elasticities of the frequency of price changes to fluctuations in both inflation and

Table 1: Cyclical properties of the frequency of price changes

	Frequency of price changes						
	incl. sales, incl. subst.				incl. sales excl. subst.	excl. sales incl. subst.	excl. sales excl. subst.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPI inflation	0.823***	0.804***	0.577***	0.691***	0.652***	0.622***	0.535***
	(0.065)	(0.090)	(0.076)	(0.069)	(0.053)	(0.044)	(0.038)
Unemployment rate	0.371***		0.260***	0.570***	0.399***	0.350***	0.356***
	(0.098)		(0.096)	(0.104)	(0.080)	(0.066)	(0.057)
Recession dummy		0.697**					
		(0.330)					
Frequency (lagged)			0.303***				
			(0.054)				
Constant	10.507***	12.564***	8.680***	8.436***	8.631***	4.776***	2.727***
	(0.749)	(0.522)	(0.786)	(0.849)	(0.612)	(0.507)	(0.435)
Linear time trend	N	N	N	Y	N	N	N
Observations	330	315	329	330	330	330	330
R^2	0.434	0.339	0.487	0.471	0.454	0.447	0.440

Notes: Linear regressions of the frequency of price changes on CPI inflation and aggregate business cycle indicators (the unemployment rate and recession dummies). All regressions include calendar month dummies and control for VAT rate changes. The frequency of price changes is calculated at the item level and aggregated to weighted medians using CPI expenditure weights using the samples of UK CPI microdata from February 1996 to December 2023, including and excluding price changes due to temporary sales and product substitution. The unemployment rate is the monthly unemployment rate for civilians aged 15 and over, according to the infra-annual labor statistics. CPI inflation is the year-on-year change in the consumer price index excluding owner-occupier housing costs from the ONS. Recessions are dated by the Organisation for Economic Co-operation and Development (OECD). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

unemployment are much smaller when temporary sales are excluded. This is consistent with the view that firms' sales policies are important for adjusting to large aggregate shocks. Using CPI microdata, Kryvtsov and Vincent (2021) show that the frequency of sales is strongly countercyclical in the United Kingdom and the United States, more than doubling during the Great Recession. Evidence for a more recent period suggests that firms responded to the large demand shock caused by the COVID-19 lockdowns in the euro area (Henkel et al., 2023) and Switzerland (Rudolf and Seiler, 2022) by adjusting the frequency of their temporary sales.

To further examine the role of price increases and decreases in driving the time variation, Table B.1 repeats the regression analyses from Table 1 above for the frequency of price increases and the frequency of price decreases, separately. The results show that while both the frequency of price increases and decreases are equally countercyclical, the positive comovement with inflation is only driven by the frequency of price increases.

In sum, there is strong evidence of cyclical patterns in price rigidity. The frequency of price changes varies over the business cycle and is strongly countercyclical: Price changes are more frequent when the economy is slowing down. The frequency of price changes is also positively correlated with inflation. Both effects are influenced more strongly by price changes due to temporary sales than by product substitution. The literature provides several examples of cyclical patterns in the frequency of price changes. While the frequency of consumer price changes in the euro area was flat from 2005 to 2019, it increased significantly during the Great Recession, when euro area inflation peaked at 4.1 percent (Gautier et al., 2024). Using Swiss CPI microdata, Rudolf and Seiler (2022) show that the frequency of price changes increased substantially after the discontinuation of the minimum exchange rate of the Swiss franc against the euro in early 2015 and more recently during the post-pandemic inflation surge in 2021 and 2022. Similar evidence for the inflation surge in 2022 comes from online prices (Cavallo et al., 2024) and survey data (Dedola et al., 2023). The presence of time variation in price rigidity may suggest some form of state dependence in price setting, where price changes occur more frequently in response to certain economic conditions or shocks. One possible implication of these temporal patterns is that the effects of monetary policy may be different in periods of economic slack (when price changes tend to be more frequent) than in periods of economic tightness (when price changes tend to be less frequent). The following sections examine this hypothesis empirically.

3 Econometric method

The empirical analysis in the previous section has shown that price setting is not uniform over time: Price rigidity shows large movements at business cycle frequencies and varies with inflation. In this section, I present the econometric method used to study the differential effects of monetary policy in periods of flexible and rigid price adjustment. It is based on the estimation of nonlinear[17] impulse responses to monetary policy shocks using local projections (Jordà, 2005) and microfounded regime dependence with a smooth transition technique (Granger and Teräsvirta, 1993). This section presents the model, describes the microfounded state variables and the smooth transition function, outlines the data and the specification of the baseline estimation, and describes the external instrument used as monetary policy shocks.

3.1 Nonlinear local projection model

Nonlinear (i.e., state-dependent) local projections[18] are a straightforward extension of their linear framework (Jordà, 2005), which estimates the impulse response of the variable of interest y_{t+h} at horizon $h \in [0, H]$ as:

$$y_{t+h} = \alpha_h + \beta_h e_t + \sum_{k=1}^{K} \gamma_{h,k} w_{t,k} + \nu_{t+h}, \tag{2}$$

where α_h is a constant, $w_{t,k}$ denotes the kth control variable (included with L lags), and ν_{t+h} captures the possibly heteroskedastic and serially correlated estimation error. The variable e_t are the shocks identified using an external instruments approach, which are monetary policy shocks (see Section 3.4). The coefficient β_h gives the response of y at time $t + h$ to the monetary policy shock e_t at time t. Hence, impulse responses are constructed as a sequence of β_h estimated in a series of single regressions for each horizon.

To test whether the impulse responses following a monetary policy shock differ across

[17] A growing body of literature uses nonlinear local projections (Jordà, 2005) to analyze state-dependent effects in empirical impulse responses, e.g., Auerbach and Gorodnichenko (2012); Caggiano et al. (2014); Tenreyro and Thwaites (2016); Ramey and Zubairy (2018); Ascari and Haber (2022).

[18] Plagborg-Møller and Wolf (2021) show that local projections and vector autoregression (VAR) models estimate the same impulse responses in population in a linear framework. In the context of state-dependent estimations, the local projection methodology offers two key advantages over VARs. First, they provide a simple way to account for state dependence. Second, unlike regime-switching VARs, they do not require one to take a stand on the duration of a given state or on the mechanism that triggers the transition between regimes. Therefore, the coefficients β_h^s represent the average effects of the monetary policy innovations conditional on the initial state and capture the possible change in state that occurs over the projection horizon.

states $s = \{F, R\}$ of flexible and rigid price adjustment[19], I adopt nonlinear local projections, which allow for the estimation of state-dependent impulse responses by interacting the right-hand side of Equation (2) with state probabilities $F(z_{t-1})$.[20] In particular, I estimate

$$\begin{aligned} y_{t+h} = F(z_{t-1})\left(\alpha_h^R + \beta_h^R e_t + \sum_{k=1}^{K} \gamma_{h,k}^R w_{t,k}\right) + \\ (1 - F(z_{t-1}))\left(\alpha_h^F + \beta_h^F e_t + \sum_{k=1}^{K} \gamma_{h,k}^F w_{t,k}\right) + \varepsilon_{t+h}, \end{aligned} \tag{3}$$

where the impulse response of y_t at horizon h in state $s \in \{F, R\}$ to a unitary monetary policy shock e_t is the sequence of the estimated coefficient β_h^s.

3.2 Microfounded state variable and smooth transition function

I use a microfounded state variable to identify regimes of flexible and rigid price adjustment. In the main specification of the nonlinear local projection model in Equation (3), the state variable z_t is the monthly frequency of price changes. The frequency of price changes is calculated as in Section 2.2 for consumer prices in the United Kingdom from 1996 to 2023 using the data sample, which includes price changes due to temporary sales and product substitution to capture all price changes relevant to the CPI.[21] To smooth out the high-frequency movements in the raw series (see Figure 1), I use the twelve-month moving average centered on each month.

Nonlinear local projections rely on the assumption that the state variable is exogenous. A potential problem arises if the frequency of price changes, which identifies the states of flexible and rigid price adjustments, responds to monetary policy shocks, thereby introducing bias. Two arguments address and mitigate such endogeneity concerns.

First, the prior literature has extensively examined how firms adjust their pricing behavior in response to aggregate shocks, particularly monetary policy shocks, through the margins of price adjustment – namely, the frequency and size of price changes (e.g., Alvarez et al., 2019; Gautier et al., 2024). These studies consistently find that

[19] The state F denotes states of flexible price adjustment, R denotes states of rigid price adjustment.

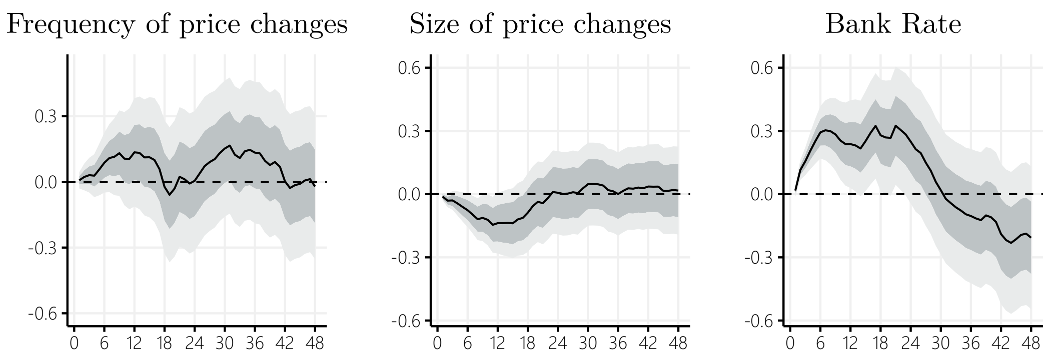
[20] Since the frequency of price changes is an endogenous variable, I use the values of the transition function with the state variable lagged by one period, z_{t-1}, to avoid contemporaneous feedback.

[21] In Section 5.1, I present results from estimating Equation (3) using state variables based on all combinations of possible treatments, including and excluding price changes due to temporary sales and product substitution. The main results prove robust to excluding these types of price changes.

firms primarily adjust the size, rather than the frequency, of price changes following monetary policy shocks. This evidence suggests that aggregate shocks are relatively small compared to firm-specific shocks, which are more salient in determining pricing decisions. Hence, idiosyncratic shocks, rather than aggregate shocks, are the dominant drivers of price adjustments.

Second, I conduct an empirical test to assess the exogeneity of the frequency of price changes within my data and econometric framework. Specifically, I employ linear local projections to estimate the response of the frequency of price changes to monetary policy shocks. The estimation results presented in Figure 2 indicate that the frequency of price changes (shown in the left panel) remains unaffected by monetary policy shocks. By contrast, the size of price changes (in the middle panel) decreases in response to a contractionary monetary policy shock. These findings alleviate endogeneity concerns and support the use of the frequency of price changes as a valid state variable in the subsequent analysis.

Figure 2: Exogeneity of the frequency of price changes



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using linear local projections as in Equation (2). The panels show the point estimates together with their 68% and 90% confidence intervals for the frequency (in the left panel), the size of price changes (in the middle panel), and the Bank Rate (in the right panel). The data used for estimation span from 1997:07 to 2023:12. The impulse responses are shown over a four-year horizon (48 months).

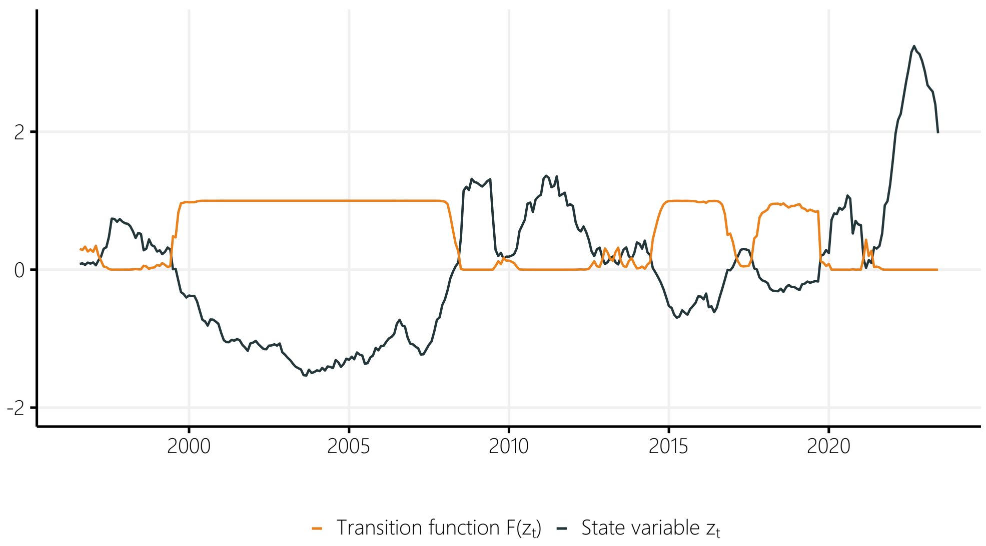
To restrict the state variable z_t to the unit interval, I follow Granger and Teräsvirta (1993) and employ the logistic function to smooth transitions between states:

$$F(z_t) = \frac{e^{-\gamma(z_t-\mu_z)/\sigma_z}}{1+e^{-\gamma(z_t-\mu_z)/\sigma_z}} \in [0,1], \quad \gamma > 0. \tag{4}$$

Since the logistic transition function $F(z_t)$ is decreasing in z_t, values of $F(z_t)$ close to zero indicate the flexible price-adjustment states. Hence, if monetary policy has a smaller effect when price adjustments are more frequent (and price rigidity is lower), I would expect $\hat{\beta}_h^R$ to be larger (in absolute values) than $\hat{\beta}_h^F$.

The parameterization of the smooth transition function in Equation (4) depends on two choices. First, I standardize the state variable z_t by subtracting its mean μ_z and dividing it by its variance σ_z. This splits the estimations roughly equally between the two states over the estimation period. Second, the parameter γ determines the switching intensity between states as z_t changes. Higher values of γ mean that $F(z_t)$ spends more time near the bounds of the unit interval, bringing the model closer to a discrete regime switching setup. Smaller values of γ mean that more observations are assumed to contain some information about behavior in both regimes. I set $\gamma = 10$, which gives an intermediate level of regime switching intensity.[22]

Figure 3: State variable and smooth transition function



Notes: The figure shows the twelve-month moving average of the frequency of price changes as a standardized state variable and the resulting smooth transition function. The sample spans from 1996:08 to 2023:06 (reduced due to the calculation of the centered moving average) and includes price changes due to temporary sales and product substitution. The parameterization of the transition function $F(z_t)$ follows the baseline specification (i.e., $\gamma = 10$).

Figure 3 shows the monthly frequency of price changes (as twelve-month moving average) as a standardized state variable, z_t, and the resulting smooth transition function, $F(z_t)$. The state variable identifies periods with a frequency of price changes above its average of 11.5 percent as flexible adjustment periods. This corresponds roughly to the periods from the beginning of the sample to the start of 2000, the period from mid-2008 to the end of 2014, and most of the period since the outbreak of the pandemic in 2020.

[22] I assess the robustness of the results to this choice in Section 5.1.

3.3 Data, estimation, and inference

The baseline specification follows a standard monetary VAR model, which I choose to be as parsimonious[23] as possible to capture the main transmission channel of monetary policy (e.g., Christiano et al., 2005). I let y include the real gross domestic product (GDP), the Consumer Prices Index excluding owner occupiers' housing costs (CPI), and the policy rate of the Bank of England (i.e., the "Bank Rate") as endogenous variables. To avoid estimating a negative inflation response to policy rate cuts–i.e., the "price puzzle" (Eichenbaum, 1992; Sims, 1992)–I follow the literature and include an index of commodity prices in dollars as an exogenous forward-looking variable. To convert the index into sterling, I further include the nominal exchange rate between the British pound and the US dollar as an endogenous variable. A detailed overview of the data and their sources can be found in Appendix A.2.

The data are monthly and span the period from 1997:07 to 2023:12.[24] The beginning of this period is determined by the date on which the Bank of England was granted operational independence over monetary policy. The policy rate is expressed in percent, and all other variables are expressed in natural logs multiplied by 100. This transformation allows us to interpret the coefficients as approximate percentage points. Figure A.1 shows the series included in the baseline model over the sample period.

I set $H = 48$, which corresponds to an impulse response horizon of four years. The lag order is set to 8. In terms of deterministics, only a constant term is included. However, the results are robust to all of these choices, as detailed in Section 5.2.

For each variable, I estimate the $H + 1$ equations of the impulse response function (IRF) at horizon $h \in [0, H]$ as a system of seemingly unrelated regression equations. For inference, I allow for potential autocorrelation and heteroskedasticity, and I estimate the variance of the coefficients using a Newey and West (1987) estimator.

3.4 Monetary policy shocks

In the baseline model, I use monetary policy shocks as external instruments, which are identified using a high-frequency identification strategy. In particular, I use the monetary policy shocks from the UK Monetary Policy Event-Study Database (UK-

[23] In Section 5.2, I report the results from extended specifications, where I add additional variables to the baseline specification.

[24] Because extreme outliers related to the COVID-19 pandemic and the resulting economic crisis distort many macroeconomic time series and the estimates based on them, I include exogenous dummy variables that take a value of one during the period when containment measures and restrictions were in place (i.e., during the period 2020:02–2022:04 in the United Kingdom), and zero otherwise.

MPD), a rich dataset of intraday monetary policy surprises for the United Kingdom (Braun et al., 2023). Building on the seminal work of Gürkaynak et al. (2005) and Swanson (2021), this database contains monetary policy surprises that capture high-frequency revisions in a wide range of asset prices (including interest rate futures, gilt yields, overnight index swaps, the stock market, and exchange rates) around monetary policy events[25] in the United Kingdom. Moreover, it contains monetary policy factors that capture market reactions to monetary policy decisions at different points of the maturity structure and thus disentangle different policy tools and measures. In particular, the database contains a factor summarizing conventional policy rate decisions at the short end ("Target" factor), a factor summarizing anticipated monetary policy changes at the medium end arising, for example, from forward guidance ("Path" factor), and a factor summarizing quantitative easing announcement at the long end ("QE" factor).

