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Using Brexit to identify the nature of price rigidities

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ABSTRACT

Using price quote data that underpin the official U.K. consumer price index (CPI), we analyze the effects of the unexpected passing of the Brexit referendum on the dynamics of price adjustments. The sizable depreciation of the British pound that immediately followed Brexit works as a quasi-experiment, enabling us to study the transmission of a large common marginal cost shock to inflation as well as the distribution of prices within granular product categories. The bulk of the aggregate inflationary effect is attributable to the size of price adjustments, an aspect matched well by the time-dependent price-setting model. The state-dependent model fares better in capturing the endogenous selection of price changes at the lower end of the price distribution. Both models miss on the magnitude of the adjustment conditional on selection.

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1. Introduction

On June 23, 2016 a small majority of 51.9 percent of voters in Great Britain voted in favor of a British exit, "Brexit," from the European Union. The outcome of this referendum was a major surprise. Opinion polls, political prediction markets, and foreign exchange futures, all signaled a broad consensus, even on the morning of the vote, that the "remain" vote would prevail (The Economist, 2016). The referendum results astonished the public, rocked careers of politicians in the "remain" camp, and, most importantly for this paper, led to a sharp depreciation of the British pound (GBP).

In the aftermath of the referendum the trade-weighted effective exchange rate of the GBP depreciated by more than 10 percent. Even by the end of 2016, the pound was still depreciated by more than 6 percent against the currencies of Britain's major trading partners. Because the U.K. is a very open economy, with imports amounting to about 30 percent of its GDP, such a negative terms-of-trade shock increases the cost of many products in the U.K. that are either imported or produced using imported

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intermediates. The Brexit shock propagated through the distribution of prices for different items in the British Consumer Price Index (CPI) and resulted in an acceleration of inflation after June 2016.

In this paper we use the Brexit shock to study the dynamics of price adjustments. The Brexit shock works as a quasi-experiment that enables us to study the transmission of a large common shock to marginal costs through the distribution of prices and inflation.[1] This allows us to distinguish between different types of price setting models with nominal rigidities. We uncover two key features of the response of prices to the Brexit shock. First, the shock induces an increase in log prices which is mostly driven by an increase in the magnitude of price adjustments rather than the incidence of price changes. Second, price dispersion does not change very much. This is because, even though the variance of inflation increases, there is a sizable mean reversion of prices. This mean reversion is largely driven by the selection in which prices change. The incidence of price changes increases more for lower prices than for higher prices. As a result, lower prices increase faster than higher ones.

Our paper is part of a long tradition of analyzing exchange rate pass-through on inflation, *e.g.*, Gagnon (2009), Gopinath and Itskhoki (2010) Auer and Schoenle (2016), Auer et al. (2017), Forbes et al. (2018), among others. Our analysis differs from these studies in two dimensions. First, we use an *explicit quasi-experimental setup* in which we split the British CPI micro-data sample up into "treatment" and "control" groups. The "treatment" group includes items whose cost is directly affected by the unanticipated movement in the exchange rate because they are either imported or their production relies on imported intermediates. The "control" group includes goods and services that are domestically produced with low import content. We then use local projections (Jordà, 2005) to estimate the impact of the shock through its differential effect on the dynamics of the distribution of log prices of the "treatment" compared to the "control" group. One concern regarding this quasi-experimental setup stems from the intrinsic differences between tradable and nontradable sectors, essentially contaminating the control group. To alleviate these concerns we apply the method of Abadie et al. (2010), creating a synthetic control that matches the treatment group along important price-setting moments, and find very similar results. Second, this dynamic differences-in-differences (DID) approach allows us to explicitly focus on the effects of the shock on the distribution of log prices over time and relate our estimates to the *transitional dynamics* of commonly-used models of price setting under nominal rigidities.

Our analysis adds to the extensive literature that uses micro data on prices to document certain empirical properties of the distribution of inflation rates and map them into canonical macroeconomic models of price adjustment.[2] We make two contributions to this literature. The first is that we use data on the *level of the* log *prices* in the micro data in addition to the information on the change of the log prices, *i.e.*, the inflation rate, that is used in the studies above. We can use these price level data because we construct a panel of separate log-price distributions within the elementary item categories. Specifically, these items are classified in very detailed categories at the regional level by type of shop over time — which we refer to as a "bin."[3] Thus, the products within each of these bins are very similar, making differences in their price levels directly interpretable. Specifically, the differences in prices within a bin directly translate to a model with constant elasticity of substitution (CES) preferences. In such a model, persistent time-varying productivity shocks are isomorphic to persistent time-varying demand (*i.e.*, quality or taste) shocks. We use this cross-sectional dimension, across the log-price distributions within a bin for a given month, for our construction of the "treatment" and "control" groups in our quasi-experimental setup.

Our second contribution to this strand of the literature is that we consider a larger set of empirical properties of the distribution of log prices than previous studies have done. We build on Berger and Vavra (2017) and Berger and Vavra (2018), who study the variance of inflation rates, by also assessing the, most-commonly analyzed statistic, the mean of the inflation rate. We use a new decomposition of the first- and second-order moments of the distribution of log prices that nests the existing analyses of both the mean and the variance of inflation rates. This decomposition contains several, never before analyzed, components that exploit the information on the relationship between the level of log prices and the incidence and magnitude of price changes.

The tight link between the empirical components of the distribution of log prices in our decomposition and canonical theoretical models of price setting under nominal rigidities allows us to use the Brexit shock to identify important aspects of the nature of price rigidities in the data. The time-dependent and menu-cost models each have aspects of the data that they fit better in terms of the response to the Brexit shock.

The time-dependent model outperforms the menu-cost model in its fit of the movement in inflation. Our results for cumulative inflation in response to the shock show that the bulk of the adjustment in prices occurs through the magnitude of price changes rather than an increase in the incidence with which prices change. This is in line with results from other studies, *e.g.* Klenow and Kryvtsov (2008) and Gagnon (2009). The increases in the magnitude of price changes implied by the time-dependent pricing model line up closer to those in the data than those of the menu-cost model. As a result, even though the time-dependent model does not include changes in the incidence, it better matches the cumulative inflation response to the shock than the menu-cost model.

However, the time-dependent model fails to capture that low prices adjust disproportionately in response to the shock. This selection of price changes means that, on average, low prices go up more than high ones. The state-dependent price setting in the menu-cost model captures this aspect of the data well. This causes a mean reversion of prices and subdues the increase in the variance of prices in response to the shock.

[1] Costa et al. (2019) also consider the Brexit shock, but instead analyze its impact on relative wages.

[2] For example, Bils and Klenow (2004), Dhyne et al. (2006), Klenow and Malin (2010), and Nakamura and Steinsson (2008), Nakamura and Steinsson (2010), Midrigan (2011), Kehoe and Midrigan (2015), and Alvarez et al. (2016). In particular, for the U.K. Kryvtsov and Vincent (2014) and Dixon and Tian (2017).

[3] An example of such a bin would be marmalade at supermarket chains in the Southwest of England.

What the menu-cost fails to match is that, conditional on adjusting, lower prices increase faster than higher prices. The menu-cost model implies the opposite; among the prices that change, high ones increase more than low ones.

2. U.K. economic performance and the Brexit referendum

To understand the macroeconomic context within which we analyze the transmission of the exchange rate shock associated with Brexit, in this section we look at the behavior of the exchange rate, economic activity, and inflation in Great Britain before and after the referendum. We then focus, in more detail, on the increase in inflation in the U.K. following the Brexit vote and show that it is concentrated in goods and services with a large import content.

Fig. 1 shows three main macroeconomic indicators for the U.K. economy, namely; the exchange rate, real GDP growth, and CPI inflation. To put the macroeconomic conditions during the Brexit vote in context, it is worthwhile to consider the 15 years leading up to it.

From 2001 through 2007, the British economy performed well. The exchange rate was relatively stable, real GDP growth came in at an average annualized rate of 2.9%, and inflation hovered between 1 and 3 percent.

Because of the global financial crisis of 2008 and the ensuing euro crisis in 2011, the British economy had seen turbulent times in the eight years preceding the Brexit referendum. British banks were hit hard by the financial crisis, and the crisis resulted in a 30 percent depreciation of the exchange rate and a 6 percent decline in real GDP. The depreciation of the GBP, combined with a spike in global commodity and food prices, caused an initial spike in inflation to 5 percent.

However, a subsequent cut in Value Added Tax (VAT) rates and the economic slack during the recession resulted in CPI inflation retreating to 1%. A reversal of the VAT cuts of 2009 and an additional VAT hike in 2011 as an "emergency budget" measure led to another spike in inflation in 2011. After that, inflation declined. Just like in many other industrialized countries, largely driven by declining energy prices in 2014 and 2015, inflation dropped well below 1% in the two years preceding the Brexit vote. As can be seen from Fig. 1, in the 12 months leading up to the Brexit referendum, CPI inflation had only been 0.3% in the United Kingdom, real GDP growth had been 2 percent, and the GBP had depreciated in light of diverging monetary policy expectations in the United Kingdom and the United States.

Then the surprise outcome of the Brexit referendum happened in June 2016. Fig. 1a shows that, immediately following the referendum, the GBP depreciated more than 10 percent against the currencies of the U.K.'s main trading partners. This depreciation of the GBP was a surprise to the extent that the outcome of the Brexit referendum was a surprise. Economic forecasts had predicted a substantial depreciation of the GBP in case the "Yes" vote would prevail (International Monetary Fund, 2016), but the referendum outcome surprised the public, market participants, and policymakers (The Economist, 2016).

Fig. 2 more clearly illustrates the effect of the surprising referendum result by plotting the daily value of the GBP against the dollar and the euro. The GBP sharply depreciated against both currencies on the day of the Brexit referendum.

Forecasts of the short-run effect of a "Yes" vote on economic activity varied substantially. Some forecasters predicted a recession in the U.K., while others foresaw only a slight slowdown in GDP growth. The International Monetary Fund (IMF), for example, entertained two scenarios; an *adverse* and a *limited* scenario (International Monetary Fund, 2016). The former had the U.K. slip into a recession after the Brexit "Yes" vote in 2017, resulting in a 5% decline in the level of GDP compared to the baseline. The latter scenario included a small decline in real GDP growth in the U.K. after a "Yes" vote, resulting in a 1.5 percent decline in the level of GDP compared to the baseline.

In hindsight, as can be seen from Fig. 1b, the IMF's *limited* impact scenario turned out to be relatively accurate. In the 18 months after the Brexit referendum, 4-quarter GDP growth in the U.K. decelerated from 2 percent to 1.2 percent. Of course, it is hard to know what the counterfactual would have been. However, over the same period, GDP growth in other G-7 economies accelerated rather than decelerated. Thus, in the wake of the Brexit referendum, the British economy has underperformed compared to other economies. Born et al. (2017) estimate this underperformance to add up to 1 percent of GDP.[4]

