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 to 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. A large portion of the inflationary effect is attributable to the size of price adjustments, implying that a time-dependent price-setting model can match the response of aggregate inflation reasonably well. The state-dependent model fares better in capturing the endogenous selection of price changes at the lower end of the distribution, however, it misses on the magnitude of the adjustment conditional on selection. In the state-dependent model, prices at the higher end of the distribution change by larger amounts, which is inconsistent with the data.

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1 Introduction

On June 23, 2016 a slim 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, as well as 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, shocked the foreign exchange market. The result was 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 had 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 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. This allows us to distinguish between different types of price setting models with nominal rigidities. The fact that the Brexit shock is large is important because, as Klenow and Kryvtsov (2008) and Alvarez, Lippi and Passadore (2016) have argued, many of these models are almost observationally equivalent, and thus indistinguishable, under small shocks.

The Brexit shock directly affects the marginal cost of goods and services that are either imported or whose production relies on imported intermediates. It only has an indirect effect on the marginal cost of other goods and services, which allows us to split goods and services up into "treatment" and "control" groups. We analyze the dynamics of the distribution of prices and inflation by decomposing the change in the mean of log prices, which turns out to be closely aligned with inflation, and the change in the variance of the distribution of log prices. We further split up these changes into the first and second moments of the distribution of log prices into readily interpretable parts that can be mapped into theoretical models of price setting under nominal rigidities. Finally, we use local projections (Jordà, 2005) to estimate the dynamic responses of the the mean and variance of log prices and their aforementioned first- and second-moment components to the Brexit shock.

Note that our analysis relies on *price levels* to obtain the components of our decomposition using the publicly-available micro-data on price quotes underlying the British CPI. These data allow us to look at the distribution of prices of elementary items, which are classified in very detailed categories at the regional level by type of shop. This enables us to construct a panel of log price distributions over time with a substantial cross-sectional dimension that we use as our "treatment units" in our quasi-experimental setup.

Our empirical findings point to 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 size of price adjustments rather than the frequency of price changes. Second, price dispersion does not change significantly. This is so because although the variance of inflation increases, there is a sizable mean reversion of prices, *i.e.*, lower prices increase faster than high ones, which offsets the former increase. The second-moment decomposition shows that the data features endogenous selection of the incidence of price adjustments, which help explain the small (dynamic) response of the variance of log prices.

Our decomposition splits the changes in these first- and second-order moments of the distribution of log prices in components whose dynamics are distinct under different price setting models. Therefore, we can conjecture on which type of price setting drives U.K. inflation by comparing the empirical dynamic response of prices (and its components) to the Brexit shock to the responses obtained from a simple model of price setting. We consider a model with menu costs that nests time- and state-dependent pricing behavior and assumes two sectors, in which one of them has its prices directly affected by the exchange rate. We explore the different responses of these two sectors to a change in the cost of imported intermediates, induced by a surprise change in the nominal exchange rate.

Our findings show that, even in response to a large shock, a time-dependent model fares well in matching the dynamic response of aggregate inflation since the latter is mainly driven by the responses of the magnitude of price changes. Moreover, the speed of the price response is also better represented by that model. The mapping between the data and the models' second-order moments show that the state-dependent model better captures the endogenous selection of the incidence of price adjustments. The latter model, however, misses on the magnitude of the adjustment conditional on selection. The data definitely show that prices at the lower end of the price distribution are more apt to adjust, but also suggest that they rise by more than prices at the higher end of the distribution. The state-dependent model accurately predicts the selection of price adjustment from the lower end of the distribution, but inaccurately predicts that higher priced (lower productivity) firms adjust by more. Taking all these results together, our findings suggest that if one is interested in the dynamic response of aggregate inflation, a time-dependent model fares reasonably well. However, a state-dependent model better captures some of the aspects of the selection of price adjustment.

Our paper contributes to the long literature that studies price adjustment, inflation dynamics, and the transmission of price changes to the economy. This literature includes papers that focus on documenting facts about price adjustments, such as Bils and Klenow (2004), Dhyne et al. (2006), Klenow and Malin (2010), and Nakamura and Steinsson (2008), among others. This literature also includes papers that focus on the mapping between the pricing data and canonical macroeconomic models of price adjustment, such as Nakamura and Steinsson (2010), Midrigan (2011), Kehoe and Midrigan (2015), and Alvarez, Lippi and Passadore (2016). Our paper also adds to a long tradition of analyzing exchange rate pass-through on inflation, *e.g.*, Gagnon (2009), Gopinath and Itskhoki (2010) Auer and Schoenle (2016), Auer, Burstein and Lein (2017), among others. More closely related to our work, Berger and Vavra (2017) and Berger and Vavra (2018) focus on higher moments of the distribution of U.S. prices. Their analyses explores a subset of the components of the change in the mean of log prices that we study in this paper, as we add a more comprehensive accounting framework. Finally, Alvarez, Lippi and Passadore (2016) complements our analysis by showing analytically how the shock size matters for the nature of pricing behavior in different types of models.

In the remainder of the paper, we first provide an overview of the macroeconomic performance of the U.K. leading up to and following Brexit. In Section 3 we describe our decomposition of the changes in the distribution of prices. In Section 4 we summarize the granular price quote data underlying the British CPI, provide an overview of our empirical analysis, and discuss the results. In Section 5, we set up a model that nests both time-dependent and state-dependent price setting firms, and compare the implications of the models with that in our empirical analysis. We offer concluding remarks in Section 6.

2 U.K. macroeconomic performance

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 exchange rate, economic activity, and inflation in Great Britain before and after the referendum. We then focus, in more detail, on the run up 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. With this in mind, we describe how we use the, publicly available, micro-data on individual price quotes underlying the British CPI to construct the panel of distributions of log price levels of similar items that we use for our analysis of the transmission of the Brexit shock into CPI inflation.

2.1 Exchange rate, activity, and inflation before and after Brexit

Figure 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 percent, 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, including the bankruptcy of Northern Rock, and the financial 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 percent. 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 percent in the two years preceding the Brexit vote. As can be seen from Figure 1, in the 12 months leading up to the Brexit referendum, CPI inflation had only been 0.3 percent in the United Kingdom, real GDP growth had been 2 percent, and 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. As can be seen from Figure 1a, 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).

Figure 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 about a five percent in 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 Figure 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.[1]

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

What has also come in line with the IMF's *limited* scenario has been 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.[2] 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 (Figure 1c).

The post-Brexit acceleration of inflation was due to an increase in the inflation rate of *tradables* goods and services. Figure 3 shows this by plotting the time series of the overall CPI inflation rate from Figure 1c together with the inflation rates of the two-digit Classification of Individual Consumption According to Purpose (COICOP) *tradables* and *nontradables* categories as classified by Allington, Kattuman and Waldmann (2005). Figure 3 reveals that the inflation rate of nontradables did not change much after the Brexit referendum, and what increased was the inflation rate of tradable goods and services.[3] We rely on this different response

[1]Estimates of long-run effects of Brexit on the level of U.K. GDP range from this 1 percent, based on static trade effects (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

[2]The 2014 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 1 for details.

[3]Other studies have noted that goods and services with a high import content have seen higher inflation

of prices of tradables and nontradable goods as our identification strategy when we turn to our empirical approach in Section 4.2.

3 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 prices to assess the impact of Brexit on prices in the U.K. We do so by relying on (public) micro-data for the United Kingdom, as we detail in Section 4.2. This decomposition is, of course, general and can be applied to other micro-data sets. In addition, there are many aspects of the distribution of prices that we one track over time. In this paper, we use this decomposition to focus on the change in the average log price and the change in the variance of log prices following the Brexit shock.

Our decomposition splits the changes in these first- and second-order moments of the distribution of log prices in components whose dynamics are distinct under different price setting models. Thus, the decomposition of these moments allows us to identify what type of price setting drives U.K. inflation of the different goods and services for which we have micro-data in the British CPI.

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 4.2, relies on *matched* price quotes. These are price quotes for which we do observe the price both in two consecutive months.[4] 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 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,

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).

[4] 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.

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 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.

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, Hobijn and Tambalotti, 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*.[5] The size of the price changes, *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 encompasses 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 $\frac{\sigma_{\pi,p_{t-1},t-1}^C}{(\sigma_{t-1}^C)^2}$ 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.

These unconditional and conditional first- and second-order moments are either measures

[5]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).

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.

3.1 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.*,

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

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

Equation (4) rewrites the previous one to yield an additive decomposition that allows us to both analyze cumulative inflation, *i.e.*, the log change in the price index since a base period, as well as the variance of inflation. 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:

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

where $\bar{\pi}$ and $\bar{\delta}$ are, respectively, average inflation and average incidence from times $t = 1$ and $t = T$, such that, $\bar{\pi}^C = \frac{1}{T}\sum_1^T \pi_t^C$ and $\bar{\delta} = \frac{1}{T}\sum_1^T \delta_t$.

Cumulative inflation can be built and split into the same parts as π_t in equation (4) by summing both the left- and right-hand sides over the relevant time period. We use this decomposition of cumulative inflation when we analyze the response of inflation to a shock to marginal cost, *i.e.*, an unexpected change in the exchange rate for goods and services that contain a large import content.

3.2 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:

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

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 *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 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 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. We call this the *mean reversion of incidence* of price changes. If prices are more apt to adjust from the bottom of the distribution than the top of the distribution than mean reversion will increase (and dispersion will expand less).

We are not the first study using CPI micro-data that splits inflation up into parts due to the incidence and magnitude of price changes (*e.g.*, Bils and Klenow, 2004, Dhyne et al., 2006, Gagnon, 2009, and Dixon and Tian, 2017), and furthermore, previous analyses of price dispersion have focused on specific components of equation (5).[6] However, we are the first study to decompose the changes in price dispersion in a comprehensive fully additive fashion. A 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.[7]

4 What Brexit reveals about price rigidities

4.1 Dissecting inflation using CPI micro-data

We use the micro-data with price quotes underlying the British CPI published by the ONS.[8] These data have been used in previous research by Kryvtsov and Vincent (2014) and Dixon and Tian (2017), among others. The variation in the effect of the Brexit referendum across COICOP categories that we analyze is best understood by considering an example of how a particular price quote is classified in these micro-data. Figure 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 Figure 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.

[6]Most studies have analyzed the dispersion of price changes, *i.e.*, the variance of the inflation rates, σ_t^2 (*e.g.*, Bils and Klenow, 2004, Gagnon, 2009, Klenow and Kryvtsov, 2008, Berger and Vavra, 2017, and Berger and Vavra, 2018).

[7]Our decomposition divides $\Delta\bar{p}_t$ 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.

[8]A comparison of the aggregated price quote data with the published CPI measure is available in Appendix B.2. We describe how we cleaned the data in Appendix B.3.

We use the sampling structure explained above and depicted in Figure 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 *bin*. For each month, we construct the distribution of log prices for all price quotes in each bin. For more detailed information on how bins were constructed please see Appendix B.1.

We exploit the fact that the inflationary effects of the Brexit shock seem to be limited to tradable goods and services (Figure 3). In our empirical analysis, we consider two sources of information to assess the degree of tradability of goods and services: (i) the 2014 Analytical Input-Output tables published by the ONS, who provides goods and services' import content based on the U.K. input-output tables and, (ii) Allington, Kattuman and Waldmann (2005), who provide a binary classification of COICOPs into *tradables* versus *nontradables*. 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, Kattuman and Waldmann (2005)'s classification.

Note from Table 1 how, at the 2-digit level of aggregation, the tradability classification and import shares are closely aligned. This 2-digit level of aggregation is the lowest level that both these measures have in common. Because we exploit differences in the inflationary effect of the Brexit shock across COICOPs at a lower levels of aggregation in the rest of this paper, we use a combination of both the tradability classification from Allington, Kattuman and Waldmann (2005) at lower levels of aggregation, and the import content shares at the level of aggregation reported in the table.

With this in mind, we split our cross-section of bins up into treatment, control, and ambiguous groups. We do so by jointly evaluating two criteria related to the elementary item in each bin. The first is 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 is the import-content tertile of the 2-digit 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.[9]

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, Kattuman and Waldmann

[9]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 apparel because, as Liegey (1993) pointed out, many matched price quotes are not for identical items but for close substitutes.

(2005) *and* are in the top tertile of import content shares in Table 1. This covers 541 bins with region-shop-type-specific distributions of prices for 41 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*.[10]

Finally, note that, for the purposes of this paper, one should view our decomposition, as detailed in Section 3, as being bin-specific. In that case, our decomposition of the bin-specific inflation rates and changes in price dispersion define the metrics that we use to quantify the differential impact that the cost shock induced by the surprise outcome of the Brexit referendum has on the bins in our control and treatment samples from Table 2.

Before we turn to our regression analysis, Table 3 provides some descriptive statistics of the different components underlying our decomposition of the log of price changes and the change in the variance of price changes, as described in equations (3) and (5), respectively. In particular, 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. The bottom half of the table reports the contributions of the variance, $\sigma^2_{\pi,t}$, and mean reversion, $2\sigma_{\pi,p_{t-1},t}$, of inflation to the change in dispersion of prices. In the Appendix Table A3, we expand Table 3 to include all subcomponents from these decompositions (as described in equation (3) and the second line of equation (5)).

The table provides summary statistics for three subsamples, pre-Brexit, post-Brexit and a longer benchmark sample that allows for a comparison of price statistics further away from the shock. The samples are such that the benchmark period covers data from January 2001 to December 2007, the pre-Brexit period covers data from June 2015 to May 2016, and the post-Brexit period covers data from July 2016 to June 2017. The pre- and post-Brexit periods are the subsamples we will consider to implement our empirical analysis that we describe in Section 4.2. The benchmark period dates were chosen based on that fact that the GBP effective exchange rate, GDP growth, and CPI inflation volatility were relatively stable over this time frame (see

[10]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.

Figure 1). We will use the statistics from this period to calibrate the steady state of the models we assess. The pre-shock period appears to more closely resemble the benchmark period than the post-shock period, giving more credence to the idea that the pre-period represents a suitable control period in our empirical setup.[11]

Some patterns are worth highlighting from Table 3. The top half of the table shows that prices of tradable goods are, on average, more flexible but change by less than those of non-tradable ones. This holds in all three samples considered. The size and frequency of price changes of both tradables and nontradables increased following the Brexit referendum. Tradable and nontradable items also differ in terms of some of their second-order moments, for example, tradeable items have a higher variance of inflation on average. Note that these types of pre-treatment differences between the treatment and control items are are accounted for in the synthetic control approach discussed in the next section.

4.2 Empirical approach

As shown in Figure 1a, the GBP effective exchange rate sharply depreciated following the announcement of the Brexit referendum. Our identification strategy rests on the assumption that in the absence of this exchange-rate shock, the relative cost of both tradable and nontradable items would have remained unchanged relative to the months prior to the Brexit referendum.[12] In the presence of the exchange rate shock (the treatment), however, the cost of tradable products (the treated group) deviates from the cost of the nontradable ones (the control group). The size of this deviation between the two types of products of goods provides a measure of the impact of the cost shock.

Our empirical approach entails applying the local projection method of Jordà (2005) to the elementary items inflation rates, its moments and components (as described in Section 3). More specifically, for a given horizon, h, and price-statistic $y_{i,t+h}$, we run regressions of the form:

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

where $h = \{0, \ldots, 12\}$, i indexes the elementary item, γ_i are elementary item fixed effects, $\mathbb{B}_t$ is

[11] Specifically, the benchmark means are closer in value to the pre-shock measures for 5 of the 7 "All" statistics in Table 3.

[12] As discussed in Section 4.1, the tradable items are those in the bottom-right corner of Table 2, while the nontradable items are in those in the top-left corner of that table. Items are arranged in these two groups based on both their import shares (as revealed by the 2014 Analytical Input-Output tables published by the ONS), and by the binary classification of Allington, Kattuman and Waldmann (2005). Items that do not fall into either of these two categories are considered *ambiguous* and are not included in our estimation.

a dummy variable that identifies the Brexit shock and equals to one from June 2016 onwards, and $\mathbb{T}_i$ is a dummy variable that identifies tradable goods and equals to one if item i is classified as tradable as in Table 2.