In the baseline model, I use the "Path" factor as my main variable for monetary policy shocks[26], for several reasons. First, because the factor is estimated on multiple contracts (sterling futures and gilt yields) at different maturities, it captures the effects of monetary policy more comprehensively than monetary policy surprises based on the high-frequency revisions of a single contract at a given maturity. Second, for a substantial period of the sample, the Bank Rate was constrained by the effective lower bound in the aftermath of the 2008 financial crisis, and monetary policy operated through unconventional measures (e.g., forward guidance and quantitative easing) aimed at influencing rates expectations at longer maturities. The "Path" factor captures such unconventional monetary policy measures. Third, the "Path" factor provides a proxy for monetary policy decisions over the entire sample, as it shows relevant variation throughout, in contrast to the "Target" (which shows little variation the effective lower bound) and "QE" (which captures only the QE announcement dates) factors. Moreover, Braun et al. (2023) show that the responses of macroeconomic and financial aggregates are stronger and more significant to the "Path" factor that elicits shocks to the medium-term policy path.

To convert the monetary policy factors on monetary policy event days into monthly average shocks for estimation in the monthly local projection model, I follow Gertler and Karadi (2015) and, first, cumulate factors on any event day over the last 31 days and, second, average these monthly shocks over each day of the month. Finally, I rescale the monetary policy shocks to be equivalent to a positive surprise in the Bank

[25] These monetary policy "events" include the announcements by the Bank of England's Monetary Policy Committee (MPC) and press conferences accompanying the publication of the quarterly Monetary Policy Report. Braun et al. (2023) provide alternative shock series based only on market surprises following MPC announcements. In Section 5.1, I show that the main results are robust to the scope of these monetary policy events.

[26] Figure A.1 shows the shock series over the sample period 1997–2023.

Rate of 100 basis points.

In Section 5.1, I conduct extensive sensitivity analyses with respect to alternative monetary policy shocks. For one, I conduct robustness exercises with monetary policy shocks based on monetary policy surprises from the UKMPD computed with different underlying contracts and at different maturities. For another, and beyond the monetary policy shocks from the UKMPD and its high-frequency approach to identifying shocks as asset price revisions around monetary policy events, the literature has developed several other ways to identify monetary policy shocks. In Section 5.1, I also conduct sensitivity analyses with respect to such alternative identification schemes. In all cases, I find broadly similar results.

4 Results

This section presents the main results on the differential effects of monetary policy in periods of flexible and rigid price adjustment. It begins with estimating the linear version of the local projections model to validate the overall empirical specification (Section 4.1). It then presents the results of estimating the nonlinear model using the frequency of price changes as a state variable (Section 4.2).

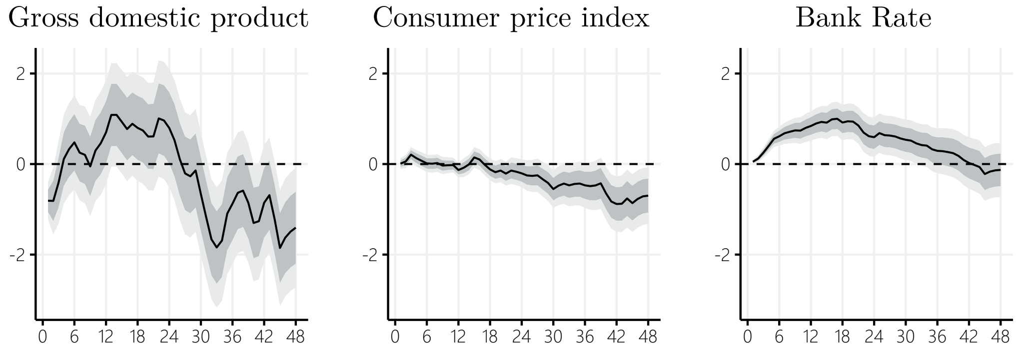
4.1 Linear impulse responses

Figure 4 shows the coefficients from estimating the linear local projection model in Equation (2) for each response variable: real GDP (in the left panel), CPI inflation (in the middle panel), and the Bank Rate (in the right panel). The light-shaded and dark-shaded areas represent the 68% and 90% confidence intervals, respectively.

The impulse responses exhibit typical and well-documented features (e.g., Christiano et al., 1999). The monetary policy shock is contractionary and corresponds to a positive surprise in the Bank Rate of 100 basis points. Its positive and persistent effect on the Bank Rate induces a statistically significant and delayed contraction in output. GDP starts to decline one year after the initial shock and reaches its minimum after three years when it contracts by 1.9 percent. The initial response of consumer prices is slightly positive but not significant, and only marginally so for a few months in the first year, suggesting a slight price puzzle. After the initial muted response, inflation falls significantly and persistently, in line with the decline in economic activity. After four years, the CPI declines by 0.7 percent.

These patterns are broadly consistent, both qualitatively and quantitatively, with

Figure 4: Linear local projection coefficients



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using linear local projections as in Equation (2). The panels show the point estimates together with their 68% and 90% confidence intervals for real GDP (in the left panel), CPI inflation (in the middle panel), and the Bank Rate (in the right panel). The data used for estimation span from 1997:07 to 2023:12. The impulse responses are shown over a four-year horizon (48 months).

previous studies of the effects of monetary policy shocks in the United Kingdom.[27] Overall, I interpret them as consistent with the conventional wisdom regarding the responses of macroeconomic variables to monetary policy shocks, validating the empirical specification of the model in a linear framework for further analysis in its nonlinear extension.

4.2 Nonlinear impulse responses across states of price rigidity

Figure 5 shows the coefficients from estimating the nonlinear local projection model in Equation (3) using the frequency of price changes as the state variable. The rows show the impulse responses by response variable: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first and second columns show the impulse responses conditional on the flexible and rigid price adjustment regimes, respectively. The third column shows the t-statistic, which tests the null of equality of the coefficients of the flexible and rigid price adjustment regimes, i.e., $\hat{\beta}_h^F = \hat{\beta}_h^R$. A negative value of the t-statistic means that the flexible price-adjustment response is smaller, while a positive value means the opposite. The light-shaded and dark-shaded areas represent the 68% and 90% confidence intervals (for the impulse responses) and z values (for the t-statistic), respectively.

[27] Table C.1 provides an overview of the responses of activity and prices from previous studies. For example, using the same monetary policy shocks as in this paper, Braun et al. (2023) find a peak decline of 1.5 percent in activity and 0.45 percent in prices to a 100 basis point increase in the policy rate.

Figure 5: Nonlinear local projection coefficients across states of price rigidity

Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The rows show the impulse responses by response variables: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first and second columns show the impulse responses conditional on the flexible and rigid price adjustment regimes, respectively. The third column shows the t-statistic, which tests the null of equality of the coefficients of the flexible and rigid price adjustment regimes, i.e., $\hat{\beta}_h^F = \hat{\beta}_h^R$. The light-shaded and dark-shaded areas represent the 68% and 90% confidence intervals (for the impulse responses) and z values (for the t-statistic), respectively. The data used for estimation span from 1997:07 to 2023:12. The impulse responses are shown over a four-year horizon (48 months).

The impulse responses for output in the first row differ markedly between the flexible (in the first column) and the rigid (in the second column) price adjustment regimes. Under flexible price adjustment, real GDP shows no significant response to a monetary policy shock. Under rigid price adjustment, on the other hand, we observe the usual hump-shaped dynamics: After an initial and only marginally significant increase, output declines significantly. Six to eight quarters after the initial shock, real GDP contracts by more than 5 percent in response to the contractionary monetary policy shock that increases the Bank Rate by 100 basis points. The difference in the impulse responses is statistically significant both in the short-term and long-term horizons.

The second row shows the impulse responses for the consumer price index. In a flexible price adjustment regime, prices begin to fall slightly after one year and fall persistently after two years. The response is faster and larger than in a rigid price adjustment regime, which exhibits a slight price puzzle and where prices do not fall until after three years. Under rigid price adjustment, the CPI declines by 0.6 percent by the end of the estimation period following the contractionary shock that raises the Bank Rate by 100 basis points, compared with a maximum decline of 1.5 percent under flexible price adjustment. The difference between the two responses is statistically significant for the price puzzle period.

The panels in the third row show the impulse responses for the Bank Rate. The policy rate increases after a monetary policy shock. On the impact of the shock, the rate is slightly higher under flexible than under rigid price adjustment. For most of the estimated horizons, the policy rates are not significantly different but diverge toward the end of the estimated horizons. In the rigid price adjustment regime, the Bank Rate starts to fall after two years, while the shock dissipates in the flexible price adjustment regime. Despite the generally smaller contractionary effect of monetary policy shocks in the rigid price adjustment regime, their impact on economic activity is larger than in the flexible price adjustment regime.

To put the results in perspective, Table 2 shows the effect of a monetary policy shock equivalent to a 100 basis point increase in the Bank Rate on real GDP and the CPI for different horizons (1, 12, 24, 36, and 48 months after the initial shock). The table shows the coefficients $\hat{\beta}_h$ from estimating linear local projections as in Equation (2) as well as the coefficients from estimating nonlinear local projections as in Equation (3), corresponding to flexible ($\hat{\beta}_h^F$) and rigid ($\hat{\beta}_h^R$) price adjustment regimes, respectively.

Table 2: Impulse responses of real GDP and the CPI to a monetary policy shock across states of price rigidity

	Horizon				
	$h = 1$	$h = 12$	$h = 24$	$h = 36$	$h = 48$
Gross domestic product					
$\hat{\beta}_h$	-0.81^{***}	$0.7^{\cdot}$	$0.8^{\cdot}$	$-0.87^{\cdot}$	-1.41^{*}
$\hat{\beta}_h^F$ (flexible price adjustment)	0.16	-1.30	0.01	-1.94	0.64
$\hat{\beta}_h^R$ (rigid price adjustment)	0.43	4.79^{*}	2.16	-5.74^{**}	$-2.62^{\cdot}$
Consumer price index					
$\hat{\beta}_h$	0.01	$-0.13^{\cdot}$	$-0.20^{\cdot}$	$-0.47^{\cdot}$	-0.70^{*}
$\hat{\beta}_h^F$ (flexible price adjustment)	0.00	-0.39^{***}	$-0.27^{\cdot}$	$-0.50^{\cdot}$	-0.70^{*}
$\hat{\beta}_h^R$ (rigid price adjustment)	0.01	-0.01	-0.19	-0.24	-0.69^{*}

Notes: The table shows the effect of a monetary policy shock equivalent to a 100 basis point increase in the Bank Rate on real GDP and the CPI for different horizons (1, 12, 24, 36, and 48 months after the initial shock). The table shows the coefficients $\hat{\beta}_h$ from estimating linear local projections as in Equation (2) as well as the coefficients from estimating nonlinear local projections as in Equation (3), corresponding to flexible ($\hat{\beta}_h^F$) and rigid ($\hat{\beta}_h^R$) price adjustment regimes. ***, **, *, and $^{\cdot}$ indicate significance at the 1%, 5%, 10%, and 32% levels, respectively.

Under rigid price adjustment regimes, economic activity contracts considerably more than under flexible price adjustment. Three years after the initial shock, the contraction of real GDP is amplified by 200% under rigid price adjustment than under flexible price adjustment. By contrast, the decline in the CPI is much faster under flexible price adjustment, falling by 0.4 percent after one year, while it does not yet fall over the same period under rigid price adjustment. At the end of the estimation horizon (four years after the initial shock), prices fall by the same amount under both regimes.

Finally, comparing the nonlinear estimates with the estimates from the linear local projections, the effect of a monetary policy shock is amplified by a factor of 3 for both variables: in the case of economic activity under rigid price adjustment in the long run, in the case of prices under flexible price adjustment in the short run. Thus, linear estimates run the risk of considerably underestimating the differential effects of monetary policy resulting from changes in price flexibility.

In sum, I find evidence that flexible and rigid price adjustment regimes, as identified by the microfounded frequency of price changes, affect the impact of monetary policy on output and prices differently. The results show that economic activity only contracts under rigid price adjustment after a monetary policy shock. Moreover, prices decline faster and more persistently under the flexible price adjustment regime.

4.3 Asymmetries in the responses to monetary policy shocks

An important question is whether the stronger real effects of monetary policy shocks during periods of rigid price adjustment reflect true state dependence or simply arise from asymmetric responses to expansionary and contractionary monetary policy shocks. Since economic downturns are systematically associated with expansionary monetary policy, one possibility is that the observed differences in responses are driven by the nature of the shocks rather than by the underlying price adjustment regime.

To investigate this, I examine whether economic activity and prices respond differently to positive and negative monetary policy shocks within both the flexible and rigid price adjustment regimes. Specifically, I estimate the nonlinear local projection model in Equation (3), using the frequency of price changes as state variable, and separately applying contractionary and expansionary monetary policy shocks to assess whether asymmetries influence the observed effects.

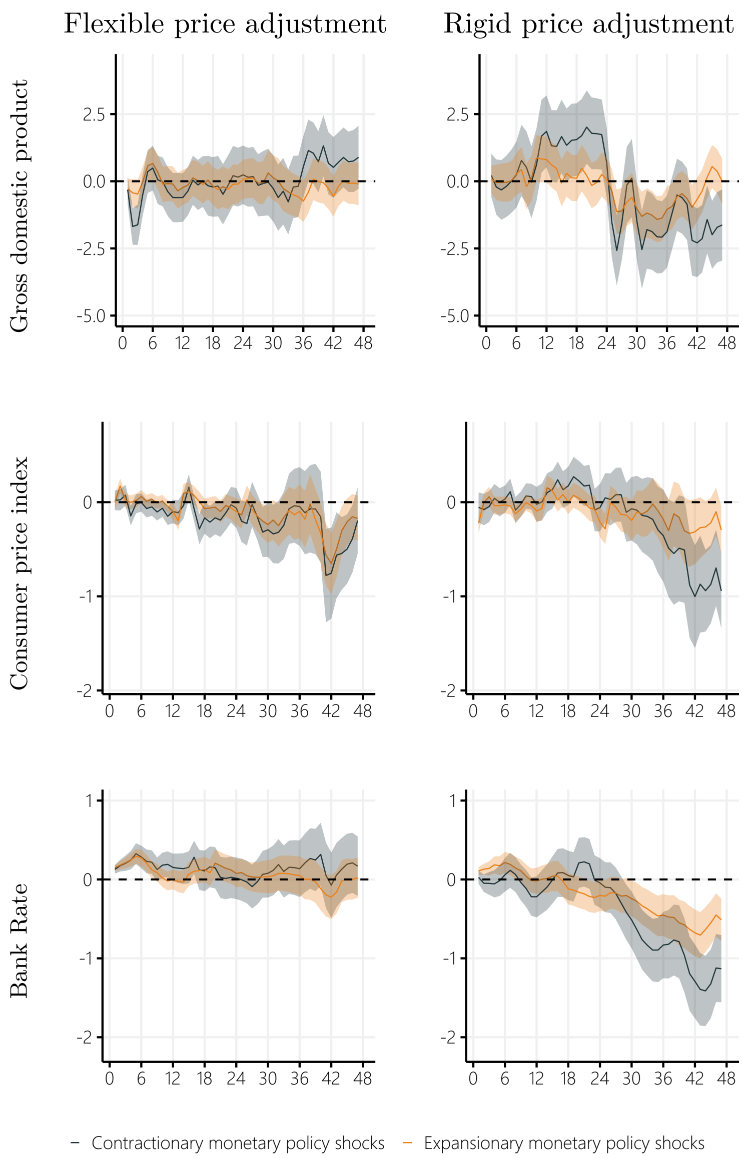
Figure 6 presents the estimation results. The rows display the impulse responses by response variable: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first column shows responses conditional on flexible price adjustment regimes, while the second column conditions on rigid price adjustment regimes. Each panel compares impulse responses in the goods sector (in blue) with those in the services sector (in orange).

The results confirm the main findings: the responses of economic activity and prices in flexible and rigid price adjustment regimes are similar regardless of the direction of the monetary policy shock. This suggests that state dependence, rather than asymmetries in policy transmission, explains the stronger effects of monetary policy during periods of price rigidity. However, I do find that the real effects of monetary policy and its impact on prices are generally stronger in response to contractionary surprises when price adjustment is infrequent, indicating that monetary tightening may have a slightly more pronounced impact on economic activity and prices than monetary easing.

4.4 Cross-sectional heterogeneity

The degree of price rigidity varies significantly across sectors. In the goods sector, the frequency of price changes is relatively high, averaging 16.3 percent over the sample period, and exhibits pronounced cyclical and seasonal fluctuations. In contrast, the services sector is characterized by a much lower frequency of price changes, averaging only 5.9 percent, with weaker cyclical and seasonal patterns.

Figure 6: Nonlinear local projection coefficients across states of price rigidity in the goods and services sectors



Notes: The figure shows impulse responses to contractionary and expansionary monetary policy shocks estimated separately using nonlinear local projections as in Equation (3) and using the frequency of price changes as the state variable. The rows show the impulse responses by response variables: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first and second columns show the impulse responses conditional on the flexible and rigid price adjustment regimes, respectively. The shaded areas represent the 68% confidence intervals. The data used for estimation span from 1997:07 to 2023:12. The impulse responses are shown over a four-year horizon (48 months).

How do these sectoral differences in price setting influence the transmission of monetary policy? To address this question, I examine whether economic activity and prices respond differently in the goods versus services sector. Specifically, I estimate the nonlinear local projection model in Equation (3) separately for each sector, distinguishing between flexible and rigid price adjustment regimes based on sector-specific frequencies of price changes. For economic activity, I use GDP data for the production and services sectors, while for prices, I analyze the goods and services components of the CPI.