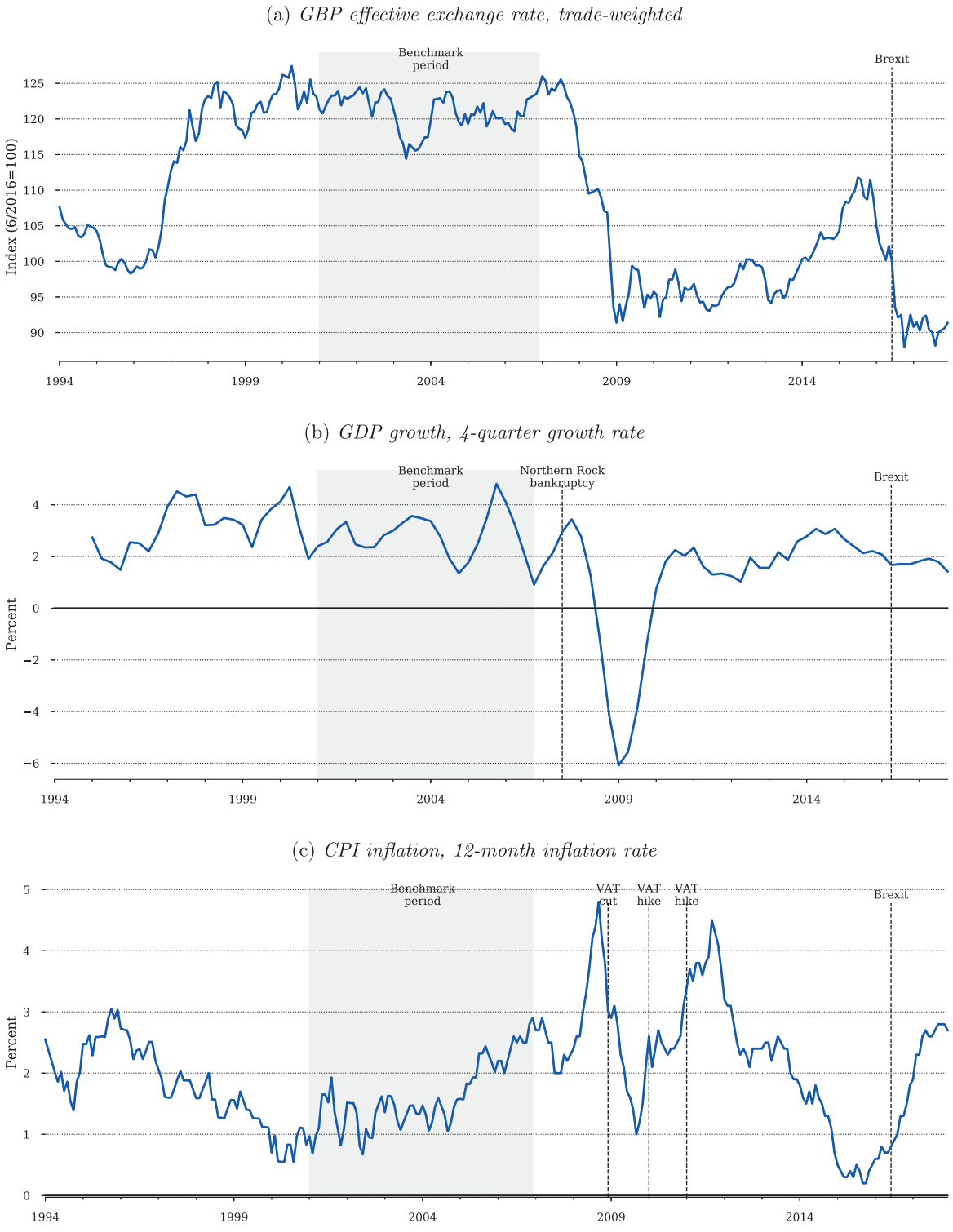
Most importantly for this paper is that, even though the Brexit vote induced some slowdown in the growth of economic activity in the U.K., it did *not* result in a major downturn or recession. That is, the immediate effects on the real side of the British economy were limited and in line with the IMF's *limited* scenario.

What also came in line with the IMF's *limited* scenario were the effects of Brexit on British CPI inflation. Because about a fifth of the expenditures in the British CPI is on directly imported goods and services or on high-import content goods and services due to imported intermediates, the 10 percent surprise depreciation of the pound resulted in a substantial increase in the cost of final goods and services sold to consumers.[5] This resulted in a run-up of inflation from 0.7 percent in the year before the referendum to 3.1 percent by November 2017 (Fig. 1c).

The post-Brexit acceleration of inflation was due to an increase in the inflation rate of *tradables* goods and services. Fig. 3 shows this by plotting the time series of the overall CPI inflation rate from Fig. 1c together with the inflation rates of the two-digit Classification of Individual Consumption According to Purpose (COICOP) *tradables* and *nontradables* categories as classified

[4] Estimates of long-run effects of Brexit on the level of U.K. GDP range from this 1%, based on static trade effects (Van Reenen, 2016), to even larger than 10 percent (International Monetary Fund, 2016), depending on what one assumes about the structure of post-Brexit trade relationships between the U.K. and European Union

[5] The Analytical Input-Output tables published by the Office for National Statistics (ONS) estimate the import content of British domestic consumption to be 19.4 percent. See Table 0 for details.



Source: (a) Bank for International Settlements (BIS), (b) ONS, (c) ONS

Fig. 1. U.K. inflation, GDP growth, and exchange rate Source: (a) Bank for International Settlements (BIS), (b) ONS, (c) ONS.

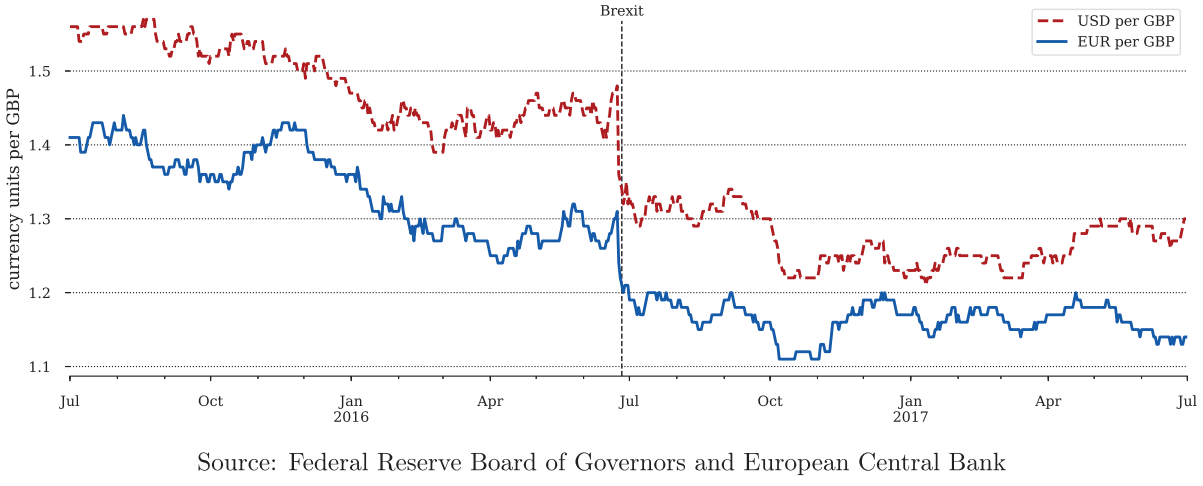


Fig. 2. Daily exchange rate of GBP against USD and EUR Source: Federal Reserve Board of Governors and European Central Bank.

by Allington et al. (2005). Fig. 3 reveals that the inflation rate of nontradables did not change much after the Brexit referendum, and that what increased was the inflation rate of tradable goods and services.[6] We rely on this different response of prices of tradables and nontradable goods for our identification strategy to uncover the nature of price rigidities in the U.K.

3. Quasi-experimental setup using British CPI micro-data

The above observation, that the increase in British inflation after the Brexit referendum was solely driven by *tradables* and that the inflation rate of *nontradables* barely responded, is the basis for the quasi-experimental setup that we use in the rest of this paper.[7]

Our main approach is to split up the sample of goods and services covered in the micro-data with price quotes underlying the British CPI published by the ONS into "treatment" and "control" groups. These data have been used in previous research by Kryvtsov and Vincent (2014) and Dixon and Tian (2017), among others.[8] We then study the differential impact of the Brexit shock on the distributions of log prices in these two groups.

The "treatment" group consists of a set of goods and services that are part of the *tradable* COICOPs plotted in Fig. 3. These are goods and services whose cost of production increased due to the depreciation of the GBP and that drove the increase in aggregate inflation in the U.K. plotted in the figure.

The "control" group consists of a sample of goods and services that are domestically produced using few or no imported intermediates. These are part of the *nontradable* COICOPs in Fig. 3 and their inflation rate was hardly affected by the unanticipated passing of the Brexit referendum.

To understand how we categorize goods and services in these "treatment" and "control" groups, it is useful to consider an example of how a particular price quote is classified in the micro-data we use. Fig. 4 illustrates how a "price quote of a jar of Marmalade at a Tesco supermarket in Southampton" is classified.

The ONS collects price quotes for goods and services grouped at the *elementary item* level. The jar of marmalade is part of the elementary item "Jar of jam, 340-454g." These jars of jam are themselves part of the 3-digit COICOP group 01.1.8 "Sugar, jam, honey, chocolate, and confectionary." This group is part of the 2-digit COICOP classification 1.1 "Food" in Table 1.

Price quotes for the British CPI are collected in 12 *regions* across the United Kingdom. Southampton is in the Southeast region. Some price quotes, such as the ones from online stores, are not particularly associated with an outlet in a specific region and are, instead, classified as "nationwide."

The outlets where the price quotes are collected are split into two *shop types*; independent outlets, and shops that are part of a chain with multiple outlets. Each specific outlet is assigned a *shop code* as its unique identifier. That is, in our example from Fig. 4, Tesco is a supermarket chain with multiple outlets, and the particular Tesco in Southampton where the price quote was collected has the unique, fictitious, shop code of 123.

We use the sampling structure explained above and depicted in Fig. 4 to construct a panel of distributions of prices of elementary items by region and shop type. We refer to each unique combination of these three variables, (item, region, shop type), as a

[6] Other studies have noted that goods and services with a high import content have seen higher inflation after Brexit: "for each 10 percentage point rise in a product group's import share, inflation increased by 0.71 percentage points in the year after the vote" (Breinlich et al., 2017).

[7] Unlike many other studies in the pass-through literature, we study consumer prices as opposed to import or export wholesale prices. Consumer prices include a buffer between exchange-rate movements and prices stemming from the retailer's markup and other markups along the supply chain, making the pass-through effect more indirect.

[8] A comparison of the aggregated price quote data with the published CPI measure is available in Appendix B.2.

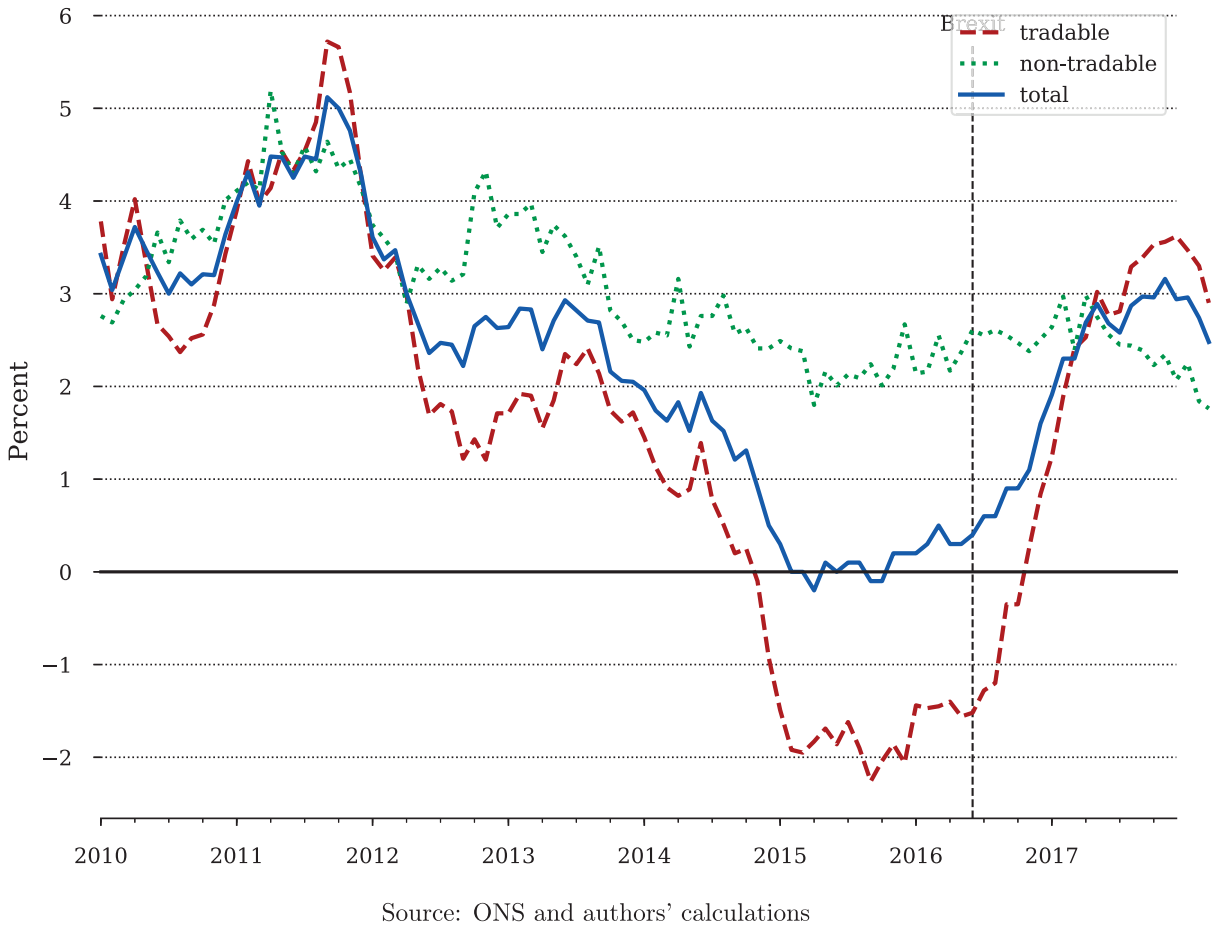


Fig. 3. U.K. CPI inflation total, for tradable COICOPs, and non-tradable COICOPs Source: ONS and authors' calculations.

bin. For each month, we construct the distribution of log prices for all price quotes in each bin. The result is that we have data on a panel of distributions of log prices, each distribution associated with a particular *bin* in our data.[9]

We group these bins into our "treatment" and "control" samples. We do so based on the degree to which the cost of the item in the bin is *a priori* more sensitive to exchange rate fluctuations.