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 equations (4) and (5), depending on the dependent variable being used. That is, $C = 3$ when considering components of equation (4), and $C = 4$ when considering components for equation (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. Although all measures are constructed at the bin level, regressions are run at the more aggregated elementary-item level to reduce attenuation bias. To do so, we aggregate the micro-data from price quotes up to the elementary item level using bin-specific weights provided by ONS.[13]

We estimate equation (6) on two sets of dependent variables $y_{i,t+h}$:[14,15]

(i) the log price level, $p_{i,t}$, and its three time-varying components described in equation (4),

(ii) the variance of log prices, $\sigma^2_{i,t}$, and its components described in equation (5).

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. We cluster standard errors at the 64 lowest (three-digit) levels of aggregation in the COICOP classification.

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 to 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 $t+h$.[16]

[13] 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 Figure 4 for an illustrative example of the data structure.

[14] See Appendix C for detailed regression specifications.

[15] In the Appendix Section C, we also consider a third set of dependent variables given by the 10^{th}, 50^{th} and 90^{th} percentiles of the log price level. Results are reported in the Appendix Figure A3.

[16] 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.

4.3 Brexit event study

Figures 5 and 6 report our main regression results.

The solid black line in the top panel of Figure 5 shows the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the log prices. In the bottom panel, 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; as described in equation (4). The top panel shows the accumulated effect on tradable (relative to nontradables) log prices following the Brexit shock. This increase turns more pronounced about 6 months after the referendum. More interestingly, the decomposition in the bottom panel reveals that the bulk (about 75 percent) of this increase in log prices is associated with an increase in the magnitude of price adjustments, while the incidence of price changes rises by a stastically-significant but economically small amount.

The solid line in the top panel of Figure 6 shows the estimated β^h for regressions in which the variable $y_{i,t+h}$ corresponds to the variance in log prices. The middle and bottom panels 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 equation (5). The top panel shows very limited effect of Brexit on price dispersion. The middle panel explains 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 that shock, effectively shrinking the distribution of prices. The net effect, if anything, is a small decline in price dispersion rather than an increase (as seen on the top panel). The bottom panels complement this analysis by reporting the remaining components of the decomposition described in equation (5). It shows that the mean reversion of incidence more than offset 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 equation (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 $\sigma^C_{\pi,p_{t-1},t}$, 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. The net effect, is a small decline, rather than an increase, in price dispersion.

In sum, our empirical results point to two key 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 so because although the variance of inflation increases, there is a sizable mean reversion of prices, *i.e.*, lower prices increase faster than high ones, which offsets the former increase. The second-moment decomposition shows that the data features endogenous selection of the incidence of price adjustments, which help explain the small (dynamic) response of the variance of log prices.

Validating our empirical approach findings

One possible concern about our empirical findings is that there is substantial heterogeneity between goods and services even at the elementary item 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 the reason that 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 Figure 6 shows. That is 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 Tables 3 and A3, 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, Diamond and Hainmueller (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_t^C), 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 (2015m6-2016m5). The synthetic control matches the statistics of the treatment group quite well (see Tables A4 and A5). 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 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. For brevity, we report details of the methodology and findings in the Appendix Section C.1.

5 Theoretical counterparts of price-dynamics components

The macroeconomic literature frequently resort to two main types of pricing models under nominal rigidities to study pricing dynamics and the response of economic variables to shocks. The first type of model assumes time-dependent price setting by firms, similar to Calvo (1983). The second type of model assumes instead state-dependent pricing, as in Golosov and Lucas (2007), for example.

The empirical evidence and the estimated impulse response functions described in the previous section contains some features of both types of models. A quick glance at our estimates would suggest that, on the one hand, the relatively stronger response of the magnitude of price changes and the somewhat stability of the incidence of price changes would favor time-dependent models. On the other hand, the important role of mean reversion in explaining the resulting price dispersion would favor a state-dependent model of pricing.

To get a sense of what the estimated impulse responses teach us about the nature of nominal rigidities underlying the British CPI, we compare the empirical impulse responses with those implied by these two alternative models of price setting. To do so, we construct a model that nests the two types of price-setting behavior and includes some of the key features of our empirical analysis. In particular, 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. Thus, we interpret the sector $i = 1$, where the marginal cost does not depend on imported intermediates, as part of our control sample, *i.e.*, an elementary item in the upper-left cell of Table 2. Oppositely, the other sector, $i = 2$, is part of the treatment sample in the lower-right cell of the same table. In the model, a sector is a representative tradable or nontradable elementary item.

In the rest of this section, we introduce a simple model of price setting with menu costs to explore the difference between the response of these two sectors to a change in the cost of imported intermediates, induced by a surprise change in the nominal exchange rate. In particular, we focus on the difference in terms of the components of the decomposition that we introduced in the previous section.

5.1 Demand, technology, and nominal rigidities

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 elasticity of substitution between these varieties, ε, is such that:

$$Y_{i,t} = \left[\int_0^1 Y_{i,j,t}^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}}, \text{ where } i \in \{1,2\}. \tag{7}$$

The inputs used in the 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:

$$Y_{1,j,t} = A_{1,j,t} L_{1,j,t}. \tag{8}$$

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

$$Y_{2,j,t} = A_{2,j,t}\tilde{A} L_{2,j,t}^{1-\alpha} M_{j,t}^{\alpha}, \text{ where } \tilde{A} = \left[\left(\frac{1-\alpha}{\alpha}\right)^{\alpha} + \left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}\right]. \tag{9}$$

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 Pounds. Because of constant returns to scale for each producer, the average cost equals marginal cost, which are given by:

$$MC_{i,j,t} = \begin{cases} \frac{W_t}{A_{i,j,t}} \text{ if } i = 1 \\ \frac{1}{A_{i,j,t}} W_t^{1-\alpha} \left(P_t^*\right)^{\alpha} \text{ if } i = 2 \end{cases}. \tag{10}$$

Note that the marginal cost of production in sector 2 is directly impacted by price of imported intermediates, which, in turn, is directly affected by changes in the exchange rate.

Producers of varieties in each of these two markets face Constant Elasticity of Substitution (CES) demand functions given by:

$$Y_{i,j,t} = \left(\frac{P_{i,j,t}}{P_{i,t}}\right)^{-\varepsilon} Y_{i,t}, \text{ where } P_{i,t} = \left[\int_0^1 P_{i,j,t}^{1-\varepsilon} di\right]^{\frac{1}{1-\varepsilon}} \tag{11}$$

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:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t}\right)^{-\theta} Y_t, \text{ where } i = 1,2 \text{ and } 0 < \theta < \varepsilon. \tag{12}$$

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

$$\Pi_i\left(\mathcal{P}_{i,j,t}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \begin{cases} Y_t\left(\mathcal{P}_{i,t}^{-\theta}\mathcal{P}_{i,j,t}^{-\varepsilon}\right)\left(\mathcal{P}_{i,t}\mathcal{P}_{i,j,t} - \frac{1}{A_{i,j,t}}\mathcal{W}_t\right) \text{ if } i = 1 \\ Y_t\left(\mathcal{P}_{i,t}^{-\theta}\mathcal{P}_{i,j,t}^{-\varepsilon}\right)\left(\mathcal{P}_{i,t}\mathcal{P}_{i,j,t} - \frac{1}{A_{i,j,t}}\left(\mathcal{W}_t\right)^{1-\alpha}\left(\mathcal{P}_t^*\right)^{\alpha}\right) \text{ if } i = 2 \end{cases}, \tag{13}$$

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.

5.2 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

$$a_{i,j,t} = \rho a_{i,j,t-1} + u_{i,j,t}, \text{ where } u_{i,j,t} \sim N\left(0, \sigma_u\right). \tag{14}$$

We introduce this firm-specific productivity shock to allow us to investigate how the dynamics of the components in our decomposition depend on the relative importance of idiosyncratic factors that impact marginal costs at the individual firm level.

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.

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, Ravenna and Tambalotti (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.*, $\pi_t = \frac{P_{t+1}}{P_t} - 1 = \bar{\pi}$. 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.[17]

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.*,

$$\mathcal{P}_t^* = \begin{cases} \underline{\mathcal{P}}_t^* & \text{for } t < 0 \\ \overline{\mathcal{P}}_t^* & \text{for } t \geq 0 \end{cases}, \tag{15}$$

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.[18] As can be seen from Figures 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.

5.3 Nominal rigidities and firms' price-setting decisions

The type of nominal rigidities that we consider is a hybrid of those analyzed in Golosov and Lucas (2007) and Dotsey, King and Wolman (1999) in which firms spend a fixed amount of time, $\ell_{i,j,t}$, in case they decide to adjust their prices. Following Dotsey, King and Wolman (1999) this amount of time is independently drawn across producers of varieties and over time from the distribution $\Lambda(\ell)$.

In particular, the distribution of $\ln \ell$ is a mixture of two normal distributions with mean and standard deviations (μ_0, σ_0) and (μ_1, σ_1). Here $\mu_0 < \mu_1$ and the weight of the first distribution in the mixture is $\lambda_0 \in [0, 1)$.

The benefit of this setup is that it nests several commonly used models of price-setting with nominal rigidities. This includes the case in which the distribution of $\ell_{i,j,t}$ is degenerate as in

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

[18] 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.

Golosov and Lucas (2007). It also includes the case in which $\ell_{i,j,t} \in \{0, \infty\}$ with probability one, which yields the time-dependent price setting case popularized by Calvo (1983).[19]

As in Golosov and Lucas (2007), firms differ in their marginal cost of production, in our case because the producer-specific TFP levels, $A_{i,j,t}$, differ across producers. The productivity disparities imply that, even in the absence of nominal rigidities, we would observe price disparities across varieties in both markets for $Y_{1,j,t}$ and $Y_{2,j,t}$.

5.4 Bellman equations and value functions

The ex-ante, *i.e.*, before observing the menu cost, real value function of a firm in sector i with productivity level $A_{i,j,t}$ that charged the relative price $\mathcal{P}_{i,j,t-1}$ in the previous period, and faces the sectoral relative price $\mathcal{P}_{i,t}$ and the aggregate state $\mathcal{S}_t$, is given by:

$$V_i\left(\mathcal{P}_{i,j,t-1}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \int_0^\infty \tilde{V}_i\left(\mathcal{P}_{i,j,t-1}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t; \ell\right) dF\left(\ell\right). \tag{16}$$

The value function $\tilde{V}\left(.\right)$ is the ex-post value function evaluated after the stochastic menu cost, $\ell_{i,j,t}$, has been realized. In particular, it is the maximum value of the two options of either *keeping* (K) the price fixed or *changing* (C) it net of the menu cost. That is:

$$\tilde{V}_i\left(\mathcal{P}_{i,j,t-1}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \max\left\{V_i^K\left(\mathcal{P}_{i,j,t-1}; A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right), V_i^C\left(A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right)\right\}, \tag{17}$$

where

$$V_i^K\left(\mathcal{P}_{i,j,t-1}, A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \Pi_i\left(\frac{\mathcal{P}_{i,j,t-1}}{1+\pi_{i,t}}, A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) + \frac{1}{1+r}\mathbb{E}_t V_i\left(\frac{\mathcal{P}_{i,j,t-1}}{1+\pi_{i,t}}, A_{i,j,t+1}, \mathcal{P}_{i,t+1}, , \mathcal{S}_{t+1}\right), \tag{18}$$

and

$$V_i^C\left(\mathcal{P}_{i,j,t-1}, A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) = \max_{\mathcal{P}_{i,j,t}}\left\{\Pi_i\left(\mathcal{P}_{i,j,t}, A_{i,j,t}, \mathcal{P}_{i,t}, \mathcal{S}_t\right) - \ell\mathcal{W}_t + \frac{1}{1+r}\mathbb{E}_t V_i\left(\mathcal{P}_{i,j,t}, A_{i,j,t+1}, \mathcal{P}_{i,t+1}, \mathcal{S}_{t+1}\right)\right\}, \tag{19}$$

where $\pi_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$ is the inflation rate of varieties from sector i and $\mathbb{E}_t$ denotes the expectation conditional on information at time t.

[19] The Golosov and Lucas (2007) case is the limit in which $\lambda_0 = 1$ and $\sigma_0 \downarrow 0$. The Calvo (1983) case is the one in which $\mu_0 \leftarrow -\infty$ and $\mu_1 \rightarrow \infty$ as well as $\sigma_0 = \sigma_1 = 0$. In that case λ_0 is the probability price adjustment.

5.5 Price-setting dynamics in steady state and after shock

To assess the model's steady state and dynamics we consider the following exercise. We parameterize the model such that some parameters are set to levels as evidence by the literature, while others are calibrated to match the summary statistics for the distribution of log prices over the benchmark period reported in Table 3 in the steady state. Next, we consider the impulse response of the various components of the dynamics of the distribution of log prices that we introduced to a 10% shock in the price of imports, *i.e.*, $\underline{\mathcal{P}}_t^* = 0$ for all periods before June 2016 and $\overline{\mathcal{P}}_t^* = 1.10$ for all periods after that date in equation (15).

Turning to our calibration of the menu cost model, we set the elasticities of substitution ε to 3 and θ to 1, which is consistent with the evidence from Hobijn and Nechio (2018), the cost share of imports in sector 2 to 40%, which is in line with the empirical evidence of Table 1, and the steady-state inflation, $\bar{\pi}$ to 2 percent annualized.[20] We calibrate the remaining parameters to closely match the moments from our data. In particular, we choose the persistence (ρ), the standard deviation (σ_u) and the menu cost parameter ℓ that closely match the incidence ($\bar{\rho}$), the mean reversion of inflation ($2\sigma_{\pi,p}$),[21] and the variance of log prices (σ_p^2) during the benchmark period (2001m1-2007m12) as reported in the top panel of Table 3. We summarize our model calibration in the Appendix Table A6. Finally, to calibrate the Calvo model choose parameters in similar matter and set the frequency of price adjustment at 0.12, which matches our data.

5.6 What Brexit tells us about the nature of price rigidities

Departing from the calibration and steady state just described, we consider a permanent increase of 10% in the price of imports, which is in line with the depreciation of the GBP we observed in the data following the Brexit referendum outcome announcement. The resulting impulse response functions are reported in red and blue in Figures 5 and 6, respectively.

Figure 5 shows that both the Calvo and the menu cost models map well the dynamics of the mean log price in response to shocks. The Calvo model, however, performs better in matching the movements of the magnitude of price adjustments, as evidenced by panel (c). The menu cost model implies a speedier adjustment than the data suggests.

Figure 6 shows that that both the Calvo and the menu models are able to decently match the dynamics of the variance of log prices. However, because of the importance of the response of the mean reversion of inflation in determining the dynamics of this variance, the menu cost

[20] This parameterization yields a slightly higher than average inflation in our sample over the benchmark period (2001m1-2007m12).

[21] Note that because the change in the variance of log prices is set to zero, the parameterization of the mean reversion of inflation pins down the variance of inflation.

model fares better than the Calvo model. The bottom panels of the Figure hep understand why. The data shows that the importance of the adjustment through the endogenous selection of the incidence of price changes (panel (g)), which by definition is zero in the Calvo model. Note however, that while the state dependent model captures well the response of the mean reversion of incidence, it completely misses the response of the mean reversion of the magnitude. This is so because in the data low prices adjust faster than higher ones, while inherently in a menu cost model it is the higher prices that adjust faster.

The comparison between empirical and model-based impulse responses functions depicted in Figures 5 and 6 suggest that the data exhibits properties of both types of models. On the one hand, a time-dependent pricing model performs relatively well in replicating the dynamics of some of the first-order moments of mean log prices. In particular, that model matches particularly well the response of the magnitude of price adjustments, which corresponds to the bulk of the response of mean log prices in the data. This finding suggest that if one's interest is to estimate the effects of a shock on aggregate inflation, relying a Calvo model is appropriate, even when the shock is as large as the one we consider in our exercise. On the other hand, if one's interest is to match the response of the variance of log prices, a state dependent model would fare better since this model is able to capture the endogenous selection in the incidence of price changes, which seems to be of particular relevance in the data.