Figure 7 presents the estimation results. The rows display impulse responses for real GDP (first row), the consumer price index (second row), and the Bank Rate (third row). The first column shows responses under flexible price adjustment regimes, while the second column conditions on rigid price adjustment regimes. Each panel compares impulse responses in the goods sector (in blue) with those in the services sector (in orange).

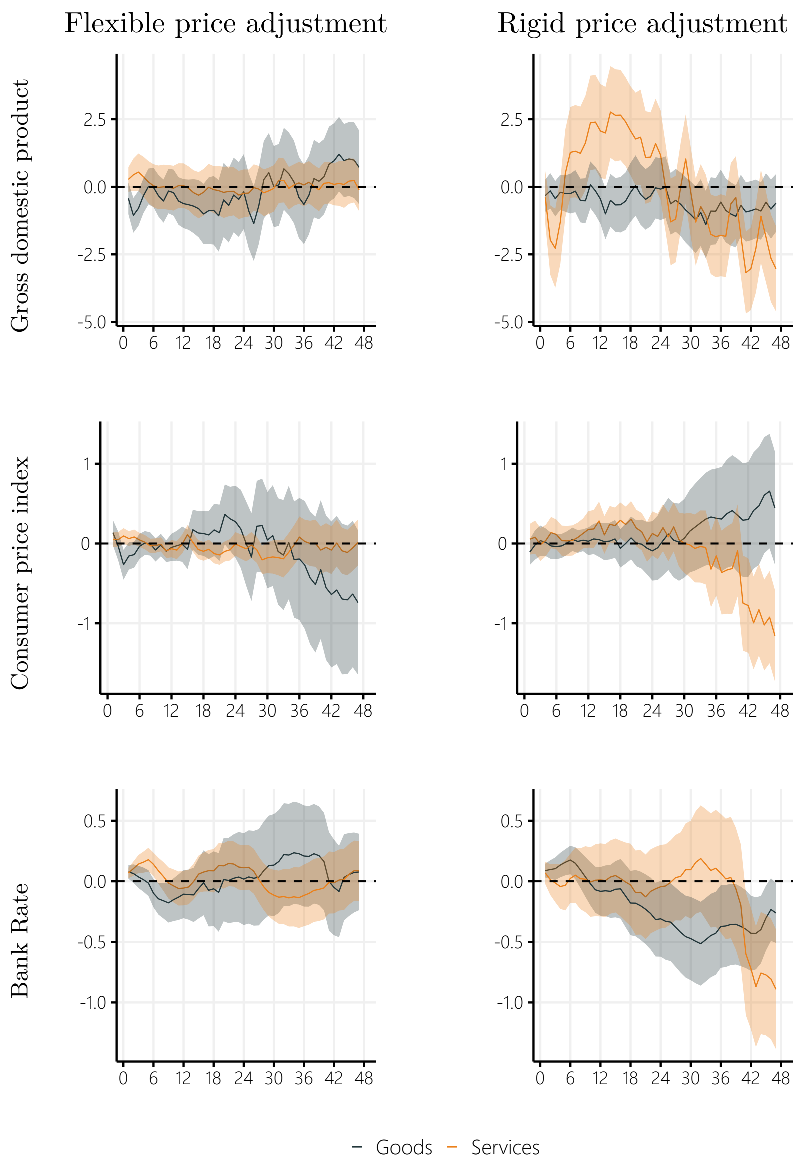
The impulse responses for GDP (first row) reveal a notable contrast across sectors. When price adjustment is flexible, output in both the goods and services sectors shows no significant response to monetary policy shocks. However, under rigid price adjustment, a stark divergence emerges: GDP in the services sector declines sharply, whereas GDP in the production sector also declines but does not significantly differ from zero over the estimation horizon. This suggests that the stronger aggregate response of economic activity to monetary policy shocks in rigid price regimes is largely driven by the services sector.

The second row presents impulse responses for consumer prices. Under flexible price adjustment, goods prices decline more rapidly than services prices, which remain largely unresponsive. However, both estimates are only imprecisely estimated. This difference aligns with the generally higher frequency of price changes in the goods sector compared to services. In contrast, under rigid price adjustment, the pattern reverses: goods prices exhibit little to no response to monetary policy shocks, whereas services prices decline with a notable delay, falling after approximately three years. This suggests that the protracted aggregate price response observed in rigid price adjustment regimes is primarily driven by price rigidity in the services sector.

5 Sensitivity analysis

In this section, I conduct a comprehensive set of robustness exercises. In particular, I perform additional tests regarding the identification of both the regimes and the monetary policy shocks used in the nonlinear local projection estimates (Section 5.1). I also analyze the sensitivity of the results concerning the model specification and

Figure 7: Nonlinear local projection coefficients of goods and services across states of price rigidity



Notes: The figure shows impulse responses to contractionary monetary policy shocks estimated separately for goods and services using nonlinear local projections as in Equation (3) and using the respective frequencies of price changes as the state variables. The rows show the impulse responses by response variables: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first and second columns show the impulse responses conditional on the flexible and rigid price adjustment regimes, respectively. The shaded areas represent the 68% confidence intervals. The data used for estimation span from 1997:07 to 2023:12. The impulse responses are shown over a four-year horizon (48 months).

data choices (Section 5.2). All figures and tables corresponding to these checks can be found in Appendix D.

5.1 Identification

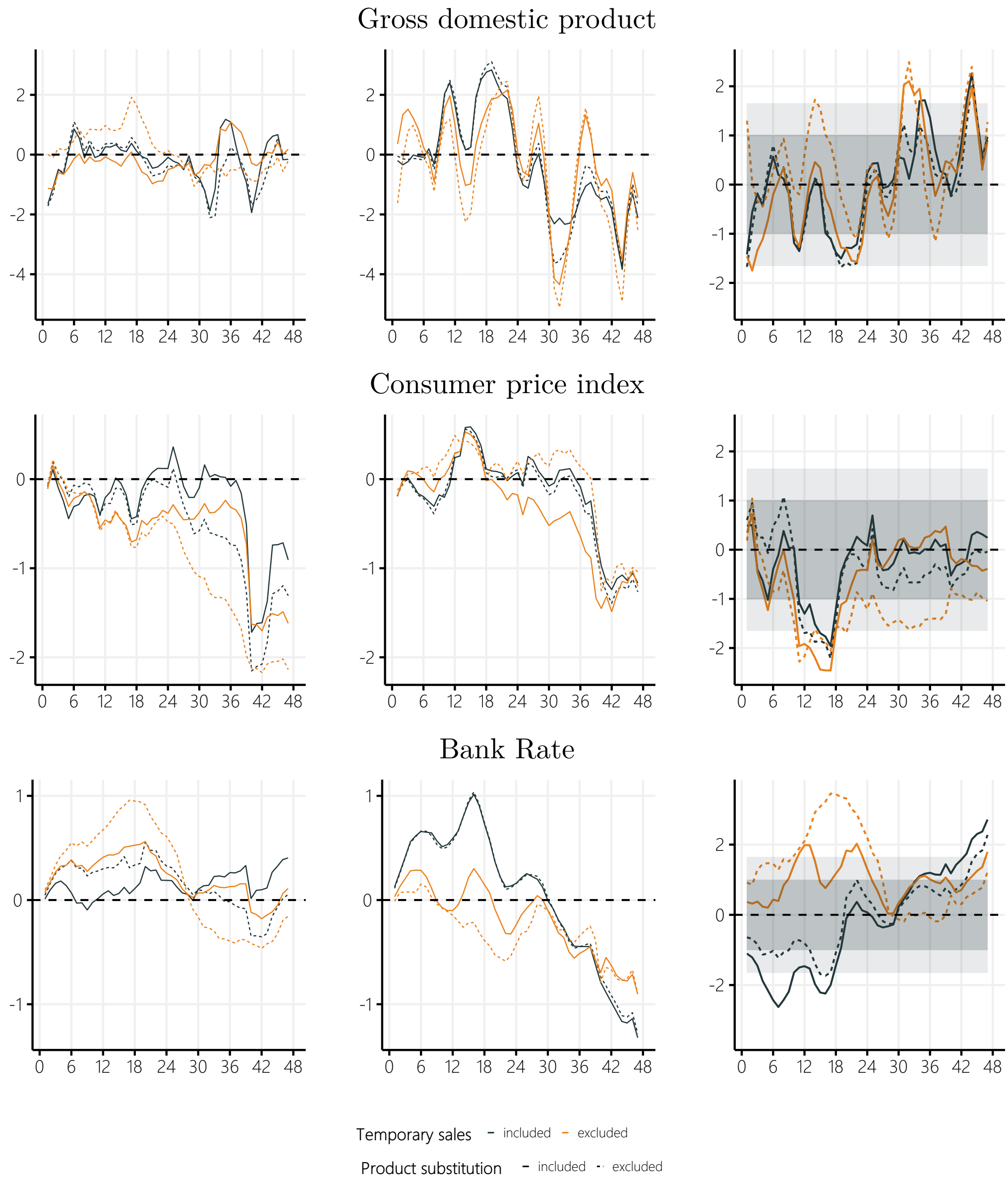
5.1.1 State variables and intensity of regime switching

The baseline model uses as the state variable the frequency of price changes estimated from the microdata sample, which includes price changes due to temporary sales and product substitution, to capture all price changes relevant to the CPI. However, temporary sales and product substitution pose particular challenges for measuring price rigidity. In the case of temporary sales, prices are typically lowered for a short period, after which they tend to return to the initial price, thereby introducing considerable high-frequency variation in the frequency of price changes (Nakamura and Steinsson, 2008). In the case of product substitution, temporarily unavailable or discontinued products are replaced by substitutes to maintain the CPI compilation, thereby introducing potentially artificial price changes or price changes between non-comparable products (Berardi et al., 2015). Therefore, measures of price rigidity are often reported for different treatments of temporary sales and product substitution (e.g., Gautier et al., 2024; Rudolf and Seiler, 2022). I adopt this approach and present results from estimating Equation (3) using state variables based on all combinations of possible treatments, including and excluding price changes due to temporary sales and product substitution.

Figure 8 presents the results that shed light on the importance of temporary sales and product substitution as factors of price rigidity and on their role in driving the differential effects of monetary policy on economic activity and prices. The main results are qualitatively robust to the treatment of temporary sales and product substitution in the state variable. The effects tend to be amplified when price changes due to temporary sales and product substitution are excluded, which may be due to the generally lower frequency of price adjustments when excluding these types of price changes. Overall, the results are more sensitive to the treatment of temporary sales than to the treatment of product substitution. This could be an indication of the importance of firms' sales policies, including in adjusting to macroeconomic shocks.

In addition to the state variables, the identification of flexible and rigid price adjustment regimes depends on the parameter γ in the smooth transition function in Equation (4), determining the intensity of switching between states. Higher values of γ mean that $F(z_t)$ spends more time near the bounds of the unit interval, bringing the model closer to a discrete regime switching setup. Smaller values of γ mean that

Figure 8: Nonlinear local projection coefficients across states of price rigidity based on the samples including and excluding price changes due to temporary sales and product substitution



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the inclusion and exclusion of temporary sales and product substitution in estimating the frequency of price changes.

more observations are assumed to contain some information about behavior in both regimes. In the baseline model, I set $\gamma = 10$. Figure D.1 shows that the main results are robust to both more abruptly changing states (i.e., higher γ) and states with smoother transitions (i.e., smaller γ).

Beyond the states of price rigidity that identify low-frequency movements in price stickiness based on the twelve-month moving average of the frequency of price changes, the differential effects of monetary policy can also be examined across states that identify higher-frequency movements in price stickiness, such as the seasonal patterns in the frequency of price adjustments (see the empirical evidence in Appendix B.6). Figure D.2 shows the coefficients from estimating the nonlinear local projection model in Equation (3) using the seasonal component of the frequency of price changes as a state variable. The seasonal component of the frequency is the de-trended version of the raw series, which I obtain by subtracting the twelve-month moving average centered on each month from the raw series. The results provide evidence that seasonal patterns in price rigidity also affect the impact of monetary policy on output and prices differently. Economic activity contracts faster to monetary policy shocks that occur early in the year (corresponding to seasons of flexible prices) than to those that occur later in the year (corresponding to seasons of rigid prices). Moreover, prices fall immediately within a year when the shock occurs in the second half of the year, in contrast to the sluggish response of prices to shocks in the first half of the year. These findings are consistent with Olivei and Tenreyro (2007, 2010), who argue that due to wage-setting patterns, shocks occurring late in the year have minimal impact because most contracts are renewed towards the beginning of the year, allowing for an immediate adjustment to the shock.

5.1.2 Monetary policy shocks

The information content of the monetary policy shocks used in the empirical analyses constitutes an essential element of the main results, and the literature has developed a number of different instruments and alternative strategies to identify monetary policy surprises. The main specification uses monetary policy shocks from the UK Monetary Policy Event-Study Database (i.e., the UKMPD, Braun et al., 2023), which are based on shocks to the medium-term policy path ("Path" factor) and estimated in the high-frequency revisions of multiple contracts at different maturities around monetary policy events in the United Kingdom. These events include announcements by the Bank of England's Monetary Policy Committee as well as press conferences accompanying the publication of the Quarterly Monetary Policy Report.

The UKMPD itself provides a large number of alternative monetary policy shocks. For one, it measures market surprises to monetary policy events in various assets (such as interest rate futures or gilt yields) at different maturities. For another, it provides the same set of policy shocks for a more restrictive concept of monetary policy events, considering only shocks associated with announcements by the Monetary Policy Committee. Figure D.3 shows that the dynamic responses identified using these alternative instruments are qualitatively very similar to the baseline results from the main part of the paper, especially for the real effects of monetary policy.

In addition to the UKMPD, there are also other sources of monetary policy shocks extracted from asset price responses to monetary policy announcements in the United Kingdom (e.g., Cesa-Bianchi et al., 2020). And besides identifying shocks in the high-frequency revisions of asset prices around monetary policy events, the literature has developed several alternative strategies for identifying monetary policy surprises. Examples include the narrative method[28] developed by Romer and Romer (2004) or more traditional identification via Cholesky-type recursive restrictions[29] in vector autoregressions (Sims, 1980). In Figure D.4, I employ these alternative external instruments[30] and identification strategies[31] to estimate the nonlinear local projections model and find results broadly similar to those in the main part of the paper.

5.2 Specification and data choices

5.2.1 Variable selection and model specification

The baseline model follows a standard monetary VAR model, kept as parsimonious as possible to capture the main transmission channel of monetary policy. In Figure D.5, I report the results of an extended specification, where I add additional variables to the baseline model. In particular, I add the 1-year government gilt yield, the investment-grade non-financial corporate bond spreads, the US BAA corporate spread (which is the difference between the Moody's BAA corporate yield and the yield on the 10-year US Treasury constant maturity), and the producer price index. The figure reveals

[28] The narrative method extracts monetary policy innovations by regressing the change in the target interest rate around the policy decision on a proxy for the information set available to the policymaker just before the decision. This information set comprises various real-time indicators and forecasts, reflecting the forward-looking nature of monetary policy.

[29] Monetary policy shocks identified recursively are based on the timing assumption that a current innovation in the instrument used by policymakers has no contemporaneous effect on macroeconomic variables, such as output, employment, or prices. They are usually extracted via Cholesky decomposition of the variance-covariance matrix of the residuals in vector autoregressions ordered with the policy variable last (e.g., Christiano et al., 1999; Kim and Roubini, 2000).

[30] I use the alternative shock series based on market surprises provided by Cesa-Bianchi et al. (2020) for the period 1997:06–2015:01, and the narrative monetary policy shocks along the lines of Cloyne and Hürtgen (2016), of which I use the series provided by Cesa-Bianchi et al. (2020) who extend the original series (1975:01–2007:12) to 2009:02.

[31] I employ the recursive (Cholesky) identification scheme, order the endogenous variables from fast-moving to slow-moving (i.e., real gross domestic product before the consumer price index), and put the Bank Rate last.

that the estimates of the coefficients on the main variables in Equation (3) are robust to this extended version of the local projection model.

An important issue in local projection models is the selection of appropriate variables, even more so in parsimonious specifications such as the baseline. In the baseline model, I use monthly estimates of real GDP as the output variable and the CPI as a measure of prices. I assess the sensitivity of the main results to the choice of these variables by replacing, respectively, GDP with the industrial production index, and the CPI with the consumer price index including owner occupiers' housing costs (CPIH) and the Retail Price Index (RPI). The main results are robust to these alternative variables for output and prices (Figure D.6).

I also perform several robustness checks with respect to the lag order (Figure D.7) and the deterministics included in the model (Figure D.8). In particular, I increase and decrease the order of the lags relative to the baseline, and I estimate a version of the model without a constant as well as with a constant and a linear trend. The results are robust to all of these choices.

5.2.2 Sample and data frequency

Individual major events over the 1997 to 2023 estimation period may drive the overall estimation results. To examine this, I estimate the model for different subsamples. Excluding the Great Recession (by excluding the period 2008:01–2009:12) or the COVID-19 pandemic (by excluding the period 2020:01–2023:12) does not change the results materially (Figure D.9).

The baseline model is estimated in monthly data. To analyze the differential effects of monetary policy on quarterly variables of interest, I estimate the nonlinear local projection model in quarterly variables: For economic activity, I use the quarterly GDP; for prices, I use the GDP deflator; and the remaining variables (including the state variable) I aggregate from monthly to quarterly frequency by taking simple averages over time. The baseline responses turn out to be very similar (Figure D.10). However, as expected, the instrument is weaker, reflecting the lower signal-to-noise ratio.

6 Conclusion

Price rigidity is at the core of the workhorse models used to study business cycle fluctuations and to analyze the effects of monetary policy. Far from being constant, there is strong evidence of non-uniformity in price setting over time. Using CPI microdata from the United Kingdom from 1996 to 2023, I uncovered distinct cyclical patterns in the frequency of price adjustment. In particular, the frequency of price adjustment is countercyclical, increasing as the economy slows down, and it increases during periods of higher inflation. In addition, price rigidity shows seasonal patterns, being lower at the beginning of the year than at the end.

