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by Carlos Carvalho and Oleksiy Kryvtsov

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Abstract

We propose a simple, model-free way to measure selection in price setting and its contribution to inflation dynamics. The proposed measure of *price selection* is based on the observed comovement between inflation and the average level from which adjusting prices departed in the previous period. When adjusting prices depart from lower-than-usual levels, the associated price increases are larger, pushing inflation above average. Using detailed micro-level consumer price data for the United Kingdom, the United States, and Canada, we find robust evidence of strong price selection across goods and services. At a disaggregate level, price selection accounts for 37% of inflation variance in the United Kingdom, 36% in the United States, and 28% in Canada. Price selection is stronger for goods with less frequent price changes or with larger average price changes. Aggregate price selection is considerably weaker. This evidence can be accounted for by a relatively standard multisector sticky-price model. The model demonstrates a monotone relationship between price selection and the extent of monetary non-neutrality.

Bank topics: Fluctuations and cycles; Inflation and prices; Transmission of monetary policy
JEL codes: E31, E51

Résumé

Dans cette étude, nous proposons un moyen simple, qui ne recourt à aucun modèle, de mesurer la sélection des prix et sa contribution à la dynamique de l'inflation. La mesure proposée est fondée sur les covariations observées entre l'inflation et le niveau moyen à partir duquel les prix se sont ajustés au cours de la période précédente. Lorsque les prix s'ajustent à partir de niveaux relativement bas, les hausses de prix sont plus marquées, ce qui pousse l'inflation au-dessus de la moyenne. L'analyse de données microéconomiques détaillées sur les prix à la consommation au Royaume-Uni, aux États-Unis et au Canada montre de façon concluante une forte sélection des prix pour les biens et les services. À un niveau désagrégé, la sélection des prix représente respectivement 37 %, 36 % et 28 % de la variance de l'inflation au Royaume-Uni, aux États-Unis et au Canada. La sélection des prix est plus forte dans le cas des biens ayant des variations de prix moins fréquentes ou en moyenne plus prononcées. À un niveau agrégé, la sélection des prix est beaucoup plus faible. Ces observations peuvent être expliquées par un modèle multisectoriel à prix rigides relativement standard. Ce modèle montre qu'il existe une relation monotone entre la sélection des prix et le degré de non-neutralité monétaire.

Sujets : Cycles et fluctuations économiques; Inflation et prix; Transmission de la politique monétaire
Codes JEL : E31, E51

Non-technical summary

Price selection is associated with the dynamics of the distribution of price adjustments across firms and products; it works in the direction of amplifying the inflation response. There is hardly any direct evidence for whether price selection is empirically important. In this paper, we provide such evidence and explain its implications for sticky price models.

We propose a simple, model-free way to measure price selection and its impact on inflation. Price selection exists when prices that change in response to macroeconomic or monetary disturbances are not representative of the overall population of prices. Due to selection, increases (decreases) in inflation can be amplified because adjusting prices tend to originate from levels far below (above) the average.

Using detailed micro-level consumer price data for the United Kingdom, the United States and Canada, we find robust evidence of strong price selection across goods and services. At a disaggregate level, price selection accounts for 37% of inflation variance in the United Kingdom, 36% in the United States, and 28% in Canada. Price selection is stronger for goods with less frequent price changes or with larger average price changes. Aggregate price selection is considerably weaker for regular price changes, but not for changes associated with price discounts.

This evidence can be accounted for by a relatively standard multisector sticky-price model. The model demonstrates a one-to-one mapping between our measure of price selection and the extent of monetary non-neutrality, which underscores that our proposed measure captures the key role of selection effects in determining the inflation-output trade-off in standard sticky-price models.

In all, by offering a direct measure of price selection in the data, our paper helps to better calibrate the features of business cycle models that help them match inflation dynamics and more accurately identify the determinants of monetary non-neutrality. Standard models have predominantly relied on Calvo nominal price adjustment and real rigidities to account for business cycles and the flat Phillips curve. Our results suggest that a significant share of inflation volatility may be unaccounted for by these models, leading them to predict a flatter Phillips curve.

1 Introduction

The extent to which prices respond to shocks is a key determinant of inflation dynamics. In leading sticky-price theories of inflation determination, that sensitivity depends critically on the degree of price rigidity. The more sticky prices are, the less inflation tends to respond to the state of the economy. For a given degree of nominal price rigidity, however, inflation can be more or less responsive to shocks depending on the behavior of prices that do change. For example, in response to a shock that increases firms' desired prices, aggregate inflation will rise relatively more if prices that respond to the shock increase by a significant amount. This can arise, for instance, if the pool of prices that change after the shock features a high share of prices that were relatively low to begin with.

The possibility that adjusting prices differ systematically from the overall population of prices is associated with the statistical concept of *selection*. In Statistics, selection exists whenever a sample drawn from a given population is *not* representative of that population. In our context, selection exists whenever prices that change (think of them as the "sample") are not representative of the distribution of pre-existing prices ("population"). The existence of selection in this general statistical sense can be tested directly given a microdata panel of individual prices. For example, one can identify prices that change between periods $t-1$ and t and statistically test for differences between the distribution of the overall population of $t-1$ prices and the distribution of $t-1$ prices that change going into period t.

Given our focus on inflation dynamics, however, our interest goes beyond testing whether selection in such general form exists. The empirical question of interest here is whether selection exists in a form that matters for inflation dynamics. To address this question, we propose a simple, model-free way of measuring selection in price setting using micro price data. Rather than testing for the presence of selection in general, we design a measure of selection that matters for inflation dynamics. To differentiate if from other forms of selection, we name it *price selection*.

Our measure of price selection explores the following idea, based on comovement. Consider a shock that increases firms' desired prices. This shock tends to produce an uptick in aggregate inflation.[1] If the uptick in inflation is associated with price increases that depart from lower-than-usual levels, those price increases tend to be larger than average, and the inflation response is greater. Hence, selection of this kind amplifies inflation fluctuations. We design our measure of selection to quantify the extent of such comovement. For the subset of prices that change between periods $t-1$ and t, we compute their average level at $t-1$ relative to the average level of *all* prices in the relevant population at $t-1$. We call this average price-relative the *preset price* or *preset price-relative*. If the preset price covaries negatively with inflation, there is price selection of the kind just described. In particular, strong negative comovement between the preset price and inflation implies that upward movements in inflation are largely driven by prices that increase from lower-than-usual levels. In

[1] Klenow and Kryvtsov (2008) provide empirical evidence that the bulk of inflation variance is due to variation in the average size of price changes (the intensive margin of inflation) rather than variation in the fraction of prices that change (the extensive margin of inflation). Hence, our measure of selection is designed to help us make sense of variation in the intensive margin of inflation. For expositional convenience, we often omit the expression "intensive margin" and refer directly to inflation.

other words, the underlying price increases tend to be larger than average because they involve prices that were relatively low to begin with.[2] Note that if adjusting prices are drawn at random from the overall population of prices, as in the workhorse sticky-price model due to Calvo (1983), the preset price-relative equals zero and does not comove with inflation. In that case, our measure yields zero price selection. More generally, our measure yields zero selection if changes in the preset price are uncorrelated with inflation fluctuations.

We employ three detailed micro price datasets to measure price selection. For the United Kingdom, we use the dataset underlying construction of the Consumer Price Index (CPI) by the U.K. Office for National Statistics (ONS). The dataset provides unit prices for goods and services that are included in the consumption expenditure component of the U.K. National Accounts, representing about 57% of the U.K. CPI basket. Prices are collected locally for more than 1,100 categories of goods and services a month and more than 14,000 retail outlets across the United Kingdom. The sample period includes 236 months, from February 1996 to September 2015. Likewise, for Canada we employ the Consumer Price Research Database (CPRD), compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices posted by retail outlets across Canada during 143 months from February 1998 to December 2009, spanning more than 700 categories of goods and services representing about 61% of the consumption basket underlying the CPI. Finally, for the United States, the Information Resources Inc (IRI) scanner dataset provides weekly expenditures and quantities for individual products across 31 product categories over 132 months from January 2001 to December 2011. The product categories cover food and personal care goods sold by grocery stores in 50 U.S. metropolitan areas.

We first compute the average price change and preset price-relative for each month, product category, and sampling stratum (given by location and store type). This level of disaggregation accords with sample design for collecting prices and constructing the CPI in the United Kingdom, the United States, and Canada (ILO, 2004). We measure the extent of price selection at the stratum level by the coefficient of a least squares regression of the preset price-relative on the average size of price changes. A standard inflation variance decomposition establishes that the absolute value of this coefficient is equal to the share of the variance of the average size of price changes explained by the preset price-relative, thus providing a convenient gauge for the economic significance of price selection. Zero price selection means that changes in the preset price are uncorrelated with inflation fluctuations.