We use two metrics of the cost sensitivity to exchange rates. The first is the import content of the goods and services in the U.K. CPI. This corresponds to the fraction of the price charged to consumers that can be traced back to the cost of imports used to produce the good or service. Measures of the import content of different categories of consumption expenditures are provided in 2014 Analytical Input-Output tables for the U.K. published by the ONS. Unfortunately, these statistics are only available at a high level of aggregation (36 two-digit COICOP groups) and miss a substantial part of cross-item variation in the exchange rate sensitivity of costs. For this reason, we supplement this first metric with one provided at a lower level of aggregation.

The second measure is a binary classification of COICOPs into *tradables versus nontradables* provided by Allington et al. (2005) for 161 three-digit COICOP groups, which is the classification we used in Fig. 3. Though this is a less direct measure than import content, it provides additional detail at lower levels of aggregation.

Table 1 summarizes the findings of both sources. The import content column of Table 1 shows the fraction of the cost of the expenditures of the different COICOPs that can be traced back to imports. The second column reports Allington et al. (2005)'s classification. The table shows that, at the 2-digit level of aggregation, the tradability classification and import shares align closely. This 2-digit level of aggregation is the lowest level that both these measures have in common.

We split our cross-section of bins up into treatment, control, and ambiguous groups in the following way. We jointly evaluate two criteria related to the exchange-rate sensitivity of an elementary item in each bin. The first is the more granular categorization of whether the low-level COICOP group that the item with which the bin is associated is classified as tradable or nontradable (as reported in the last column of Table 1). The second, a broader categorization, is the import-content tertile of the 2-digit

[9] For more detailed information on how bins were constructed please see Appendix B.1.

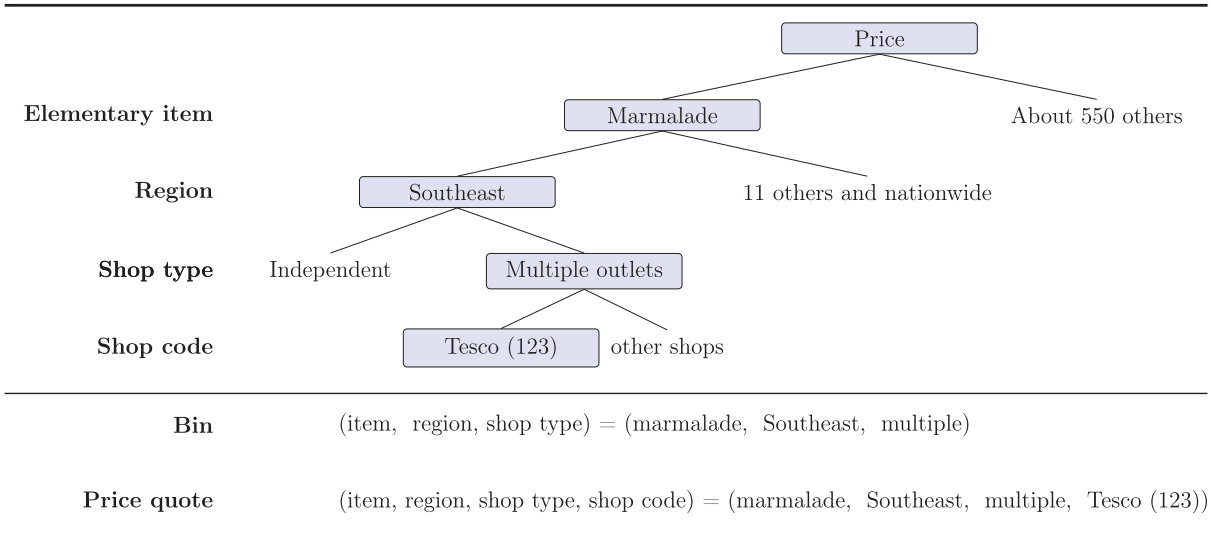


Fig. 4. Structure of U.K. CPI data Classification of price quote of: "*Jar of marmalade at a particular Tesco supermarket in Southampton.*"

COICOP group, from Table 1, that the item belongs to. The joint evaluation of these two criteria allows us to split our sample of bins up into a 2-by-3 grid, which we report in Table 2.[10]

As our *treatment* sample we use price quotes for tradable items with a high import content. This sample consists of the bins in the lower-right cell of Table 2. These are the bins for elementary items that are both classified as tradable by Allington et al. (2005) *and* are in the top tertile of import content shares in Table 1. This covers 529 bins with region-shop-type-specific distributions of prices for 40 different elementary items.

As our *control* sample we use bins associated with items that are classified as nontradable *and* are in the bottom tertile in terms of the import share. This sample consists of bins in the upper-left cell of Table 2 and covers 938 bins with distributions of prices for 80 different elementary items.

Thus, we choose the treatment and control samples to include the items whose costs are the most and the least affected by imports, respectively. We do so to maximize the difference in the impact of the surprise depreciation of the GBP after Brexit on the distributions of prices in both samples. We exclude the bins in the other cells of Table 2 for which the importance of imports for the costs of the items is more *ambiguous*.[11]

The bins in the treatment sample contain 42 items and the control bins are made up of 80 items, listed in Table A3 in the appendix. The treatment items are mostly household appliances and furnishings, car and bike related, and fuels. Food, at home and away-from-home, beverages, books, and personal and health services make up the bulk of the control items.

One concern is that the surprise result of the Brexit referendum has a differential impact on the price setting for these two groups of items for reasons different from the movement in the exchange rate. These effects beyond the exchange rates could be, for example, increases in trade costs and elevated uncertainty in the wake of the referendum.

What makes the referendum special is that it was not the moment of Brexit, but, instead, was a vote in favor of the U.K. exiting the E.U. two or more years down the road. These two years are beyond the expected price setting horizon for the most of the items in our sample. Thus, increases in trade and other costs anticipated to occur when the actual Brexit took place are not likely to have affected the price setting in the year after the referendum which is the horizon we study in this paper.

Exogenous shocks to exchange rates are often interpreted as due to an increase in uncertainty. But, though uncertainty about economic policy going forward reached historical highs in the U.K. in the wake of the Brexit vote, financial market volatility, as measured by the VIX, remained subdued. The behavior of the VIX was notably different from that during the financial crisis of 2008 and the euro crisis in 2011. Both were periods during which the VIX spiked.[12] Increased uncertainty subdues the demand of durables, many of which are in our treatment sample, compared to other goods (Bernanke, 1983).

[10] The price quotes we include are "regular" prices and exclude sales. We do so because regular prices are best captured by the dynamics of price-setting models with nominal rigidities (Kehoe and Midrigan, 2015). Moreover, we also exclude petrol (due to its high price volatility) and clothing because, as Liegey (1993) pointed out, many matched price quotes are not for identical items but for close substitutes. Results do not substantially change when these categories are not excluded in the analysis. See Appendix B.3 for full details of how the data were cleaned.

[11] The specific numbers and estimates that we present in the rest of our analysis do, of course, depend on this split of our sample. However, the qualitative conclusions from our analysis do not change when we alter our sample split shown in Table 2.

[12] See Fig. A1 in the Appendix for the time series of policy uncertainty and VIX in the U.K.

Table 1
COICOP classifications, their import content, and tradability.

Coicop	Description	Import content	Tradable
0.0	Total	19.4	–
1.1	Food	25.4	True
1.2	Non-alcoholic beverages	24.0	True
2.1	Alcoholic beverages	20.0	True
2.2	Tobacco	20.0	True
2.3	Narcotics	25.8	True
3.1	Clothing	22.9	True
3.2	Footwear	26.6	True
4.1	Actual rentals for households	4.8	False
4.2	Imputed rentals for households	4.6	False
4.3	Maintenance and repair of the dwelling	24.6	True
4.4	Water supply and miscellaneous dwelling services	8.7	False
4.5	Electricity, gas and other fuels	36.5	True
5.1	Furniture, furnishings, carpets etc	27.2	True
5.2	Household textiles	34.6	True
5.3	Household appliances	35.2	True
5.4	Glassware, tableware and household utensils	32.9	True
5.5	Tools and equipment for house and garden	34.3	True
5.6	Goods and services for household maintenance	10.7	False
6.1	Medical products, appliances and equipment	26.8	True
6.2	Out-patient services	7.6	False
6.3	Hospital services	7.6	False
7.1	Purchase of vehicles	41.7	True
7.2	Operation of personal transport equipment	45.3	True
7.3	Transport services	19.3	False
8.1	Postal services	14.4	False
8.2	Telephone and telefax equipment	36.3	True
8.3	Telephone and telefax services	23.2	False
9.1	Audio-visual, photo and info processing equipment	32.4	True
9.2	Other major durables for recreation and culture	37.2	True
9.3	Other recreational equipment etc	24.4	True
9.4	Recreational and cultural services	15.1	False
9.5	Newspapers, books and stationery	18.9	False
10.0	Education	3.6	False
11.0	Restaurants and hotels	16.9	False
12.0	Miscellaneous goods and services	16.8	False

Note: Import content based on the 2014 Analytical Input-Output tables published by the ONS. Classification of trabability based on Allington et al. (2005), aggregated from the original 161 three-digit COICOP items to the two-digit level listed here. COICOP 9.6, "package holidays", has no import content data and is omitted.

Table 2
Observation counts for quasi-experiment sample 2015:6 to 2017:6.

	Import share tertile			
Tradability classification	Low	Middle	High	Total
	0–21	21–34	34–100	0–100
Nontradable (obs)	**331,122**	16,956	44,814	392,892
(bins)	**938**	58	149	1145
(items)	**80**	5	13	98
Tradable (obs)	341,870	1,034,287	**113,980**	1,490,137
(bins)	1250	4062	**532**	5844
(items)	97	283	**40**	420
Total (obs)	672,992	1,051,243	158,794	1,883,029
(bins)	2188	4120	681	6989
(items)	177	288	53	518

Note: Classification of trabability based on Allington et al. (2005) and at a lower level of aggregation than the import content calculated from the 2014 analytical input-output tables for the U.K. Second row of import share header is ranges of import content shares in percent included in tertiles. The bold cells contain the statistics for the control and treatment samples used in our empirical analysis.

We do our analysis under the assumption that the differential impact of uncertainty on the demand for treatment and control items is negligible compared to the change in the cost increase due to the exchange rate. To the extent this is not the case, and the outcome was a combination of both a relative cost and a relative demand shock for our two samples, our estimates can be interpreted as a lower bound on the impact of a cost-shock on price-setting and inflation. Just like in the aggregate analysis in Forbes et al. (2018), the pass-through of an exchange rate depreciation due to a decline in domestic demand is lower than that of an increase in foreign demand.

Of course, for any (quasi-)experimental setup one needs to not only define the *treatment* and *control* samples, but also the outcomes one considers to measure the impact of the treatment. Our samples consist of distributions of log prices by bin. So, the outcomes we consider are the differences in the dynamics of the distributions of log prices of the *treatment* and *control* samples after the Brexit referendum. In the next section, we introduce a new decomposition of these dynamics, the components of which we use as our outcome measures in the rest of our analysis.

4. Components of dynamics of the distribution of log prices

One of the contributions of our analysis is that we use a new decomposition of the changes in the distribution of log prices in a bin in our data to assess the impact of Brexit on prices in the U.K. This decomposition is general and can be applied to other micro-data sets. In addition, there are many aspects of the distribution of prices that one can track over time. Our decomposition, in particular, applies to the change in the average log price and the change in the variance of log prices following the Brexit shock. The reason we use this decomposition is that it splits the changes in these first- and second-order moments of the distribution of log prices into components whose dynamics are distinct under different price setting models.