Using these patterns to inform nonlinear local projection models of states of flexible and rigid price adjustment, I found strong, microfounded evidence for the state dependence of monetary policy on the price-setting behavior of firms. In particular, economic activity exhibits larger responses to monetary policy shocks in periods of rigid prices than in periods of flexible prices. At the same time, prices respond faster when price adjustment is flexible. These results are robust to several variations in the empirical methodology. States of rigid price adjustment, as identified by the frequency of price changes, correspond to periods of economic expansion and low inflation. Furthermore, monetary shocks that occur early in the year have larger real effects than shocks that occur later in the year, as indicated by local projections that identify states with the seasonal component of the frequency of price changes.

Given the different effects of monetary policy depending on the degree of price rigidity, stronger actions are needed in states with flexible price adjustments than in states with rigid price adjustments to achieve the same outcome for economic activity. Conversely, to achieve the same outcome for prices, stronger actions are required in states with rigid price adjustments than in states with flexible price adjustments. The usual estimates in the literature, which do not take account of nonlinear impulse responses, risk obscuring the differential effects of monetary policy resulting from changes in the effective price flexibility due to more state-dependent elements, such as cyclical patterns. This calls for greater consideration of such aspects in nonlinear, state-dependent models of monetary policy transmission.

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Appendix

A Data

This appendix provides additional information on the data (sources) used in the paper.

A.1 UK CPI microdata

Table A.1 illustrates the effect of all sample restrictions on the sample size. I exclude duplicate price quotes (because of reasons of confidentiality, the ONS does not always publish all available local information, resulting in product identifiers containing duplicate price quotes), “invalid” price quotes (which do not pass the ONS cross-checking procedures and are not included in the calculation of the official CPI), imputed prices, outliers (by excluding monthly price changes larger than the 99th percentile of absolute log price changes and smaller than the 1st percentile of absolute log price changes for each expenditure item), price changes that coincide with changes in product units, and price changes that coincide with changes in VAT rates.

Table A.1: Sample restrictions and sample size

	# price quotes	# products	# price changes
Raw data	40,373,585	891,316	9,437,097
− exclude invalid price quotes	3,555,461	558,580	1,672,539
− exclude duplicate price quotes	6,424,603	63,211	1,958,276
− exclude imputed prices	1,893,224	314,675	1,035,917
− exclude $\lvert\Delta p\rvert < \text{P1}$, $\lvert\Delta p\rvert > \text{P99}$	97,046	62,998	97,046
− exclude product unit changes	9,686	8,029	4,205
− exclude/dummy VAT price changes	348,408	158,476	151,606
Baseline sample	30,904,793	777,330	5,314,893

Notes: The table illustrates the effect of all sample restrictions on the sample size. I exclude duplicate price quotes (because of reasons of confidentiality, the ONS does not always publish all available local information, resulting in product identifiers containing duplicate price quotes), “invalid” price quotes (which do not pass the ONS cross-checking procedures and are not included in the calculation of the official CPI), imputed prices, outliers (by excluding monthly price changes larger than the 99th percentile of absolute log price changes and smaller than the 1st percentile of absolute log price changes for each expenditure item), price changes that coincide with changes in product units, and price changes that coincide with changes in VAT rates.

A.2 Data sources

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

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

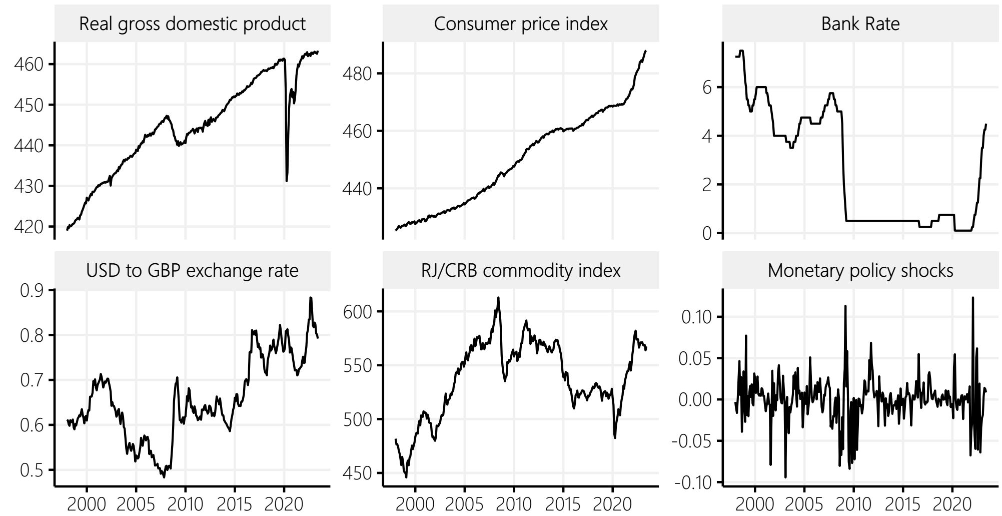
Variable	Description	Source	Sample
Microdata			
CPI price quotes	Price quote data that underpin consumer price inflation statistics in the United Kingdom	ONS	1996:01–2023:12
CPI item indices	Item index data that underpin consumer price inflation statistics in the United Kingdom	ONS	1996:01–2023:12
Monetary policy shocks			
Path	Monetary event factors estimated in multiple sterling futures and gilt yields (Baseline)	UKMPD	1997-06-06–2021-03-18
FSScm3	Monetary event surprises in the 3M Libor 3rd quarterly contract	UKMPD	1997-06-06–2021-03-18
SON3c3	Monetary event surprises in the 3M Sonia 3rd quarterly contract	UKMPD	2021-05-06–2023-06-22
FSScm1	Monetary event surprises in the 3M Libor 1st quarterly contract	UKMPD	1997-06-06–2021-03-18
SON3c1	Monetary event surprises in the 3M Sonia 1st quarterly contract	UKMPD	2021-05-06–2023-06-22
FSScm2	Monetary event surprises in the 3M Libor 2nd quarterly contract	UKMPD	1997-06-06–2021-03-18
SON3c2	Monetary event surprises in the 3M Sonia 2nd quarterly contract	UKMPD	2021-05-06–2023-06-22
FSScm4	Monetary event surprises in the 3M Libor 4th quarterly contract	UKMPD	1997-06-06–2021-03-18
SON3c4	Monetary event surprises in the 3M Sonia 4th quarterly contract	UKMPD	2021-05-06–2023-06-22
GBP1YT=RR	Monetary event surprises in 1-year gilt yields	UKMPD	2021-05-06–2023-06-22
GBP5YT=RR	Monetary event surprises in 5-year gilt yields	UKMPD	2021-05-06–2023-06-22
GBP10YT=RR	Monetary event surprises in 10-year gilt yields	UKMPD	2021-05-06–2023-06-22
FSScm3_mpc	Monetary MPC surprises in the 3M Libor 3rd quarterly contract	UKMPD	1997-06-06–2021-03-18
SON3c3_mpc	Monetary MPC surprises in the 3M Sonia 3rd quarterly contract	UKMPD	2021-05-06–2023-06-22
FFIc1	Monetary event surprises in the FTSE100 future first month contract	UKMPD	1997-06-06–2023-06-22
FTSE	Monetary event surprises in the FTSE 100 Index	UKMPD	1997-06-06–2023-06-22
FTMC	Monetary event surprises in the FTSE 250 Index	UKMPD	1997-06-06–2023-06-22
FTAS	Monetary event surprises in the FTSE All Share Index	UKMPD	1997-06-06–2023-06-22
CTV	High-frequency monetary policy surprises	Cesa-Bianchi et al. (2020)	1997:06–2015:01
CH	Narrative monetary policy surprises of Cloyne and Hürtgen (2016), extended by Cesa-Bianchi et al. (2020)	Cesa-Bianchi et al. (2020)	1997:06–2009:02
Baseline variables			
GDP	Real gross domestic product (GDP) monthly estimate, seasonally adjusted	ONS	1997:01–2023:12
D7BT	UK consumer price index (CPI), all items (2015=100)	ONS	1988:01–2023:12
RATE	Bank Rate	BoE	1972-10-16–2023-08-03
DEXUSUK	US Dollars to UK Pound Sterling Spot Exchange Rate	FRED	1971-01-04–2023-12-31

wocind0265_m	RJ/CRB Commodity Price Index, Total Return, End of Period, USD	Commodity Research Bureau	1994:01–2023:12
Additional variables			
Economic activity			
GBRRECDM	Recession Indicators for the United Kingdom from the Peak through the Trough	OECD	1952:02–2022:09
UKNGDP	Real gross domestic product (GDP), quarterly	ONS	1955:I–2023:IV
gbprod00571	Industrial production index, Total, Constant prices, SA	ONS	1948:01–2023:12
LRHUTTTTGBM156S	Infra-Annual Labor Statistics: Monthly unemployment rate total: 15 years or over	OECD	1983:01–2023:12
Prices			
CHAW	UK retail price index (RPI), all items (Jan 1987=100)	ONS	1987:01–2023:12
L522	UK consumer price index (CPIH) including owner occupiers' housing costs, all items (2015=100)	ONS	1988:01–2023:12
gbpric27001	UK producer price index (PPI), output, manufactured products for the domestic market, index (2015=100)	ONS	1957:01–2023:12
GBRGDPDEFQISMEI	GDP deflator, SA, index (2015=100)	ONS	1960:I–2023:IV
Financial variables			
gbpric27001	UK government benchmarks, 1-year gilt yield	Macrobond	1979-01-02–2023-12-31
BAMLC0A0CM	Investment-grade non-financial corporate bond spreads: ICE BofA US Corporate Index Option-Adjusted Spread	Ice Data Indices	1996-12-31–2023-12-31
BAA10Y	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Federal Reserve Bank of St. Louis	1986-01-02–2023-12-31

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

Figure A.1 shows the series included in the baseline local projection model over the sample period 1997–2023.

Figure A.1: Transformed data series in the baseline local projection model



Notes: The figure shows the series included in the baseline local projection model over the sample period 1997–2023. Real GDP, the consumer price index, and the commodity price index are in log levels multiplied by 100. The Bank Rate is in percent.

B Empirical evidence on the non-uniformity of price rigidity over time

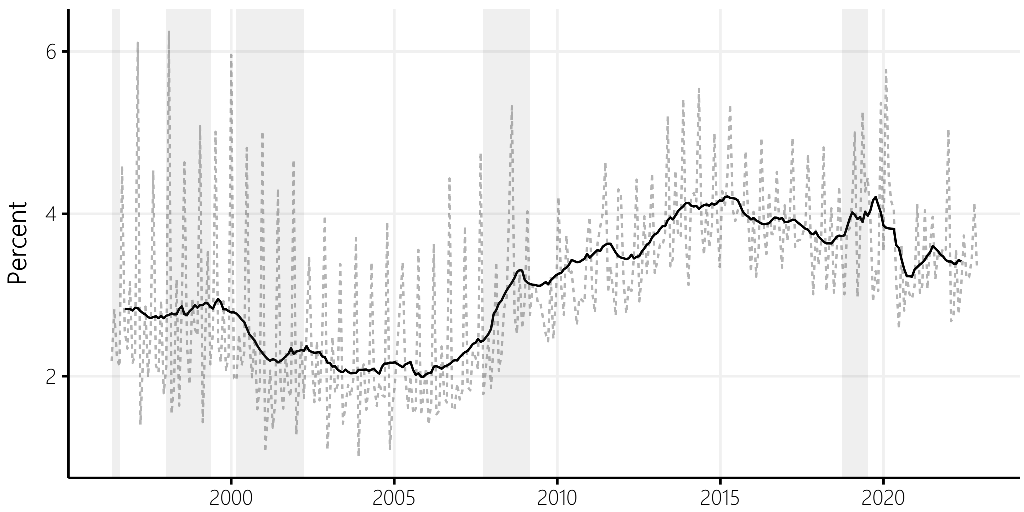
This appendix refers to Section 2 and provides additional information on the empirical evidence of the non-uniformity of price rigidity over time. It provides figures and tables that are not included in the main body of the paper.

B.1 Cyclicality of temporary sales

A salient feature of price spells is their high-frequency variation due to temporary sales. Temporary sales involve price discounts for a limited period of time, after which the price usually returns to the original price.

Price changes due to such temporary sales are frequent. Figure B.1 shows the average frequency of sales price changes over the period 1996–2023, capturing the share of price changes due to temporary sales in all price changes. The figure shows the raw series (in dashed lines) as well as its 12-month moving average centered on each month (in solid lines).

Figure B.1: Cyclical patterns in temporary sales



Notes: Average frequency of sales price changes for consumer prices in the United Kingdom from February 1996 to December 2023. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the raw series (in dashed lines) and the 12-month moving average centered on each month (in solid lines). Outliers related to VAT rate changes are excluded. Recessions (shaded areas) are dated by the Organisation for Economic Co-operation and Development (OECD).

Starting in 2008, the frequency of sales price changes increased over the sample period. It averages 2.4 percent before 2008 and 3.7 percent after. Since 2014, the

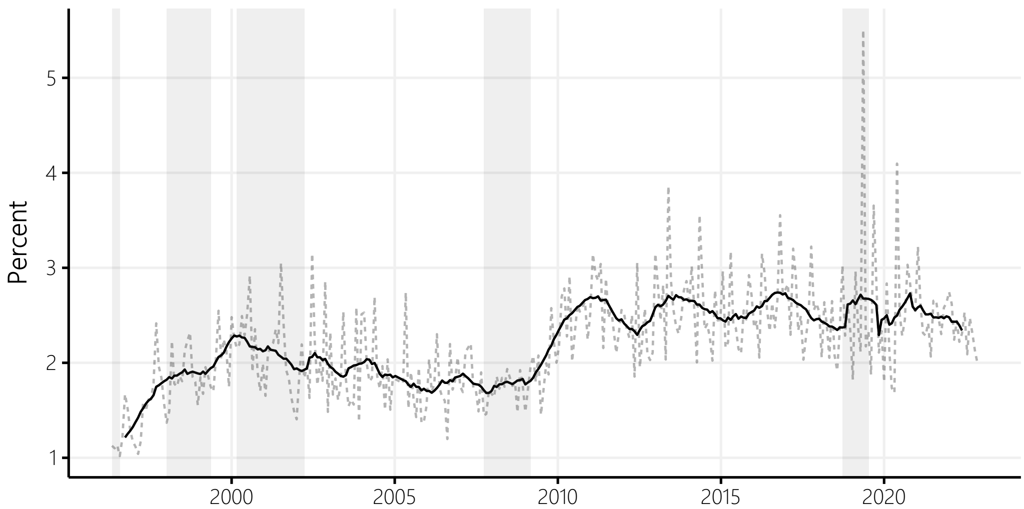
12-month moving average of the share of price changes due to temporary sales hovers around 4 percent.

B.2 Cyclicality of product substitution

An important principle of price collection is to collect prices of the same items over time to capture only the evolution of prices. However, consumer markets evolve rapidly, and no single product is likely to be observed for several years. It is common for items to change, for new items to enter the market while others disappear and need to be replaced, or for items to become temporarily or permanently unavailable.

Price changes due to such product substitution are common. Figure B.2 shows the average frequency of price changes due to product substitution over the period 1996–2023. The figure shows the raw series (in dashed lines) as well as its 12-month moving average centered on each month (in solid lines).

Figure B.2: Cyclical patterns in product substitutions



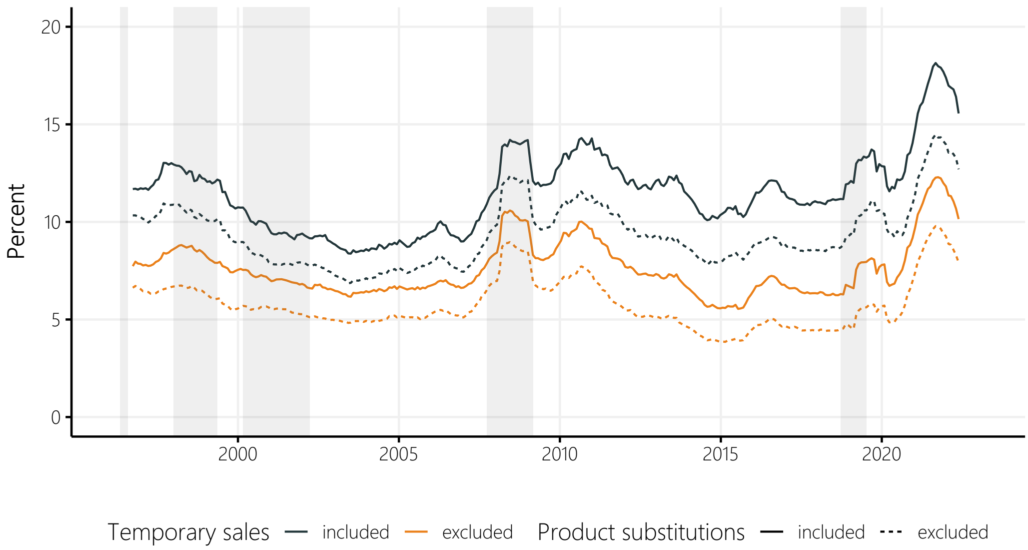
Notes: Average frequency of price changes due to product substitution for consumer prices in the United Kingdom from February 1996 to December 2023. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the raw series (in dashed lines) and the 12-month moving average centered on each month (in solid lines). Outliers related to VAT rate changes are excluded. Recessions (shaded areas) are dated by the Organisation for Economic Co-operation and Development (OECD).

The frequency of price changes due to product substitution has increased slightly over the sample period. It averages 1.9 percent before 2010 and 2.5 percent after. During the COVID-19 pandemic, price changes due to product substitution peaked at 5.5 percent.