For our baseline panel specification, we exclude price changes associated with price discounts and product substitutions and control for stratum and calendar-month fixed effects. The weighted mean price selection across strata is –0.371 for the United Kingdom, –0.360 for the United States, and –0.285 for Canada, all highly statistically significant and robust to different empirical specifications.

[2] It is worth emphasizing that our measure of selection does *not* require products' desired prices to be the same. For example, there can be firms or products whose prices are usually below-average, and others whose prices are usually above-average. Because our measure of selection is based on comovement, what matters is whether there is systematic covariation between the departing levels of adjusting prices—relative to their "typical" position in the relative-price distribution—and inflation.

Including price changes associated with price discounts or substitutions does not materially influence price selection at a stratum level.

By exploiting rich variation in price adjustment across product strata, we document that price selection is stronger for strata where prices change less frequently. A 10 percentage point decrease in the frequency of price changes is associated with an additional 1.9 to 6.7 percentage points of inflation variance explained by preset prices. Furthermore, we find that price selection is stronger in strata with a larger size of price changes.

Finally, we measure the degree of price selection at the *aggregate* level. We find that regular-price selection is substantially weakened. For the baseline case—no discounts or substitutions—price selection is –0.197 for the United Kingdom, and it is not significantly different from zero for the United States and Canada. Similar to the stratum-level evidence, including substitutions does not change price selection at the aggregate level. By contrast, including price discounts restores a substantial degree of price selection in the United Kingdom (–0.394) and meaningful price selection in the United States (–0.140). Hence, aggregation largely washes out price selection for regular price changes, but not for price discounts. This finding reflects a special nature of price discounts as an additional margin of price flexibility and underscores their role for amplifying cyclical variation of the aggregate price level, as recently emphasized for the United Kingdom and United States by Kryvtsov and Vincent (2021). In Canada, aggregate price selection is close to zero for either regular or all posted prices, consistent with less cyclicality in price discounts and coarser strata in the Canadian sample.

In exploring micro data to perform a variance decomposition of inflation, our paper is related to Klenow and Kryvtsov (2008), who decompose inflation into components due to extensive and intensive margins of price adjustment. Our paper is also related to Bils, Klenow, and Malin (2012), who use microdata to construct what they call a "reset price inflation" measure, which they employ to assess sticky-price models. Their measure relies on observations of individual reset prices of adjusters, which are then used to impute unobserved reset prices for non-adjusters. We provide complementary results by exploiting price selection, which relies on (observed) *preset* prices of adjusters. Our findings are also complementary to those of Campbell and Eden (2014), who show evidence that a store's price is more likely to adjust when it differs substantially from the average price of other stores.

In the second part of the paper, we study the implications of our empirical evidence for business cycle models with pricing frictions. The sticky-price literature has emphasized so-called "selection effects" as a key determinant of the inflation-output trade-off. Selection effects tend to increase the sensitivity of aggregate inflation to economic slack for a given degree of microeconomic price stickiness, and hence they often lead to a lower degree of monetary non-neutrality (e.g., Caballero and Engel, 2007). Caplin and Spulber (1987), Danziger (1999) and Golosov and Lucas (2007) emphasize selection effects in menu-cost models, where firms can choose to incur a menu cost to change their prices. Selection effects also arise in models with time-dependent price adjustment, where after a shock some prices are expected to take longer to adjust than others (Carvalho and Schwartzman, 2015). Under specific assumptions, some models yield sufficient statistics for selection effects that can be computed from moments estimated from price micro data (Carvalho and Schwartzman, 2015; Alvarez, Le Bihan, and Lippi, 2016). The extent of selection effects can also be estimated indirectly from applied theoretical models matched to observed micro price behavior. Recent papers by Vavra (2013), Coibion, Gorodnichenko, and Hong (2015), Sheremirov (2020) use time variation in price- or price-change dispersion to discriminate across models with different degrees of selection effects. Other examples in the literature show that the degree of selection effects may be affected by factors such as product-level disturbances (Gertler and Leahy, 2008), economies of scale in price-adjustment technology (Midrigan, 2011; Bonomo et al., 2020), stochastic volatility of idiosyncratic shocks (Karadi and Reiff, 2019), the number of products per retailer (Bhattarai and Schoenle, 2014; Alvarez and Lippi, 2014), the risk of pricing mistakes (Costain and Nakov, 2011b), the slope of the hazard rate of price adjustment (Carvalho and Schwartzman, 2015), and sectoral heterogeneity in price stickiness (Carvalho, 2006; and Nakamura and Steinsson, 2010).[3] The most widely used Calvo (1983) sticky-price model with random and exogenous timing of price adjustments represents an extreme case with no selection effects. In sum, sticky-price models predict a wide range for the size of selection effects and the associated monetary non-neutrality.

We rely on a standard sticky-price model as a laboratory to study our measure of price selection. In particular, we study whether aggregation affects price selection, how price selection relates to selection effects, and what our estimates of price selection imply for the response of the aggregate price level to nominal shocks—and, hence, for the extent of monetary non-neutrality. Although our measure is model free and does not rely on any of the aforementioned model features that are material for selection effects in sticky-price models, we show price selection accurately captures the macroeconomic implications of selection effects in the most commonly used sticky-price models.

We rely on a multisector sticky-price model that nests the Golosov and Lucas (2007) and Calvo (1983) models, calibrated to match price-setting statistics for a number of consumption sectors in the U.K. data. In the model, price selection at the sector level can be calibrated by a proper choice of the nesting parameter that controls for the occurrence of random ("Calvo") price changes. Using numeric simulations, we first show that aggregation weakens price selection in the model, in line with our empirical evidence. We then show that, conditional on the frequency of price changes, the degree of monetary non-neutrality is monotone in our measure of price selection. The tight link between price selection and monetary non-neutrality underscores that our proposed measure is useful not only because it is model free, but also because it captures the key role of selection effects in determining the inflation-output trade-off in standard sticky-price models. Finally, we study whether price selection interacts with real rigidities in the sense of Ball and Romer (1990) and Kimball (1995). For a given degree on nominal price stickiness, real rigidities are known to increase the degree of monetary non-neutrality. We demonstrate that these effects of real rigidities on monetary non-neutrality are orthogonal to the effects induced by selection.

These findings offer important insights for our understanding of monetary non-neutrality in sticky-

[3] Some related empirical work focuses on the price pass-through of firm- or product-level shocks to marginal costs and also provides a wide range of estimates: from none or very small (Carlsson, 2017) to virtually full pass-through (Eichenbaum, Jaimovich, and Rebelo, 2011). Gagnon, López-Salido, and Vincent (2012) study the effect of large inflationary shocks on the timing of price changes using Mexican CPI data: they provide evidence for the response of the timing of price changes to inflation shocks, although they do not identify how much of this response is due to selection effects.

price models. In a large class of such models, non-neutrality can be thought of as a function of the frequency of price changes, the degree of selection, and the strength of real rigidities. The frequency of price changes can be measured directly from micro price data without the need to identify either selection effects or real rigidities. We show that price selection can also be estimated directly from micro price data. This reinforces the importance of identifying real rigidities. While the literature provides indirect estimates based on applied theoretical models matched to observed micro price behavior (e.g., Gopinath and Itskhoki, 2011; Kryvtsov and Midrigan, 2013; Klenow and Willis, 2016), it may be useful to develop a model-free approach for identifying real rigidities, similar to what we do in regards to price selection.

The paper proceeds as follows. The concept of price selection is introduced in Section 2. Section 3 explains the data sources and empirical definitions. Section 4 discusses how we identify and measure price selection in U.K., U.S. and Canadian micro data. Section 5 distills the implications of the empirical findings for sticky-price models. Section 6 concludes.