Because most theoretical models of price setting under nominal rigidities abstract from entry and exit of items in the market, the decomposition described below, as well as our empirical analysis in Section 5, relies on *matched* price quotes. These are price quotes for which we do observe the price in two consecutive months.[13] Other empirical studies of CPI micro-data also have focused on a matched sample (*e.g.*, Bils and Klenow, 2004; Gagnon, 2009; Dixon and Tian, 2017).

We denote the number of price quotes in a bin in month t by n_t and index these price quotes by $j = 1 \ldots n_t$. We denote the log of the price j in month t as $p_{j,t}$. For each of these matched observations we can approximate the percent change in the price, $\pi_{j,t}$, by the change in the log of the price level, *i.e.*, $\pi_{j,t} = p_{j,t} - p_{j,t-1}$.

We consider the sample mean and variance of these matched log prices and write them, respectively, as:

$$\bar{p}_t = \frac{1}{n_t}\sum_{j=1}^{n_t} p_{j,t} \text{ and } \sigma_t^2 = \frac{1}{n_t}\sum_{j=1}^{n_t}\left(p_{j,t} - \bar{p}_t\right)^2. \tag{1}$$

Our focus in this paper is on the change in these two sample moments of the distribution of log prices between months $t-1$ and t, *i.e.*, on $\Delta\bar{p}_t = \bar{p}_t - \bar{p}_{t-1}$ and $\Delta\sigma_t^2 = \sigma_t^2 - \sigma_{t-1}^2$.

We focus on $\Delta\bar{p}_t = \bar{p}_t - \bar{p}_{t-1}$ because the inflation rate for an item in our sample (in the CPI), π_t, is measured using an equally-weighted geometric price index over all matched price quotes. That is, the item-level inflation rate in the CPI is the sample mean of the percent change in prices for all matched observations, *i.e.*,

$$\pi_t = \frac{1}{n_t}\sum_{j\in M}\pi_{j,t} = \Delta\bar{p}_t, \tag{2}$$

which equals the change in the mean of log prices of the matched price quotes. Thus, we focus on the mean of the log-price levels by bin for our analysis.

We also consider $\Delta\sigma_t^2 = \sigma_t^2 - \sigma_{t-1}^2$ because the degree of price dispersion in many models with nominal rigidities is directly related to the welfare losses due to nominal rigidities (Eusepi et al., 2011; Nakamura et al., 2016). Moreover, considering the dynamics of this second moment helps us distinguish between several models of price setting under nominal rigidities in the data.

We split the matched observations up into two groups. The first are those price quotes for which the price *stays the same* between $t-1$ and t. These n_t^S observations, which we denote by the set S, are those, j, for which $p_{j,t-1} = p_{j,t}$. The second set, which we denote by C, consists of those n_t^C price quotes for which the price changes, *i.e.*, $p_{j,t-1} \neq p_{j,t}$. Note that $n_t = n_t^S + n_t^C$.

The fraction of matched items for which the price changes over a given month t, *i.e.*, $\delta_t = \frac{n_t^C}{n_t}$, is known as the *incidence of price changes*.[14] The average change in price, *i.e.*, $\Delta\bar{p}_t^C$, is the *magnitude of price changes*. The variance of log prices, *i.e.*, σ_t^2, is a measure of *price dispersion*. The variance of inflation rates for the items whose price change, *i.e.*, $(\sigma_{\pi,t}^C)^2$, is a measure of *inflation dispersion*. Our decomposition also includes a covariance term, $\sigma_{\pi,p_{t-1},\,t-1}{}^C$, that allows us to quantify the degree of *mean reversion* in log prices in the data. To see how this covariance term implies a mean reversion, note that the ratio $\frac{\sigma^C_{\pi,p_{t-1},t-1}}{\left(\sigma^C_{t-1}\right)^2}$ is the regression coefficient for a regression of the percent change in prices that change ($\Delta\bar{p}_t^C$) on the initial log prices (p_{t-1}). In the case in which all prices in C are set to the same reset price, then there is perfect mean reversion in prices that change, and this coefficient is equal to -1.

[13] We present our decomposition here for matched price quotes and derive a generalized decomposition that takes into account entry and exit in Appendix A, where we denote the set of these matched price quotes by M. In practice, most entry and exit of price quotes in the CPI micro-data has little to do with economic concepts of entry and exit. Instead, it largely reflects seasonal item rotations in stores and sample rotation of outlets and items. In our data, some exit is due to ONS price collectors not being able to find the same item in the store in two consecutive months.

[14] This incidence of price changes is the focus of many studies of nominal rigidities (Bils and Klenow, 2004; Nakamura and Steinsson, 2010; Dhyne et al., 2006, for example), including for the United Kingdom (Dixon and Tian, 2017).

These unconditional and conditional first- and second-order moments are either measures that are commonly analyzed in empirical studies of price rigidities or are directly related to theoretical concepts from and implications of models of price setting under nominal rigidities.[15]

4.1. Decomposition of the inflation rate

Splitting the sample of matched price quotes up into these two subsets allows us to write inflation as the product of the incidence and magnitude of price change, *i.e.*,

$$\pi_t = \Delta \overline{p}_t = \delta_t \Delta \overline{p}_t^C. \tag{3}$$

This allows us to use a shift-share-type decomposition to analyze the variation in the inflation rate in the bin over time.

Following Bils and Klenow, 2004, Dhyne et al., 2006, Gagnon, 2009, and Dixon and Tian, 2017, we rewrite the above equation to obtain eq. (4). It is an additive decomposition that allows us to analyze cumulative inflation, *i.e.*, the log change in the price index since a base period. It shows that inflation can be high, relative to its average, for three reasons. First, because the *magnitude* of price changes is high. Second, because the *incidence* of price changes is high and many items change prices. Third, because of the positive *interaction* between times when many prices change, and times when prices change by a lot. These three reasons are, respectively, captured in the second through fourth terms on the right-hand side of:

$$\pi_t = \overline{\delta}\overline{\pi}^C + \underbrace{\overline{\delta}\left(\pi_t^C - \overline{\pi}^C\right)}_{\text{Magnitude}} + \underbrace{\overline{\pi}^C\left(\delta_t - \overline{\delta}\right)}_{\text{Incidence}} + \underbrace{\left(\delta_t - \overline{\delta}\right)\left(\pi_t^C - \overline{\pi}^C\right)}_{\text{Interaction}}, \tag{4}$$

where $\overline{\pi}$ and $\overline{\delta}$ are, respectively, average inflation and average incidence over the sample period $t = 1 \ldots T$, such that, $\overline{\pi}^C = \frac{1}{T}\sum_1^T \pi_t^C$ and $\overline{\delta} = \frac{1}{T}\sum_1^T \delta_t$.

Cumulative inflation can be built and split into the same parts as π_t in eq. (4) by summing both the left- and right-hand sides over the relevant time period. We use this decomposition of cumulative inflation in our empirical analysis. The base period relative to which we calculate the cumulative inflation response is May 2016, *i.e.* the month before the Brexit referendum.

4.2. Decomposition of the change in price dispersion

In Appendix A, we show that the change in the dispersion of the matched price quotes in a month can be split up into four parts:

$$\begin{aligned} \Delta\sigma_t^2 &= \overbrace{\sigma_{\pi,t}^2}^{\text{Variance of inflation}} + \overbrace{2\sigma_{\pi,p_{t-1},t}}^{\text{Mean reversion of inflation}} \\ &= \underbrace{\delta_t\left(\sigma_{\pi,t}^C\right)^2}_{\text{Variance of magnitude}} + \underbrace{(1-\delta_t)\delta_t\left(\pi_t^C\right)^2}_{\text{Variance of incidence}} + \underbrace{2\delta_t\sigma_{\pi,p_{t-1},t}^C}_{\text{Mean reversion of magnitude}} + \underbrace{2\delta_t\pi_t^C\left(\overline{p}_{t-1}^C - \overline{p}_{t-1}\right)}_{\text{Mean reversion of incidence}}. \end{aligned} \tag{5}$$

The first line in this equation shows that the increase in the variance of log prices is due to the dispersion in inflation rates, *i.e.*, $\sigma_{\pi,t}^2$, plus the extent to which these price changes revert to the mean, *i.e.*, $\sigma_{\pi,p_{t-1},t}$. The latter term is best understood by realizing that if high prices tend to increase faster than low ones, then this causes the spread in the distribution of log prices to increase (and *vice versa*). The higher the variance and the less the mean reversion (*i.e.*, the more the price expansion) will act to increase the dispersion of prices.

The variance and mean reversion terms can be further decomposed into "magnitude" and "incidence" components. The first term on the second line captures the *variance of magnitude* of the changes in the price quotes in *C*. The variance of inflation will be smaller the more similar the magnitudes of price changes. The second term captures the *variance of incidence* of price changes. Whether or not a matched price quote changes between months $t-1$ and t can be interpreted as a draw from a Bernoulli distribution with mean δ_t. The associated variance is, hence, $\delta_t(1-\delta_t)$. This term will be maximized when half of the prices in the distribution adjust. The next two terms are decompositions of the mean reversion of inflation. The term, $\delta_t\sigma_{\pi,p_{t-1},t}^C$, reflects the degree to which inflation reduces (or magnifies) initial differences in log prices among the prices that change. We call this the *mean reversion of magnitude* of price changes. If prices at the bottom of the distribution increase by a larger amount than prices at the top of the distribution then there will be more mean reversion (*i.e.*, less price expansion). The last term reflects the extent to which the fact that the prices that change are not randomly selected from the matched price quotes reduces (or magnifies) price differences. If prices are more apt to adjust from the bottom of the distribution than the top of the distribution, then mean reversion will increase (and dispersion will expand less).

[15] Our decomposition divides $\Delta\overline{p}_t$ and $\Delta\sigma_t^2$ into conditional moments are listed in the Appendix Table A1. The note below the table provides examples of how these moments are defined. Before we use them in our decomposition, it is useful to first consider the economic interpretation of some of them.

Previous analyses of price dispersion have focused on specific components of eq. (5).[16] However, we are the first study to decompose the changes in price dispersion in a comprehensive fully additive fashion. This full decomposition allows us to quantify which components drive the response of price dispersion to a large shock, which can then be compared to different price-setting models.

What enables us to calculate this full decomposition is that we can use the information on price levels necessary to calculate the terms related to the mean reversion of inflation in eq. (5). This is because we consider the distributions for very specific items, in particular regions, sold at specific types of stores, which makes price quotes in each bin comparable to each other.

5. Key empirical findings

In this section we use a dynamic DID method, based on Jordà (2005), to estimate the difference in the impact of the unexpected passing of the Brexit referendum on the distributions of log prices between our *treatment* and *control* samples. This yields two main findings. First, the Brexit shock is followed by an increase in log prices, which is mostly driven by the size of price adjustments rather than the frequency (incidence) of price changes. Second, price dispersion does not change significantly. This is because, although the variance of inflation increases, there is a sizable mean reversion of prices, *i.e.*, lower prices increase faster than high ones. The second-moment decomposition shows that the data features endogenous selection of the incidence of price adjustments, which helps explain the small (dynamic) response of the variance of log prices.

5.1. Summary statistics before and after Brexit referendum

Before we turn to our regression analysis, we first compare our treatment (Treat.) with our control sample (Cont.) as well as with the whole sample (All) before the Brexit shock occurred in Table 3. The table provides summary statistics for three periods, pre-Brexit, post-Brexit and a longer benchmark sample that allows for a comparison of price statistics further away from the shock.

The pre- and post-Brexit years together are the period we consider in our empirical analysis in this section. The benchmark period was chosen based on the fact that the GBP effective exchange rate, GDP growth, and CPI inflation volatility were relatively stable over this time frame (see Fig. 1). We use this period for calibration of our models in the next section.

The top half of Table 3 reports the contributions of the magnitude of price changes, π_t^C, and the incidence of price changes, δ_t, to the log of price changes.[17] Similarly, the bottom half of the table reports the contributions of the variance, $\sigma_{\pi,t}^2$, and mean reversion, $2\sigma_{\pi,p_{t-1},\,t}$, of inflation to the change in dispersion of prices, based on eq. (5).[18] In addition, the table contains the variance of log prices as well as the number of price quotes used to calculate the statistics reported.

Note that for almost all combinations of periods and measures, the point estimates for the whole sample (all) is in between those for the treatment (treat.) and control (cont.) samples. This is because the whole sample also includes the items classified as *ambiguous* in Table 2. For all the three subsamples and periods the mean reversion of inflation is negative, indicating that higher prices exhibit lower inflation than lower prices across the whole sample in our data.