Finally, we note that the fact that we can clearly distinguish between models and match the data with a state-dependent pricing model has to do with the size of the shock we focus on. The fact that the Brexit shock is large is important because, as Klenow and Kryvtsov (2008) and Alvarez, Lippi and Passadore (2016) have argued, many of these models are almost observationally equivalent, and thus indistinguishable, under small shocks.

6 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 underpins 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 percent) of the inflationary effect 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 assessing 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 clearly 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 evolves following a cost shock. The state-dependent pricing model is better able to match some of these distributional effects, as it accurately captures the selection of price changes from the lower end of the price distribution. However, the model misses on where in the distribution magnitude of price changes is largest, predicting that high-price firms (low productivity) adjust by more conditional on changing their price, while the data suggest the opposite is true. A potentially interesting avenue for future research would be to better uncover why the state-dependent model misses on this front.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association*, 105(490): 493–505.

Allington, Nigel F.B., Paul A. Kattuman, and Florian A. Waldmann. 2005. "One Market, One Money, One Price?" *International Journal of Central Banking*, 1(3).

Alvarez, Fernando, Francesco Lippi, and Juan Passadore. 2016. "Are State- and Time-Dependent Models Really Different?" *NBER Macroeconomics Annual 2016, Volume 31*, 379–457. University of Chicago Press.

Auer, Raphael A., and Raphael S. Schoenle. 2016. "Market structure and exchange rate pass-through." *Journal of International Economics*, 98: 60 – 77.

Auer, Raphael, Ariel Burstein, and Sarah M. Lein. 2017. "Price and Consumption Responses to Large Exchange Rate Shocks: Evidence from the 2015 Appreciation in Switzerland." mimeo.

Berger, David, and Joseph Vavra. 2017. "Shocks vs. Responsiveness: What Drives Time-Varying Dispersion?" National Bureau of Economic Research, Inc NBER Working Papers 23143.

Berger, David, and Joseph Vavra. 2018. "Dynamics of the U.S. price distribution." *European Economic Review*, 103: 60 – 82.

Bils, Mark, and Peter J. Klenow. 2004. "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy*, 112(5): 947–985.

Born, Benjamin, Gernot Muller, Moritz Schularick, and Petr Sedlacek. 2017. "The Economic Consequences of the Brexit Vote." C.E.P.R. Discussion Papers CEPR Discussion Papers 12454.

Breinlich, Holger, Elsa Leromain, Dennis Novy, and Thomas Sampson. 2017. "The Brexit Vote, Inflation and UK Living Standards."

Calvo, Guillermo A. 1983. "Staggered prices in a utility-maximizing framework." *Journal of Monetary Economics*, 12(3): 383 – 398.

Dhyne, Emmanuel, Luis J. Alvarez, Herve Le Bihan, Giovanni Veronese, Daniel Dias, Johannes Hoffmann, Nicole Jonker, Patrick Lunnemann, Fabio Rumler, and Jouko Vilmunen. 2006. "Price Changes in the Euro Area and the United States: Some Facts from Individual Consumer Price Data." *Journal of Economic Perspectives*, 20(2): 171–192.

Dixon, Huw David, and Kun Tian. 2017. "What We can Learn About the Behaviour of Firms from the Average Monthly Frequency of Price-Changes: An Application to the UK CPI Data." *Oxford Bulletin of Economics and Statistics*, 79(6): 907–932.

Dotsey, Michael, Robert G. King, and Alexander L. Wolman. 1999. "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output." *The Quarterly Journal of Economics*, 114(2): 655–690.

Eusepi, Stefano, Bart Hobijn, and Andrea Tambalotti. 2011. "CONDI: A Cost-of-Nominal-Distortions Index." *American Economic Journal: Macroeconomics*, 3(3): 53–91.

Gagnon, Etienne. 2009. "Price Setting during Low and High Inflation: Evidence from Mexico." *The Quarterly Journal of Economics*, 124(3): 1221–1263.

Golosov, Mikhail, and Robert E. Lucas. 2007. "Menu Costs and Phillips Curves." *Journal of Political Economy*, 115: 171–199.

Gopinath, Gita, and Oleg Itskhoki. 2010. "Frequency of Price Adjustment and Pass-Through." *The Quarterly Journal of Economics*, 125(2): 675–727.

Hobijn, Bart, and Fernanda Nechio. 2018. "Sticker Shocks: Using VAT Changes to Estimate Upper-Level Elasticities of Substitution." *Journal of the European Economic Association*, jvy009.

Hobijn, Bart, Federico Ravenna, and Andrea Tambalotti. 2006. "Menu Costs at Work: Restaurant Prices and the Introduction of the Euro." *The Quarterly Journal of Economics*, 121(3): 1103–1131.

International Monetary Fund. 2016. "United Kingdom." *IMF Country Reports*, 16/169.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1): 161–182.

Kehoe, Patrick, and Virgiliu Midrigan. 2015. "Prices are sticky after all." *Journal of Monetary Economics*, 75(C): 35–53.

Klenow, Peter J., and Benjamin A. Malin. 2010. "Microeconomic Evidence on Price-Setting." In *Handbook of Monetary Economics*. Vol. 3, , ed. Benjamin M. Friedman and Michael Woodford, Chapter 6, 231–284. Elsevier.

Klenow, Peter J., and Oleksiy Kryvtsov. 2008. "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent U.S. Inflation?" *The Quarterly Journal of Economics*, 123(3): 863–904.

Kryvtsov, Oleksiy, and Nicolas Vincent. 2014. "On the Importance of Sales for Aggregate Price Flexibility."

Liegey, Paul R., Jr. 1993. "Adjusting Apparel Indexes in the Consumer Price Index for Quality Differences." *Price Measurements and Their Uses*, 209–226. University of Chicago Press.

Midrigan, Virgiliu. 2011. "Menu Costs, Multiproduct Firms, and Aggregate Fluctuations." *Econometrica*, 79(4): 1139–1180.

Nakamura, Emi, and Jón Steinsson. 2008. "Five Facts about Prices: A Reevaluation of Menu Cost Models." *The Quarterly Journal of Economics*, 123(4): 1415–1464.

Nakamura, Emi, and Jón Steinsson. 2010. "Monetary Non-neutrality in a Multisector Menu Cost Model." *The Quarterly Journal of Economics*, 125(3): 961–1013.

Nakamura, Emi, Jón Steinsson, Patrick Sun, and Daniel Villar. 2016. "The Elusive Costs of Inflation: Price Dispersion during the U.S. Great Inflation." National Bureau of Economic Research, Inc NBER Working Papers 22505.

Reenen, John Van. 2016. "Brexit's Long-Run Effects on the U.K. Economy." *Brookings Papers on Economic Activity*, 47(2 (Fall)): 367–383.

The Economist. 2016. "Who said Brexit was a surprise?" *The Economist (Online)*. Last updated - 2016-06-26.

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, Kattuman and Waldmann (2005). 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

Tradability classification	*Import share tertile*			
	Low	**Middle**	**High**	**Total**
	0-21	21 - 34	34 - 100	0 - 100
Nontradable (obs)	**422,365**	21,678	56,865	500,908
(bins)	**938**	58	149	1,145
(items)	**80**	5	13	98
Tradable (obs)	471,921	1,400,443	**181,924**	2,054,288
(bins)	1,242	4,042	**541**	5,825
(items)	97	283	**41**	421
Total (obs)	894,286	1,422,121	238,789	2,555,196
(bins)	2,180	4,100	690	6,970
(items)	177	288	54	519

Note: Classification of trabability based on Allington, Kattuman and Waldmann (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

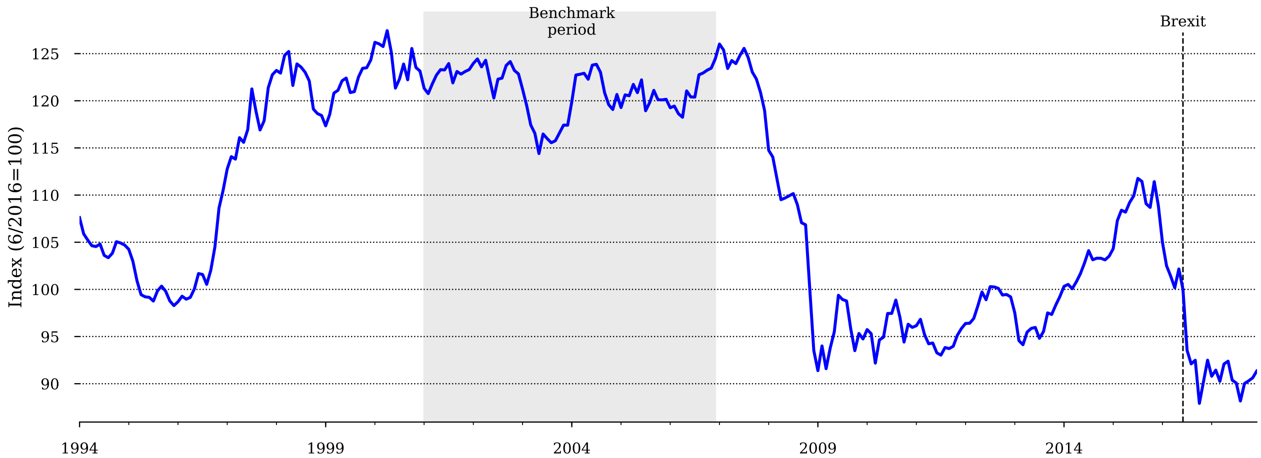
Table 3: Summary statistics over samples

		Benchmark 2001m1 - 2007m12			Pre-shock 2015m6 - 2016m5			Post-shock 2016m7 - 2017m6		
		All	Treat.	Cont.	All	Treat.	Cont.	All	Treat.	Cont
Equation (3)										
π_t	Inflation	0.1572	0.0714	0.2655	0.0567	0.1081	0.1464	0.2627	0.4496	0.2053
		(0.005)	(0.010)	(0.005)	(0.011)	(0.027)	(0.019)	(0.012)	(0.034)	(0.025)
δ_t	Incidence of price changes	11.979	13.955	6.772	8.239	10.813	7.596	10.249	15.973	8.297
		(0.029)	(0.111)	(0.043)	(0.055)	(0.254)	(0.134)	(0.061)	(0.294)	(0.154)
$\Delta\bar{p}_t^C$	Inflation of price changes	1.5427	0.4456	4.2926	0.8564	0.8220	2.5987	2.7858	2.9393	3.5112
		(0.022)	(0.070)	(0.040)	(0.072)	(0.221)	(0.115)	(0.067)	(0.220)	(0.111)
Equation (5)										
$\Delta\sigma_t^2$	Change in var. of log prices	1.709	2.153	0.132	2.369	11.770	0.788	2.192	4.808	2.680
		(0.156)	(0.490)	(0.325)	(0.485)	(1.769)	(0.924)	(0.532)	(2.230)	(1.146)
$\sigma_{\pi,t}^2$	Variance of inflation	25.089	19.276	11.670	29.120	22.060	19.893	33.754	36.523	25.538
		(0.147)	(0.404)	(0.331)	(0.398)	(0.950)	(0.887)	(0.475)	(1.560)	(1.186)
$2\sigma_{\pi,p_{t-1},t}$	Mean reversion of inflation	-23.380	-17.123	-11.538	-26.752	-10.289	-19.104	-31.562	-31.715	-22.858
		(0.212)	(0.630)	(0.467)	(0.616)	(1.877)	(1.267)	(0.699)	(2.687)	(1.578)
$\sigma_{p,t}^2$	Var. of log prices	11.576	15.187	9.503	13.871	22.582	8.755	14.525	23.321	8.458
		(0.026)	(0.079)	(0.066)	(0.069)	(0.281)	(0.106)	(0.072)	(0.300)	(0.100)
N		412,638	39,514	53,186	66,188	5,198	9,830	66,189	5,002	9,640

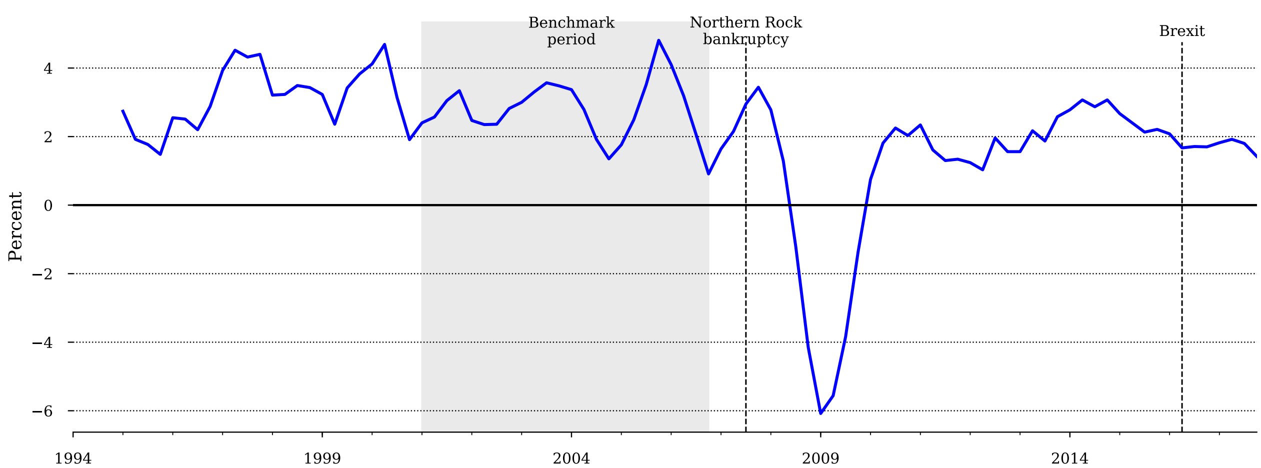
Note: Values are means across bins in the sample designated by the column. Values in parentheses are standard errors of the mean. Equation (3) terms are scaled by 100. Equation (5) terms are scaled by 10,000.