2 Definition of price selection

2.1 Inflation decomposition and price selection

Consider an economy with a continuum of goods, and let $G_t(p)$ denote the distribution of prices in period t (all prices are in logs). The aggregate price level in period t, P_t, can be defined as the mean of G:

$$P_t = \int_{-\infty}^{\infty} p \, dG_t(p) .$$

Inflation, therefore, can be fully characterized by the sequence of price distributions $\{G_t(p)\}$:

$$P_t - P_{t-1} = \int_{-\infty}^{\infty} p \, d\left[G_t(p) - G_{t-1}(p)\right] . \tag{1}$$

We can simplify this expression by focusing on prices that change from $t-1$ to t. Let $\Lambda_{t|t-1}(p)$ denote the measure of prices in the interval $[p, p+dp]$ in period $t-1$ that adjust between periods $t-1$ and t; and let $H_{t|t-1}(p' \mid p)$ denote their distribution in period t. The measure of prices in the interval $[p, p+dp]$ in period t is

$$\begin{aligned} G_t(p)\, dp = & \left(1 - \Lambda_{t|t-1}(p)\right) dG_{t-1}(p) \\ & + \left[\int_{-\infty}^{\infty} H_{t|t-1}(p \mid \widetilde{p})\, \Lambda_{t|t-1}(\widetilde{p})\, dG_{t-1}(\widetilde{p})\right] dp. \end{aligned} \tag{2}$$

The first term on the right-hand side is the measure of prices that were in the interval $[p, p+dp]$ in period $t-1$ and did not change. The second term is the measure of prices that did change to the level in the interval $[p, p+dp]$ in period t. To obtain this measure, first, for each price $\widetilde{p}$ in the domain, compute the measure of prices from an interval $[\widetilde{p}, \widetilde{p}+dp]$ in period $t-1$ that are adjusted to a point in the interval $[p, p+dp]$ in period t. This measure is given by $H_{t|t-1}(p \mid \widetilde{p})\, \Lambda_{t|t-1}(\widetilde{p})\, dG_{t-1}(\widetilde{p})$.

Second, sum across all prices $\widetilde{p}$. Using (2) to substitute for $G_t(p)\,dp$ in (1) yields

$$P_t - P_{t-1} = -\int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,dG_{t-1}(p) + \int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})\right]dp. \tag{3}$$

The first term on the right-hand side is (the negative of) the weighted mean of time-$(t-1)$ level of those prices that change between periods $t-1$ and t, and the second term is their weighted mean time-t level, with both means weighted by the measure of adjusting prices.

It is convenient to rewrite expression (3) in terms of price levels conditional on price adjustment. Let Fr_t denote the measure of price changes in period t. P_t^{pre} is the preset price-relative, i.e., the average time-$(t-1)$ level of prices that adjust between periods $t-1$ and t relative to the aggregate price level at $t-1$, and P_t^{res} is their average time-t level relative to the aggregate price level at $t-1$, which we call the *reset price*:

$$Fr_t = \int_{-\infty}^{\infty} \Lambda_{t|t-1}(p)\,dG_{t-1}(p),$$

$$P_t^{pre} = \int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,Fr_t^{-1}dG_{t-1}(p) - P_{t-1},$$

$$P_t^{res} = \int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,Fr_t^{-1}dG_{t-1}(\widetilde{p})\right]dp - P_{t-1}.$$

Inflation decomposition (3) can be written as

$$\pi_t \equiv P_t - P_{t-1} = Fr_t\left(P_t^{res} - P_t^{pre}\right), \tag{4}$$

where $DP_t \equiv P_t^{res} - P_t^{pre}$ is the average size of price changes, or intensive margin of inflation.

In this inflation-accounting framework, testing for selection in the general statistical sense amounts to testing for differences between the distribution of the population of time-$(t-1)$ prices, $G_{t-1}(p)$, and the distribution of those time-$(t-1)$ prices that change from $t-1$ to t, $\int_{-\infty}^{p} \Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})$. Note that the two distributions are equal when $\Lambda_{t|t-1}(\cdot)$ is the uniform distribution—i.e., when adjusters are randomly drawn from the population of prices, as in the Calvo (1983) model.

Our empirical research question, however, is whether there exists a form of selection that matters for inflation dynamics. Hence, we propose to identify price selection from comovement between preset price-relative P_t^{pre} and the intensive margin of inflation DP_t. More concretely, our measure of price selection is the coefficient of an Ordinary Least Squares regression of the preset price-relative on the average size of price changes:

$$P_t^{pre} = \gamma DP_t + error_t. \tag{5}$$

From inflation decomposition (4), it takes only a little algebra to establish that the absolute value of the γ coefficient in (5) gives the share of the variance of the average size of price changes explained by the preset price-relative, thus providing a convenient gauge for the economic significance of price selection.[4]

2.2 Comparisons to alternative inflation decompositions

Decomposition (4) provides a novel take on the decomposition in Klenow and Kryvtsov (2008), who cast inflation as the product of the average fraction of price changes and their average size conditional on adjustment. Our decomposition represents the average size of price changes, DP_t, as the difference between the average price level of newly set prices and their average level prior to adjustment, $DP_t \equiv P_t^{res} - P_t^{pre}$.[5]

Bils, Klenow, and Malin (2012) study the relationship between inflation and reset price inflation. They define reset price inflation as the estimated rate of change of new prices (set by the subset of price changers) relative to new prices in the previous period (set by price changers in that period). Since the subset of price changers varies from month to month, reset price inflation depends on both selection effects and strategic pricing complementarities. Using simulations of the Smets and Wouters (2007) business cycle model, Bils, Klenow, and Malin (2012) show that the model is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. Kara (2015) shows that these dynamics can be partially reconciled if business cycle models incorporate different degrees of price flexibility across consumption sectors. Price selection makes inflation more sensitive to shocks, and thus may partly drive Bils et al.'s reset price inflation.

Following a model-based approach, Caballero and Engel (2007), Costain and Nakov (2011a), and Dotsey and Wolman (2020), propose decompositions of the inflation response to a monetary shock. This response is due to the cumulative impact of desired log price adjustments (price gaps), $p_i - p_i^*$, and can be decomposed into the contributions from changes in the size of adjustments by those prices that adjust regardless of the shock (the intensive margin) and from the changes in the fraction of price increases and decreases caused by the shock (the extensive margin). These definitions rely on assumptions about the process for desired price levels, p_i^*, and the conditional probability of adjustment as a function of the price gap. While this approach is well suited for demonstrating theoretical implications of selection effects, it is less useful for empirical assessment because the unobserved desired price level is difficult to measure in the micro data.[6] Caballero and Engel (2007)

[4]Because $Var(DP_t) = Var(P_t^{res}) + Var(P_t^{pre}) - 2Cov(P_t^{res}, P_t^{pre}) = Cov(P_t^{res}, DP_t) - Cov(P_t^{pre}, DP_t)$, the share of variance of DP_t explained by P_t^{pre} is $\frac{-Cov(P_t^{pre}, DP_t)}{Var(DP_t)}$, which is the expression for (the absolute value of) coefficient γ in (5). In general, selection effects—captured by how P_t^{pre} and DP_t respond to a sequence of shocks—vary over time. For example, in a state-dependent pricing model, very large shocks will drive almost all firms to change prices, driving selection toward zero. But for smaller shocks, selection is stronger and may depend on the distribution of price gaps at the time of such shocks. The price selection statistic captures the *average* relationship between P_t^{pre} and DP_t. Therefore, the error term in (5) picks up variation in selection effects around the average. We illustrate this explanation using the Taylor (1980) model as an analytical example (Section C in Supplementary Material).

[5]Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) decompose the variance of DP_t into terms due to price increases and decreases. Using U.S. CPI micro data, they find that price increases play an important role in inflation fluctuations, while the role of price decreases may depend on the definitions of the time series and other controls.

[6]Carlsson (2017) uses producer price and cost micro data from Sweden to estimate firm-specific marginal cost changes; he finds a weak response of the timing of individual price changes to firms' marginal costs. In contrast, Eichenbaum, Jaimovich, and Rebelo (2011) find an almost perfect pass-through of cost to prices using scanner data for retail prices.

argue selection effects are neither necessary nor sufficient to increase the response of inflation to a nominal shock and propose instead focusing on the extensive margin. They clarify, however, that the effect of the extensive margin stems from a combination of selection of price adjustments and their respective impacts on the average price response to a common nominal shock.[7]

In contrast to these approaches, our method is model free, requiring only information about price adjustments at the micro level, and it does not mix in the other adjustment margins, such as reset price changes or the extensive margin. Decomposition (4) focuses solely on selection of prices that adjust from month to month and their average starting and ending price levels relative to the aggregate price—i.e., preset and reset price-relatives. The difference between price-relatives, multiplied by the fraction of price adjustments, is identically equal to inflation. The contribution of movements in the preset price-relative to inflation dynamics then identifies price selection.[8]

3 U.K., U.S. and Canadian micro data

Measuring inflation, reset, and preset price levels requires price data at the level of individual goods and services. We employ three datasets for the United Kingdom, the United States, and Canada. The datasets from the U.K. Office for National Statistics (ONS) and Statistics Canada provide prices for goods and services collected monthly from retail outlets used for the construction of the consumer price index (CPI) in these countries. The IRI dataset provides weekly scanner transactions data for grocery stores in the United States. Unlike ONS and Statistics Canada datasets that provide prices posted by retailers, the IRI dataset provides transaction prices. To the extent possible, our treatments of these datasets make the statistics comparable. The U.K. dataset has a broader coverage than the IRI dataset, and it is also available online, unlike the Canadian dataset, for which we have confidential access. We therefore rely extensively on the U.K. dataset for the multitude of our robustness checks. We also describe it in more detail below. The three datasets provide rich coverage of micro price adjustment in three advanced economies (see Table 1).