When we look across the three subperiods, the *control* sample shows relatively similar magnitudes of the contributions of the subcomponents of eqs. (4) and (5). This is not the case for the *treatment* sample. For the *treatment* sample the contributions of the components of (4) and (5) during the benchmark and pre-shock periods are of comparable magnitude. However, in the post-shock period the magnitude of price changes, *i.e.*, $\Delta\bar{p}_t^C$, the variance of inflation, *i.e.*, $\sigma_{\pi,t}$, and the mean reversion of inflation, *i.e.*, $2\sigma_{\pi,p_{t-1},\,t}$, are all much larger than in the other two periods reported. This is indicative of the significant effect of Brexit on the price setting in the *treatment* sample that we quantify using our dynamic did below.

When we compare the *treatment* with the *control* sample, we find significant differences between them in the benchmark and pre-shock periods. This is reflective of the quasi-experimental nature of our analysis. If we would have been able to assign the treatment randomly across items in the British CPI then we could have made sure that these two samples looked the same in terms of the summary statistics in Table 3 during the benchmark and pre-shock periods. However, this is not feasible in our setup. To make sure these differences are not driving our key results, we account for these types of pre-treatment differences between the treatment and control items in a robustness check that uses a synthetic-control approach in Appendix C.

5.2. Dynamic DID specification using local projection method

We apply the local projection method of Jordà (2005) to the change in the mean of log prices, $\Delta\bar{p}_t$, and the change in price dispersion, $\Delta\sigma_t$, as well as their components from eqs. (4, 5), respectively. This method allows us to estimate the differential impact of the Brexit shock on these variables between the *treatment* and *control* samples over different horizons.

[16] Most studies have analyzed the dispersion of price changes, *i.e.*, the variance of the inflation rates, $\sigma_{\pi,\,t}^2$ (*e.g.*, Bils and Klenow, 2004; Gagnon, 2009; Klenow and Kryvtsov, 2008; Berger and Vavra, 2017, and Berger and Vavra, 2018). However, many studies in the industrial organization literature, *e.g.*, Cornia et al. (2012), have examined the dispersion of price levels.

[17] The contributions are calculated by applying a variance decomposition to Eq. (4), *i.e.*, $\mathrm{Var}[\pi_t] = \mathrm{Cov}\left[\pi_t, \bar{\pi}^C(\delta_t - \bar{\delta})\right] + \mathrm{Cov}\left[\pi_t, \bar{\delta}\left(\pi_t^C - \bar{\pi}^C\right)\right] + \mathrm{Cov}\left[\pi_t, (\delta_t - \bar{\delta})\left(\pi_t^C - \bar{\pi}^C\right)\right]$. Our final sample shows an average monthly incidence of price change of 10.7% over the benchmark period (2001–2007). This is lower than in the United States, 24.8% ((Bils and Klenow (2004)), but more in line with the average frequency in the Euro area 15.1% (Dhyne et al. (2006)). One reason for the relatively low frequency of adjustment in our sample is that we removed sales, petrol, and clothing (see Appendix B.3).

[18] In the Appendix Table A4, we expand Table 3 to include all subcomponents from these decompositions (as described in Eq. (4) and the second line of Eq. (5)).

Table 3
Summary statistics over samples.

		Benchmark			Pre-shock			Post-shock		
		2001 m1–2007 m12			2015 m6–2016 m5			2016 m7–2017 m6		
		All	Treat.	Cont.	All	Treat.	Cont.	All	Treat.	Cont
Eq. (3)	1st Moment									
π_t	Inflation	0.1948	0.0286	0.2498	0.1102	0.1162	0.1878	0.2806	0.4422	0.2689
		(0.010)	(0.029)	(0.008)	(0.023)	(0.066)	(0.041)	(0.025)	(0.078)	(0.047)
δ_t	Incidence of price changes	0.106	0.113	0.079	0.091	0.111	0.096	0.110	0.148	0.111
		(0.001)	(0.003)	(0.001)	(0.0012)	(0.007)	(0.005)	(0.002)	(0.008)	(0.006)
$\Delta\overline{p}_t^C$	Inflation of price changes	2.3354	0.1399	3.7790	2.0226	0.6055	3.3144	3.1659	2.8821	3.9020
		(0.049)	(0.234)	(0.074)	(0.165)	(0.675)	(0.222)	(0.155)	(0.574)	(0.191)
Eq. (5)	2nd Moment									
$\Delta\sigma_t^2$	Change in var. of log prices	1.338	2.493	−0.246	0.546	10.600	−0.886	4.776	8.436	5.676
		(0.279)	(1.152)	(0.532)	(0.895)	(3.903)	(1.378)	(1.139)	(5.971)	(2.226)
$\sigma^2_{\pi,\,t}$	Variance of inflation	18.476	20.928	14.214	26.605	24.270	24.156	31.947	35.314	32.318
		(0.303)	(0.659)	(0.868)	(0.930)	(2.068)	(2.396)	(1.196)	(2.763)	(3.463)
$2\sigma_{\pi,\,p_{t-1},\,t}$	Mean reversion of inflation	−17.138	−18.435	−14.459	−26.059	−13.669	−25.042	−27.171	−26.878	−26.643
		(0.410)	(1.318)	(1.047)	(1.325)	(3.859)	(2.921)	(1.536)	(6.366)	(3.762)
$\sigma^2_{p,\,t}$	Var. of log prices	12.363	21.517	10.186	13.875	29.677	9.515	14.663	30.215	9.441
		(0.082)	(0.288)	(0.168)	(0.214)	(0.964)	(0.296)	(0.225)	(0.998)	(0.288)
N		34,653	3731	4854	5785	552	910	5791	539	887

Note: Values are means across bins in the sample designated by the column. Values in parentheses are standard errors of the mean. Eq. (3) terms are scaled by 100 (except of incidence of price changes). Eq. (5) terms are scaled by 10,000.

The Brexit shock is captured by the dummy variable $\mathbb{B}_t$ that equals one from June 2016 onwards. We differentiate between the *treatment* and *control* samples using the dummy variable $\mathbb{T}_i$ which is one if item i is classified as tradable, as in Table 2, and is part of our *treatment* sample. The horizon is the number of months over which we capture the impact of the shock. We denote it by $h \in \{0,\ldots,12\}$ and study the response of the cumulative change in the first- and second-order moments of the distribution of log prices, and their components, over the year following the Brexit referendum.

We quantify this response using the regression equation:

$$y_{i,t+h} - y_{i,t-1} = \gamma_i + \delta^h \mathbb{B}_t + \beta^h \mathbb{B}_t{}^* \mathbb{T}_i + \sum_{c=1}^{C} \sum_{k=1}^{12} \left(\alpha^h_{c,k} \Delta C_{c,i,t-k} + \phi^h_{c,k} \Delta C_{c,i,t-k}{}^* \mathbb{T}_i \right) + \varepsilon_{i,t}. \tag{6}$$

We estimate eq. (6) for two sets of dependent variables $y_{i,t}$[19]:

(i) the log-price level, $p_{i,t}$, and its three time-varying components described in eq. (4),
(ii) the variance of log prices, $\sigma^2_{i,t}$, and its components described in eq. (5).

The coefficients of interest are the estimates of β^h, which trace out the path of $y_{i,t+h}$ for the treatment group items relative to control group items in the h months following Brexit. Under the null hypothesis, the coefficients β^h all equal zero, meaning that the treatment and control groups remained on the same relative pre-Brexit path during the post-Brexit period. Therefore, our identification assumption attributes any deviation of β^h away from zero as being caused by the exchange rate shock. Note that since our analysis relies on matched (by shop) price quotes between months $t-1$ and t, the dependent variable for each horizon h is measured as the sum of monthly changes for each type of variable $y_{i,t+h}$, providing the cumulative effect of the shock on variable $y_{i,t+h}$ by time $t+h$.[20]

We include a set of control variables, $C_{c,i,t}$, aimed to remove pre-Brexit trends. In particular, we include 12 lags of the time-varying components of eqs. (4) and (5), depending on the dependent variable being used. That is, $c = 1, \ldots, 3$ in case (i) when we consider components of Eq. (4), and $c = 1, \ldots, 4$ in case (ii) when $y_{i,t}$ is one of the components of eq. (5). We also include 12 lags of each component interacted with the treatment-group dummy, which allows for different pre-trends for treatment- and control-group items. To account for Nickell bias we employ the Arellano-Bond estimator.[21] We cluster standard errors at the 64 lowest (three-digit) levels of aggregation in the COICOP classification.

[19] See Appendix C for detailed regression specifications. In that we also consider a third set of dependent variables given by the 10th, 50th and 90th percentiles of the log price level. Results are reported in the Appendix Figure A4.

[20] For example, for the log-price level we have $p_{i,\,t+h} - p_{i,\,t-1} = \sum_{\tau=1}^{h} \pi_{i,\,t+\tau}$. The inflation rate for item i is $\pi_{i,\,t} = \sum \omega_{b,\,i} \pi_{b,\,i,\,t}$, where $\omega_{b,\,i}$ is the bin weight and $\pi_{b,\,i,\,t} = \sum \omega_{s,\,b,\,i} (p_{s,\,b,\,i,\,t} - p_{s,\,b,\,i,\,t-1})$ is the matched-shop log change in prices for item i in b and shop s, and $\omega_{s,\,b,\,i}$ are shop weights provided by ONS.

[21] Results did not substantially change using OLS or replacing the Arellano-Bond instruments with their principal components (Bai and Ng, 2010).

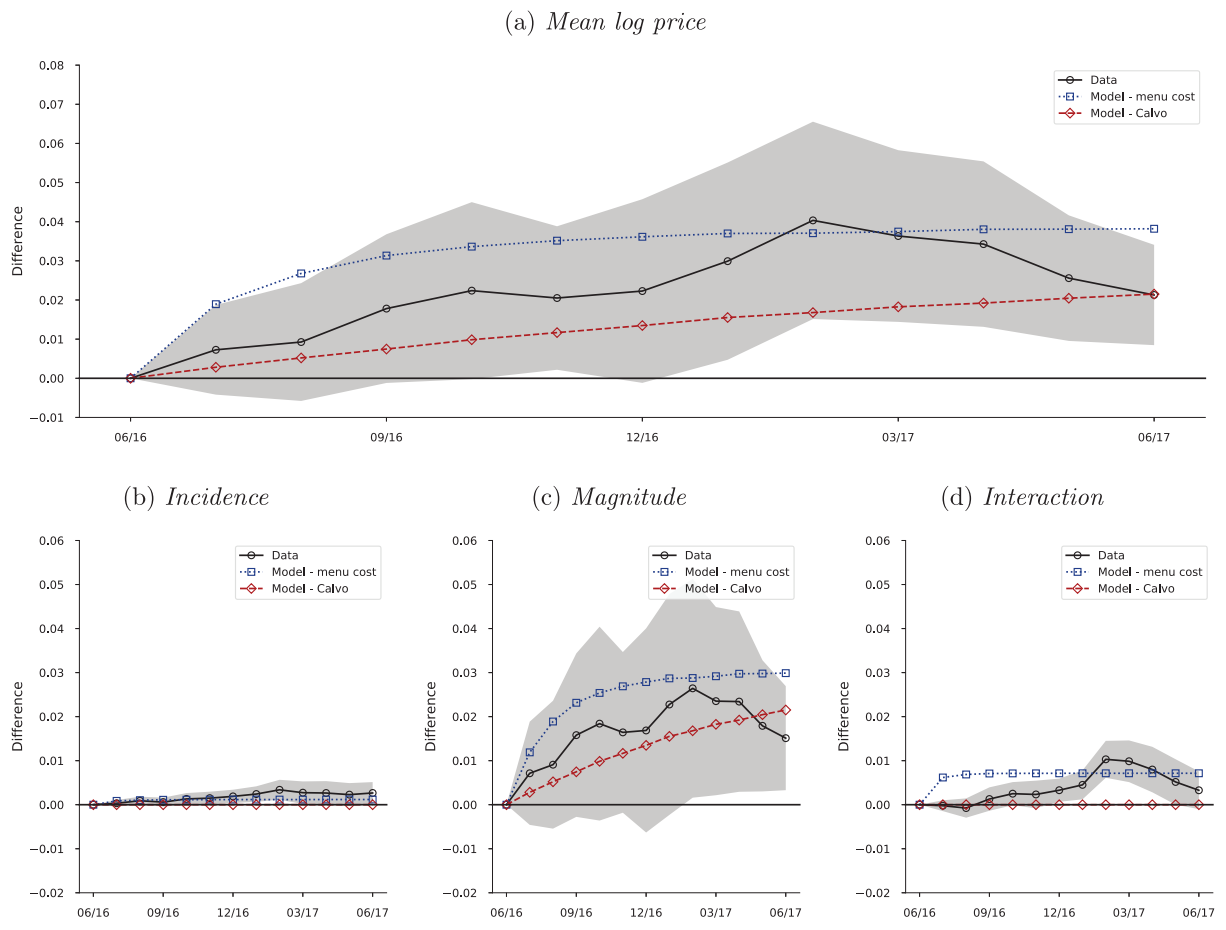


Fig. 5. Model and data impulse responses: First-order moments.