Figure 1: U.K. inflation, GDP growth, and exchange rate

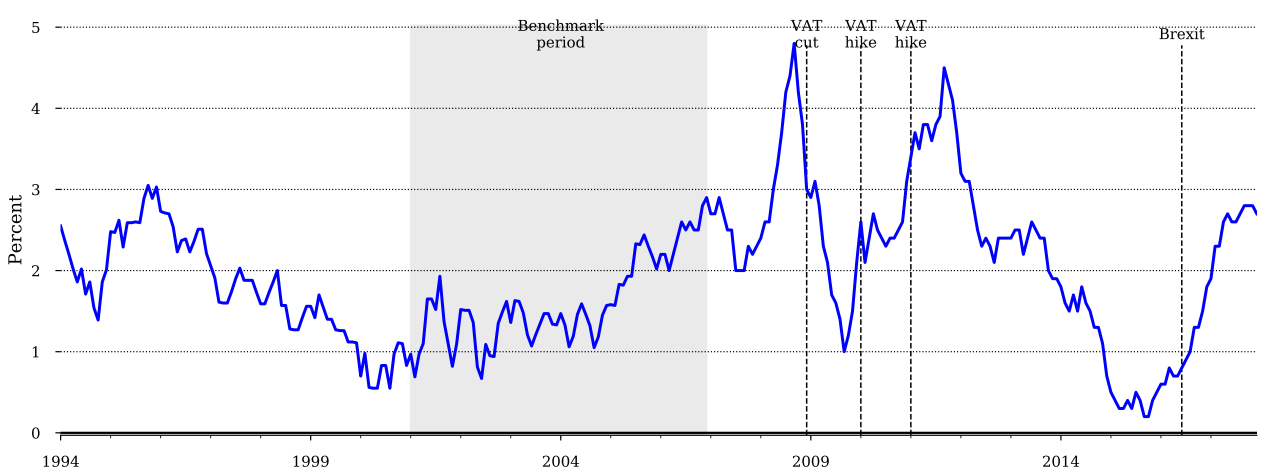
(a) *GBP effective exchange rate, trade-weighted*



(b) *GDP growth, 4-quarter growth rate*

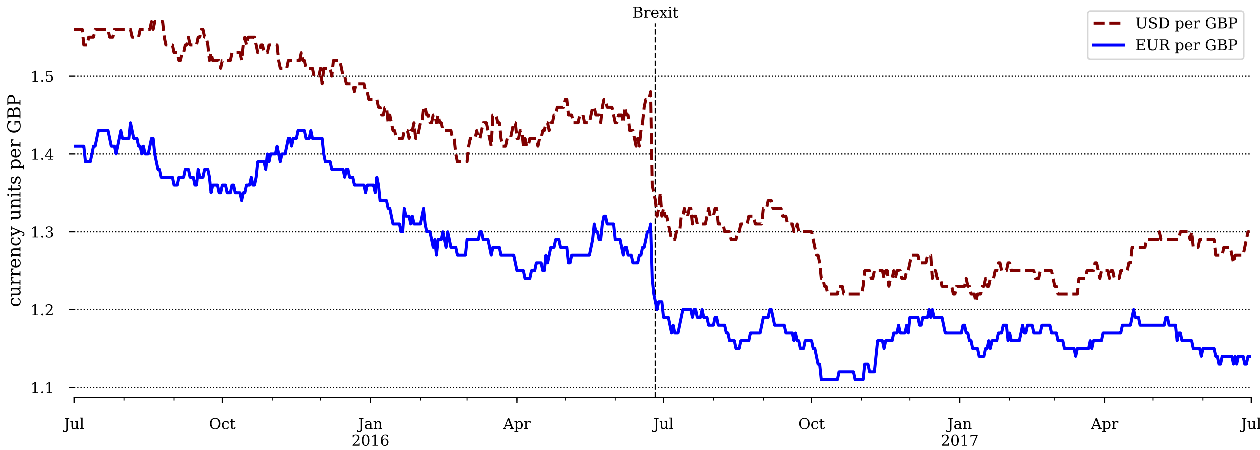


(c) *CPI inflation, 12-month inflation rate*



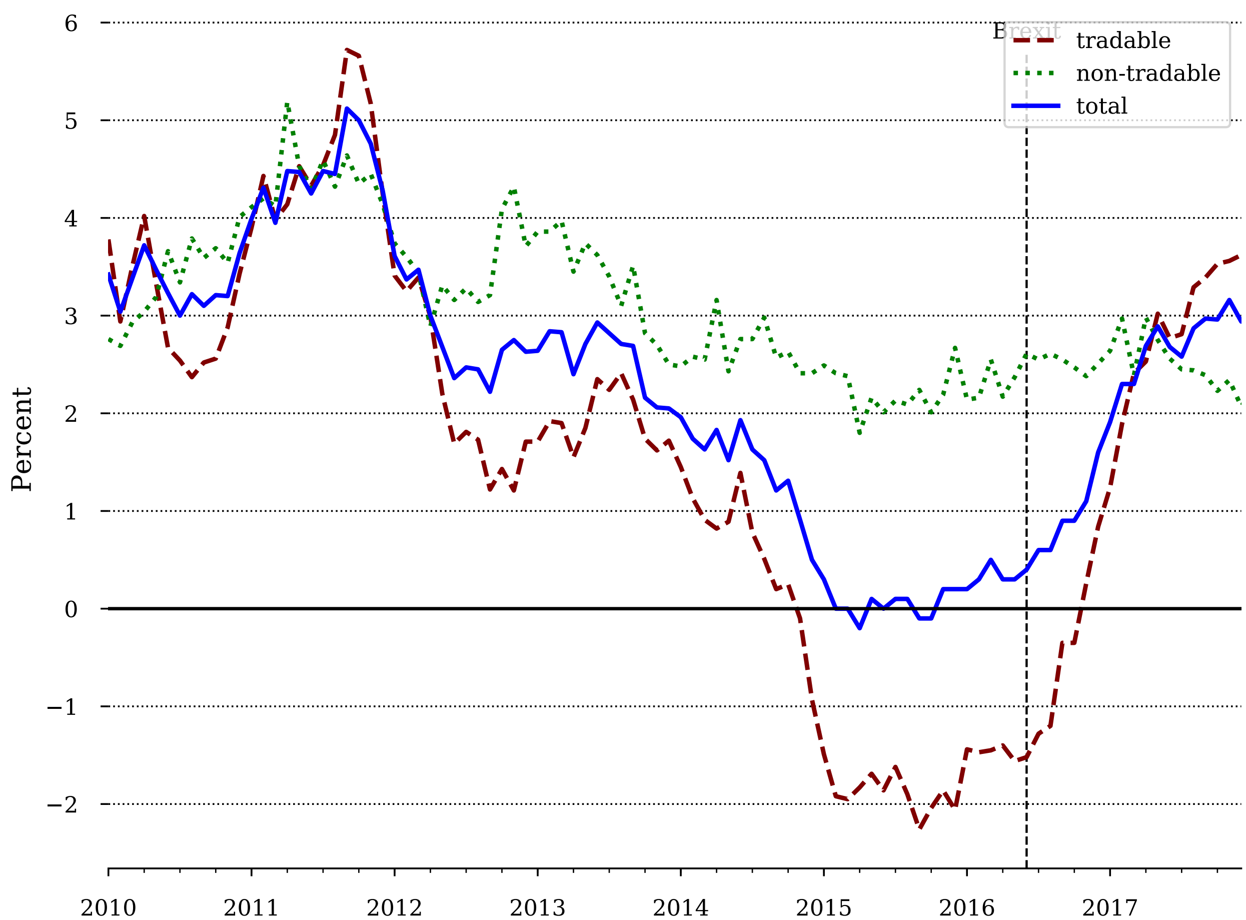
Source: (a) Bank for International Settlements (BIS), (b) ONS, (c) ONS

Figure 2: Daily exchange rate of GBP against USD and EUR



Source: Federal Reserve Board of Governors and European Central Bank

Figure 3: U.K. CPI inflation total, for tradable COICOPs, and non-tradable COICOPs



Source: ONS and authors' calculations

Figure 4: Structure of U.K. CPI data

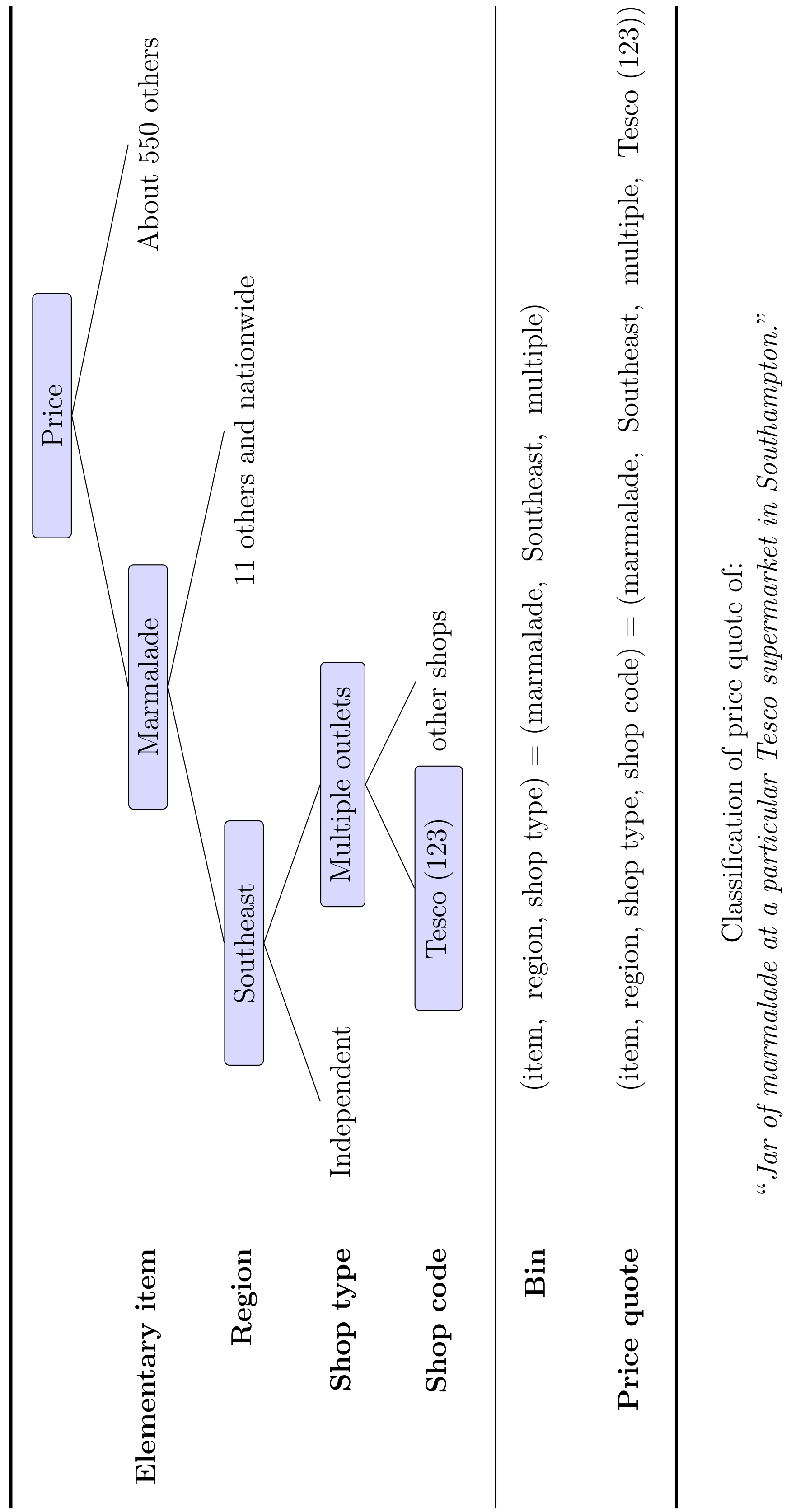
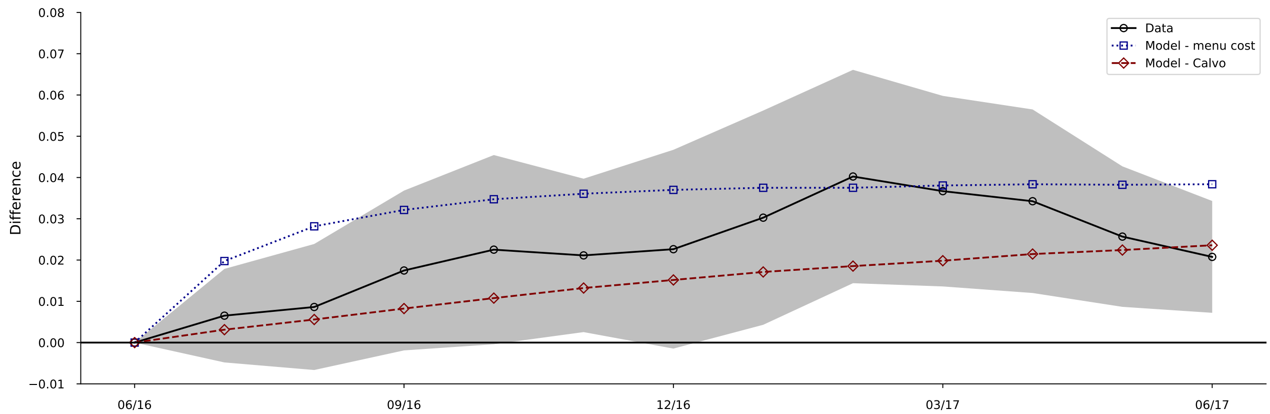
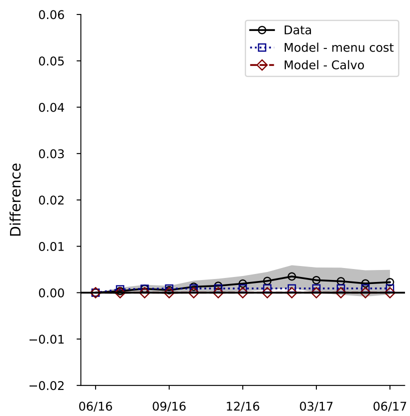


Figure 5: Model and data impulse responses: First-order moments

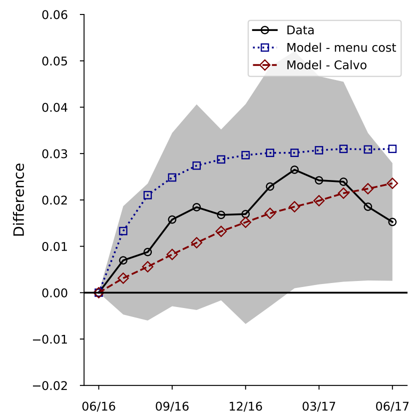
(a) *Mean log price*



(b) *Incidence*



(c) *Magnitude*



(d) *Interaction*

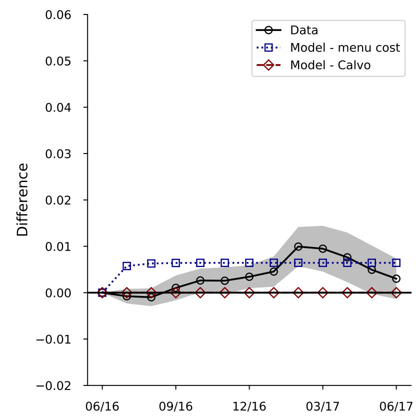
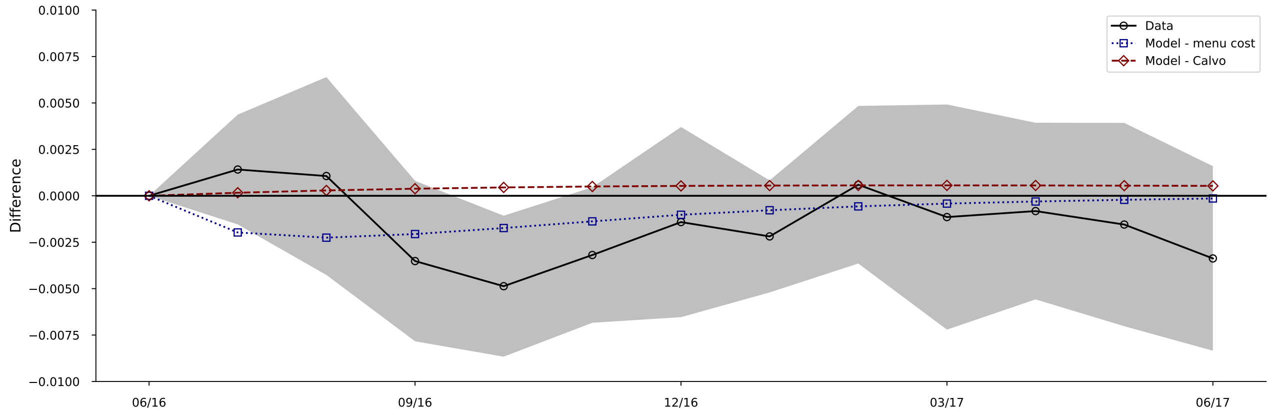
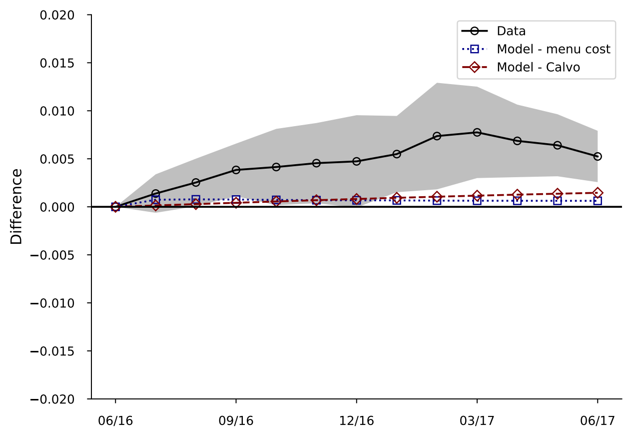