3.1 U.K. CPI micro data

The dataset is compiled from the survey of prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts. The survey includes prices for more than 1,100 individual goods and services a month, collected from more than 14,000 retail stores across the United Kingdom. The survey excludes the housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees. Expenditures for purposes other than final consumption are also excluded, e.g., those

[7] Gagnon, López-Salido, and Vincent (2012) provide evidence of the quantitative importance of the extensive margin using Mexican CPI data in response to large nominal shocks—peso devaluation in 1994 and VAT hikes in 1994 and 2010.

[8] In Supplementary Material (Section D) we provide intuition on the workings of selection effects in sticky-price models using the Calvo and Golosov-Lucas models as examples. We also illustrate how our model-free measure of price selection accurately captures the implications of selection effects in these models.

for capital and financial transactions, direct taxes, or cash gifts. The portion of the data published on the ONS website includes only locally collected prices, covering about 57% of the U.K. CPI basket.

Most prices are collected monthly, except for some services in household and leisure groups, and seasonal items. The sample period covers 236 months, from February 1996 to September 2015. The total number of observations is over 24 million, or about 100,000 per month.[9] Prices are collected across 12 geographical regions, e.g., London, Wales, East Midlands. There are four levels of sampling for local price collection: locations, outlets within location, product categories, and individual product varieties. For each geographical region, locations and outlets are based on a probability-proportional-to-size systematic sampling, with a size based on the number of employees in the retail sector (locations) and the net retail floor space (outlets). The dataset contains prices collected locally in around 150 locations with an average of more than 90 outlets per location.

Product or service categories—or "representative items"—are selected based on a number of factors, including expenditure size and product diversity, variability of price movements, and availability for purchase throughout the year (except for certain goods that are seasonal). There are currently more than 1,100 categories in the basket. Examples of categories include onions, Edam, envelopes, men's suit (ready-made), electric heater, single beds. Finally, for each category-outlet-location, individual products and varieties are chosen by price collectors based on their shelf size and regular stock replenishment.

For each category, ONS stratifies the sample by 24 strata, given by region and shop type pairing. For each category and stratum, the ONS dataset provides sampling weights that reflect that category-stratum's relative importance in households' consumption expenditures.[10] For constructing the CPI, ONS first constructs elementary price indices for each product category-stratum bin by taking geometric means of all prices within the bin, with equal weights. These elementary indices are then aggregated into the CPI using consumption expenditure weights.[11]

Throughout the paper, we provide two alternative treatments of price changes at the individual product level. First, we distinguish price changes associated with temporary price discounts (sales). While sales are relatively infrequent—4.6% per month in the United Kingdom—they usually come with much larger and shorter-lived price swings than regular prices. We adopt ONS' definition of sale prices as temporary reductions on goods that are likely to be available again at regular prices

[9]A detailed description of the CPI data sampling and collection can be found in ONS (2014) and Clews, Sanderson, and Ralph (2014). The price quote data are available via the ONS website: http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Recent related work and additional details on data cleaning can be found in Kryvtsov and Vincent (2021) and Chu et al. (2018).

[10]Categories in the CPI are classified into 71 classes, according to the international classification of household expenditure, Classification of Individual Consumption by Purpose (COICOP). A CPI class represents a basic group category, such as meat, liquid fuels, or new cars. Category and class weights are calculated based on the Household Final Monetary Consumption Expenditure (HFMCE) and the ONS Living Costs and Food Survey (LCF). Changes in the expenditure weights over time reflect changes in the expenditure composition of households' consumption baskets. Using class, category, stratum and shop type weights, we follow ONS methodology to construct observation-specific weights for our sample.

[11]The geometric mean, also known as the Jevons index, is used for calculating an elementary price index for CPI in the United States and Canada, whereas in the United Kingdom, a mixture of geometric mean and average of price relatives (the Dutot index) is used. See Diewert (2012) for a detailed discussion of various CPI measures in the United Kingdom. To keep our statistics directly comparable across country datasets, we use geometric mean elementary indices everywhere.

or as end-of-season reductions. When the posted price is discounted, the unobserved regular price equals to the posted price in the month preceding the first month of the sale; it is equal to the posted price if there is no sale. These definitions are reliable for describing sales behavior and are commonly used in the literature.[12]

Second, we differentiate price changes associated with product substitutions. When a previously collected price-product is no longer available to field agents, they make a substitution for another product from the same category. Such substitutions—5.6% per month in the United Kingdom—are more commonly associated with price increases (68% of price changes during substitutions).[13] IRI data contain prices for uniquely defined products, and therefore we do not apply this treatment to these data.

3.2 Statistics Canada CPI data

The Consumer Price Research Database (CPRD) is compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices for goods and services posted by retail outlets across Canada from February 1998 to December 2009, or 143 months. Overall, the CPRD contains more than 8.4 million observations (almost 60,000 per month) and covers about 61% of the consumption basket underlying the CPI. Since the CPRD is a dataset of individual prices, it excludes goods for which prices are aggregated indexes, such as utility rates, insurance premiums, transportation fares, sport and theater tickets, books and newspapers, entertainment CDs and DVDs, and computer equipment.

Similar to ONS, Statistics Canada defines a product category (representative item)—a single commodity, such as potatoes, yogurt, gas barbecues, women's gloves, oil filters—selected to represent a basic class of goods and services in the index. There are 705 specific product categories in the dataset. The selection of these items takes into account the following criteria: the price movement of the item should represent the price movement of the given class, and the item has to be available on the market for a reasonable length of time.

Prices are collected from a variety of retail outlets, including supermarkets, specialty shops, department stores, garages, dental offices, and salons. In most cases, the main determining factor in the selection of outlets is the value of sales revenues for the items being priced. However, geographic dispersion and outlet type are also important factors taken into consideration. Pricing information is collected in up to 92 urban centres across Canada, generally in urban centres with a population of 30,000 or more. Due to confidentiality restrictions for this dataset, strata are defined by a coarser geographical definition, spanning 13 Canadian provinces and territories.

Like the U.K. dataset, the Canadian dataset provides flags for observations that correspond to a sale (9.0% of monthly observations) or to a product substitution (3.5%). We therefore treat those

[12] Nakamura and Steinsson (2008) show that sales affect the measurement of the extent of nominal price stickiness in the U.S. CPI data. Kryvtsov and Vincent (2021) provide evidence of the countercyclical variation in the number of sales in the United Kingdom and United States; they also discuss different definitions of sales in the data.

[13] Klenow and Malin (2010) provide an overview of the incidence of sales and substitutions and their implications for price adjustment. Bils (2009) and Kryvtsov (2016) document the occurrence of price substitutions and assess the extent of the associated quality bias in the U.S. and Canadian CPI data, respectively.

observations the same way we treat the U.K. dataset.

3.3 IRI data for the United States

IRI is a marketing and market research dataset that contains scanner data, product description data, store data and household data.[14] The scanner data are provided at a weekly frequency for a panel of 31 grocery products, such as beer, coffee, milk, razors, laundry detergent, and frozen pizza. To make the IRI dataset comparable to the CPI datasets, we convert weekly observations into monthly by using the first available weekly observations from that month. In all, the dataset contains around 1.5 billion observations, or 36.2 million monthly observations, covering the span of 132 months, from January 2001 to December 2011, or around 274,000 per month.

The data are provided for grocery stores in 50 U.S. metropolitan areas. Each store has a unique identifier, so its prices and quantities can be tracked over time. Scanner data include the revenue and quantity for weekly purchases for each product, identification for the product, display indicator and sale indicator. For each individual product in a product category, we define a unique product identifier by matching UPC codes for that product with product description (e.g., Budweiser lager 355ml). We include only stores belonging to chains that exist throughout the entire sample period. We exclude products that belong to a store's private label (their coding was changed by IRI in 2007 and 2008), products that have fewer than two observations per week, and observations with a unit price less than $0.10.

Similar to strata in the ONS and Statistics Canada data, we define an elementary bin in IRI data to be represented by a category and metropolitan location. The share of nominal revenues over the sample period in total revenues over the sample period is used as a stratum weight. In a given week, unit prices for each UPC are constructed by dividing weekly revenue by the quantity sold. For weeks in which transactions occur during price discounts, regular unit prices are equal to the last observed regular unit price. Around 9.0% of monthly observations are price discounts.[15]

3.4 Empirical definitions

The micro data used in this paper present us with two challenges for accurate measurement of price selection: heterogeneity across products, locations and stores, and measurement error. These issues are known to affect the estimates of price moments in the data and may as well apply to measurement of price selection.[16]

To deal with these issues, we apply inflation decomposition (4) at the category-stratum level—the most disaggregate available level in our datasets. We also exclude observations in the top percentile

[14] More details are provided in Bronnenberg, Kruger, and Mela (2008).