B.3 Cyclicality of price rigidity

Figure B.3 shows the frequency of price changes as a 12-month moving average across sample combinations, distinguished by the inclusion and exclusion of price changes due to temporary sales and product substitution. The treatment of temporary sales and product substitution affects the levels but not so much the cyclical patterns of the series.

Figure B.3: Cyclicality of the frequency of price changes across samples including and excluding price changes due to temporary sales and product substitution



Notes: Average frequency of consumer price changes in the United Kingdom from February 1996 to December 2023 across samples including and excluding price changes due to temporary sales and product substitution. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the 12-month moving average centered on each month. Outliers related to VAT rate changes are excluded.

B.4 Cyclicality of the size of price changes

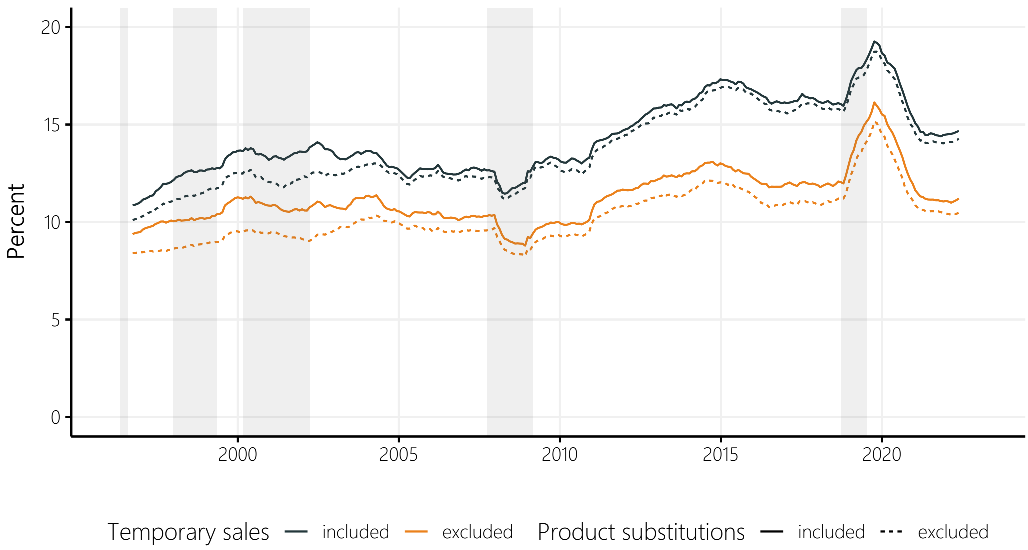
The absolute size of price changes for item i in month t captures the average of all non-zero log price changes of product p of item i that change from one month to another in absolute value and is calculated as

$$|\Delta p_{i,t}| = \frac{\sum_{p,s} \omega_{p,s,t} I_{p,s,t} (|\log P_{p,s,t} - \log P_{p,s,t-1}|)}{\sum_{p,s} \omega_{p,s,t} I_{p,s,t}}. \tag{5}$$

Similarly to the frequency of price changes, I also consider the size of price increases, $\Delta p^{+}_{i,t}$, and the size of price decreases, $\Delta p^{-}_{i,t}$. The aggregate absolute size of price changes, $|\Delta p_t|$, is the weighted median absolute size across items using average CPI expenditure weights.

Figure B.4 shows the absolute size of price changes as a 12-month moving average across sample combinations, distinguished by the inclusion and exclusion of price changes due to temporary sales and product substitution.

Figure B.4: Cyclicality of the size of price changes across samples including and excluding price changes due to temporary sales and product substitution



Notes: Average absolute size of consumer price changes in the United Kingdom from February 1996 to December 2023 across samples including and excluding price changes due to temporary sales and product substitution. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the 12-month moving average centered on each month. Outliers related to VAT rate changes are excluded. Recessions (shaded areas) are dated by the Organisation for Economic Co-operation and Development (OECD).

Starting in 2010, the absolute size of price changes increases over the sample period, particularly for the sample that includes sales. It averages about 12 percent before 2010 and almost 16 percent thereafter. Overall, the treatment of temporary sales and product substitution affects the levels but not so much the cyclical patterns of the series.

B.5 Cyclicality of the frequency of price increases and decreases

Table B.1 repeats the regression analyses from Table 1 for the frequency of price increases and the frequency of price decreases, separately. The results show that while both the frequency of price increases and decreases are equally countercyclical, the positive comovement with inflation is only driven by the frequency of price increases.

Table B.1: Cyclical properties of the frequency of price increases and decreases

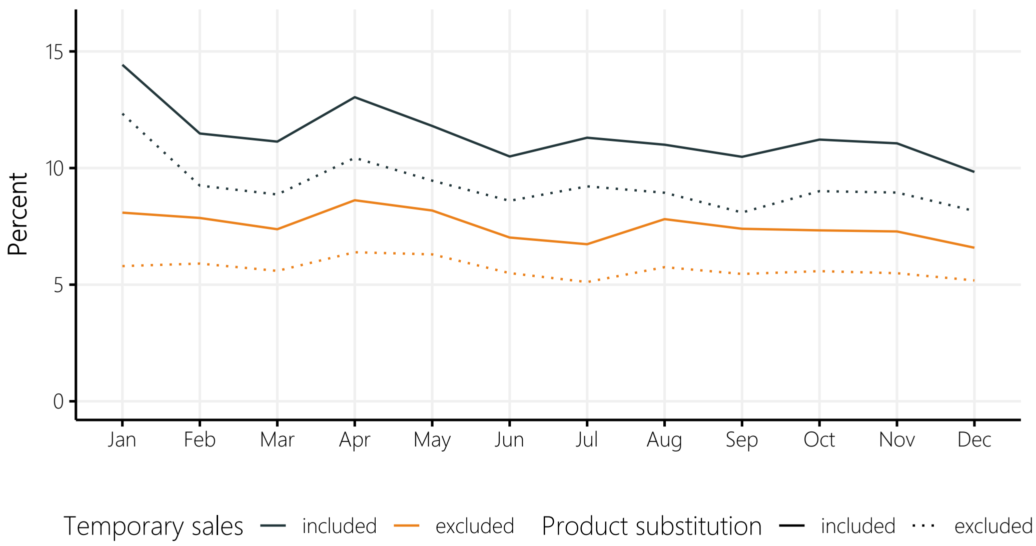
	Frequency of price increases				Frequency of price decreases			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPI inflation	0.562***	0.595***	0.377***	0.560***	0.035*	0.048	0.020	−0.024
	(0.033)	(0.045)	(0.043)	(0.037)	(0.021)	(0.030)	(0.019)	(0.021)
Unemployment rate	0.206***		0.131***	0.209***	0.191***		0.111***	0.280***
	(0.050)		(0.049)	(0.055)	(0.031)		(0.030)	(0.032)
Recession dummy		0.576***				0.102		
		(0.167)				(0.110)		
Frequency (lagged)			0.332***				0.415***	
			(0.053)				(0.052)	
Constant	2.795***	3.880***	2.241***	2.766***	2.305***	3.345***	1.789***	1.381***
	(0.383)	(0.264)	(0.374)	(0.449)	(0.238)	(0.174)	(0.227)	(0.260)
Time trend	No	No	No	Yes	No	No	No	Yes
Observations	330	315	329	330	330	315	329	330
R^2	0.509	0.415	0.564	0.509	0.234	0.144	0.365	0.333

Notes: Linear regressions of the frequency of price increases and decreases on CPI inflation and aggregate business cycle indicators (the unemployment rate and recession dummies). All regressions include calendar month dummies and control for VAT rate changes. The frequencies are calculated at the item level and aggregated to weighted medians using CPI expenditure weights using the samples of UK CPI microdata from February 1996 to December 2023, including price changes due to temporary sales but excluding price changes due to product substitution. The unemployment rate is the monthly unemployment rate for civilians aged 15 and over according to the infra-annual labor statistics. CPI inflation is the year-on-year change in the consumer price index excluding owner-occupier housing costs from the ONS. Recessions are dated by the Organisation for Economic Co-operation and Development (OECD).
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

B.6 Seasonality of price rigidity

This section presents empirical evidence on seasonal patterns in price rigidity. Figure B.5 shows the frequency of price changes by month for consumer prices in the United Kingdom from February 1996 to December 2023. The moments are computed for different sample combinations, distinguished by the inclusion or exclusion of price changes due to temporary sales and product substitution.

Figure B.5: Seasonality of the frequency of price changes



Notes: Average frequency of price changes by calendar month for consumer prices in the United Kingdom from February 1996 to December 2023. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows moments for all sample combinations, including (in blue) and excluding temporary sales (in orange), as well as including (solid lines) and excluding product substitution (dotted lines). Outliers related to VAT rate changes are excluded. All values are in percent.

The treatments of temporary sales and product substitution differ in their effect on the seasonal patterns of the frequency of price changes. While the inclusion of price changes due to product substitution has a minimal effect on the aggregate seasonal patterns[32], the treatment of temporary sales significantly alters both the levels and the seasonal patterns of the series.[33] In particular, the seasonal patterns

[32] The aggregate seasonal patterns are little affected by the inclusion or exclusion of price changes due to product substitution. Their treatment only affects the level of the series: Excluding price changes due to product substitution reduces the average frequency by two percentage points and the average size by one percentage point compared to the versions computed with the sample including product substitution.

[33] The treatment of price changes due to discounts and promotions has a greater impact on both the levels and the seasonal patterns of the series. The series based on the sample without price changes due to temporary sales are, on average, three to four percentage points lower than those calculated with temporary sales. In addition, the seasonal patterns are less pronounced when price changes due to temporary sales are excluded.

are less pronounced when price changes due to discounts and promotions are excluded. Thus, temporary sales play a disproportionate role in generating seasonality in price changes. In the following, I will focus on the sample that includes price changes due to both temporary sales and product substitution to capture all price changes relevant to the compilation of the CPI. However, I also present statistics using the sample without temporary sales price changes for the analysis of seasonal patterns in price rigidity.

Figure B.5 reveals large and distinct seasonal movements in the frequency of price changes, many of which are strikingly similar to the seasonal patterns documented in CPI microdata in other regions (e.g., by Nakamura and Steinsson (2008, 2013) for the United States, Alvarez et al. (2006) and Gautier et al. (2024) for the euro area, Aucremanne and Dhyne (2004) for Belgium, or Berardi et al. (2015) for France) as well as in other micro price data (e.g., in PPI microdata by Nakamura and Steinsson (2008) for the United States and by Dedola et al. (2021) for Denmark). Four observations stand out.

First, the frequency of price changes including sales declines monotonically over the four quarters. It is 10.1% in the first quarter, 9.5% in the second quarter, 8.8% in the third quarter, and 8.7% in the fourth quarter. This regularity indicates a strong seasonal pattern in the frequency of price adjustments: It is highest at the beginning of the year and declines as the year progresses. Overall, the range between the month with the highest (i.e., January) and the lowest (i.e., December) frequency of price changes is 4.1 percentage points. The frequency of regular price changes also decreases over the quarters of the year, but the decrease is less pronounced and not monotonous.

Second, in all four quarters, the frequency of price changes including sales is highest in the first month of the quarter and declines monotonically within the quarter. This gives rise to the pattern of local peaks in the frequency of price changes in January, April, July, and October. However, there is no comparable pattern for the frequency of regular price changes.

Third, the seasonal variation within quarters in the frequency of price changes including sales declines over the year. It is largest in the first quarter, where the difference between the month with the highest (i.e., January) and lowest (i.e., March) average frequency of price changes is 3.4 pp, and smallest in the fourth quarter, where the difference is 0.9 pp between October and December. For the frequency of regular price changes, the intra-quarter variation also decreases over the year, but again, to a lesser extent.

Fourth, the frequency of price changes including sales is much higher in January than in other months. Table B.2 reports more detailed results on this "January effect," where I regress January dummies on the item-level frequencies of price changes, increases, and decreases for consumer prices in the United Kingdom from February 1996 to December 2023 using the samples with and without temporary sales. The regressions include month and year fixed effects and dummies for VAT rate changes.

Table B.2: "January effect" on the frequency of price changes

Sector	Variable	Including sales			Excluding sales		
		Effect	N	% CPI	Effect	N	% CPI
Aggregate	Price changes	10.19	438	45.95	6.84	231	29.66
	Price decreases	5.70	458	48.01	2.05	154	18.86
	Price increases	5.78	293	36.58	5.67	269	34.02
Food	Price changes	8.41	42	3.62	7.57	35	3.03
	Price decreases	-2.21	80	6.85	0.83	27	1.94
	Price increases	10.65	66	6.63	7.08	56	5.56
NEIG	Price changes	9.98	305	26.00	1.18	105	9.99
	Price decreases	9.11	311	27.28	1.06	69	6.19
	Price increases	0.17	131	12.81	1.76	118	11.40
Services	Price changes	10.93	91	16.33	10.10	91	16.65
	Price decreases	2.83	66	13.74	2.83	58	10.72
	Price increases	8.16	95	17.06	7.83	95	17.06

Notes: "January effect" from item-level regressions of January dummies on the frequency of price changes, increases, and decreases for consumer prices in the United Kingdom from February 1996 to December 2023 using the samples with and without temporary sales. Price changes due to product substitution are excluded. Regressions include month and year fixed effects and dummies for VAT changes. "Effect" indicates the weighted average size of significant January-dummy coefficients. "N" and "% CPI" indicate the absolute number and weighted share of items with significant January-dummy coefficients. Significance is evaluated at the 5% significance level. The total number of items used in the estimation is 1,260. The CPI weights refer to the average CPI expenditure weight over the sample period.

The effect is significant for 46% of the items and the average weighted effect is 10.2 pp for the frequency of price changes including sales. The effect is similar for price increases and price decreases (5.7 pp).

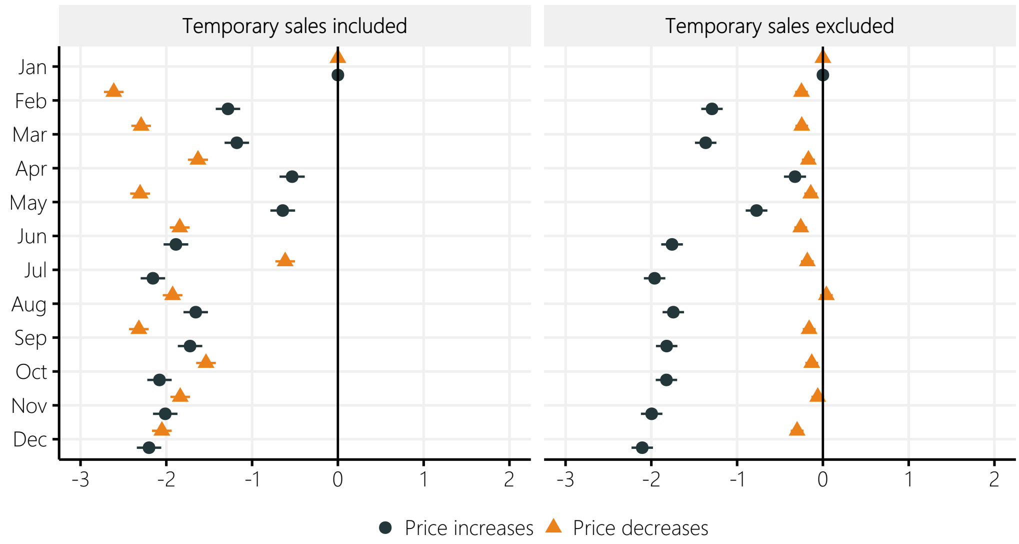
When sales are excluded, I still find that the frequency of price changes is higher in January than in other months of the year for some items (30%). However, the overall effect is smaller (6.8 pp), driven by a much smaller effect for price decreases (2.1 pp). In turn, the January effect excluding sales is about the same for price increases as when sales are included (5.7 pp). This suggests that the exclusion of price changes due to temporary sales particularly affects the frequency of price decreases.

To further investigate the role of price increases and decreases in driving the seasonal patterns, I adopt the approach of Gautier et al. (2024) and estimate weighted panel regressions relating the item-level frequencies of price increases and decreases to month and year fixed effects. In particular, I estimate

$$y_{i,t} = \mu_i + \mu_m + \mu_y + \beta \text{VAT}_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where μ_j is an item-level fixed effect, μ_m is a calendar month fixed effect, μ_y is a year fixed effect, and $\text{VAT}_{i,t}$ is a dummy variable that controls for the VAT changes in December 2008, January 2010 and January 2011 in the sample. This regression framework is independent of both the choice of the measure of central tendency[34] used for cross-sectional aggregation (by estimating month fixed effects at the most disaggregated product level) and of any trend in the frequency of price changes (by estimating year fixed effects). The dependent variables include the frequency of price increases and decreases, calculated using the samples including and excluding temporary sales.

Figure B.6: Month-effects of the frequency of price increases and decreases



Notes: Coefficient plots of month-effects from weighted item-level panel regressions as specified in Equation (6) with robust standard errors and 95% confidence intervals. The dependent variables are the frequency of price increases and decreases for consumer prices in the United Kingdom from February 1996 to December 2023. The base month is January. Price changes due to product substitution are excluded. Outliers identified as values of the dependent variables smaller (larger) than the 1st (99th) percentiles are excluded beforehand.

Figure B.6 plots the month-effects from the weighted item-level panel regressions as specified in Equation (6) with robust standard errors and 95% confidence intervals.

Temporary sales in January and July play a key role in explaining the seasonality of the frequency of price increases and decreases. When sales are excluded, the pattern for increases persists, while the seasonality for price decreases disappears and is close to zero. Thus, most of the seasonality in the frequency of price changes comes from the frequency of price increases.