Although all measures are constructed at the bin level, regressions are run at the more aggregated elementary-item level to reduce attenuation bias, such that i in the regression indicates an elementary item. To do so, we aggregate the bin measures up to the elementary-item level using bin-specific weights provided by ONS.[22]

The regression is estimated for the sample period from June 2015 to June 2017, and we take the first year of the sample (June 2015 to May 2016) as the pre-Brexit period, and the second year of the sample (July 2016 to June 2017) as the post-shock period. The results obtained using this regression specification are plotted in Figs. 5 and 6.

5.3. Impact of Brexit on price-setting decisions for treatment CPI items

The solid black line in the top panel of Fig. 5 shows the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the mean log-price level. In the bottom three panels, the figure reports the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the three time varying components of the change in log prices; *i.e.*, magnitude, incidence and interaction. Because we include the same explanatory variables in all regressions underlying the panels in Fig. 5, the estimated β^h's in the bottom three panels add up to the one reported in the top panel.

The top panel shows the accumulated effect of the Brexit shock on the mean log prices of tradable CPI items (relative to nontradables). It reveals a significant, but delayed, impact that peaks at 3.2% about 8 months after the referendum. The average import share of the items in the control group is around 40% and the depreciation in response to Brexit was about 10%. A year

[22] For example, the inflation rate for item i is $\pi_{i,t} = \sum \omega_{b,i}\pi_{b,i,t}$, where $\omega_{b,i}$ is the weight for bin b and item i. Bin weights are provided by ONS which refers to them as "stratum" weights. See Appendix B.1 for more details on bin construction and Fig. 3 for an illustrative example of the data structure.

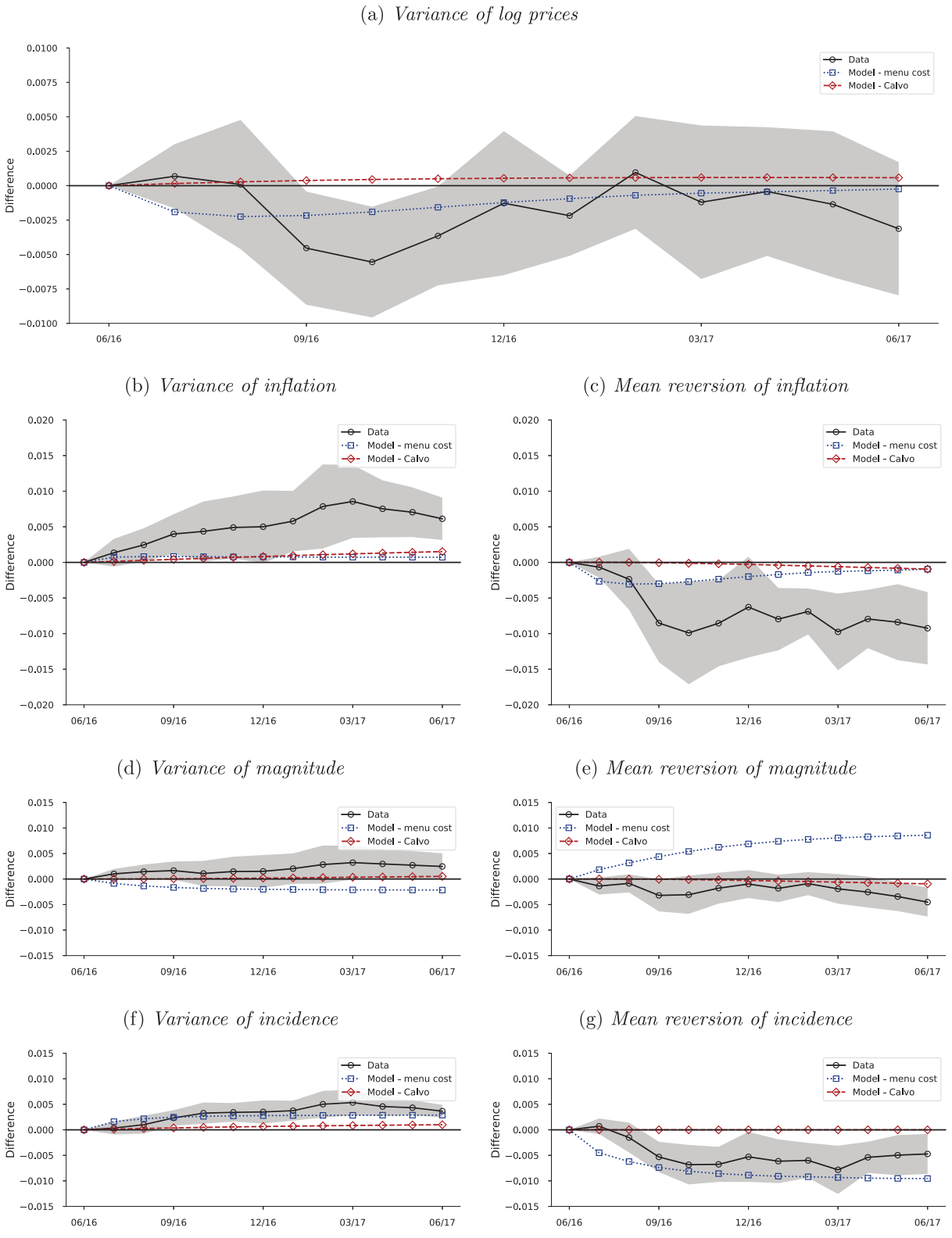


Fig. 6. Model and data impulse responses: Second-order moments.

after the Brexit referendum this had declined to half of the cost increase. In terms of the exchange-rate pass through into the total CPI, our estimates correspond to a coefficient of approximately 0.1, comparable to the pass-through estimates found in Forbes et al. (2018).[23]

The decomposition in the bottom panels shows our first key finding. The bulk (about 75%) of the increase in log prices of tradables after the Brexit shock is associated with an increase in the magnitude of price adjustments, while the incidence of price changes rises by a statistically significant but economically small amount.

The solid line in the top panel of Fig. 6 shows the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the variance of log prices. Our second key finding can be seen from the middle and bottom panels of the figure. They report the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the components of the change in the variance of log prices as described in eq. (5). The top panel shows a very limited effect of Brexit on price dispersion. The middle panels explain this finding by showing that, while there is an increase in the variance of inflation, this effect is more than offset by the covariance term, *i.e.*, the mean reversion in prices. The negative and relatively sizable mean reversion indicates that it is lower prices that increased by more in response to the shock, compressing the distribution of log prices. The net effect, if anything, is a small decline in price dispersion rather than an increase (as seen in the top panel). The bottom panels complement this analysis by reporting the remaining components of the decomposition described in eq. (5). It shows that the mean reversion of incidence more than offsets the small but positive effects of the increases in the variance of magnitude and incidence.

Note that the finding that the variance of magnitude increases is in line with the results of Berger and Vavra (2017), who also find that, in the U.S. data, $\sigma^C_{\pi,t}$ increases in response to exchange rate shocks. Of course, our decomposition implies that this only partially captures the impact of the exchange rate on the disparity of price *levels*. By focusing only on $\sigma^C_{\pi,t}$ in eq. (5), one might conclude that price disparities increase when the disparity of inflation rates increases. However, the addition of the terms that involve the price *levels*, most importantly, the covariance term $\sigma_{\pi,\, p_{t-1},\, t}{}^{C}$, reveals that that is not the case. The increase in the variance of inflation rates of prices that change, *i.e.*, of $\sigma^C_{\pi,t}$, in response to the shock, is more than offset by the mean-reversion term.

5.4. Robustness and validation

One possible concern about our empirical findings is that there is substantial heterogeneity between goods and services, even at the bin level. This heterogeneity would be reflected in terms of disparities in (log) prices that are not necessarily related to differences in markups or marginal costs but instead to quality differences across goods. This is why researchers have mostly ignored the micro-data on price levels. However, if this heterogeneity was of first-order importance in the data, one would not expect movements in the covariance between inflation and the initial price level to be such an important component of price dynamics, as Fig. 6 shows, because this heterogeneity would drive the term related to this covariance in the decomposition to zero.

Another source of concern regarding our empirical findings and methodology may arise from the intrinsic differences between the tradable and nontradable sectors. In an ideal experiment, the treated and control units are identical, on average, in the absence of the treatment. However, the summary statistics, reported in Table 3, indicate some differences in the treatment and control items in the nontreatment periods (*i.e.*, the benchmark and pre-Brexit periods). Most notably, the treated group (tradables) includes items whose prices change more frequently than those in the control group. Although the local projection method used in this study includes controls aimed to correct for pre-Brexit trends, it does not account for differential effects of the treatment in the post-Brexit period. For example, flexibly-priced items may react to a cost shock differently than sticky-priced items do. Such differences in characteristics of the treated group from the comparison group could potentially convolute the empirical results.

To alleviate the latter concern, we apply the synthetic control method of Abadie et al. (2010) to our data. More specifically, we construct a "synthetic" control group as a convex combination of control items that most closely resembles the characteristics of the treated group. The synthetic control group is build such that it matches the frequency of price changes (δ_t), the inflation of price changes (π^C_t), the variance of inflation ($\sigma^2_{\pi,t}$), and the mean reversion of price changes ($2\sigma_{\pi,\, p_{t-1},\, t}$) of the treated group over the pre-Brexit period (2015 m6-2016m5). The synthetic control matches the statistics of the treatment group quite well (see Tables A6 and A7). We then perform our empirical approach to obtain the relative response of the treated group to the Brexit shock.

The results from the synthetic control method, reported in Appendix Section C.1, reinforce our main empirical findings and show that the effect of the exchange rate shock on tradables through local projections and the synthetic control methods are quite close to one another across all variables.

It is possible that the endogenous response of macroeconomic variables could be affecting our results to the extent that they impact the relative price response of the treatment and control groups. Most notably, following the Brexit vote, some borrowing rates declined, which could be amplifying the differential effects in the treatment group through an increase in demand for durables. However, the growth rate of household consumption of durables declined in the quarters following the Brexit vote, which indicates that, if present, this bias is not large.

[23] To derive this calculation of exchange-rate pass-through, we take the weighted average of price effects in both the treatment group (6% share of the CPI) and the ambiguous group (69% share of the CPI). Specifically, we performed an additional regression of the price level using the ambiguous group as the treatment group and found the cumulative 12-month impact of the exchange rate shock relative to the control to be 1%. As expected, considerably less than the 6% price impact found using the treatment group. This results in a price effect (due to a 10% depreciation) of 0.9% = 0.06*3 + 0.69*1 + 0.29*0, or an exchange-rate pass through of approximately 0.1.

Our regression specification (6) restricts the estimated impact of Brexit to be constant irrespective of the import content of the item. When we allow the impact to vary by the size of the cost shock, we find that a small positive but insignificant relationship between the size of the inflationary impact of Brexit and the import content of an item. Higher-order effects, that allow for asymmetries in this relationship, are all insignificant as well. Thus, our data reveals little cross-item asymmetry in response to the shock.[24]

Finally, from Fig. 1a it can be seen that the GBP already depreciated against major currencies before the surprise outcome of the Brexit referendum. Thus, part of the price-setting response we attribute to the Brexit shock might be due to the depreciation of the pound before Brexit. This would mean we overestimate the impact of the Brexit shock in our results. If this was the case, we would already have seen significant differences in price-setting between the control and treatment groups before the referendum.

This is not what we find, however. We show this by repeating our analysis with an alternative date for the shock. We choose February 2016, which is the actual date of the referendum announcement (February 20th 2016)..[25] When we do so, we find no significant treatment effects until 4 months after the shock, *i.e.* until after the actual referendum in June 2016.