[15] Coibion, Gorodnichenko, and Hong (2015) use the IRI dataset to study retail prices and household expenditures across metropolitan areas, finding that reallocation of expenditures across retailers during local recessions lowers average prices paid by consumers.

[16] For example, Alvarez, Le Bihan, and Lippi (2016) show how heterogeneity and measurement error introduce an upward bias in measured kurtosis of price changes. Heterogeneity of price behavior across products, stores, and locations has been well documented, including not only the differences in the frequency and size of price changes, but also the incidence of price discounts, product churning, and stockouts. Klenow and Malin (2010) and Nakamura and Steinsson (2013) provide detailed reviews of microeconomic evidence on price dynamics and the extent of heterogeneity.

of absolute log price changes within each category-stratum; this helps to filter out coding errors or other outliers in month-to-month price movements (see Alvarez, Le Bihan, and Lippi, 2016). Finally, we exclude strata with less than 10 price changes over the sample period.

The empirical counterparts of the four variables entering inflation decomposition (4) are constructed as follows. Let p_{ist} denote log price of product i in category-stratum s and in month t, where subscript i uniquely identifies an individual product in a particular location (and also the type of retail outlet in the U.K. data). Denote by Ω_{st} the set of products in stratum s with price observations in both periods t and $t-1$, and let P_{st-1} denote the arithmetic mean of log prices in month $t-1$ for all products in Ω_{st}. Let N_{st} be the number of price observations in stratum s in month t, and I_{ist} be an indicator of a price change for product i in month t—i.e. $I_{ist} = 1$ if $p_{ist} - p_{is,t-1} \neq 0$, and 0 otherwise. Noting that $p_{ist} - p_{is,t-1} \equiv I_{ist} \left(p_{ist} - P_{s,t-1} + P_{s,t-1} - p_{is,t-1}\right)$, we can write inflation in category-stratum s in month t as the mean of log price changes in that bin and month, and express it identically as follows:

$$\begin{aligned} \pi_{st} &\equiv \frac{\sum_{i \in \Omega_{st}} (p_{is,t} - p_{is,t-1})}{N_{st}} \\ &\equiv \underbrace{\frac{\sum_{i \in \Omega_{st}} I_{is,t}}{N_{st}}}_{Fr_{st}} \times \left[\underbrace{\frac{\sum_{i \in \Omega_{st}} I_{is,t} \left(p_{ist} - P_{s,t-1}\right)}{\sum_i I_{is,t}}}_{P^{res}_{st}} - \underbrace{\frac{\sum_{i \in \Omega_{st}} I_{is,t} \left(p_{is,t-1} - P_{s,t-1}\right)}{\sum_i I_{is,t}}}_{P^{pre}_{st}} \right]. \end{aligned} \tag{6}$$

Equation (6) takes the same form as (4):

$$\pi_{st} \equiv Fr_{st} \cdot \underbrace{\left[P^{res}_{st} - P^{pre}_{st}\right]}_{DP_{st}}, \tag{7}$$

where Fr_{st} is the mean fraction of products in category-stratum s changing price in month t; reset price P^{res}_{st} is the mean of log prices that changed in month t relative to the corresponding stratum population mean log price in month $t-1$; and preset price P^{pre}_{st} is their corresponding mean level *prior* to change, in period $t-1$, relative to stratum s population mean log price level in month $t-1$. The term in brackets is the average size of non-zero price changes in month t, $DP_{st} \equiv P^{res}_{st} - P^{pre}_{st}$. Decomposition (7) nests the breakdown of inflation into extensive and intensive margins (represented by Fr_{st} and DP_{st}, respectively), proposed by Klenow and Kryvtsov (2008), namely, $\pi_{st} \equiv Fr_{st} \cdot DP_{st}$. In the empirical analysis in the next section, we assess price selection for stratum-level time series, using the variables defined in (7).

Table 1 provides descriptive statistics for the U.K., U.S. and Canadian data for the case that excludes price changes due to sales and substitutions.[17] Regular price inflation in both the United Kingdom and Canada averaged 0.12% and 0.18% per month, or around 1.5% and 2.2% per year, during respective sample periods. In the U.S. grocery data, it was twice as high, at 0.29% per month, or 3.5% per year. In a given month, 12.7% of regular prices change in the United Kingdom, or around

[17] Section A in Supplementary Material provides descriptive statistics for different treatments of sales and substitutions.

once every 8 months. Prices in Canada and grocery prices in the United States change 21.7% and 22.3% of the time, or once in every 4 to 5 months on average. Table 1 also reports auxiliary statistics that we use for calibrating and evaluating sticky-price models.

4 Price selection in the U.K., U.S. and Canadian micro data

4.1 Evidence at the category-stratum level

We start by providing visual evidence of price selection. Figure 1 shows scatter plots for the largest strata in nine selected product categories in the United Kingdom, including oil, milk, and cigarettes, for regular prices and excluding substitutions. For each category, each point on the plot represents a monthly observation for the average size of non-zero price changes (x-axis) and preset price level (y-axis). Hence, each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across months for a given stratum. There is substantial variation in both variables for each category-stratum and across strata, and they tend to correlate negatively—i.e., above-average inflation is associated with price changes that come from below-average levels.[18] This indicates the prevalence of price selection that amplifies stratum-level inflation variation.

To quantify the degree of price selection at a category-stratum level, we estimate the following baseline empirical specification:

$$P_{st}^{pre} = \gamma DP_{st} + \delta_{cal} + \delta_s + error_{st}, \tag{8}$$

where the dependent variable, P_{st}^{pre}, is the preset price-relative for a product category-stratum s in month t, and the independent variable of interest is the average size of non-zero price changes for category-stratum s in month t, DP_{st}. Since, by definition, $DP_{st} \equiv P_{st}^{res} - P_{st}^{pre}$, the absolute value of the estimated regression coefficient γ is equal to the estimated fraction of DP_{st} variance accounted for by variation in preset price P_{st}^{pre}, with the remaining fraction due to reset price. Hence, we adopt the estimated $\hat{\gamma}$ as our measure of price selection. Values of $\hat{\gamma}$ that are significantly different from zero are interpreted as evidence of price selection; negative (positive) values indicate that price selection amplifies (attenuates) inflation fluctuations in response to the underlying shocks. Our baseline specification (8) also includes calendar-month fixed effects δ_{cal}, and category fixed effects δ_s. Equation (8) is estimated by a pooled weighted least squares regression, with weights given by the share of expenditures in category-stratum s in month t (ω_{st}).[19]

[18] Variation in the average size of price changes, DP_{st}, accounts for most of the variation in inflation, as pointed out by Klenow and Kryvtsov (2008)—71% for the United Kingdom at a category level. Hence, if we regress P_{st}^{pre} (multiplied by the mean fraction of price changes Fr_c) on inflation π_{ct}, instead of the average size of price changes DP_{ct}, the estimated coefficients remain significant and negative. We also experimented taking out stochastic trends at a category-stratum level—price selection is stronger by about a third. Finally, we gauged the extent of a high-frequency component of price selection by bandpass-filtering regression variables using the Baxter-King (12, 96, 24) filter. As a result, price selection remains highly statistically significant, although its magnitude is roughly half of the magnitude estimated with unfiltered data.

[19] We exclude strata with price selection in the top and bottom 0.5 percentile from the analysis. Stratum-specific estimates of price selection are presented below.