Figure 6: Model and data impulse responses: Second-order moments

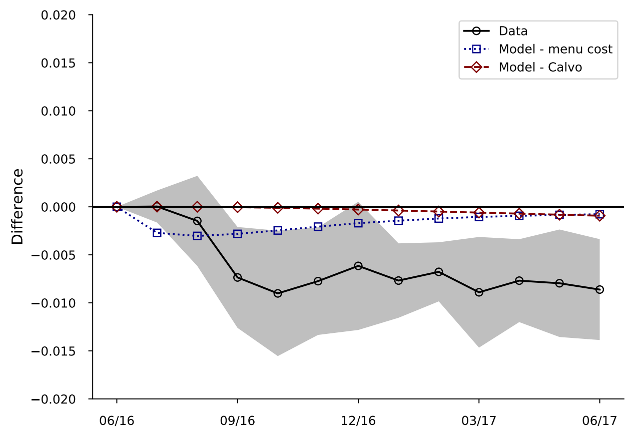
(a) *Variance of log prices*



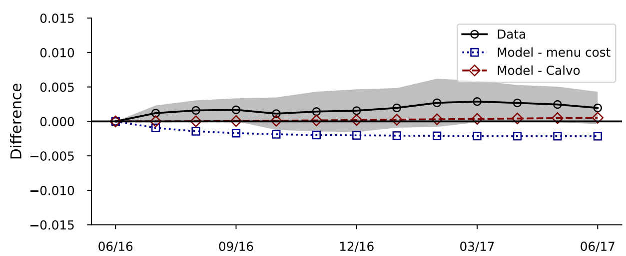
(b) *Variance of inflation*



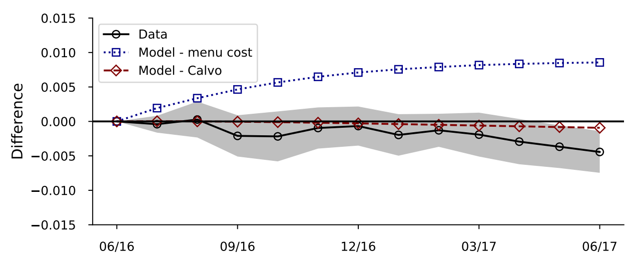
(c) *Mean reversion of inflation*



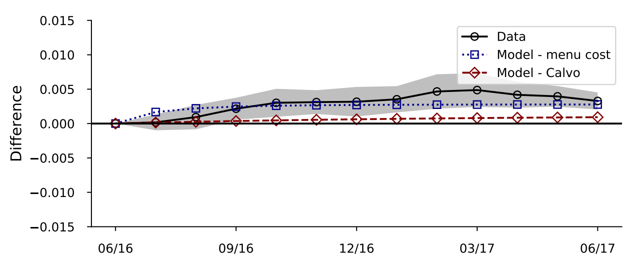
(d) *Variance of magnitude*



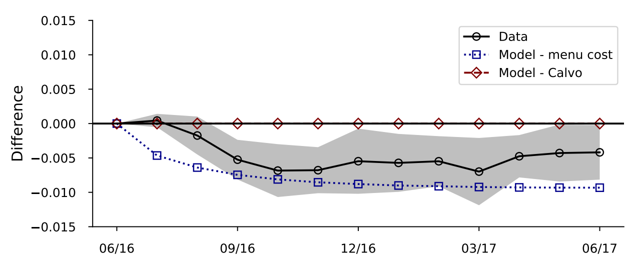
(e) *Mean reversion of magnitude*



(f) *Variance of incidence*



(g) *Mean reversion of incidence*



Appendix to "Using Brexit to Identify the Nature of Price Rigidities"

A Mathematical details

A.1 Details on decomposition of price dynamics

We derive the decompositions of the change in the mean of the log prices and price disparity including entry into and exit out of the sample of price quotes. We then show how these generalized decompositions nest the those in the main text for matched models when there is no such entry and exit.

To do so, we introduce notation to capture the potential existence of non-matched price quotes in the sample of quotes in a bin in month t. Let the set A denote *all* region-store-type-store-code-specific price quotes we have on an elementary item in a bin in months $t-1$ and t. These quotes include the matched sample, $M = S \cup C$, that we focus on in the main text. They also include two additional sets of quotes. The first are those for which we have a price quote in month $t-1$ but not in month t. These are the n^X_{t-1} quotes that have *exited*, E, the sample of quotes for the bin. The second are those price quotes for which we observe the price in month t but for which no price was reported in $t-1$. These are the n^E_t quotes that *enter* the sample in month t. These set of all price quotes is $A = M \cup X \cup E$.

However, with entry and exit, we decompose the change in the mean and variance of the distribution of *all* price quotes. The set of n^A_{t-1} price quotes in month $t-1$ is made up of the matched, M, and exiting, X, quotes, *i.e.*, $n^A_{t-1} = n^M_t + n^X_{t-1}$. The set of price n^A_t quotes in month t is made up of the matched, M, and entering, E, quotes, *i.e.*, $n^A_t = n^M_t + n^E_t$. So, what the additional notation for entry and exit allows us to do is to specifically account for sample turnover.

Decomposition of the change in the sample mean of log prices

The notation that includes entry, E, and exit, X, allows us to define the sample mean of these price quotes in months $t-1$ and t as

$$\bar{p}^A_{t-1} = \frac{1}{n^A_{t-1}} \sum_{j \in \{M,X\}} p_{j,t-1} \text{ and } \bar{p}^A_t = \frac{1}{n^A_t} \sum_{j \in \{M,E\}} p_{j,t}. \tag{A.1}$$

Our focus here is on decomposing the change in this mean between months $t-1$ and t, i.e $\Delta \bar{p}^A_t$, in terms of the sample means conditional on changing prices, M, keeping prices the same, S, entering, E, and exiting, X.

These conditional means are defined as

$$\bar{p}_{t-1}^{S} = \frac{1}{n_t^S}\sum_{j\in S} p_{j,t},\ \bar{p}_{t-1}^{C} = \frac{1}{n_t^C}\sum_{j\in C} p_{j,t-1},\text{ and } \bar{p}_{t-1}^{X} = \frac{1}{n_{t-1}^X}\sum_{j\in X} p_{j,t-1} \tag{A.2}$$

at $t-1$ and as

$$\bar{p}_{t}^{S} = \frac{1}{n_t^S}\sum_{j\in S} p_{j,t},\ \bar{p}_{t}^{C} = \frac{1}{n_t^C}\sum_{j\in C} p_{j,t},\text{ and } \bar{p}_{t}^{E} = \frac{1}{n_t^E}\sum_{j\in E} p_{j,t} \tag{A.3}$$

at t. Note that, because for $j \in S$ the price does not change such that $p_{j,t} = p_{j,t-1}$, it is also the case that $\bar{p}_{t-1}^S = \bar{p}_t^S$.

Using these conditional means and sample sizes, we can write

$$\bar{p}_{t-1}^{A} = \frac{n_t^M}{n_{t-1}}\bar{p}_{t-1}^{M} + \frac{n_{t-1}^X}{n_{t-1}}\bar{p}_{t-1}^{X}, \tag{A.4}$$

and

$$\bar{p}_{t}^{A} = \frac{n_t^M}{n_{t}}\bar{p}_{t}^{M} + \frac{n_{t}^E}{n_{t}}\bar{p}_{t}^{E}. \tag{A.5}$$

Of course, because we do not observe prices in adjacent months for the non-matched quotes in the bin, we can only calculate the inflation rate $\pi_{j,t} = p_{j,t} - p_{j,t-1}$ for matched items. The ONS uses the equally-weighted matched-model geometric price index inflation rate as the inflation rate for bin:

$$\pi_t = \frac{1}{n_t^M}\sum_{j\in M}\Delta p_{j,t} = \bar{p}_t - \bar{p}_{t-1} \tag{A.6}$$

$$= \left(\frac{n_t^S}{n_t}\bar{p}_t^S + \frac{n_t^C}{n_t}\bar{p}_t^C\right) - \left(\frac{n_t^S}{n_t}\bar{p}_{t-1}^S + \frac{n_t^C}{n_t}\bar{p}_{t-1}^C\right) = \frac{n_t^C}{n_t}\Delta\bar{p}_t^C = \delta_t\Delta\bar{p}_t^C. \tag{A.7}$$

This is what we as the bin-specific inflation rate in the main text and it shows how it is the product of the incidence and magnitude of price changes in the sample of matched price quotes.

This then allows us to rewrite

$$\bar{p}_t^A = \frac{n_t}{n_t^A}\bar{p}_{t-1}^A + \frac{n_t}{n_t^A}\pi_t + \frac{n_t^E}{n_t^A}\bar{p}_t^E \tag{A.8}$$

$$= \frac{n_{t-1}^A}{n_t^A}\bar{p}_{t-1}^A - \frac{n_{t-1}^X}{n_t^A}\bar{p}_{t-1}^X + \frac{n_t}{n_t^A}\pi_t + \frac{n_t^E}{n_t^A}\bar{p}_t^E. \tag{A.9}$$

In terms of the change in the conditional means of log price, this yields

$$\Delta\bar{p}_t^A = \bar{p}_t^A - \bar{p}_{t-1}^A = \frac{n_t}{n_t^A}\pi_t - \frac{n_{t-1}^X}{n_t^A}\left(\bar{p}_{t-1}^X - \bar{p}_{t-1}^A\right) + \frac{n_t^E}{n_t^A}\left(\bar{p}_t^E - \bar{p}_{t-1}^A\right). \tag{A.10}$$

This equation captures the following intuition. The mean log price level can changes for three reasons. First, the mean of the matched price quotes changes. This is captured by the first terms that is directly related to measured inflation. Second, the mean log price of the items that drop out of the sample is not equal to that of those who remain. Third, items enter the sample at a mean log price that is different from the goods in it.

Note how when there is not entry and exit, *i.e.*, $n_t^E = N_{t-1}^X = 0$, the second and third terms of the above equation are zero and $n_t = n_t^A$. Thus, in that case, (A.10) simplifies to (A.7) used in the main text.

Decomposition of the change in price dispersions

A similar derivation can be done for the variance of log prices, *i.e.*, price disparities. We denote this sample variance by

$$\sigma_{A,t}^2 = \frac{1}{n_t^A} \sum_{j \in A} \left(p_{j,t} - \bar{p}_t^A \right)^2 . \tag{A.11}$$

Our decomposition splits the change in this variance, $\Delta\sigma_{A,t}^2$, into parts related to conditional means and variances based on the four subsamples, $\{S, C, E, X\}$. In particular, we consider

$$\sigma_{\pi,t}^2 = \frac{1}{n_t} \sum_{j \in M} \left(\pi_{j,t} - \pi_t \right)^2 , \tag{A.12}$$

$$\sigma_{\pi p_{t-1},t} = \frac{1}{n_t} \sum_{j \in M} \left(\pi_{j,t} - \pi_t \right) \left(p_{j,t-1} - \bar{p}_{t-1} \right) , \tag{A.13}$$

$$\sigma_{X,t-1}^2 = \frac{1}{n_{t-1}^X} \sum_{j \in X} \left(p_{j,t-1} - \bar{p}_{t-1}^X \right)^2 \tag{A.14}$$

$$\sigma_{E,t}^2 = \frac{1}{n_t^E} \sum_{j \in E} \left(p_{j,t} - \bar{p}_t^E \right)^2 . \tag{A.15}$$

Given this notation, we can write

$$\sigma_{\pi,t}^2 = \frac{n_{t-1}^A}{n_t^A} \sigma_{A,t-1}^2 + \frac{n_t}{n_t^A} \sigma_{\pi,t}^2 + 2 \frac{n_t}{n_t^A} \sigma_{\pi p_{t-1},t} - \frac{n_{t-1}^X}{n_t^A} \sigma_{X,t-1}^2 + \frac{n_t^E}{n_t^A} \sigma_{E,t}^2 \tag{A.16}$$

$$+ \frac{n_t}{n_t^A} \left(\bar{p}_t - \bar{p}_t^A \right)^2 - \frac{n_t}{n_t^A} \left(\bar{p}_{t-1} - \bar{p}_{t-1}^A \right)^2 - \frac{n_{t-1}^X}{n_t^A} \left(\bar{p}_{t-1}^X - \bar{p}_{t-1}^A \right)^2 + \frac{n_t^E}{n_t^A} \left(\bar{p}_t^E - \bar{p}_t^A \right)^2 . \tag{A.17}$$

Writing this in terms of the first difference of the sample variance yields

$$\begin{aligned}
\sigma^2_{A,t} - \sigma^2_{A,t-1} &= \frac{n_t}{n^A_t}\sigma^2_{\pi,t} + 2\frac{n_t}{n^A_t}\sigma_{\pi,p_{t-1},t} - \frac{n^X_{t-1}}{n^A_t}\left(\sigma^2_{X,t-1} - \sigma^2_{A,t-1}\right) + \frac{n^E_t}{n^A_t}\left(\sigma^2_{E,t} - \sigma^2_{A,t-1}\right) && \text{(A.18)}\\
&+ \frac{n_t}{n^A_t}\left(\bar{p}_t - \bar{p}^A_t\right)^2 - \frac{n_t}{n^A_t}\left(\bar{p}_{t-1} - \bar{p}^A_{t-1}\right)^2 && \text{(A.19)}\\
&- \frac{n^X_{t-1}}{n^A_t}\left(\bar{p}^X_{t-1} - \bar{p}^A_{t-1}\right)^2 + \frac{n^E_t}{n^A_t}\left(\bar{p}^E_t - \bar{p}^A_t\right)^2.
\end{aligned}$$

The interpretation of the above equation is as follows. The variance in the log prices changes for the following reasons:

- **$\sigma^2_{\pi,t}$:** Because prices do not go up at the same rate.
- **$\sigma_{\pi,p_{t-1},t}$:** Because prices that were already high increased more than low prices (or vice versa). This is what this covariance captures.
- **$\left(\sigma^2_{X,t-1} - \sigma^2_{A,t-1}\right)$:** Because there was more (or less) variation in the prices of the items that exited than in the matched items.
- **$\left(\sigma^2_{E,t} - \sigma^2_{A,t-1}\right)$:** Because there was more (or less) variation in the prices of the items that entered than in the matched items.

The last four terms capture the effect locational shift effects on the variance when the mean log price of exiting and entering items is different from those that are matched. Notice that, in the absence of entry and exit, i.e $n_t = N^A_t$ and $n^X_{t-1} = n^E_t = 0$, all but the first two terms of the above expression are zero. These remaining two terms in the absence of entry and exit are the *variance of inflation*, $\sigma_{\pi,t}$, and the *mean reversion of inflation*, *i.e.*, $\sigma_{\pi p_{t-1},t}$.

The decomposition of the change in price disparities in the main text, which abstracts from entry and exit divides the the variance of inflation, $\sigma_{\pi,t}$, up into two parts. In particular, it uses that

$$\begin{aligned}
\sigma^2_{\pi,t} &= \frac{1}{n_t}\sum_i\left(\pi_{j,t} - \pi^C_t + \pi^C_t - \pi_t\right)^2 && \text{(A.20)}\\
&= \frac{1}{n_t}\sum_i\left(\pi_{j,t} - \pi^C_t\right)^2 + 2\frac{1}{n_t}\sum_i\left(\pi_{j,t} - \pi^C_t\right)\left(\pi^C_t - \pi_t\right) + \frac{1}{n_t}\sum_i\left(\bar{\pi}^C_t - \bar{\pi}_t\right)^2 && \text{(A.21)}\\
&= \frac{n_t - n^C_t}{n_t}\left(\pi^C_t\right)^2 + \frac{1}{n_t}\sum_{i\in C}\left(\pi_{j,t} - \pi^C_t\right)^2 - \left(\pi^C_t - \pi_t\right)^2 && \text{(A.22)}\\
&= \frac{n^C_t}{n_t}\left(\sigma^C_{\pi,t}\right)^2 - \left(\pi^C_t - \pi_t\right)^2 + \frac{n_t - n^C_t}{n_t}\left(\pi^C_t\right)^2 && \text{(A.23)}\\
&= \delta_t\left(\sigma^C_{\pi,t}\right)^2 + \left(1-\delta_t\right)\delta_t\left(\pi^C_t\right)^2. && \text{(A.24)}
\end{aligned}$$

The first term on the last line captures that the variance of inflation across all matched items is increasing in *the variance of magnitude* of the changes in the price quotes in C. The second term captures that the variance of inflation also depends on 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 from a Bernoulli distribution with mean δ_t. The associated variance is $\delta_t(1-\delta_t)$ which is what is included in the second term of the last line above.