5.5. Comparison with the 2008 financial crisis

The Brexit shock was a particular episode in which financial markets responded rapidly to the expectation of a future event — the U.K. leaving the E.U. two years, or more, down the road. This limited the contemporaneous real effects of the shock, in terms of demand and policy responses, and is why we can use it as a quasi-natural experiment to assess the impact of a cost-shock on price setting.

Fig. 1a shows that there are other movements in the GBP exchange rate that we could have exploited for our analysis. The largest such movement is the depreciation of the GBP during the financial crisis of 2008. As Forbes et al. (2018) point out, the composition of the aggregate shocks underlying the depreciation of the GBP during the financial crisis was different from those underlying the Brexit shock and, as a result, so was the aggregate inflation response.

For our analysis, because we include time fixed effects in our regression (6), the composition of aggregate shocks only matters for our results to the extent that it has a different impact on the control and treatment items. The GBP depreciation in the financial crisis coincided with both fiscal and monetary policy responses, such as a reduction in VAT from 17.5% to 15%, implemented on December 1, 2008. Consumer durables, household appliances, and car-related goods, which make up a large part of our treatment sample, are affected by the December 2008 VAT reduction. As a result, applying our methodology to the global financial crisis would imply results that are contaminated by the fiscal policy response to the crisis.

Fig. 7 plots the estimated cumulative inflation response to the depreciation related to the financial crisis, using September 2008 as the shock date. It shows how the difference in the composition of the relative shocks to the treatment and control items results in a markedly different inflation response to the GBP depreciation in 2008 compared to 2016. The top panel shows how the VAT reduction put downward pressure on the price level in December 2008. The decomposition of the top-panel results into the three parts in eq. (4) plotted in the bottom three panels of the figure reveal how this price adjustment happened. The results show that the VAT reduction caused a sharp decrease in the interaction component in December. Meaning that, in December, items that had an unusually high incidence of a price change also saw large price decreases. The magnitude effect shows an increase in prices, indicating that those items not seeing an unusually high incidence of price changes had large price increases (presumably from the exchange rate depreciation).

6. Comparison with canonical models of price rigidities

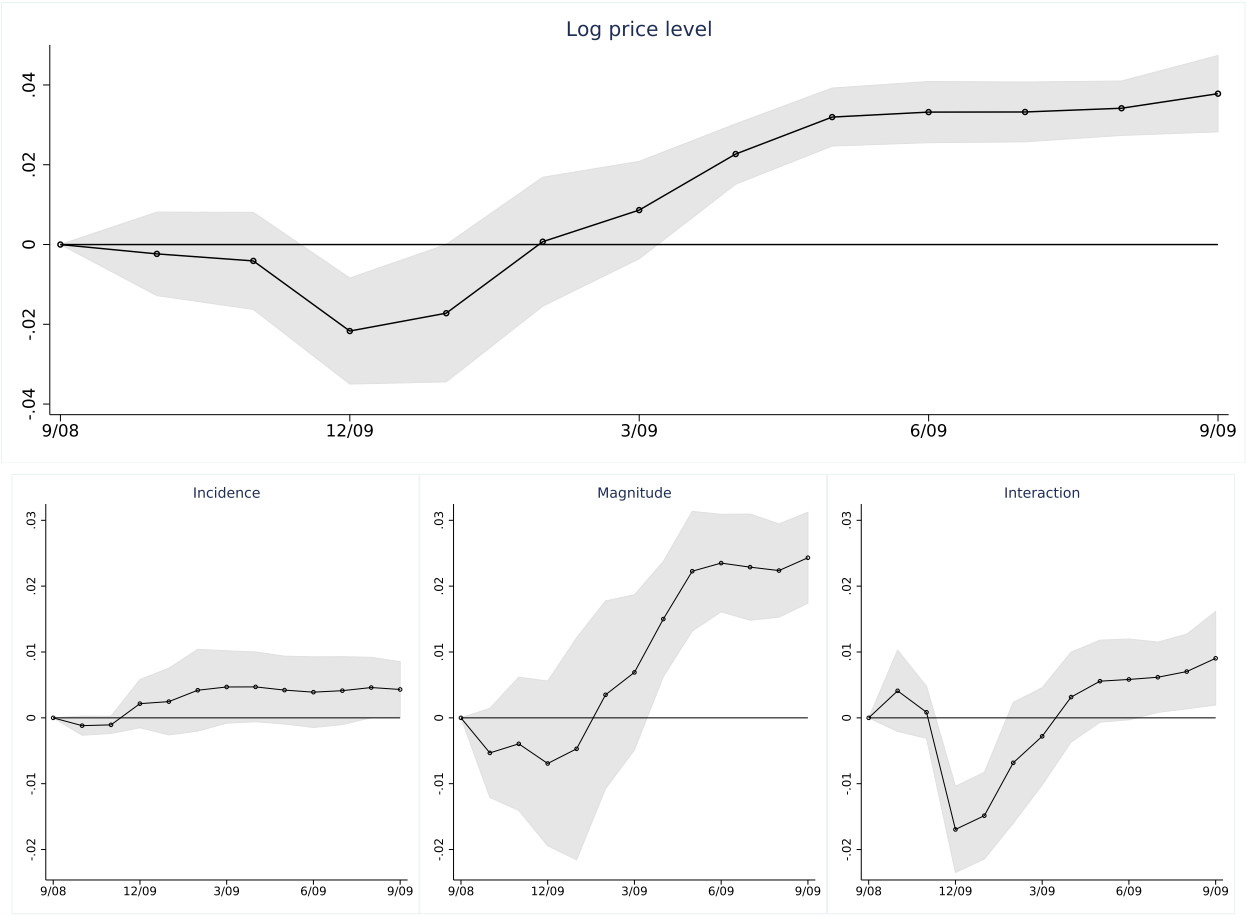
To understand what the estimated impulse responses teach us about the nature of nominal rigidities underlying the British CPI, we compare the empirical impulse responses to those obtained from two canonical models of price setting. They are the basic model of price setting with time-dependent nominal rigidities, based on Calvo (1983), and a model with state-dependent price setting under menu costs, as in Golosov and Lucas (2007) for example. Our analysis is definitely not the first to compare these two models.[26] What is new here is that we study the differences between these two models in terms of their transitional dynamics of the components of price setting dynamics, from eqs. (4, 5), in response to a permanent cost shock. We compare these transitional dynamics with the estimates from the previous section.

In both models, we consider an economy composed of two sectors, $i = 1, 2$ that differ in the extent to which the exchange rate affects the marginal cost of production through imported intermediates. We index these sectors by i to emphasize that they are the equivalent of an elementary item in our data. We interpret the sector $i = 1$, where the marginal cost does not depend on imported intermediates, as part of our control sample. The other sector, $i = 2$, is part of the treatment sample. Just like in our empirical analysis, we study the difference in the responses of these two sectors to a change in the cost of imported intermediates, induced by a surprise change in the nominal exchange rate.

[24] This result is possibly due to attenuation bias because the import content measure we use is provided at a higher level of aggregation than the items that we use in our sample.

[25] The results of this falsification analysis are plotted in the Appendix in Figure A7

[26] Most of the existing studies focus on differences in steady-state properties of these two models under various rates of steady-state inflation (*e.g.*, Alvarez et al., 2016; Nakamura et al., 2016).



Source: ONS and authors' calculations
Note: Estimated treatment effect during 2008 financial crisis. Base date is September 2008.

Fig. 7. Estimated cumulative inflation response during 2008 financial crisis Source: ONS and authors' calculations. *Note*: Estimated treatment effect during 2008 financial crisis. Base date is September 2008.

6.1. Model with nominal rigidities and permanent cost shock

Both sectors are made up of a continuum of monopolistic competitors of mass one that produce varieties. We index these producers by $j \in (0,1)$ and interpret the prices they set as the theoretical counterparts of the price quotes we measure in the data. The inputs used in production distinguish the two types of output, $i = 1, 2$. The first type, $i = 1$, is produced solely using labor, while the second, $i = 2$, is produced using both labor and imported intermediates. In both sectors, producers of different varieties have different total factor productivity (TFP) levels, which we denote by $A_{i,j,t}$.

Variety j in sector 1 is produced using a linear production technology in labor:

$$Y_{1,j,t} = A_{1,j,t} L_{1,j,t}. \tag{7}$$

Variety j in sector 2 is produced using a Cobb-Douglas technology in labor and imported intermediates:

$$Y_{2,j,t} = A_{2,j,t} \widetilde{A} L_{2,j,t}^{1-\alpha} M_{j,t}^{\alpha}, \text{ where } \widetilde{A} = \left[\left(\frac{1-\alpha}{\alpha} \right)^{\alpha} + \left(\frac{\alpha}{1-\alpha} \right)^{1-\alpha} \right]. \tag{8}$$

In both sectors, producers of each variety can flexibly adjust their input choices. All producers take the prices of the inputs as given. In particular, W_t is the nominal wage and P_t^* is the price of imported intermediates denominated in GBP. Because of constant returns to scale for each producer, average cost equals marginal cost, which is given by:

$$MC_{i,j,t} = \begin{cases} \frac{W_t}{A_{i,j,t}} & \text{if } i = 1 \\ \frac{1}{A_{i,j,t}} W_t^{1-\alpha} \left(P_t^*\right)^{\alpha} & \text{if } i = 2 \end{cases}. \tag{9}$$

Note that the marginal cost of production in sector 2 is directly impacted by the price of imported intermediates, which, in turn, is directly affected by changes in the exchange rate. The exchange rate shock has an immediate effect on the marginal cost, corresponding to the evidence in Chen et al. (2019) showing that vehicle-currency pricing (VCP)and producer-currency pricing (PCP) are the most common price-setting strategies for U.K. importers.[27]

Producers of varieties in each of these two markets face Constant Elasticity of Substitution (CES) demand functions, with the elasticity of substitution between these varieties ε, given by:

$$Y_{i,j,t} = \left(\frac{P_{i,j,t}}{P_{i,t}}\right)^{-\varepsilon} Y_{i,t}, \text{where } P_{i,t} = \left[\int_0^1 P_{i,j,t}^{1-\varepsilon} di\right]^{\frac{1}{1-\varepsilon}} \tag{10}$$

Demand for each of the goods is determined by their price, $P_{i,t}$, relative to the aggregate price level, P_t, and the level of aggregate demand, Y_t. The sector-specific demand functions are given by:

$$Y_{i,t} = \left[\int_0^1 Y_{i,j,t}^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}} = \left(\frac{P_{i,t}}{P_t}\right)^{-\theta} Y_t, \text{where } i = 1,2 \text{ and } 0<\theta<\varepsilon. \tag{11}$$

To simplify notation in the rest of our exposition, we introduce $\mathcal{P}_{i,j,t} = \frac{P_{i,j,t}}{P_{i,t}}$, $\mathcal{P}_{i,t} = \frac{P_{i,t}}{P_t}$, and $\mathcal{P}_t^* = \frac{P_t^*}{P_t}$ for the relevant relative prices, as well as $\mathcal{W}_t = \frac{W_t}{P_t}$ for the real wage. This notation, along with the cost and demand functions above, allows us to write the *real* profits of varieties' producers as

$$\Pi_i\left(\mathcal{P}_{i,j,t}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \begin{cases} Y_t\left(\mathcal{P}_{i,t}^{-\theta}\mathcal{P}_{i,j,t}^{-\varepsilon}\right)\left(\mathcal{P}_{i,t}\mathcal{P}_{i,j,t} - \frac{1}{A_{i,j,t}}\mathcal{W}_t\right) & \text{if } i = 1 \\ Y_t\left(\mathcal{P}_{i,t}^{-\theta}\mathcal{P}_{i,j,t}^{-\varepsilon}\right)\left(\mathcal{P}_{i,t}\mathcal{P}_{i,j,t} - \frac{1}{A_{i,j,t}}(\mathcal{W}_t)^{1-\alpha}\left(\mathcal{P}_t^*\right)^{\alpha}\right) & \text{if } i = 2 \end{cases}, \tag{12}$$

where $\mathcal{S}_t = \{\mathcal{W}_t, \mathcal{P}_t^*, P_t Y_t\}$ are the aggregate variables that firms take as given when they make their price-setting decisions.

6.2. Evolution of $A_{i,j,t}$, $\mathcal{P}_{i,t}$, and $\mathcal{S}_t$

The log of the firm-specific productivity level, $a_{i,j,t}$, evolves independently across firms over time according to an AR(1)-process of the form

$$a_{i,j,t} = \rho a_{i,j,t-1} + u_{i,j,t}, \text{where} u_{i,j,t} \sim N(0, \sigma_u). \tag{13}$$

We introduce this firm-specific productivity shock to match the substantial level of price disparities we find during the benchmark period, reported in the bottom row of Table 3.