In sum, there is strong evidence of seasonal patterns in price rigidity. In particular, price changes tend to be more frequent early in the year than later, a pattern that is driven mainly by price increases and influenced more strongly by temporary sales

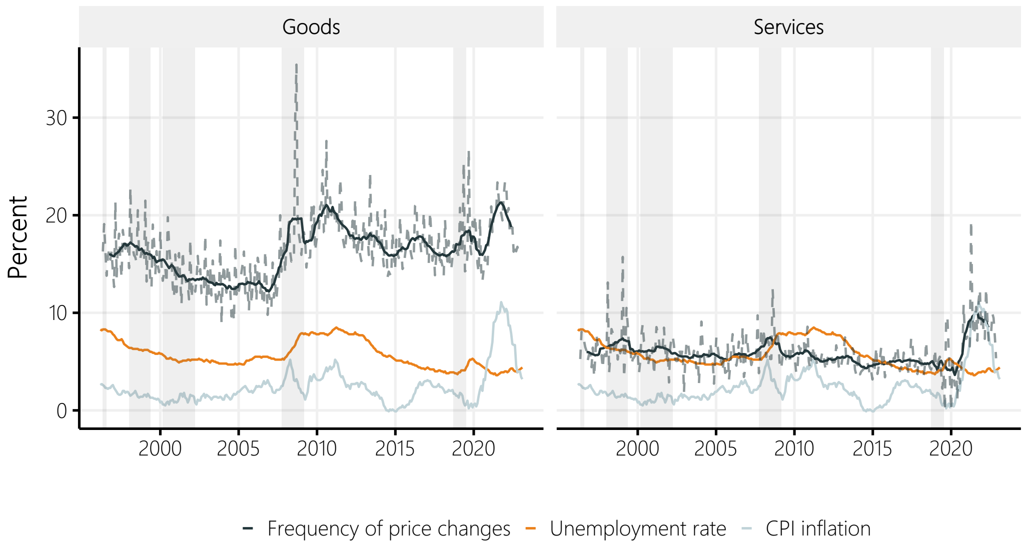
[34]Estimates aggregated using mean and median moments can vary widely depending on cross-sectoral heterogeneity. In the euro area, the median frequency of consumer price changes is only about 2.5 pp lower than the mean frequency (Gautier et al., 2024). By contrast, the difference is larger than 6 pp in the United States (Nakamura and Steinsson, 2008), France (Gautier and Le Bihan, 2022), or Switzerland (Rudolf and Seiler, 2022).

than by product substitution. The literature offers a number of different theories to explain seasonal patterns in price setting, including seasonality in cost changes such as wages (Nakamura and Steinsson, 2008), in product life cycles (Dhyne et al., 2006), in product turnover (Berardi et al., 2015), or in seasonal sales (Gautier et al., 2024).

B.7 Cross-sectional heterogeneity

Figure B.7 shows the evolution of the frequency of consumer price changes across the goods (in the left panel) and services sectors (in the right panel) together with the UK unemployment rate and CPI inflation from February 1996 to December 2023.

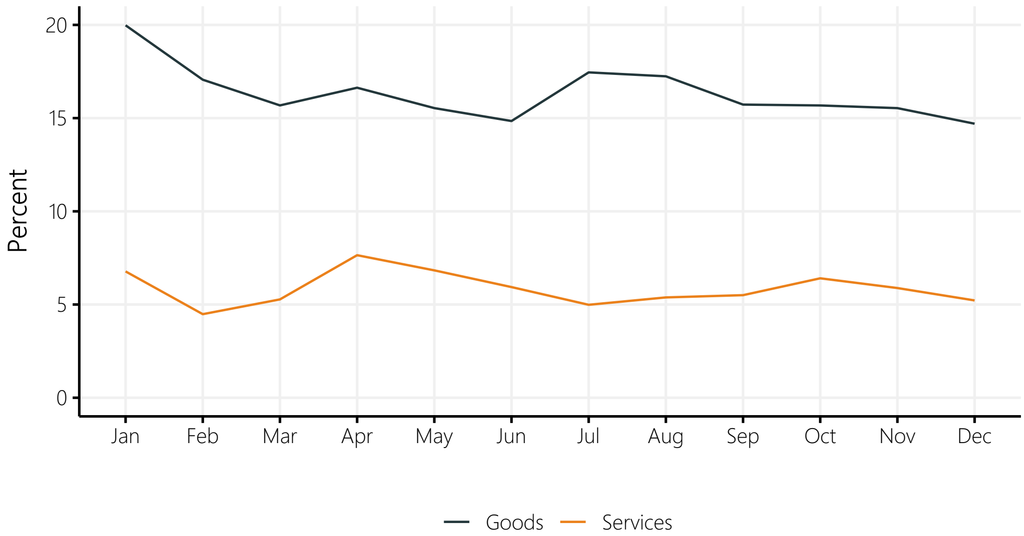
Figure B.7: Cyclicality of the frequency of price changes across the goods and services sectors



Notes: Average frequency of consumer price changes across the goods (in the left panel) and services sectors (in the right panel) in the United Kingdom from February 1996 to December 2023 using the sample including price changes due to temporary sales and product substitution. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows the raw series (in dashed lines) and the 12-month moving average centered on each month (in solid lines). Outliers related to VAT rate changes are excluded. The unemployment rate is the monthly unemployment rate for civilians aged 15 and over, according to the infra-annual labor statistics. CPI inflation is the year-on-year change in the consumer price index excluding owner-occupier housing costs from the ONS. Recessions (shaded areas) are dated by the Organisation for Economic Co-operation and Development (OECD). All values are in percent.

Figure B.8 shows the frequency of price changes by month for consumer prices across the goods and services sectors in the United Kingdom from February 1996 to December 2023.

Figure B.8: Seasonality of the frequency of price changes



Notes: Average frequency of price changes by calendar month for consumer prices across the goods and services sectors in the United Kingdom from February 1996 to December 2023. Moments are computed at the item level and aggregated to weighted medians using CPI expenditure weights. The figure shows moments for the sample including price changes due to temporary sales and product substitution. Outliers related to VAT rate changes are excluded. All values are in percent.

C Results

This appendix refers to Section 4 and provides additional information not included in the main body of the paper.

C.1 Linear impulse responses

Table C.1 is an update and extension of the tables reported in Cloyne and Hürtgen (2016) and Cesa-Bianchi et al. (2020) and provides an overview of the responses of activity and prices from previous studies.

Table C.1: The effects of monetary policy shocks in the United Kingdom in previous studies

Study	Method	Period	Peak Effects		
			Quarter	Activity (in %)	Prices (in %)
Dedola and Lippi (2005)	VAR	1975:1-1997:3	6–8	-0.5 (IP)	0.2 (CPI)
Mountford (2005)	Sign Rest.	1974:I-2001:II	6	-0.6 (GDP)	-0.15 (GDP Defl)
Ellis et al. (2014)	FAVAR	1992:I-2005:IV	3	-2.0 (IP)	-2 (CPI)
Cloyne and Hürtgen (2016)	Narrative	1975:3-2007:12	3-4 (IP), 11 (CPI)	-0.5 (IP)	-1.0 (CPI Infl)
Gerko and Rey (2017)	Proxy-SVAR	1982:1-2015:1	10	-1.8 (IP)	1.0 (RPIX)
Cesa-Bianchi et al. (2020)	Proxy-SVAR	1992:1-2015:1	8 (GDP), 3-4 (CPI)	-1.6 (GDP)	-0.3 (CPI)
Braun et al. (2023)	Proxy-SVAR	1997:1-2019:12	8	ca. -1.5 (GDP)	ca. -0.45 (CPI)

Notes: The table is an update and extension of the tables reported in Cloyne and Hürtgen (2016) and Cesa-Bianchi et al. (2020). The results are from impulse responses displayed in previous studies for the United Kingdom and are the response of prices and indicators of economic activity to a one percentage point increase in the short-term nominal rate (Exceptions: In Gerko and Rey (2017), the shock increases the UK 5-year-rate by 20 basis points on impact; in Cesa-Bianchi et al. (2020), the shock increases the 1-year gilt rate by 25 basis points on impact). In brackets, I include the specific measures of economic activity and prices (IP denotes industrial production, GDP denotes gross domestic product, CPI denotes consumer price index, and RPIX denotes the Retail Price Index excluding mortgage interest payments).

D Sensitivity analyses

This appendix refers to Section 5 and provides the figures and results of the sensitivity checks that are not included in the main body of the paper.

Unless otherwise stated, the figures follow the same structure as Figure 5, which presents the main results. The rows show the impulse responses by response variable: real GDP (in the first row), the consumer price index (in the second row), and the Bank Rate (in the third row). The first and second columns show the impulse responses conditional on the flexible and rigid price adjustment regimes, respectively. The third column shows the t-statistic, which tests the null of equality of the coefficients of the flexible and rigid price adjustment regimes. The light-shaded and dark-shaded areas represent the 68% and 90% confidence intervals (for the impulse responses) and z values (for the t-statistic), respectively. The data used for the estimation span from 1997:07 to 2023:12. The impulse responses are plotted over a four-year horizon (48 months).

D.1 Intensity of switching between states

Changing the intensity of switching between states from $\gamma = 10$ in the baseline specification of Equation (3) to a lower transition speed (e.g., $\gamma \in \{3, 5\}$) or to a higher transition speed (e.g., $\gamma \in \{25, 50\}$) does not significantly affect the impulse responses using the frequency of price changes as the state variable (Figure D.1).

D.2 Nonlinear impulse responses across seasonal states of price rigidity

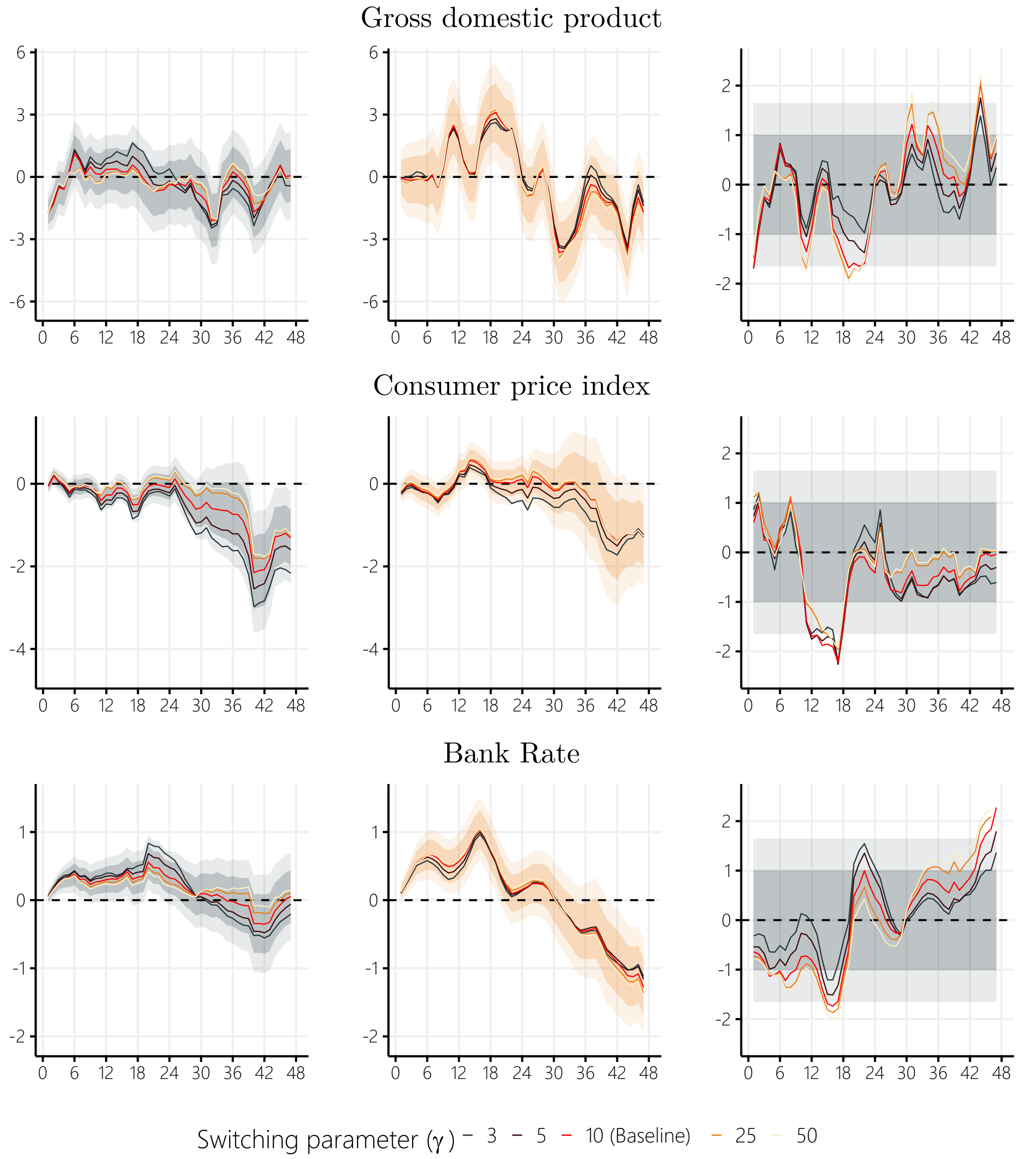
Figure D.2 shows the coefficients from estimating the nonlinear local projection model in Equation (3) using the seasonal component of the frequency of price changes as a state variable. The seasonal component of the frequency is the de-trended version of the raw series, which I obtain by subtracting the twelve-month moving average centered on each month from the raw series.

The results provide evidence that seasonal patterns in price rigidity also affect the impact of monetary policy on output and prices differently. Economic activity contracts faster to monetary policy shocks that occur early in the year (corresponding to seasons of flexible prices) than to those that occur later in the year (corresponding to seasons of rigid prices). Moreover, prices fall immediately within a year when the shock occurs in the second half of the year, in contrast to the sluggish response of prices to shocks in the first half of the year.

D.3 Monetary policy surprises in different underlying contracts and concept of monetary policy events

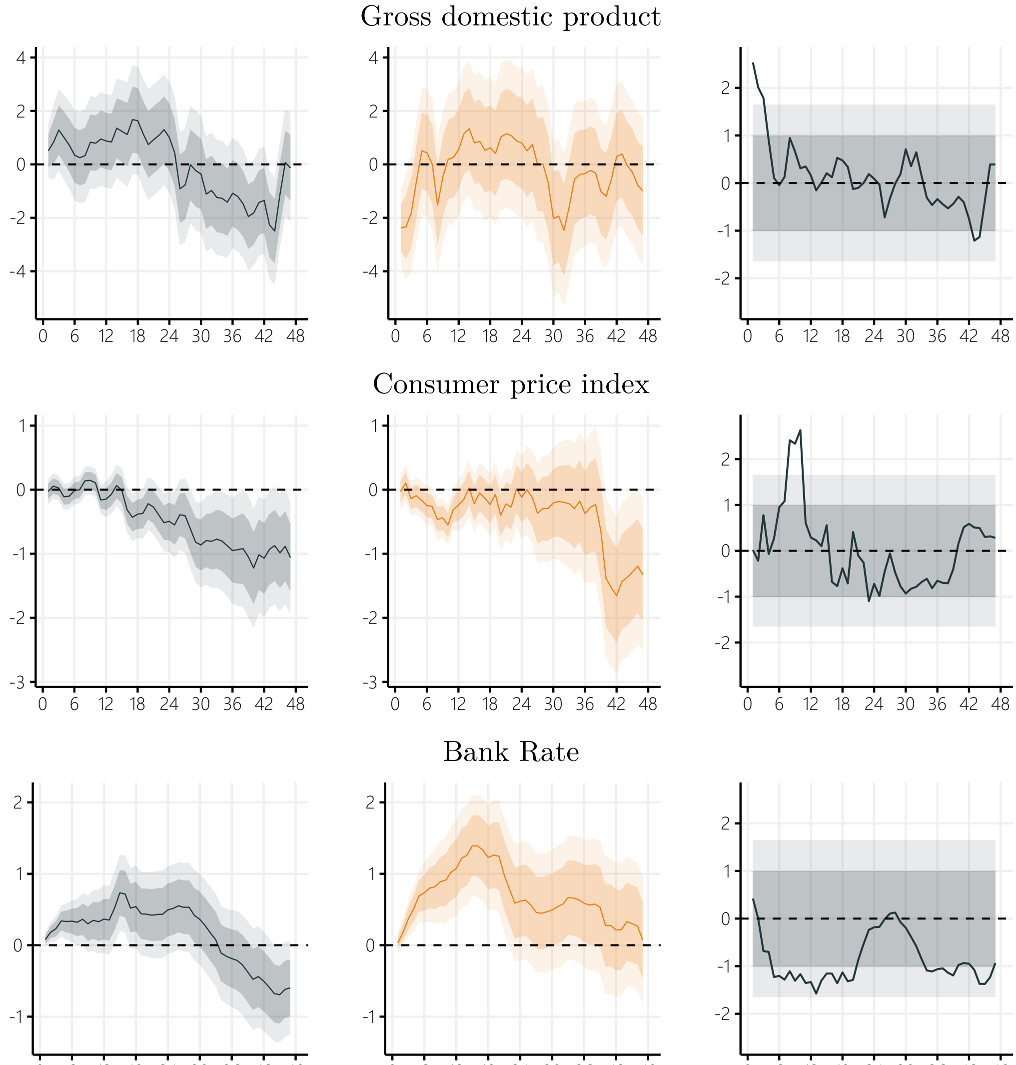
The UKMPD provides a large number of alternative monetary policy shocks. For one, it measures market surprises to monetary policy events in a variety of different assets (such as interest rate futures or gilt yields) at different maturities. For another,

Figure D.1: Nonlinear local projection coefficients across states of price rigidity with varying intensity of switching between states



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to varying the intensity of switching between states governed by the parameter γ in Equation (4). The confidence intervals shown in the first and second columns correspond to the baseline results.