As for the *mean reversion of inflation*, *i.e.*, $\sigma_{\pi,p_{t-1},t}$, we use that it can be split up as follows:

$$\begin{aligned}
\sigma_{\pi,p_{t-1},t} &= \frac{1}{n_t}\sum_{j\in M}(\pi_{j,t}-\pi_t)(p_{j,t-1}-\bar{p}_{t-1}) = \frac{1}{n_t}\sum_{j\in M}\left(\pi_{j,t}-\pi_t^C\right)(p_{j,t-1}-\bar{p}_{t-1}) && \text{(A.25)}\\
&= -\frac{n_t-n_t^C}{n_t}\pi_t^C\frac{1}{n_t^S}\sum_{j\in S}(p_{j,t-1}-\bar{p}_{t-1}) + \frac{n_t^C}{n_t}\frac{1}{n_t^C}\sum_{j\in C}\left(\pi_{j,t}-\pi_t^C\right)(p_{j,t-1}-\bar{p}_{t-1}) && \text{(A.26)}\\
&= \delta_t\sigma_{\pi,p_{t-1},t}^C - (1-\delta_t)\pi_t^C\left(\bar{p}_{t-1}^S-\bar{p}_{t-1}\right) = \delta_t\sigma_{\pi,p_{t-1},t}^C + \delta_t\pi_t^C\left(\bar{p}_{t-1}^C-\bar{p}_{t-1}\right) && \text{(A.27)}
\end{aligned}$$

The first term here, $\delta_t\sigma_{\pi,p_{t-1},t}^C$, 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. The second 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. We call this the *mean reversion of incidence* of price changes.

Combining the above two results with equation (A.18) without entry and exit yields that

$$\begin{aligned}
\sigma_t^2-\sigma_{t-1}^2 &= \sigma_{\pi,t}^2 + 2\sigma_{\pi,p_{t-1},t} && \text{(A.28)}\\
&= \delta_t\left(\sigma_{\pi,t}^C\right)^2 + (1-\delta_t)\delta_t\left(\pi_t^C\right)^2 + 2\delta_t\sigma_{\pi,p_{t-1},t}^C + 2\delta_t\pi_t^C\left(\bar{p}_{t-1}^C-\bar{p}_{t-1}\right),
\end{aligned}$$

which is equation (5) in the main text.

B Data Appendix

B.1 Bin construction

Shop price quotes are collected in the United Kingdom by the Office of National Statistics (ONS) to measure inflation at a monthly rate. ONS classifies each shop price quote by: month, item, region, and shop type. A region refers to the 12 geographic regions (defined by ONS) and shop type refers to either “multiples” (chain stores with 10 or more outlets) or “independents” (less than 10 outlets). ONS defines another layer of classification, called stratification which divides the data into different “stratum.” They refer to four different “stratum types:” not stratified, region, region and shop type, and shop type. They also refer to "stratum cells" which track subgroups within a stratum type.[22] They provide a region identifier for all price quotes, even those with stratum type "shop type." In order to control for any regional heterogeneity across the entire data set, we added a region identifier to ONS stratum types "not stratified" and "shop type." For any given item, this places each shop quote into one of 72 "bins:"[23]

Stratum Type	# of bins per item
Not stratified (with region identifier)	12 bin (1 per region)
Region	12 bins (1 per region)
Shop type (with region identifier)	24 bins (12 regions × 2 shop types)
Region and Shop type	24 bins (12 regions × 2 shop types)

For a given region, there will be up to 6 separate bins. For example, for a given item sold in a shop in London there is a bin called "London, not stratified," "London, stratified by region," "London, multiple, stratified by shop type," "London, multiple, stratified by region/shop type," "London, independent, stratified by shop type," and "London, independent, stratified by region/shop type."

B.2 Comparison of price quote data with published CPI

The price quotes collected are aggregated up a tree of item groupings and weighting systems to eventually arrive at an overall aggregate measure of national inflation, the consumer price index (CPI). The aggregation tree from shop price quotes to headline CPI is below:

$$\text{shop price quotes} \rightarrow \text{item-stratum} \rightarrow \text{item} \rightarrow \text{COICOP Class} \rightarrow \text{COICOP Group} \rightarrow \text{COICOP Division} \rightarrow \text{Headline}$$

where at higher levels of aggregation, the Classification of Individual Consumption According to Purpose (COICOP) system is used. Price quotes are not available for all items in the published CPI. Specifically, price quotes are available for 61 percent of the UK data, representing 69 of the 85 COICOP classes (see columns 1 through 3 of Table A2).[24] Figure A1 shows three inflation series:[25] (1) the headline CPI inflation published by the ONS; (2) published item-index inflation,

[22] For example, stratum type "region" has 12 cells, while stratum type "shop type" has 2 cells.

[23] Note that not all items are in every bin in the data.

[24] These 16 excluded COICOP classes are insurance connected with dwelling, insurance connected with health, insurance connected with transport, other financial services, water supply, sewage collection, electricity, gas, new cars, second hand cars, passenger transport by railway, passenger transport by air, passenger transport by sea, postal services, newspapers and books, package holidays.

[25] All series are year-over-year percentage change in the index.

for all items that are available in the price quote data,[26]; and (3) price quote inflation, using the price-quotes published by the ONS. The available price quote data does a fairly good job of representing the headline published CPI data. Furthermore, the differences between series (2) and (3) are minimal, showing the consistency of the price quote and weighting methods used in this study.

B.3 Data cleaning

In addition to removing sales, recoveries, and clothing, we removed price quotes that were likely errors or that we did not have enough data per bin. Specifically, we cleaned the data with the following steps:

- Removed prices quotes ONS deemed invalid or non-comparable.
- Removed noisy bins:
  - Removed all observations with less than 4 shop quotes (not frequency weighted by shop weight) in an item-bin-month.
  - Dropped item-bin-months with very large confidence intervals. Construct a 95 percent confidence interval around the variance of log prices using the χ^2 distribution, for each item-bin-month. We then drop item-bin-months with confidence intervals in the top 1 percent of all confidence intervals.
- Winsorized on the variable $\Delta\sigma_t^2$ at the item-bin level at the 1^{st} and 99^{th} percentile.
- Corrected for an error found in the price quote data where base prices were incorrectly inputed as the value .0004. All price quotes with base price equal to .0004 are removed.
- Removed incorrect quotes from the January 1999 release. The item IDs of items removed are: 510209, 510226, 510121, 510206, 510220, 510230, 510231, 510428, 510506, 510511, 510514, 510521, 510523.
- Removed other items from the January 1999 release. These item indices created from the price quote data were significantly greater than the item indices published by the ONS. We remove items in the top 15 percent of the distribution of item indices created from price quotes relative to item indices published by the ONS.

[26] ONS publishes indexes aggregated up to the item level

- Removed observations in which shops have the same identification code in the same region and stratum. The ONS is not authorized to release the remaining variables to uniquely identify shops.
- Dropped observations from May 2005, for which most price quote data are missing.
- Exclude sales from the sample.

Figure A2 illustrates the effects of data cleaning on the inflation series: the time series labeled as (3) reproduces the price quote inflation series in Figure A1, the series labeled as (4) removes sale and recoveries, (5) removes clothing, as well as sale and recoveries, and (6) reports the final cleaned data. Most of the discrepancy between the final data (series 6) and the original PQ series (series 3) stems from dropping sales. However, this is mainly a level shift as the time series patterns remain similar.

Table A2 shows the effects of data cleaning on the sample size. The final price quote data represents 54 percent of the headline CPI number, but approximately 90 percent (*i.e.*, .54/.61) of the available price quote data.

C Estimation details

We estimate equation (6) on three sets of dependent variables ($y_{i,t+h}$):

(i) the log price level, $p_{i,t}$, and its three time-varying components described in equation (4):

$$p_{i,t+h} - p_{i,t-1} = \beta^h \mathbb{B}_t * \mathbb{T}_i + \delta^h \mathbb{B}_t + \gamma_i + \sum_{c=1}^{3} \sum_{k=1}^{12} \left(\alpha_{c,k}^h \Delta C_{c,i,t-k} + \phi_{c,k}^h \Delta C_{c,i,t-k} * \mathbb{T}_i \right) + \varepsilon_{i,t}, \quad \text{(C.29)}$$

$$C_{c,i,t+h} - C_{c,i,t-1} = \beta^h \mathbb{B}_t * \mathbb{T}_i + \delta^h \mathbb{B}_t + \gamma_i + \sum_{c=1}^{3} \sum_{k=1}^{12} \left(\alpha_{c,k}^h \Delta C_{c,i,t-k} + \phi_{c,k}^h \Delta C_{c,i,t-k} * \mathbb{T}_i \right) + \varepsilon_{i,t}, \quad \text{(C.30)}$$

where $c = 1, 2, 3$.

(ii) the variance of log prices, $\sigma_{i,t}$, and its components described in equation (5),

$$\sigma_{i,t+h} - \sigma_{i,t-1} = \beta^h \mathbb{B}_t * \mathbb{T}_i + \delta^h \mathbb{B}_t + \gamma_i + \sum_{c=1}^{4} \sum_{k=1}^{12} \left(\alpha_{c,k}^h \Delta C_{c,i,t-k} + \phi_{c,k}^h \Delta C_{c,i,t-k} * \mathbb{T}_i \right) + \varepsilon_{i,t}, \quad \text{(C.31)}$$

$$C_{c,i,t+h} - C_{c,i,t-1} = \beta^h \mathbb{B}_t * \mathbb{T}_i + \delta^h \mathbb{B}_t + \gamma_i + \sum_{c=1}^{4} \sum_{k=1}^{12} \left(\alpha_{c,k}^h \Delta C_{c,i,t-k} + \phi_{c,k}^h \Delta C_{c,i,t-k} * \mathbb{T}_i \right) + \varepsilon_{i,t}, \quad \text{(C.32)}$$

where $c = 1, 2, 3, 4$. Note that, although we take the 4 subcomponents of equation (5) as dependent and control variables, we also consider the variance of inflation ($\sigma^2_{\pi,t}$) and $\sigma_{\pi,p_{t-1},t}$ as dependent variables.

(iii) the log price level ($p^z_{i,t+h}$) of the $z \in \{10^{th}, 50^{th}, 90^{th}\}$ price percentile firm

$$p^z_{i,t+h} - p^z_{i,t-1} = \beta^h \mathbb{B}_t * \mathbb{T}_i + \delta^h \mathbb{B}_t + \gamma_i + \sum_{k=1}^{12} \left(\alpha^h_k \pi^z_{i,t-k} + \phi^h_k \pi^z_{i,t-k} * \mathbb{T}_i \right) + \varepsilon_{i,t}, \tag{C.33}$$

for $z = \{10^{th}, 50^{th}, 90^{th}\}$ percentiles.

For each horizon h the dependent variables are constructed as such that, 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 $\pi_{b,i,t} = \sum \omega_{s,b,i} \frac{p_{s,b,i,t}}{p_{s,b,i,t-1}}$ 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.

For the components in equations (4) and (5), $C_{c,i,t+h} - C_{c,i,t-1} = \sum_{\tau=1}^{h} \Delta C_{c,i,t+\tau}$ for each $c \in \{1, 2, 3\}$ and $c \in \{1, 2, 3, 4\}$, respectively.

Finally, $\pi^z_{i,t} = \sum \omega_{b,i} \pi^z_{b,i,t}$ and $\pi^z_{b,i,t}$ is the change in log price for the shop whose price was the z^{th} percentile in bin b at time $t-1$ and $\omega_{b,i}$ are bin-weights provided by ONS. That is, $\pi^z_{b,i,t} = [\frac{p_{s,b,i,t}}{p_{s,b,i,t-1}} | p_{s,b,i,t-1} = p^z_{s,b,i,t-1}]$, where $p^z_{s,b,i,t-1}$ represents the z^{th} percentile price (frequency weighted) in bin b for item i. It follows that the dependent variable is the sum of the monthly price changes: $p^z_{i,t+h} - p^z_{i,t-1} = \sum_{\tau=1}^{h} \pi^z_{i,t+\tau}$. Since we do not decompose this variable, the controls include lags of the dependent variable as opposed to the components.

Results for the estimation of the regressions described in items (i) and (ii) are reported in the main text. Results for the estimation of the regresions described in item (iii) are reported in the Appendix Figure A3. The latter set of plots confirm the shrinking of the distribution of prices as the prices at lower percentiles are adjusted by more.

C.1 Synthetic control approach

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 Tables 3 and A3, 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, *i.e.* 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 do sticky-priced items. Such differences in characteristics of the treated group from the comparison group could potentially convolute the empirical results.

In this section, we implement the synthetic control method of Abadie, Diamond and Hainmueller (2010) which alleviates the possible concern that the treated and control items have different characteristics. The authors propose a "synthetic" control group that can be constructed as a convex combination of control items that most closely resembles the characteristics of the treated group. They refer to this set of goods as the "donor pool," which, in our context, includes items are that are both nontradable and in the lower tertile import share.[27]

To construct the synthetic control group, one needs to choose the set of characteristics to be matched with the treated group. We include as predictors the frequency of price changes (δ_t), the inflation of price changes (π_t^C), the variance of inflation ($\sigma^2_{\pi,t}$), and the mean reversion of price changes ($2\sigma_{\pi,p_{t-1},t}$). The statistics of interest are obtained by averaging over the pre-Brexit period (2015m6-2016m5). By construction, the synthetic control group closely resembles the treated group in the pre-Brexit period.

Tables A4 and A5 compare pre-Brexit mean characteristics of tradables (the treated group) and the synthetic control group. By construction, the synthetic control group closely resembles the treated group.[28] Notably, Table A4 shows that the frequency of adjustment for the synthetic control and the treated group are approximately the same for almost all variables of interest.[29]

The effect of the exchange rate shock is measured as the difference between the treated and control groups in the post Brexit period. We plot this difference in Figures A4 and A5 as a red dashed line along with the main results of our study. The results from the synthetic control method reinforce our main empirical findings. Figures A4 and A5 show that the effect of the exchange rate shocks on tradables through local projections and the synthetic control methods are quite close to one another across all variables.

[27]The synthetic approach is known to be sensitive to the set of items included in the donor poll. For that reason, we exclude "books" from the donor pool, as the synthetic control method are particularly sensitive to this group of items. None of our main results of Section 4.2 (using local projections) change when books are excluded from that sample.

[28]Note that the means of the treated group shown in Tables A4 and A5 are weighted means (by ONS provided item weights) and therefore do not match the summary statistics in Tables 3 and A3 which are ordinary arithmetic means.

[29]Appendix Tables A4 and A5 compare pre-Brexit mean characteristics of tradables (the treated group) and the synthetic control group. Notably, Table A4 shows that the frequency of adjustment for the synthetic control and the treated group are approximately the same for almost all variables of interest.

Figures **??** and **??** plot the synthetic control against the treated group. More specifically, the plots normalize levels to 2016m6 and extrapolate the changes in each variable forward and backwards. The Figures show that the synthetic control and the treated group have similar trends before Brexit, which lends further support that the synthetic control resembles the treated group in the pre-treatment period.