The relative price level of sector i, $\mathcal{P}_{i,t}$, is an equilibrium variable that is determined by the price-setting choices of all the firms in sector i. Hence, we solve for a fixed point in which the price-setting response of firms to the path of $\mathcal{P}_{i,t}$ aggregates to this path.

To keep our analysis focused on the first-order effect of the change in $\mathcal{P}_t^*$ on the distribution of prices in the two sectors, we abstract from general equilibrium effects of the shock to $\mathcal{P}_t^*$ on the aggregate variables, P_t, Y_t, $\mathcal{W}_t$, and $\mathcal{P}_t^*$.

Similar to Hobijn et al. (2006), we assume that relevant aggregate variables are constant along the equilibrium path. In particular, we assume that aggregate inflation is constant at the target rate, *i.e.*, $\pi_t = \frac{P_{t+1}}{P_t} - 1 = \overline{\pi}$. The real interest rate is constant such that $r_t = r$. In addition, we abstract from growth in overall activity such that output, Y_t, and the real wage, $\mathcal{W}_t$, are constant over time.[28] We also abstract from aggregate uncertainty in that there are no aggregate shocks in our model. Karadi and Reiff (2019) show, in a similar model, that type of uncertainty does not affect the model results much. This is largely due to the

[27] Further evidence from the official customs records show that only 20% of the value of non-EU imports in the U.K. were invoiced in pounds. Thus our implicit assumption of non-local-currency-invoicing is valid for the bulk of imports into the U.K.

[28] We abstract from growth, because adding growth to the model only complicates the math and does not materially change the results.

fact that, in order to match the within bin disparity of log prices, the idiosyncratic shocks are an order of magnitude larger than aggregate shocks.

Most importantly, we assume that there is a surprise increase in the relative price of imported intermediates at time t. Consistent with our assumptions about other aggregate variables, $\mathcal{P}_t^*$ is constant along the equilibrium path except that it jumps at time $t = 0$, *i.e.*,

$$\mathcal{P}_t^* = \begin{cases} \underline{\mathcal{P}}_t^* & \text{for } t < 0 \\ \overline{\mathcal{P}}_t^* & \text{for } t \geq 0 \end{cases}, \tag{14}$$

where $\overline{\mathcal{P}}_t^* > \underline{\mathcal{P}}_t^*$. This jump reflects a permanent shock to the exchange rate that leads to an increase in the GBP-denominated price of imported intermediates.[29] As can be seen from Figs. 1a and 2, this simplifying assumption of the permanent shock to $\mathcal{P}_t^*$ aligns with the depreciation of the GBP exchange in the year following the Brexit referendum.

6.3. Two types of nominal rigidities

We consider the price-setting decisions of firms in the two sectors $i = 1, 2$ in this model under two different forms of nominal rigidities. Both of them involve the firms spending an amount of time, $\ell_{i,j,t}$, in the case they decide to adjust their prices. Because the menu cost is in terms of time, the actual cost of changing prices is given by $\ell_{i,j,t} P_t \mathcal{W}_t$.

Following Dotsey et al. (1999), this menu cost is independently drawn in each period and across producers of varieties from the distribution function $\Lambda(\ell) : [0, \infty) \to [0, 1]$. In the time-dependent price-setting model, based on Calvo (1983), we consider

$$\Lambda(\ell) = \delta \text{ for } 0 < \ell < \infty, \tag{15}$$

such that firms can freely adjust their prices with a probability δ and otherwise adjusting prices is infinitely expensive. In the state-dependent menu cost model

$$\Lambda(\ell) = \begin{cases} 0 & \text{for } \ell < \overline{\ell} \\ 1 & \text{for } \ell \geq \overline{\ell} \end{cases}. \tag{16}$$

Thus, in this case, the menu cost distribution is degenerate and all firms face a certain (fixed) menu cost equal to $\overline{\ell}$.

In both cases, firms set their prices in order to maximize the expected present discounted value of their current and future profits. They do so in response to the path of the sector-specific relative price level, $\mathcal{P}_{i,t}$. Equilibrium is that path of $\mathcal{P}_{i,t}$ for which the firms' price setting decisions aggregate to this path of the sector-specific relative price level.[30]

6.4. Transitional dynamics in response to a Brexit-like shock

To compare these two models with the data, we consider the difference in impulse response of the two sectors with respect to the various components of the dynamics of the distribution of log prices that we introduced to a permanent 10% increase in the price of imports.[31] This increase is in line with the depreciation of the GBP we observed in the data following the Brexit referendum.

We present the impulse responses for a set of parameters that is chosen as follows. We choose the elasticities of substitution, ε and θ, as well as the cost share of imports in sector $i = 2$, α, based on evidence from other data. In particular, consistent with the evidence from Hobijn and Nechio (2018) on the inflation response to VAT changes in the E.U., we set $\varepsilon = 3$ to $\theta = 1$. The cost share of imports in sector $i = 2$ is $\alpha = 0.4$ to match the evidence in Table 1. We set the steady-state rate of inflation, $\overline{\pi}$ to 2% annualized, which is the Bank of England's inflation target as of 2016.[32]

The remaining parameters of the model are the persistence, ρ, and standard deviation, σ_u, of the idiosyncratic productivity shocks as well as the menu cost parameters, δ for the time-dependent and $\overline{\ell}$ for the state-dependent model. We choose them to match the model's steady-state properties in terms of the components of eqs. (4, 5) with the summary statistics for the

[29] We assume this shock is permanent in order to avoid having to make specific assumptions about the stochastic process that drives $\mathcal{P}_t^*$. Our results can be interpreted as the limiting case in which this process becomes increasingly persistent in the $\overline{\mathcal{P}}_t^*$ state. The assumption of permanence means that the model impulse responses we present are an upperbound on the implied impact of the cost shock on inflation. We abstract from a wage effect of the FX shock. Costa et al. (2019) provide evidence that wages in sectors that use more imported intermediates declined in response to Brexit relative to other sectors. This would partly offset the positive cost shock we calibrate here.

[30] The associated Bellman equations as well as the solution method we apply to solve for the transitional dynamics of these models are discussed in Appendix Section A.2.

[31] In terms of the model parameters this means that $\mathrm{P}_t^* = 1$ for all periods before June 2016 and $\overline{\mathcal{P}}_t^* = 1.10$ for all periods after that date in Eq. (14).

[32] This choice of steady-state inflation rate yields a slightly higher than average inflation in our sample over the benchmark period (2001 m1-2007 m12). This does not affect the qualitative properties of our results. Small changes in the other parameters neither do as well.

whole sample (All) over the benchmark period reported in Table 3. In particular, we match the average incidence of price changes, δ_t, the variance of inflation, $\sigma^2_{\pi,t}$, and price disparities, $\sigma^2_{p,t}$.[33]

The resulting impulse response functions for the cumulative change in the average log price, *i.e.* cumulative inflation in eq. (4), are reported in Fig. 5. Those for the change in price disparity, *i.e.* the variance of log prices in eq. (5), are in Fig. 6.

Fig. 5 shows that both models fit the dynamics of cumulative inflation in response to the cost shock relatively well. The menu-cost model yields a more rapid adjustment of prices than we estimate in the data. The adjustment in the Calvo (time-dependent) model is more gradual and matches the data better. The faster adjustment in the price level in the menu-cost model is due to the combination of two things.

From Panel 5c one can see that conditional on adjusting, firms adjust their prices more under state-dependent prices than under time-dependent pricing. This reflects that under state-dependent pricing firms only adjust when they hit the boundary of the sS-bands. Under time-dependent pricing they adjust their price in case the adjustment cost is zero, no matter how far they are from their reset price.

The second thing is that the period with the higher adjustment of prices in the menu-cost model coincides with an above average fraction of firms adjusting their prices. This can be seen from the interaction term in Panel 5d. Thus, though one of the merits of the menu-cost model is that it endogenizes firms' decisions to change prices, it is exactly this margin that makes it overstate the speed of adjustment in the price level in our model. The Calvo-price model, on the other hand, does, by definition, not match the change in the incidence and interaction terms and solely captures the impact of the magnitude of price changes.

In the end, our results imply that, if one is mainly interested in the cumulative inflation response to a cost shock, then the simplicity of the Calvo model and its relatively accurate fit of the estimated impulse response outweighs the increased complexity of the menu-cost model that makes it overstate the speed of the price adjustment.

But, there are other aspects of the data that the menu-cost model fits better and helps us understand. In particular, it provides an explanation of why the variance of log prices declines in the wake of a cost shock. This can be seen from Fig. 6. Panel 6c shows that the menu-cost model qualitatively matches the negative mean reversion of inflation we observe in the data. What it matches particularly well is that relatively more low prices adjust in response to the cost shock than high prices, *i.e.* the mean reversion of incidence plotted in Panel 6 g. Thus, if one is interested which prices are most likely to adjust in response to a cost shock the menu-cost model turns out to be a useful tool to predict this, while the time-dependent model does not provide any prediction of this at all.

Though the menu cost model helps us understand why the mean reversion of inflation results in a reduction in price disparities in response to a cost shock rather than an increase, it does not fit this very well quantitatively. The menu cost model is off in terms of the mean reversion of the magnitude. The model yields that, for the prices that change, higher prices increase at a higher percentage. The reason for this is that, similar to Golosov and Lucas (2007), the sS-bands are wider for higher prices (with lower productivity levels, $A_{i,j,t}$).[34] This means a *positive* mean reversion of magnitude effect in the model, while that in the data is slightly negative. In the data, among the prices that change, lower prices tend to change at a slightly higher percentage.[35] The shape of the sS-bands in the menu cost model is largely a function of assumptions about CES preferences, the AR(1)-process that drives the idiosyncratic shocks, and the trend inflation rate that are the baseline in models of price rigidities.

As a result, neither model matches the size of the offsetting effects of the cost shock on the variance of the inflation rates and the mean reversion of inflation. The latter is what we were able to estimate because of our use of the information about the level of the prices in each detailed bin. A further understanding of what drives these two effects, and their impact on price disparities, is important for the assessment of the welfare effects of monetary policy in general equilibrium models with price rigidities, *e.g.*, Nakamura et al. (2016).

7. Conclusion

In this study, we exploit the quasi-experiment that stemmed from the depreciation of the British pound following the unexpected passing of the Brexit referendum. Using micro-level price quote data that underpin the official U.K. CPI, we develop a novel methodology to decompose the change in the dispersion of prices at the granular item, region, and shop level which allows us to quantify how the cost shock transmits through to the distribution of prices as well as inflation. Our results show that a large portion (about 75%) of the inflationary effect from Brexit was attributable to the magnitude of price changes, conditional on the price adjusting. Due to the importance of the magnitude-effect, we show that a time-dependent price-setting model can match the dynamics of the inflation response following the cost shock fairly well.

Our results on the response of the distribution of prices allow us to assess which firms adjust prices, and by how much, following a cost shock. The data show that selection effects occur in response to a cost shock. Specifically, firms at the lower end of the price distribution—that is, firms with relatively low prices—are more apt to adjust their price. Time-dependent models inherently do not allow for any selection effects, meaning these types of models will misrepresent how the distribution of prices

[33] Because the steady-state inflation rates is set to 2% annualized, matching the incidence of price changes pins down the steady-state magnitude of price changes. Similarly because in the steady state, variance of log prices is constant (*i.e.*, its change is zero), matching the variance of inflation pins down the mean reversion of inflation. The matched moments and parameter calibration are reported in the Appendix Table A5. We have verified that our qualitative results and the magnitude of our quantitative results are robust to alternative calibration strategies.

[34] See Fig. A8b for a graphical depiction of these bands in steady state.

[35] Part of this might reflect that cheaper goods have a higher import content, as discussed in Cravino and Levchenko (2017), which is something we abstract from in our model.

evolves following a cost shock. The state-dependent pricing model is better able to match some of these distributional effects, as it more accurately captures the selection of price changes from the lower end of the price distribution. However, the state-dependent model misses on where in the distribution magnitude of price changes are largest, predicting that high-price firms (low productivity) adjust by more conditional on changing their price, while the data suggest the opposite is true. This result in the state-dependent model is at least partly attributable to the commonly-used assumptions of a constant-elasticity of substitution and of an AR(1)-process for the idiosyncratic productivity shocks.

Data availability

Using Brexit to Identify the Nature of Price Rigidities (Original data)

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Appendix A. Supplementary data

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