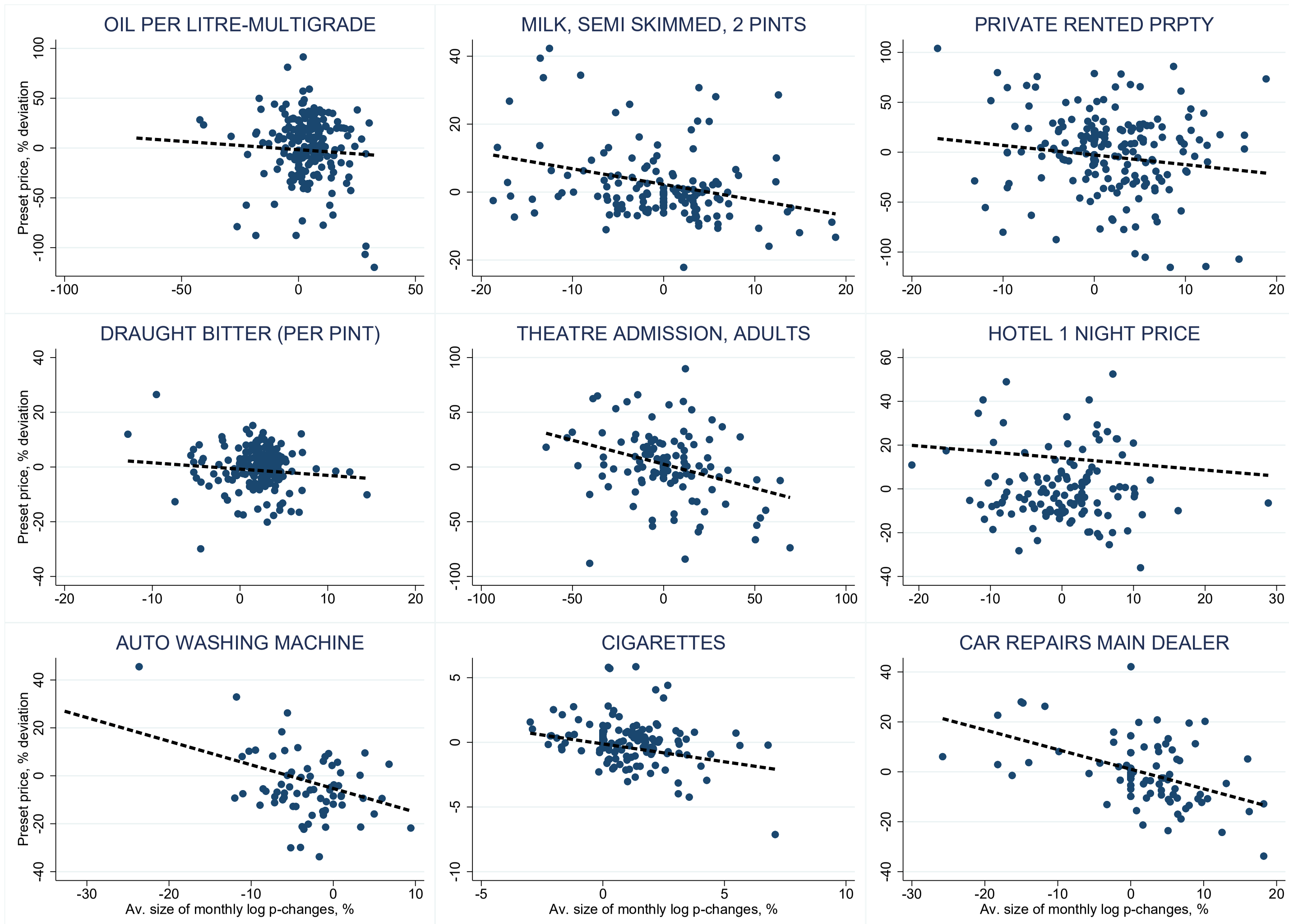
Table 1: Descriptive statistics

	Statistic	U.K.	Canada	U.S.
	Consumption coverage	Non-shelter goods and services	Non-shelter goods and services	Grocery products
	Sample	1996:02–2015:09	1998:02–2009:12	2001:01–2011:12
	# of months	236	143	132
	# of obs/month	102,801	58,670	274,369
	# of categories	1,152	705	31
	# of strata/category	24 (12 regions x 2 store types)	13 provinces and terrirtories	50 metropolitan locations
(1)	π	0.121	0.182	0.291
(2)	Fr	0.127	0.217	0.223
(3)	$DP = \pi/Fr$	0.955	0.842	1.306
(4)	adp	12.22	8.25	8.43
(5)	corr	-0.032	0.164	-0.027
(6)	frac of sales	5.6	9.0	9.0
(7)	frac of subs	4.6	3.5	N/A

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html, the Statistics Canada's Consumer Price Research Database, and the Symphony IRI Inc. Sample period: [UK]: from February 1996 to September 2015; [Canada]: from February 1998 to December 2009; [U.S.]: from January 2001 to December 2011.

The entries are weighted means of stratum-level monthly variables. Observations across strata are based on consumption expenditure weights; observations across months are weighted equally. For computing statistics in rows (1) to (7), price changes due to sales or substitutions are excluded (Tables 1-3 in Supplementary Material provide statistics for other cases). π - inflation, in %; Fr - the fraction of items with changing prices; DP - the size of price changes, in %; *adp* - the average absolute size of price changes, in %; *corr* - serial correlation of newly set prices for an individual product; *frac of sales* - fraction of observations with discounted price, in %; *frac of subs* - mean fraction of observations with product substitutions, in %.

Figure 1: Preset price level and average size of price changes, variation over time for largest strata in selected product categories, U.K. CPI data



Notes: Figure provides scatter plots for largest strata in nine selected product categories in the United Kingdom (including oil, milk, hotel, and cigarettes), for regular prices and excluding substitutions. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). Each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across months for a given category-stratum s. The slope of the trend line is equal to $\hat{\gamma}_s$, representing the estimated degree of price selection corresponding to the stratum.

Table 2 provides the results of this estimation for all three datasets. For our baseline, we consider the case with regular prices and exclude price changes due to product substitutions. The estimated price selection is –0.371 for the United Kingdom, –0.360 for the United States, and –0.285 for Canada, all statistically significant at a 1% level (column 1).[20] The estimates are largely consistent across the three countries; a somewhat lower absolute value for Canada (i.e., weaker selection) can be attributed to aggregation across locations within a province (see Section 4.3). The degree of price selection is virtually unchanged with different configurations of fixed effects, inclusion of category-specific linear trends, or in unweighted regressions (columns 2 through 4).

Column 5 in Table 2 provides the results for all price changes—both regular and those associated with price discounts. Including price discounts makes price selection at a category-stratum level slightly weaker for the United Kingdom and the United States, –0.333 and –0.303, respectively, and slightly stronger for Canada, –0.327. Including price changes associated with product substitutions, shown in column 6, makes price selection a bit stronger in the United Kingdom, and slightly weaker in Canada, –0.415 and –0.268; substitutions do not arise in the IRI dataset. Hence, price discounts and substitutions do not appear to materially influence price selection at a stratum level.

Because variation of prices at the micro level is substantial, one may be concerned that price selection at a stratum level can be measured inaccurately due to potentially small sizes of strata and the dominance of large idiosyncratic shocks. We assess this concern directly using the U.K. data (see Supplementary Material Section A for details).[21] For the baseline case (regular prices, no substitutions), we split all price change observations into two random subsamples of roughly equal sizes. First, for each subsample, we estimate price selection at a stratum level using the same specification (8) as for the full subsample. We find that price selection coefficients for subsamples 1 and 2, –0.387 and –0.388, are highly significant and very close to –0.371 estimated for the full sample. Second, we use DP_{st} from one subsample as an instrumental variable for DP_{st} in the other subsample. Such instrumental variable is valid because the (classical) measurement error and idiosyncratic shocks are uncorrelated across two randomly assigned subsamples. Price selection is –0.341 in both cases, which is close to the baseline for the full sample. Hence, measurement error and idiosyncratic shocks are unlikely to drive the results.

To what extent does price selection differ across categories? Figure 2 shows the weighted histogram of price selection coefficients estimated individually for each category-stratum in the United Kingdom, for the case with regular prices and no substitutions and allowing calendar-month effects. The empty red bars show the weights for all estimated coefficients. The histogram shows negative selection coefficients for 89.3% of strata. The weighted mean (median) across all price selection values is –0.392 (–0.400), which is close to the estimate of stratum-level price selection obtained in the baseline panel specification (8). Positive coefficients are predominantly those that are not statistically different from zero. We also plot the weighted histogram for the coefficients that are statistically different from zero at 95% significance level (solid bars). Virtually all of these coefficients

[20] Section A in Supplementary Material provides comparisons with alternative standard errors: Driscoll and Kraay (1998), clustered by strata, and clustered by month. The results remain highly significant.

[21] We thank Yuriy Gorodnichenko for suggesting this exercise.