Table A1: Sample set up for price quotes at bin level at times $t-1$ and t

Panel (a): First-order unconditional and conditional moments

Category	Name	log prices $t-1$	log prices t	sample size $t-1$	sample size t	sample mean $t-1$	sample mean t	inflation t	incidence t
M	matched	$p_{j,t-1}$	$p_{j,t}$	n_t	n_t	$\bar{p}_{t-1}$	$\bar{p}_t$	$\pi_t = \Delta\bar{p}_t$	δ_t
C	price change	$p_{j,t-1}$	$p_{j,t}$	n_t^C	n_t^C	$\bar{p}_{t-1}^C$	$\bar{p}_t^C$	$\pi_t^C = \Delta\bar{p}_t^C$	1
S	same price	$p_{j,t}$	$p_{j,t}$	n_t^S	n_t^S	$\bar{p}_t^S$	$\bar{p}_t^S$	0	0
		Entry and exit of price quotes (Appendix A)							
A	All	$p_{j,t-1}$	$p_{j,t}$	n_{t-1}^A	n_t^A	$\bar{p}_{t-1}^A$	$\bar{p}_t^A$	-	-
E	entering items	-	$p_{j,t}$	0	n_t^E	-	$\bar{p}_t^E$	-	-
X	exiting items	$p_{j,t-1}$	-	n_{t-1}^X	0	$\bar{p}_{t-1}^X$	-	-	-

Panel (b): Second-order unconditional and conditional moments

Category	Name	sample variance of log prices $t-1$	sample variance of log prices t	sample variance of inflation t	sample covariance between $\pi_{j,t}$ and $p_{j,t-1}$ t
M	matched	σ_{t-1}^2	σ_t^2	$\sigma_{\pi,t}^2$	$\sigma_{\pi,p_{t-1},t-1}$
C	price change	$\sigma_{C,t-1}^2$	$\sigma_{C,t}^2$	$\sigma_{C,\pi,t}^2$	$\sigma_{C,\pi,p_{t-1},t-1}$
S	same price	$\sigma_{S,t}^2$	$\sigma_{S,t}^2$	0	0
		Entry and exit of price quotes (Appendix A)			
A	All	$\sigma_{A,t-1}^2$	$\sigma_{A,t}^2$	$\sigma_{A,\pi,t}^2$	-
E	entering items	-	$\sigma_{E,t}^2$	-	-
X	exiting items	$\sigma_{X,t-1}^2$	-	-	-

Note: For example, $\bar{p}_{t-1}^X = \frac{1}{n_{t-1}^X}\sum_{j\in X} p_{j,t-1}$, $\delta_t = \frac{n_t^C}{n_t^M}$ $\sigma_{S,t}^2 = \frac{1}{n_t^S}\sum_{j\in S}\left(p_{j,t} - \bar{p}_t^S\right)^2$, $\sigma_{C,\pi,t}^2 = \frac{1}{n_t^C}\sum_{j\in C}\left(\pi_{j,t} - \pi_t^C\right)^2$, and $\sigma_{\pi,p_{t-1},t} = \frac{1}{n_t}\sum_{j\in M}\left(\pi_{j,t} - \pi_t\right)\left(p_{j,t-1} - \bar{p}_{t-1}\right)$.

Table A2: Effects of Data Cleaning on Sample Size

	Published Aggregated Data: CPI	Published Aggregated Data: Item Indexes in PQ data	Price Quote (PQ) Data: All	Price Quote (PQ) Data: No Sales or Clothing	Price Quote (PQ) Data: Final
Weighted Share	1	0.61	0.61	0.55	0.54
Num. Coicop Class	85	69	69	65	65
Num. Item	1446	1163	1163	973	945
Num. Bins	-	-	2,322,346	1,823,117	1,318,542
Num. Obs	-	-	26,629,004	19,755,231	14,524,641

Table A3:

Summary Statistics over Samples

		Benchmark 2001m1 - 2007m12			Pre-shock 2015m6 - 2016m5			Post-shock 2016m7 - 2017m6		
		All	Treat.	Cont.	All	Treat.	Cont.	All	Treat.	Cont
Equation (4)										
π_t	Inflation	0.1572	0.0714	0.2655	0.0567	0.1081	0.1464	0.2627	0.4496	0.2053
		(0.005)	(0.010)	(0.005)	(0.011)	(0.027)	(0.019)	(0.012)	(0.034)	(0.025)
$\bar{\delta}\bar{\pi}^C$	Constant	0.150	0.134	0.242	0.172	0.227	0.207	0.173	0.242	0.206
		(0.0005)	(0.001)	(0.0005)	(0.001)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)
$\bar{\delta}(\pi_t^C - \bar{\pi}^C)$	Magnitude	-0.011	-0.037	0.012	-0.054	-0.056	0.006	0.069	0.091	0.024
		(0.004)	(0.008)	(0.005)	(0.011)	(0.027)	(0.020)	(0.011)	(0.027)	(0.020)
$\bar{\pi}^C(\delta_t - \bar{\delta})$	Incidence	-0.018	-0.023	-0.008	-0.064	-0.062	-0.041	-0.030	0.018	-0.029
		(0.0006)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.005)	(0.003)
$(\delta_t - \bar{\delta})(\pi_t^C - \bar{\pi}^C)$	Interaction	0.036	-0.002	0.019	0.002	-0.002	-0.026	0.051	0.099	0.004
		(0.003)	(0.005)	(0.002)	(0.007)	(0.014)	(0.011)	(0.007)	(0.016)	(0.010)
Equation (5)										
$\Delta\sigma_t^2$	Change in var. of log prices	1.709	2.153	0.132	2.369	11.770	0.788	2.192	4.808	2.680
		(0.156)	(0.490)	(0.325)	(0.485)	(1.769)	(0.924)	(0.532)	(2.230)	(1.146)
$\sigma_{\pi,t}^2$	Variance of inflation	25.089	19.276	11.670	29.120	22.060	19.893	33.754	36.523	25.538
		(0.147)	(0.404)	(0.331)	(0.398)	(0.950)	(0.887)	(0.475)	(1.560)	(1.186)
$\delta_t(\sigma_{\pi,t}^C)^2$	Variance of magnitude	12.743	7.865	6.710	11.527	9.231	12.933	14.924	18.672	18.414
		(0.111)	(0.169)	(0.301)	(0.266)	(0.533)	(0.786)	(0.322)	(0.970)	(1.077)
$(1-\delta_t)\delta_t(\pi_t^C)^2$	Variance of incidence	12.345	11.411	4.959	17.594	12.829	6.960	18.829	17.851	7.125
		(0.079)	(0.351)	(0.106)	(0.257)	(0.675)	(0.308)	(0.301)	(0.874)	(0.304)
$2\sigma_{\pi p_{t-1},t}$	Mean reversion of inflation	-23.380	-17.123	-11.538	-26.752	-10.289	-19.104	-31.562	-31.715	-22.858
		(0.212)	(0.630)	(0.467)	(0.616)	(1.877)	(1.267)	(0.699)	(2.687)	(1.578)
$2\delta_t\sigma_{\pi p_{t-1},t}^C$	Mean reversion of magnitude	-12.638	-7.394	-7.237	-10.901	-3.138	-13.039	-14.864	-18.219	-17.681
		(0.151)	(0.336)	(0.405)	(0.394)	(1.046)	(1.108)	(0.463)	(1.712)	(1.437)
$2\delta_t\pi_t^C(\bar{p}_{t-1}^C - \bar{p}_{t-1})$	Mean reversion of indcidence	-10.742	-9.728	-4.301	-15.851	-7.151	-6.065	-16.697	-13.496	-5.177
		(0.145)	(0.543)	(0.224)	(0.472)	(1.600)	(0.649)	(0.508)	(1.921)	(0.635)
N		412,638	39,514	53,186	66,188	5,198	9,830	66,189	5,002	9,640

Note: Values are means across bins in the sample designated by the column. Values in parantheses are standard errors of the mean. Equation (4) terms are scaled by 100. Equation (5) terms are scaled by 10,000.

Table A4: Predictor Means, first moment variables

	Log Price		Incidence		Magnitude		Interaction	
	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.
Frequency of Price Changes	0.126	0.120	0.126	0.118	0.126	0.113	0.126	0.106
Inflation of Price Changes	0.011	0.011	0.011	0.012	0.011	0.013	0.011	0.014
Variance of Inflation	0.0024	0.0020	0.0024	0.0020	0.0024	0.0025	0.0024	0.0018
Mean Reversion	-0.0012	-0.0019	-0.0012	-0.0020	-0.0012	-0.0028	-0.0012	-0.0021
Dep. Var. (2015m7-2015m12 avg.)	0.0008	0.0008	-0.0004	-0.0004	-0.0018	-0.0017	0.0006	0.0004
Dep. Var. (2016m1-2016m5 avg.)	0.0024	0.0025	-0.0004	-0.0004	0.0009	0.0009	-0.0005	-0.0003

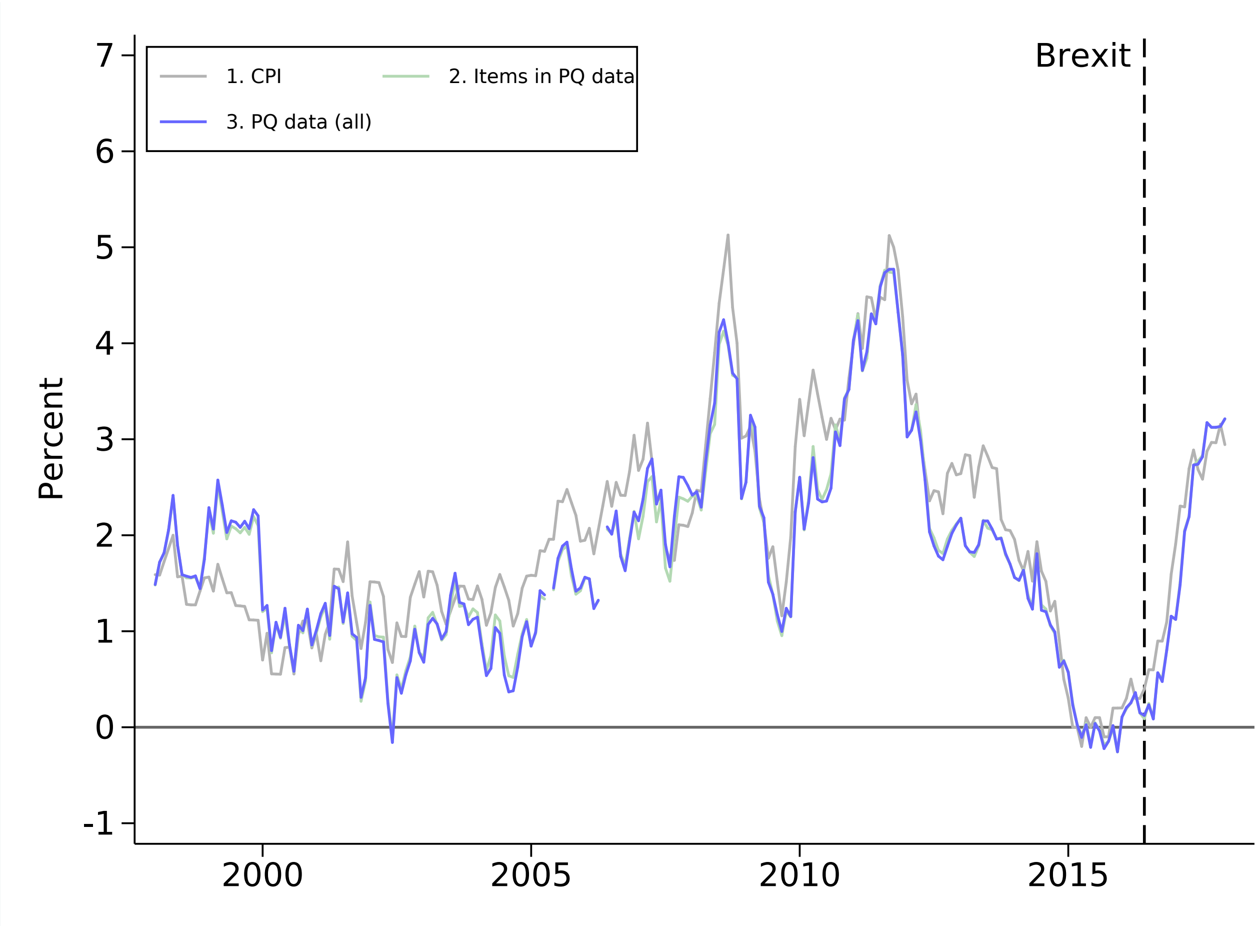
Note: All variables except lagged dependent variable are averaged over the pre-shock period, *i.e.*, 2015m6-2016m5.

Table A5: Predictor Means, second moment variables

	Price disparity		Var. of inf.		Mean rev. of infl.		Var. of mag.		Mean rev. of mag.		Var. of inc.		Mean rev. of inc.	
	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.
Frequency of Price Changes	0.126	0.111	0.126	0.123	0.126	0.123	0.126	0.123	0.126	0.121	0.126	0.104	0.126	0.116
Inflation of Price Changes	0.011	0.009	0.011	0.011	0.011	0.012	0.011	0.011	0.011	0.012	0.011	0.012	0.011	0.013
Variance of Inflation	0.0024	0.0039	0.0024	0.0021	0.0024	0.0015	0.0024	0.0016	0.0024	0.0012	0.0024	0.0033	0.0024	0.0025
Mean Reversion	-0.0012	-0.0036	-0.0012	-0.0021	-0.0012	-0.0016	-0.0012	-0.0017	-0.0012	-0.0013	-0.0012	-0.0035	-0.0012	-0.0027
Dep. Var. (2015m7-2015m12 avg.)	0.0018	0.0003	0.0024	0.0020	-0.0006	-0.0014	0.0013	0.0012	0.0002	-0.0008	0.0012	0.0010	-0.0008	-0.0007
Dep. Var. (2016m1-2016m5 avg.)	0.0002	0.0002	0.0023	0.0023	-0.0021	-0.0020	0.0010	0.0014	-0.0008	-0.0010	0.0013	0.0012	-0.0013	-0.0011

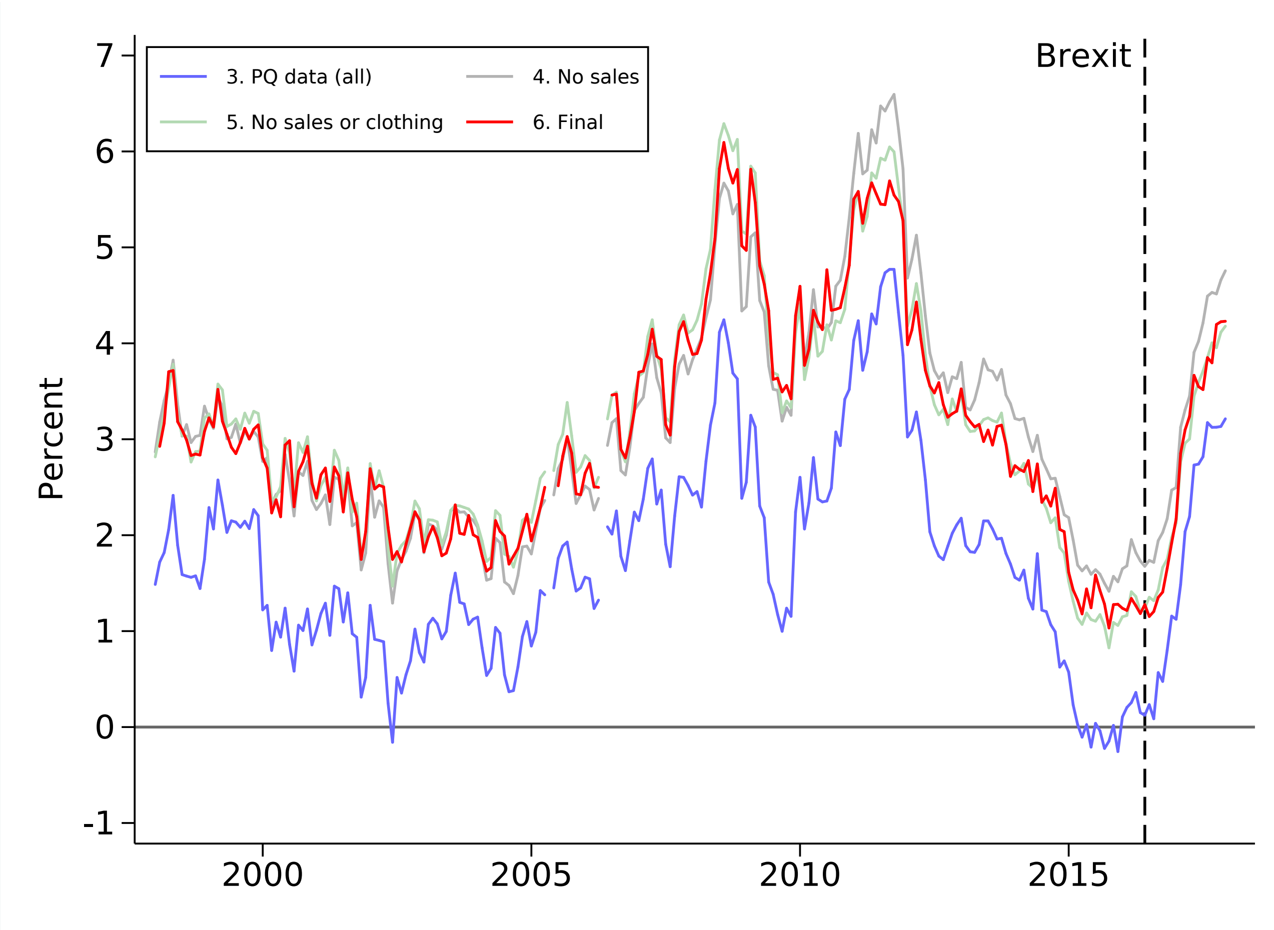
Note: All variables except lagged dependent variable are averaged over the pre-shock period, *i.e.*, 2015m6-2016m5.