Figure D.2: Nonlinear local projection coefficients across seasonal states of price rigidity



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the seasonal component of the frequency of price changes as a state variable.

it provides the same set of policy shocks for a more restrictive concept of monetary policy events, considering only shocks associated with announcements by the Monetary Policy Committee. Figure D.3 shows that the dynamic responses identified using these alternative instruments are very similar to the baseline results from the main part of the paper.

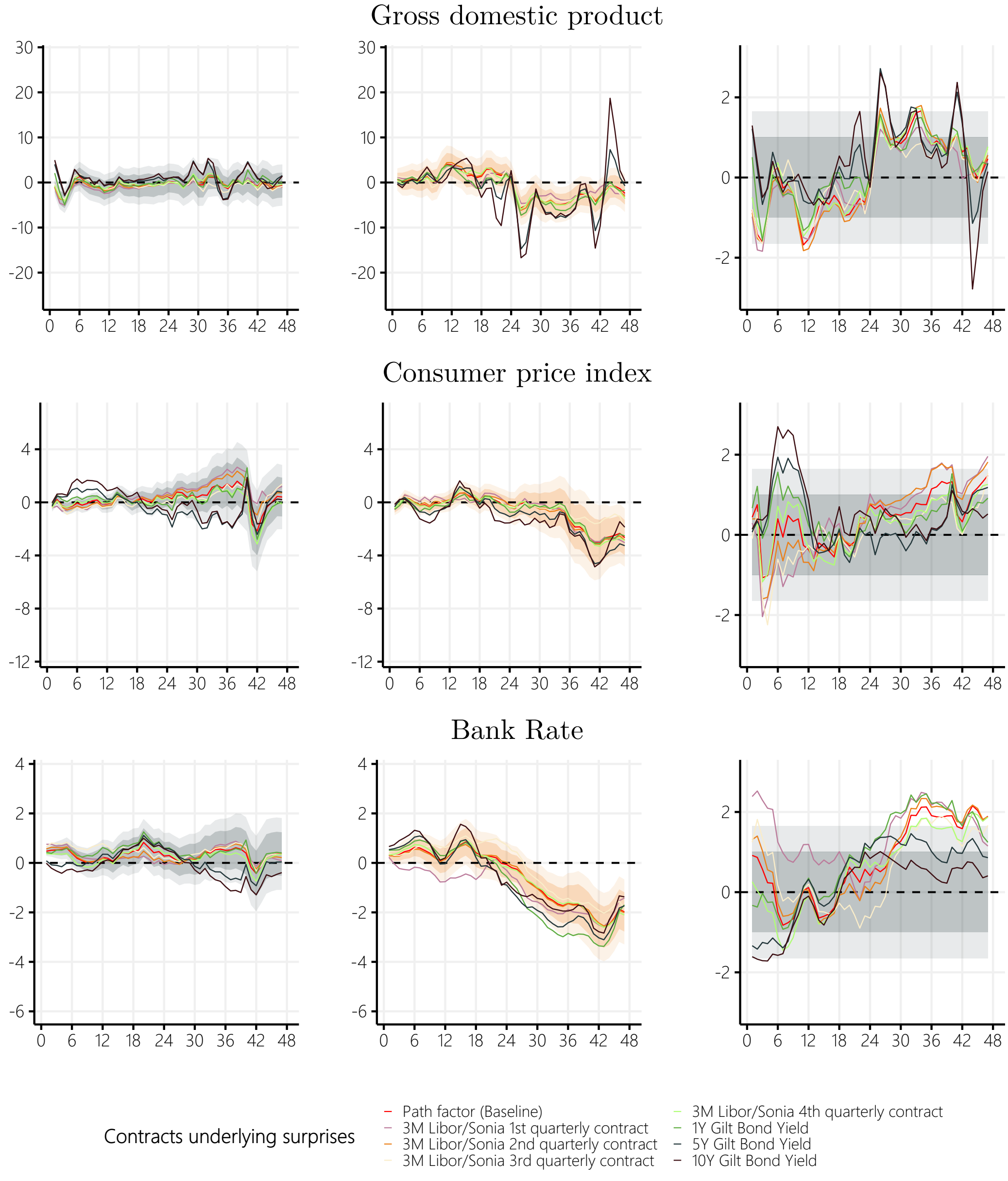
D.4 Alternative monetary policy shocks

In Figure D.4, I employ alternative monetary policy shocks. For one, I use alternative external instruments: the shock series based on market surprises provided by Cesa-Bianchi et al. (2020) for the period 1997:06–2015:01, and the narrative monetary policy shocks along the lines of Cloyne and Hürtgen (2016), of which I use the series provided by Cesa-Bianchi et al. (2020) who extend the original series (1975:01–2007:12) to 2009:02. For another, I employ an identification strategy that does not rely on external instruments: I employ the recursive (Cholesky) identification scheme, order the endogenous variables from fast-moving to slow-moving (i.e., real gross domestic product before the consumer price index), and put the Bank Rate last. The results with these alternative shocks are broadly similar to those in the main part of the paper.

D.5 Extended model specification

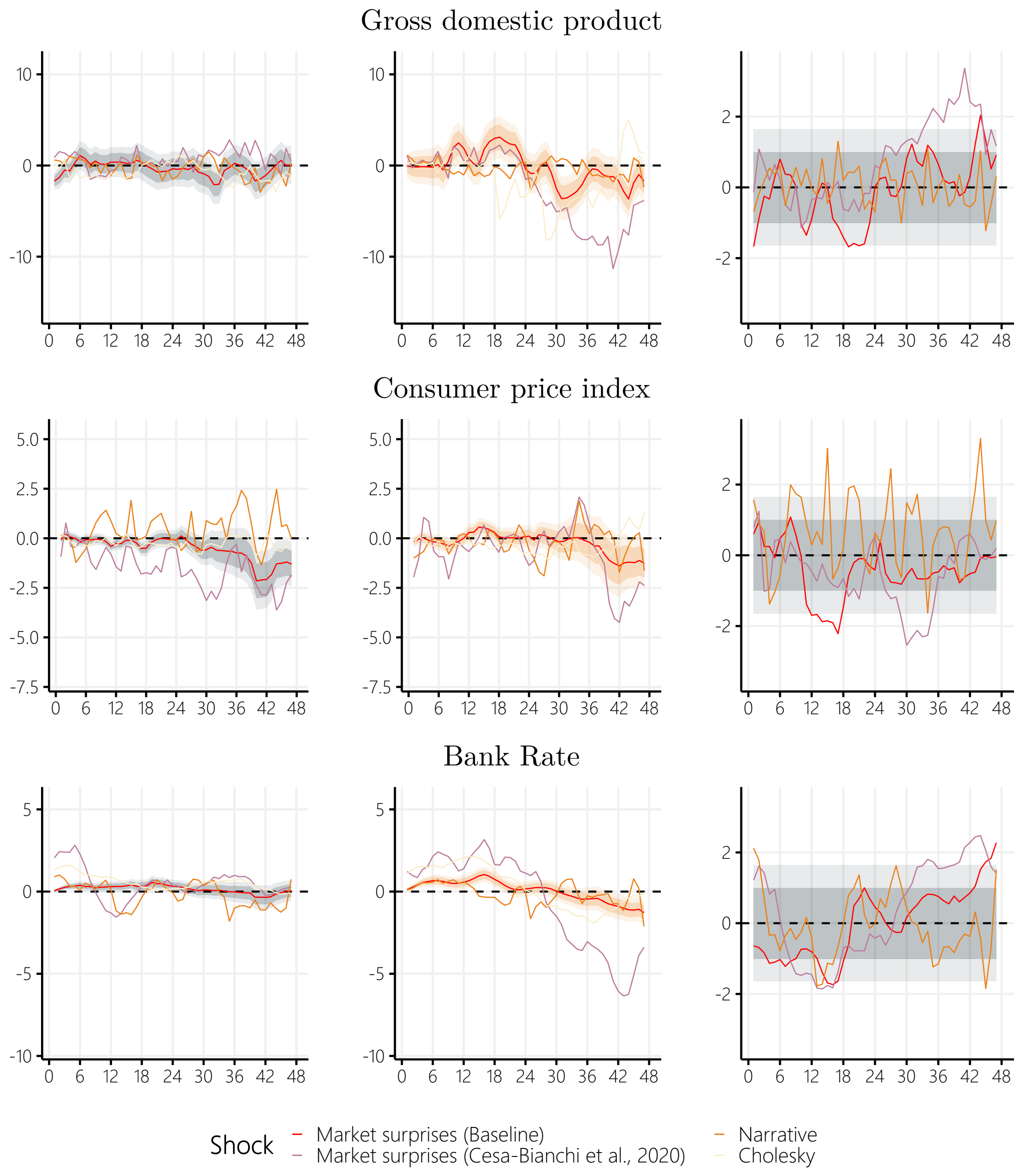
The baseline model follows a standard monetary VAR model, kept as parsimonious as to capture the main transmission channel of monetary policy. In Figure D.5, I report the results of an extended specification, where I add additional variables to the baseline model. In particular, I add the 1-year government gilt yield, the investment-grade non-financial corporate bond spreads, the US BAA corporate spread (which is the difference between the Moody's BAA corporate yield and the yield on the 10-year US Treasury constant maturity), and the producer price index. The figure reveals that the estimates of the coefficients on the main variables in Equation (3) are robust to this extended version of the local projection model.

Figure D.3: Nonlinear local projection coefficients across states of price rigidity with monetary policy shocks identified by monetary policy surprises in varying underlying contracts



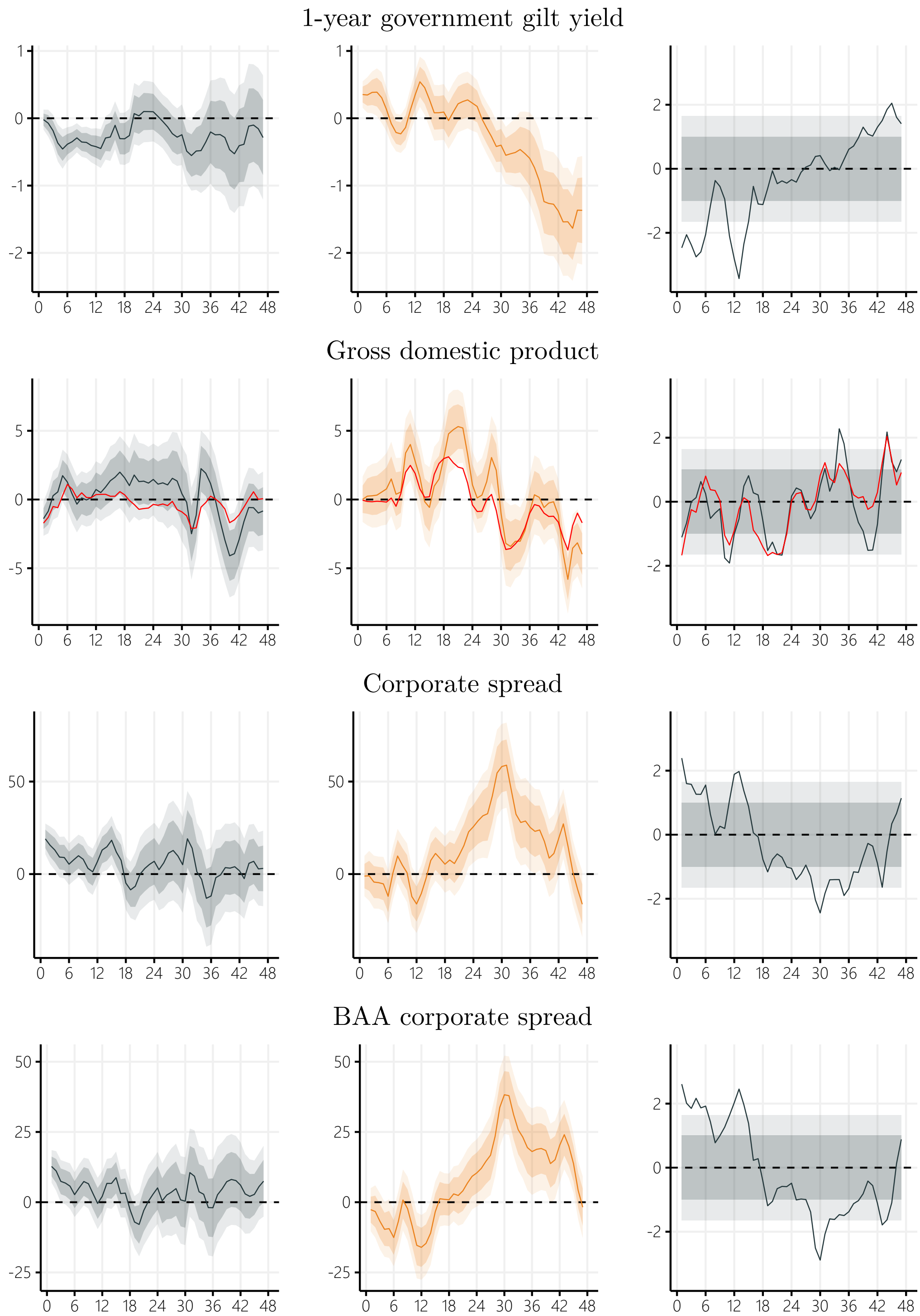
Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to using alternative monetary policy surprises from the UKMPD (Braun et al., 2023) identified in varying underlying contracts. The confidence intervals shown in the first and second columns correspond to the baseline results. The sterling futures are based on the 3-month Libor from 1997 to 2021 and on the 3-month SONIA rate at equivalent maturity from 2021 onward.

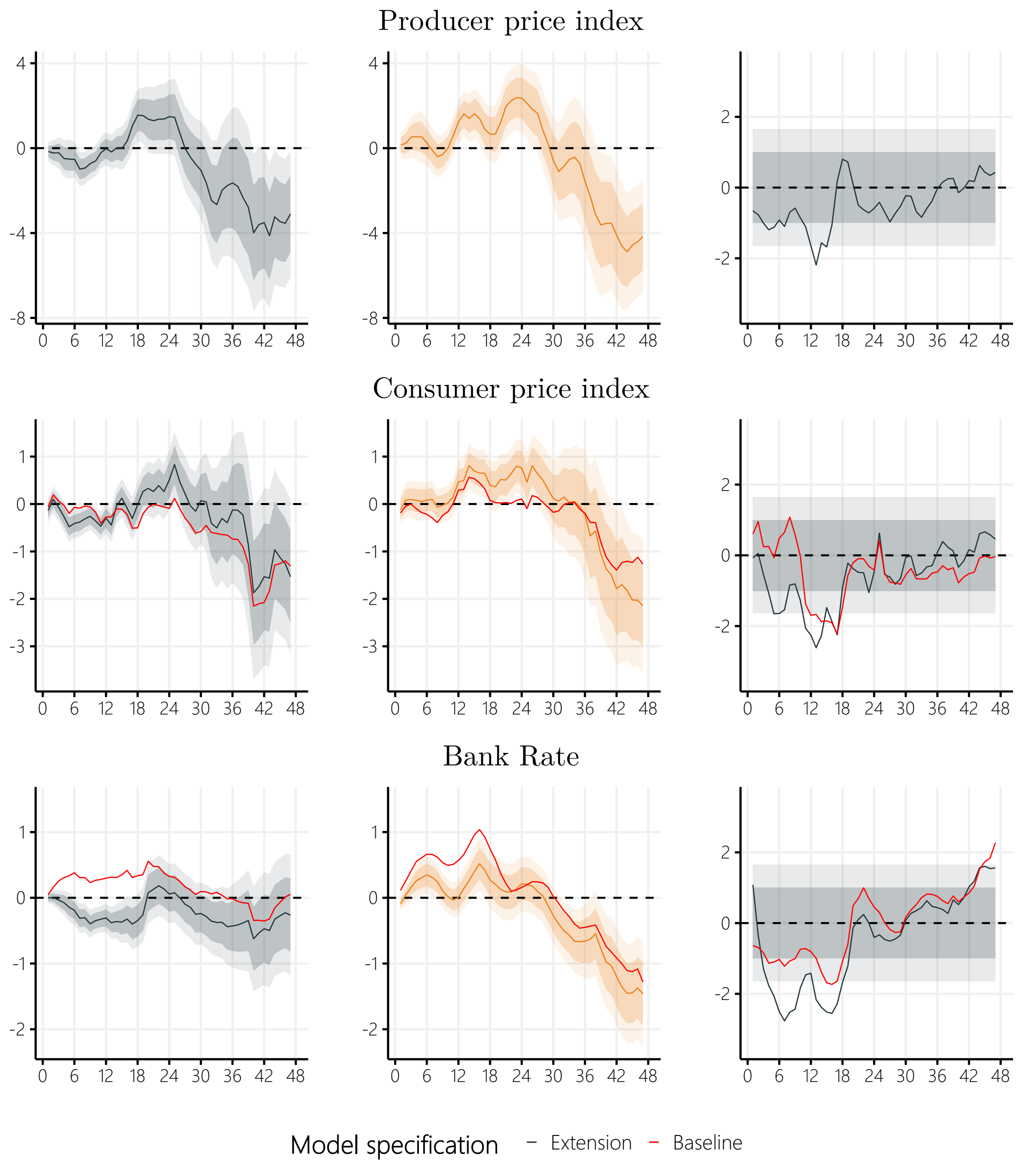
Figure D.4: Nonlinear local projection coefficients across states of price rigidity with alternative monetary policy shocks



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the use of alternative monetary policy shocks: The market surprises provided by Cesa-Bianchi et al. (2020), the narrative monetary policy shocks along the lines of Cloyne and Hürtgen (2016) and extended by Cesa-Bianchi et al. (2020), and the monetary policy shocks identified using the recursive (Cholesky) identification scheme. The confidence intervals shown in the first and second columns correspond to the baseline results.

Figure D.5: Nonlinear local projection coefficients across states of price rigidity with an extended version of the baseline model





Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to extending the baseline model with additional variables: the 1-year government gilt yield, the investment-grade non-financial corporate bond spreads, the US BAA corporate spread, and the producer price index. The confidence intervals shown in the first and second columns correspond to the baseline results.