(99.5% of the weight) are negative, indicating pervasive price selection that increases sensitivity of stratum-level inflation to shocks; the remaining 0.5% of strata exhibit price selection of the opposite sign.[22]

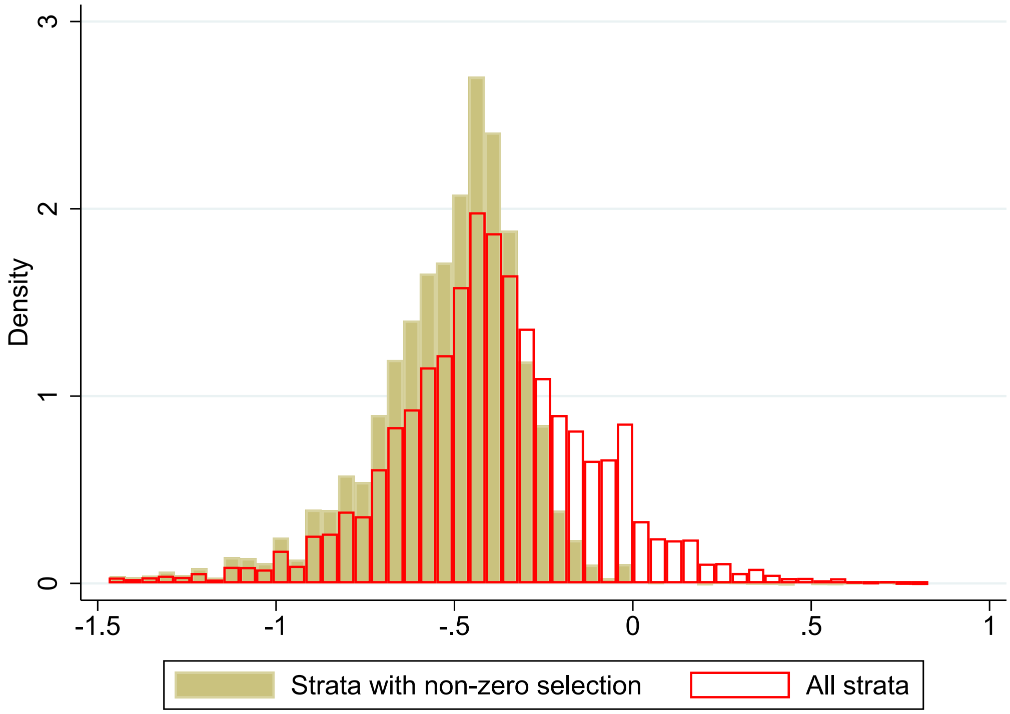
Table 2: Price selection at a category-stratum level

	Regular prices, excluding subs			Unweighted	All prices	Incl. subs
	(1)	(2)	(3)	(4)	(5)	(6)
A. U.K.						
Price selection	**-0.371*****	**-0.371*****	**-0.369*****	**-0.357*****	**-0.333*****	**-0.415*****
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Calendar-month effects	Y	N	Y	Y	Y	Y
Stratum linear trend	N	N	Y	N	N	N
Number of observations	1,073,089	1,073,089	1,073,089	1,073,089	1,075,108	1,077,371
R^2	0.032	0.032	0.032	0.046	0.039	0.055
B. Canada						
Price selection	**-0.285*****	**-0.284*****	**-0.283*****	**-0.310*****	**-0.327*****	**-0.268*****
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
Calendar-month effects	Y	N	Y	Y	Y	Y
Stratum linear trend	N	N	Y	N	N	N
Number of observations	568,264	568,264	568,264	568,264	619,489	604,027
R^2	0.022	0.022	0.022	0.027	0.073	0.018
C. U.S.						
Price selection	**-0.360*****	**-0.363*****	**-0.361*****	**-0.369*****	**-0.303*****	**N/A**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Calendar-month effects	Y	N	Y	Y	Y	
Stratum linear trend	N	N	Y	N	N	
Number of observations	18,402,238	18,402,238	18,402,238	18,402,238	22,930,586	
R^2	0.198	0.200	0.198	0.233	0.281	

Notes: Data sources are described in notes for Table 1. The entries in "Price selection" are the estimated values of the coefficient in the weighted panel regression (8) of monthly stratum preset price levels on the monthly average stratum size of price changes, with stratum fixed effects. Columns (1) to (3) provide estimates for the sample excluding price discounts and product substitutions; column (4) - unweighted regression. Column (5) uses all prices and excludes substitutions. Column (6) includes substitutions, regular prices. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[22] We find that 21 out of 45 strata with positive and significant price selection coefficients are in Food and Beverage sectors. High-volume, perishable food products, such as milk, bread, eggs and soda, tend to have flexible and volatile prices as they respond to sector/stratum-specific disturbances or to manufacturer's costs in case of direct-to-store products. It is possible that such disturbances trigger adjustments of prices that adjusted only recently and/or adjustments in the direction opposite to average adjustment in that stratum or sector. Also, selection coefficient for *Liquid Fuels* is small positive and statistically significant. This is not surprising, since prices are virtually flexible in this sector, and therefore we would expect selection to be close to zero.

Figure 2: Price selection across product strata, U.K. CPI data



Notes: Figure shows the weighted histogram of price selection coefficients estimated for each stratum using regression (11), in the United Kingdom, for the case with regular prices and no substitutions, controlling for calendar-month effects. We exclude values in top/bottom 0.5%. The empty red bars show the weights for all estimated coefficients. Solid bars show the weights for coefficients that are statistically different from zero at 95% confidence level.

4.2 Price selection and price-setting moments

How does price selection vary with pricing behavior? To answer this question, we first explore wide product coverage of the datasets and follow with insights from business cycle models in Section 5. We modify the panel regression (8) by allowing price selection to vary with price adjustment moments computed at a stratum level, so that $\gamma = \gamma_1 + \gamma_2 \Gamma_{st}$, where Γ_{st} are price adjustment moments for category-stratum s in month t:

$$P_{st}^{pre} = \gamma_1 DP_{st} + \gamma_2 DP_{st} \times \Gamma_{st} + \delta_t + error_{st}, \tag{9}$$

where $DP_{st} \times \Gamma_{st}$ are the interaction terms between DP_{st} and Γ_{st}, and δ_t are time fixed effects. For the interaction terms, we consider three price adjustment moments commonly reported in the empirical literature: the frequency and average size of price changes, Fr_{st} and DP_{st}, and the average absolute size of individual price changes ADP_{st}.

Table 3 provides the estimation results. For the baseline case with regular prices and no substitutions, price selection across strata is consistent with price selection obtained by exploiting time variation, reported above: –0.367 for the United Kingdom, –0.373 for the United States, and –0.295 for Canada, all highly statistically significant. We visualize our cross-sectional findings in Figure 3, which provides scatter plots for nine selected months in the United Kingdom, for regular prices and excluding substitutions. For each month, each point on the plot represents an observation for the largest stratum in a particular category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each circle represents that stratum's consumption weight. Hence, each plot shows joint variation of P_{st}^{pre} and DP_{st} across strata in a given month. Similar to the case for time variation, there is substantial variation in both variables across strata in a given month, and they tend to correlate negatively for most months, pointing to common incidence of price selection that amplifies inflation fluctuations.

The other columns in Table 3 provide the results for the full specification (9), including all three interaction terms, for the baseline case and for alternative cases incorporating price discounts and product substitutions.[23]