Figure A1: Published UK CPI Inflation vs. Inflation based on available price quotes



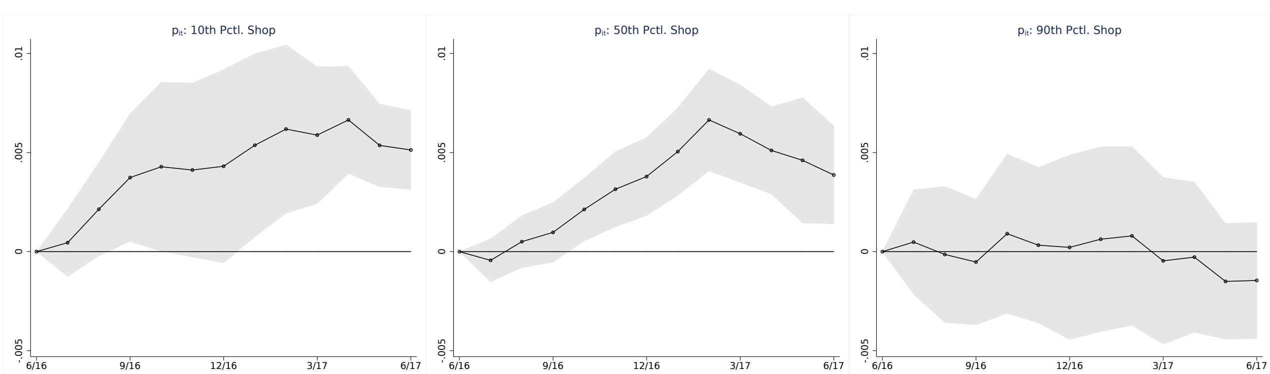
Source: ONS and authors' calculations
Note: Series (1) is the published UK CPI inflation series. Series (2) is the inflation series for all items available in the price quote data, generated using the published item indexes. Series (3) is the inflation series generated from aggregating up the price quote data. All series are year-over-year percentage changes.

Figure A2: Effects of Data Cleaning on Price Quote Inflation



Source: ONS and authors' calculations
Note: Series (3) is the inflation series generated from aggregating up the price quote data. Series (4) removes sales/recoveries. Series (5) removes sales/recoveries and clothing. Series (6) is the final data set.

Figure A3: Brexit treatment effect on percentile of price quotes (at beginning of month) in bin.



Source: ONS and authors' calculations
Note: Treatment effect in terms of average log price of x^{th} percentile. Plotted are 90 percent confidence bands.

Figure A4: Treated group minus synthetic control, first moment variables

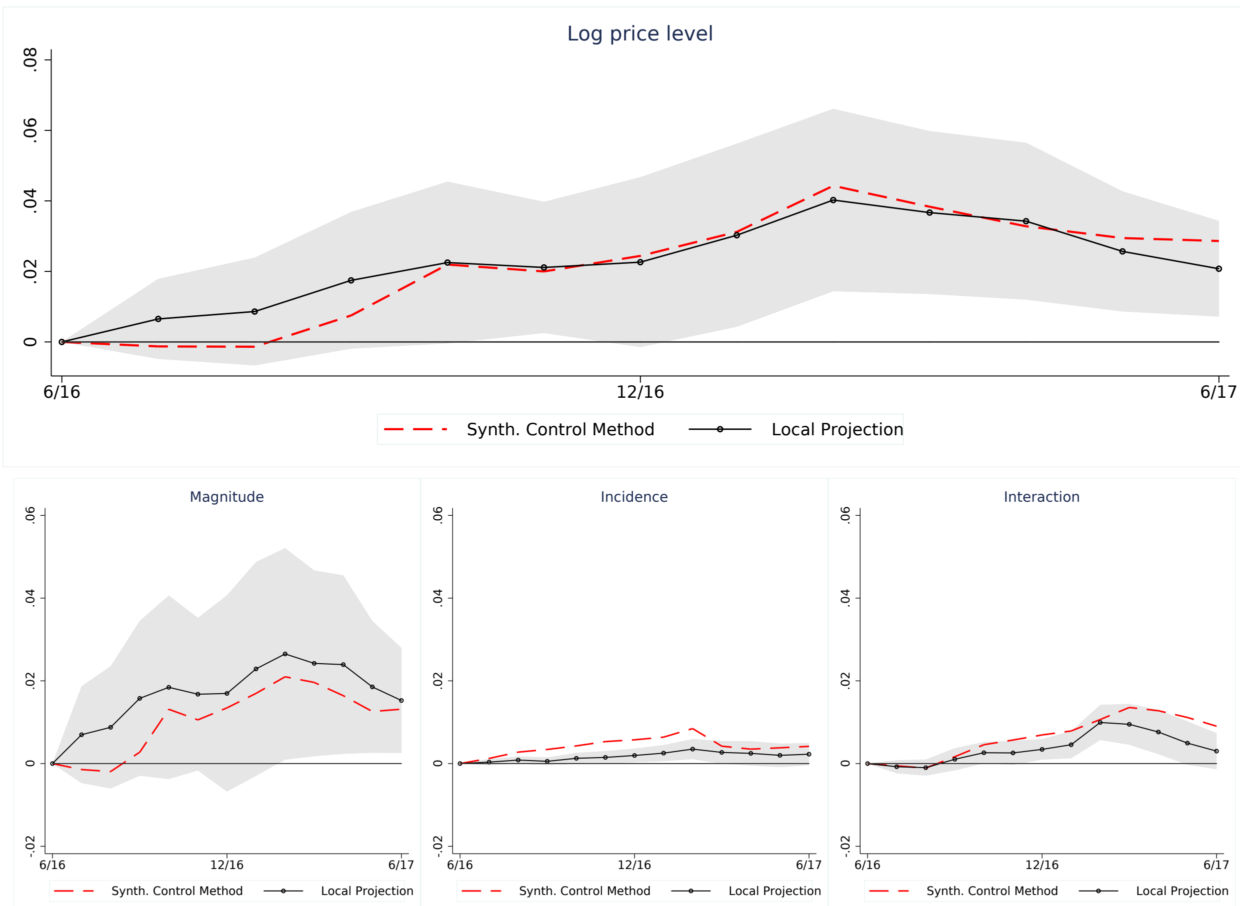


Figure A5: Treated group minus synthetic control, second moment

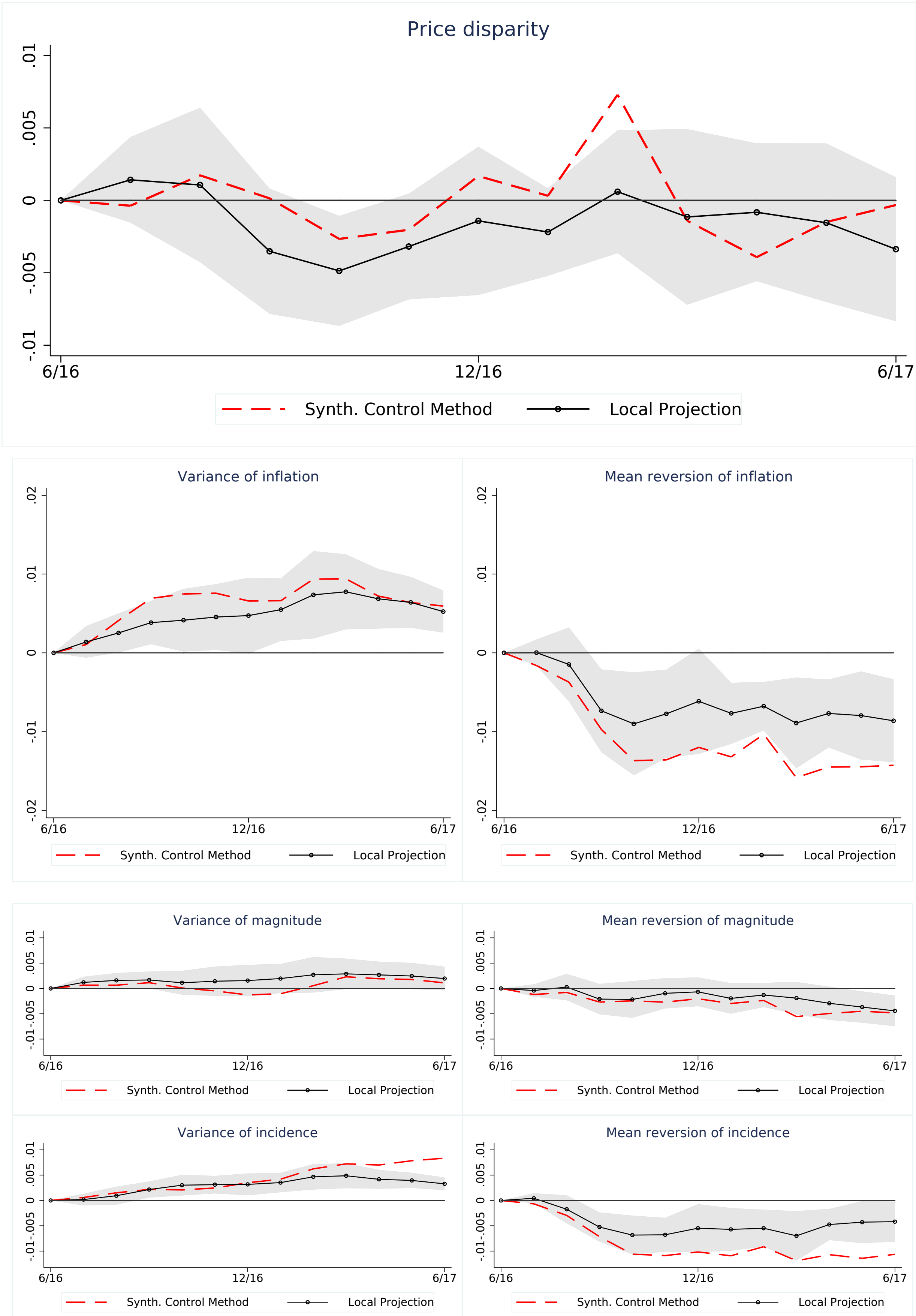


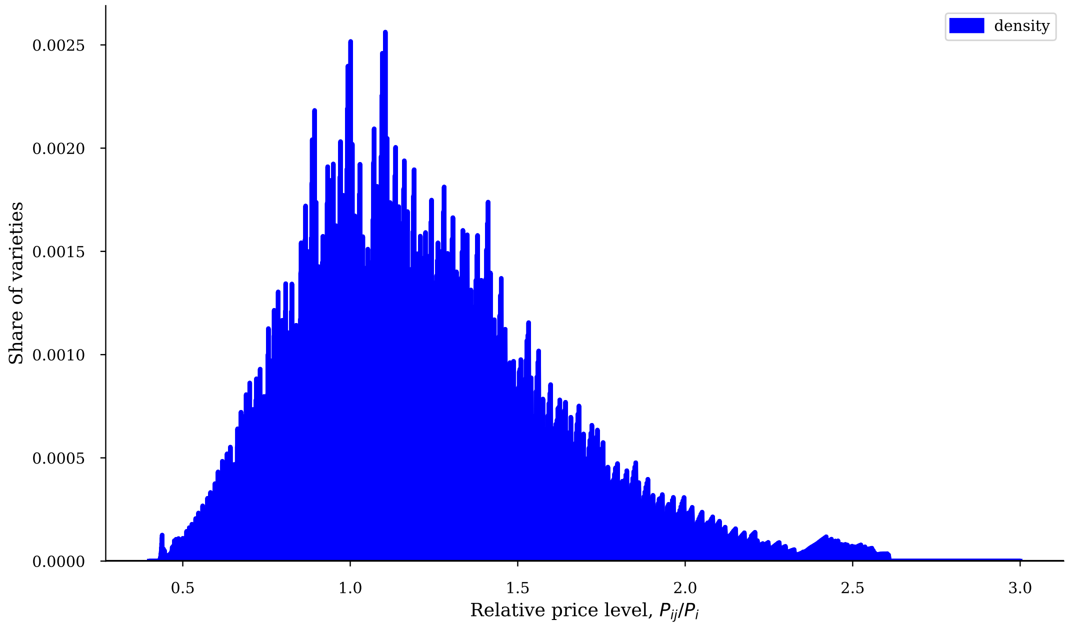
Table A6: Steady-state calibration of model parameters

Description	Parameter	Data	Model Menu cost	Model Calvo
(i) Literature- and data-based parameters				
Elasticity of substitution across varieties	ε	—	3	3
Elasticity of substitution across sectors	θ	—	1	1
Cost-share of imports in sector 2	α	—	0.4	0.4
(ii) Calibrated parameters				
Persistence of idiosyncratic productivity shock	ρ	—	0.9875	0.9825
Standard deviation of idiosyncratic productivity shock	σ_u	—	0.05	0.0625
Menu cost	$\bar{\ell}$	—	0.025	—
Probability of changing prices		—		0.12
(iii) First and second moments of inflation and log prices				
Inflation	$\bar{\pi}$	0.157	0.167	0.167
Incidence	$\bar{\delta}$	11.979	11.922	12.000
Magnitude	$\Delta\bar{p}^C$	1.543	1.398	1.389
Change in the variance of log prices	$\Delta\sigma^2$	0.017	0.000	0.000
Variance of inflation	σ_π^2	0.251	0.239	0.290
Mean reversion of inflation	$2\sigma_{\pi,p}$	-0.234	-0.239	-0.290
Variance of log prices	σ_p^2	0.116	0.106	0.117

The first two parameters on item (*i*) are set according to the literature, while the third matches the data described on Table 2. Parameters on item (*ii*) are chosen such that the models nearly matches the gray shaded row parameters on item (*iii*). The "Data" column corresponds to the "Benchmark" column from Table 3. Steady-state inflation, $\bar{\pi}$, is calibrated to 2 percent annualized, which is slightly higher than average inflation in our sample over the benchmark period (2001m1-2007m12).

Figure A6: Steady-state distribution of log prices and price-setting rules

(a) *Distribution of log prices*



(b) *Price-setting rule*