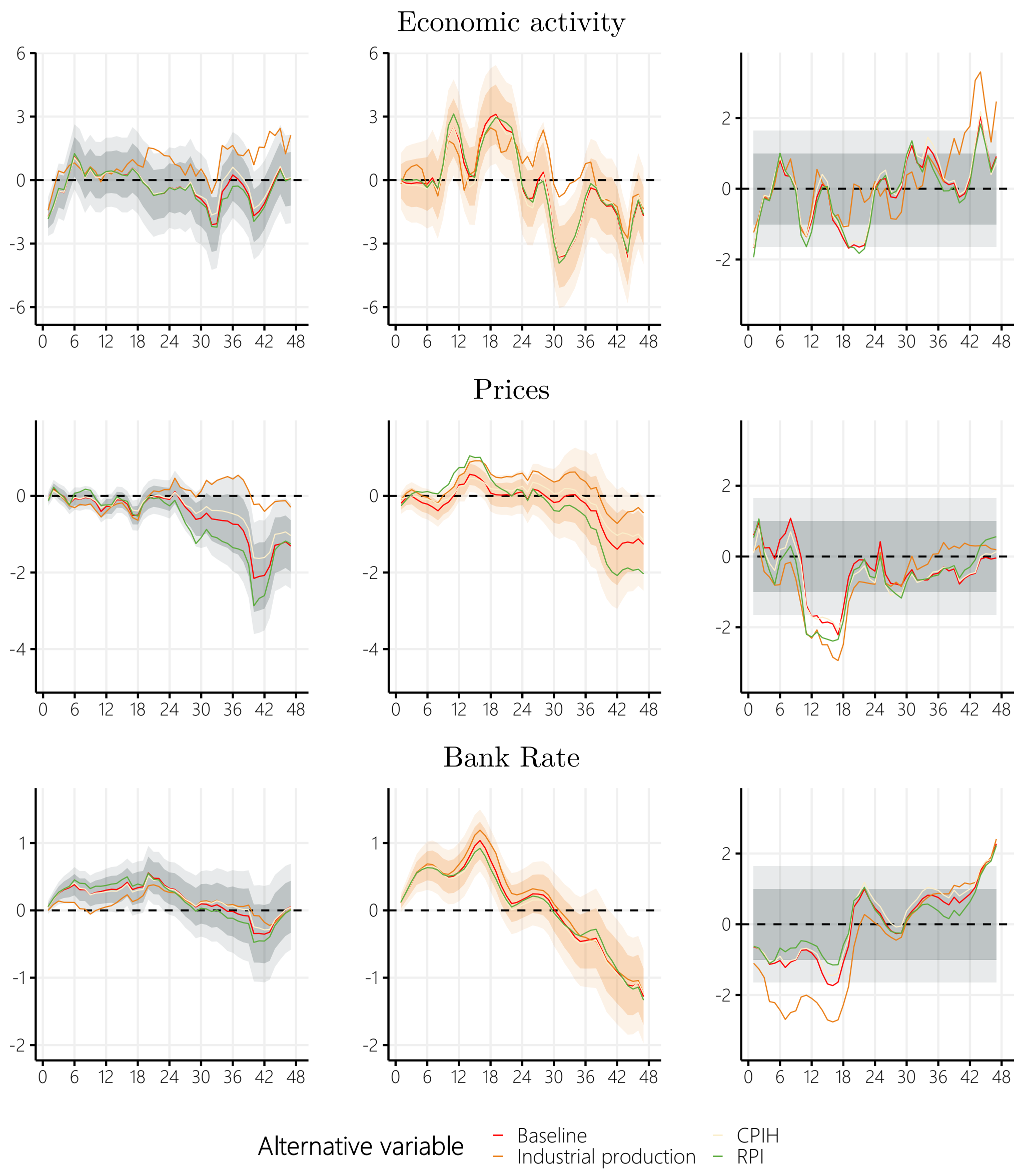
D.6 Alternative variables for economic activity and prices

In Figure D.6, I assess the sensitivity of the main results to the choice of the baseline variables by replacing, respectively, GDP with the industrial production index, and the CPI with the consumer price index including owner occupiers' housing costs (CPIH) and the Retail Price Index (RPI). The main results are robust to these alternative variables for output and prices.

D.7 Selection of lag order

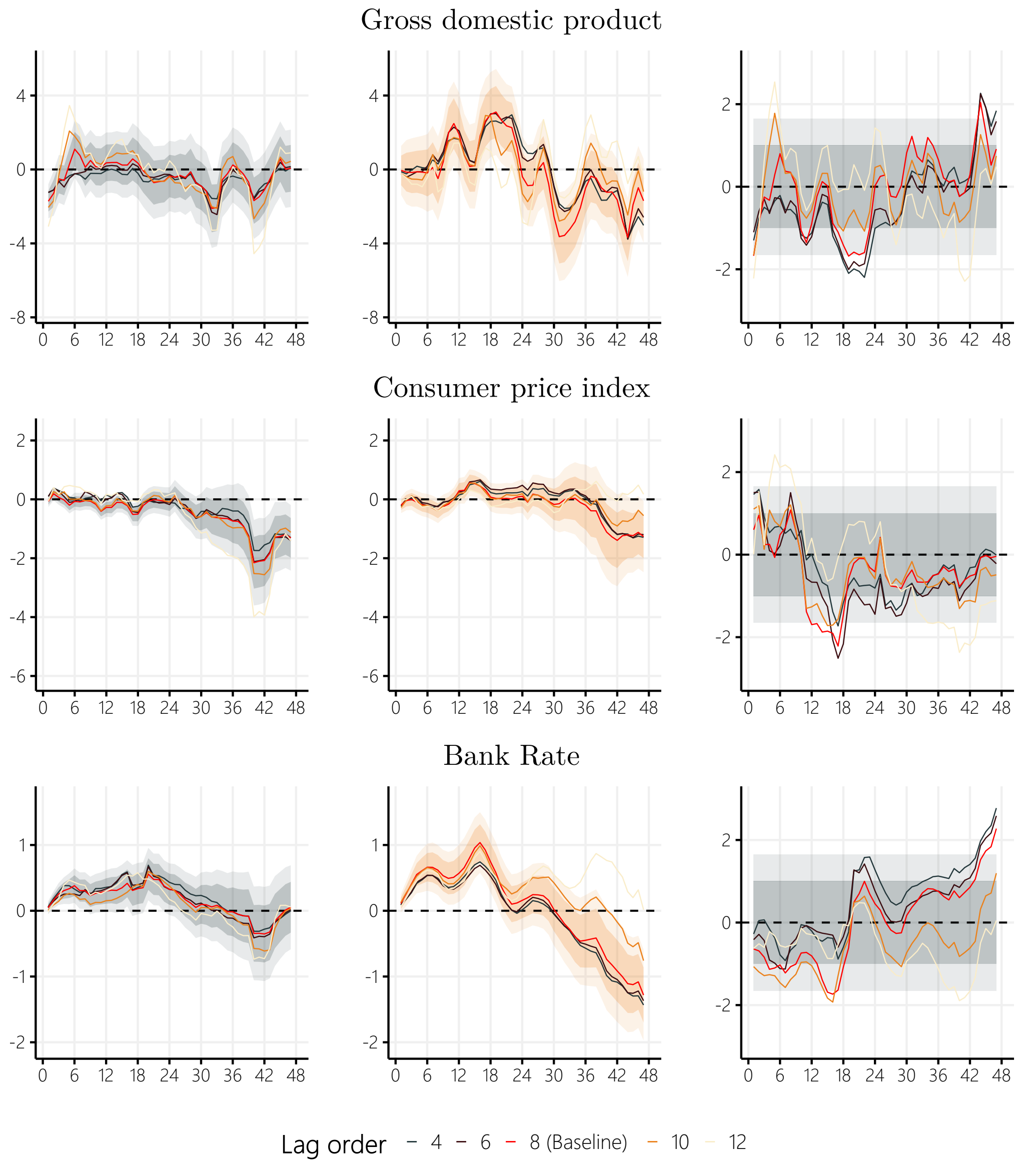
In Figure D.7, I perform robustness checks with respect to the lag order by increasing and decreasing the order of the lags relative to the baseline. The baseline results are robust to these choices.

Figure D.6: Nonlinear local projection coefficients across states of price rigidity with alternative variables for economic activity and prices



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the use of alternative variables of economic activity (industrial production and unemployment) and prices (CPIH and RPI). Only one variable is replaced at a time, while the remaining variables correspond to the baseline variables. The confidence intervals shown in the first and second columns correspond to the baseline results.

Figure D.7: Nonlinear local projection coefficients across states of price rigidity with different lag orders

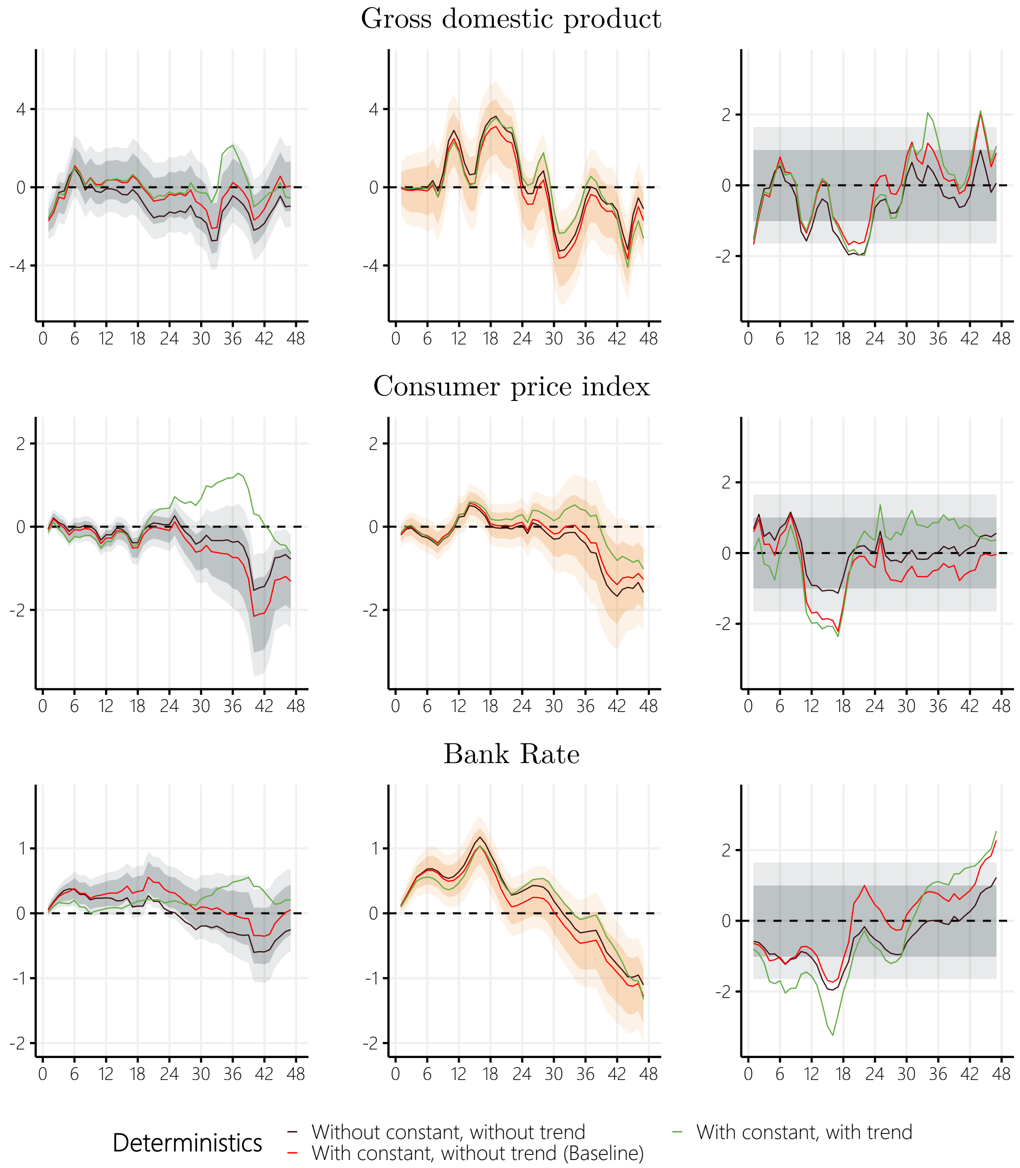


Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the number of lags included. The confidence intervals shown in the first and second columns correspond to the baseline results.

D.8 Model deterministics

In Figure D.8, I perform robustness checks with respect to the deterministics in the model by estimating versions of the model without a constant as well as with a constant and a linear trend. The baseline results are robust to these choices.

Figure D.8: Nonlinear local projection coefficients across states of price rigidity with different model deterministics



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the use of different model deterministics (including and excluding a constant or linear time trend). The confidence intervals shown in the first and second columns correspond to the baseline results.

D.9 Samples excluding the Great Recession or the period since the COVID-19 pandemic

In Figure D.9, I estimate the model excluding the Great Recession (by excluding the period 2008:01–2009:12) or the COVID-19 pandemic (by excluding the period 2020:01–2023:12). The results show that such individual major events over the estimation period from 1997 to 2023 do not drive the overall estimation results.

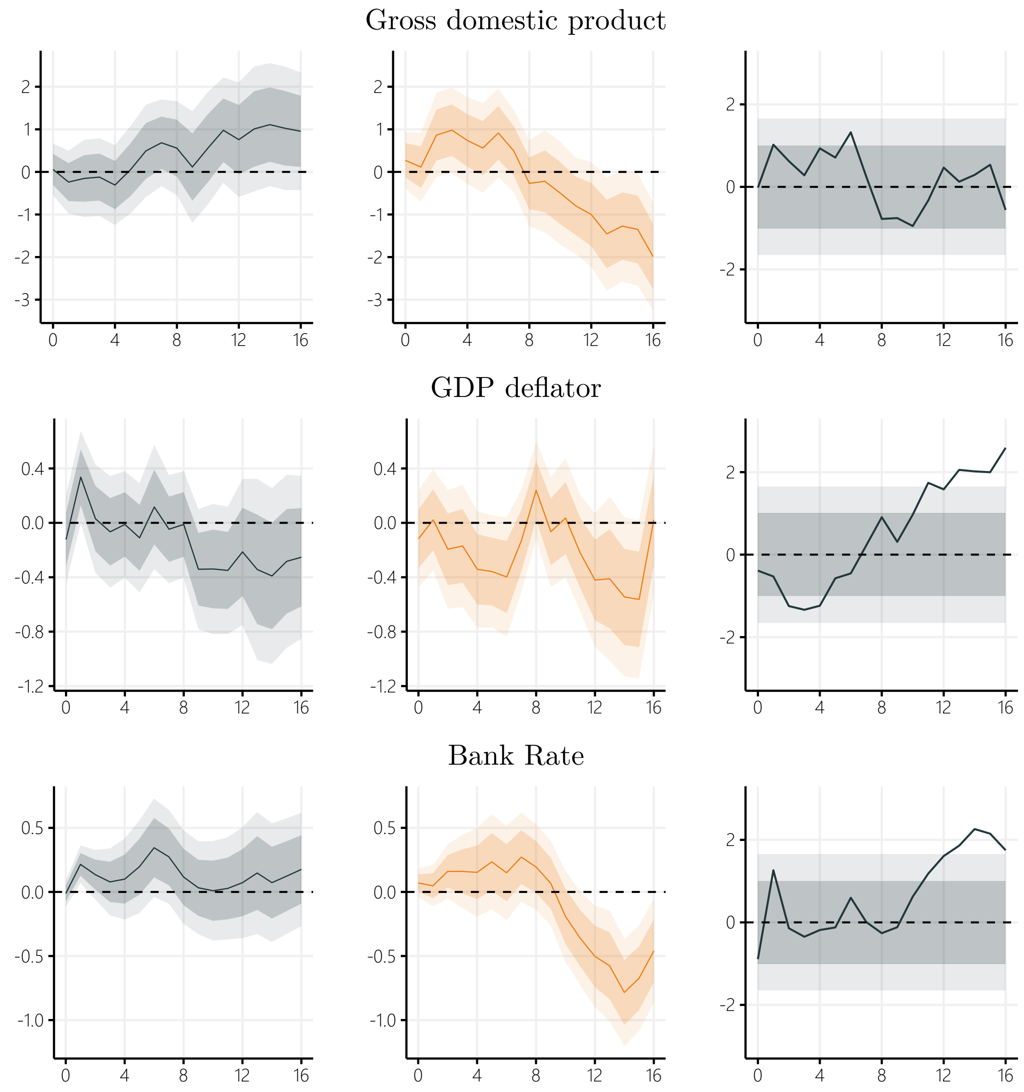
Figure D.9: Nonlinear local projection coefficients across states of price rigidity estimated on different subsamples

Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the estimation using different subsamples (excluding the Great Recession and the period since the COVID-19 pandemic). The confidence intervals shown in the first and second columns correspond to the baseline results.

D.10 Quarterly data

In Figure D.10, I estimate the nonlinear local projection model in quarterly variables: For economic activity, I use the quarterly GDP, and for prices, I use the GDP deflator. I aggregate the remaining variables (including the state variables) from monthly to quarterly frequency by taking simple averages over time. The baseline responses turn out to be very similar. However, as expected, the instrument is weaker, reflecting the lower signal-to-noise ratio.

Figure D.10: Nonlinear local projection coefficients across states of price rigidity estimated using quarterly data



Notes: The figure shows impulse responses following a contractionary monetary policy shock estimated using nonlinear local projections as in Equation (3) using the frequency of price changes as the state variable. The figure assesses the robustness of the baseline results to the estimation using quarterly data (quarterly GDP for economic activity and GDP deflator for prices).