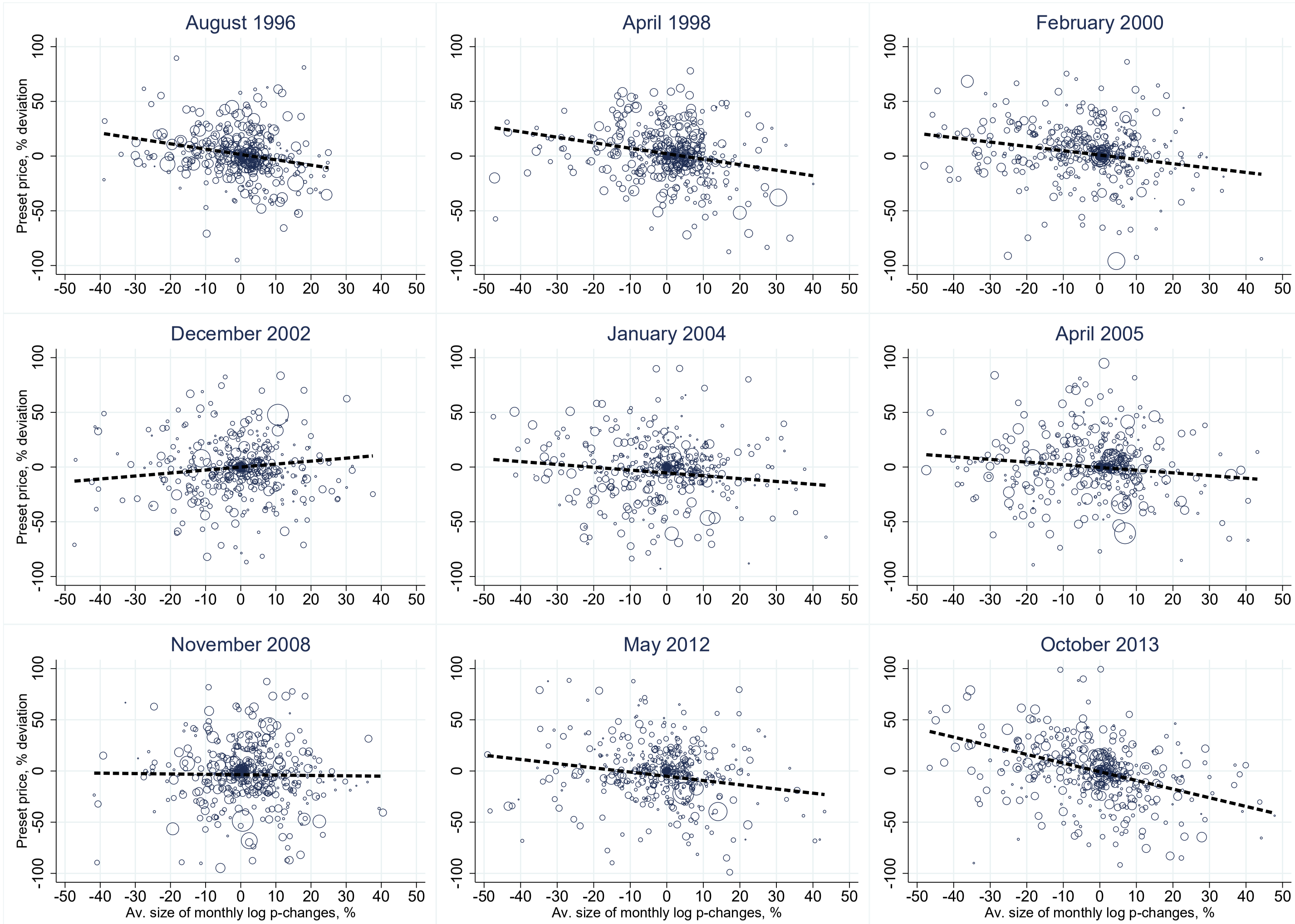
Two robust results emerge for all specifications and across all three datasets. First, price selection is stronger for category-strata where price changes are less frequent, given by the estimated elasticity $\hat{\gamma}_2$ for the interaction term $DP_{st} \times Fr_{st}$. For the baseline case, the estimates imply that in a category-stratum with a 10 percentage point lower fraction of price changes, price selection accounts for a higher fraction of its inflation variance: by 2.2 percentage points for the United Kingdom (from –0.367 to –0.389), by 6.7 percentage points for the United States (from –0.373 to –0.440), and by 5.7 percentage points for Canada (from –0.295 to –0.352). Across all datasets and all treatments, the range of additional price selection due to a 10 percentage point lower frequency of price adjustment lies between 1.9 and 6.7 percentage points, with an average around 4.5 percentage points.

The second robust finding is that price selection is stronger (weaker) when average price changes DP_{st} are above (below) average, given by $\hat{\gamma}_2$ for the interaction term $DP_{st} \times DP_{st}$. If the average size of price changes is higher by 5 percentage points, price selection strengthens by 1.5 percentage points for the United Kingdom (from –0.367 to –0.382) and for the United States (from –0.373 to –0.388) and by 2.5 percentage points for Canada (from –0.295 to –0.320). We also find that price selection becomes stronger with ADP_{st} although the effects are weak quantitatively; this is consistent with predictions of non-linear menu cost models, where a response to a larger monetary shock leads to a disproportionately larger response of inflation (Burstein, 2006; Alvarez, Lippi, and Passadore, 2017).

To glean further into possible determinants of price selection across sectors, we compare price selection by sector groups and by sector characteristics (see details in Supplementary Material Section A). We find that *Services* and *Non-durables* feature the strongest and the weakest price selection, respectively, and *Durables* and *Semi-durables* have intermediate selection values. This ranking of price selection is in line with the ranking of the degree of price rigidity in those sectors: prices in *Services* (*Non-durables*) are *least* (*most*) flexible, and prices in *Durables* and *Semi-durables* are in between. Moreover, *Food* and *Fuel* sectors, where prices are flexible and volatile, exhibit price selection below average. Hence, price selection across sector groups is roughly aligned with price rigidity and volatility.

[23] Estimating interaction coefficients separately, instead of all together, does not alter the conclusions. Results are available upon request.

Figure 3: Preset price level and average size of price changes, variation over product categories for selected months, U.K. CPI data



Notes: Figure provides scatter plots for nine selected months in the United Kingdom for regular prices and excluding substitutions. For each month, each point on the plot represents an observation for the largest stratum in a particular category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each point represents that stratum's consumption weight. Each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across strata in a given month. The slope of the trend line is equal to $\hat{\gamma}_s$, representing the estimated degree of price selection.

Table 3: Price selection and price changes across product strata

Independent variables	U.K.				Canada				U.S.		
	Baseline	Baseline	All prices	Incl. subs	Baseline	Baseline	All prices	Incl. subs	Baseline	Baseline	All prices
		With interaction terms				With interaction terms				With interaction terms	
DP_{st}	-0.367***	-0.370***	-0.368***	-0.437***	-0.295***	-0.560***	-0.561***	-0.467***	-0.373***	-0.546***	-0.490***
	(0.002)	(0.010)	(0.009)	(0.008)	(0.003)	(0.013)	(0.013)	(0.009)	(0.000)	(0.000)	(0.000)
Interaction terms											
DP_{st} x Fr_{st}		0.220***	0.193***	0.396***		0.566***	.617***	0.456***		0.668***	0.474***
		(0.012)	(0.010)	(0.011)		(0.011)	(0.011)	(0.007)		(0.001)	(0.000)
DP_{st} x DP_{st}		-0.003***	-0.003***	-0.001***		-0.005***	-0.004***	-0.003***		-0.003***	-0.004***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
DP_{st} x ADP_{st}		0.001**	0.001***	-0.001***		0.003***	0.002***	-0.001***		-0.001***	-0.001**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Number of obs	1,073,089	1,072,899	1,075,029	1,077,315	568,264	567,573	600,427	619,303	18,402,238	18,393,701	1,072,899
R^2	0.033	0.036	0.049	0.059	0.023	0.033	0.027	0.086	0.182	0.224	0.036

Notes: Data sources are described in notes for Table 1. The entries are coefficients in the weighted panel regression (9) of monthly stratum preset price levels on independent variables, with month fixed effects. The column "Baseline" corresponds to the case when price changes due to sales or substitutions are excluded. Other columns break down price selection via interaction with stratum-level variables: Fr_{st} -- mean fraction of price changes in stratum s month t, DP_{st} - mean average size of price changes, ADP_{st} - mean absolute size of price changes in stratum s. *** p<0.01, ** p<0.05, * p<0.1.

To explore other sector characteristics that affect price selection, we merge the results by sector with four types of sector-specific information. First, we add the data on life expectancy for durable goods, obtained from Bils and Klenow (1998) for the United States (we mapped 18 U.K. basic classes to this measure). Second, we add 5-firm concentration ratios for the United Kingdom in 2004 from Mahajan (2006) (we mapped 50 U.K. basic classes to this measure). Finally, we add quarterly real consumption expenditures from the Household Final Consumption Expenditures database from the U.K. Office for National Statistics, for the period from 1996Q1 to 2014Q3 (we mapped 65 U.K. sectors). For each sector, we construct the standard deviation of the quarterly change in the log of real consumption and a measure of sector cyclicality—the regression coefficient of sector log consumption growth on aggregate log consumption growth (Klenow and Malin, 2010).

We find that cyclicality and volatility of sector consumption growth, or life expectancy (for durable goods) do not correlate with price selection. By contrast, there is a statistically significant positive correlation between price selection and sectors' 5-firm concentration ratios, i.e., more concentrated sectors tend to exhibit weaker selection, even after controlling for price rigidity. Examples of sectors with high 5-firm concentration ratios and weak selection are *Tobacco* and *Liquid Fuels*, and sectors with low concentration ratios and strong selection include *Dry-cleaning*, *Repair and Hire of Clothing*, *Tools and Equipment for House and Garden*, *Passenger Transport by Road*, and *Canteens*. This relationship is intuitive: firms with more market power have less need to move their prices in response to competitors' prices.

4.3 Aggregate price selection

We have provided evidence of significant price selection at elementary levels—for products in the same category and location. This evidence implies that in response to shocks that move stratum-level inflation up, the subset of prices that adjust tend to originate from lower-than-usual levels. The key question then is to what degree price selection matters for the response of aggregate inflation to shocks.

Similar to inflation identity at a stratum level (equations (6)–(7)), we can write aggregate inflation in month t as the product of the aggregate fraction of adjusting prices and their average size in month t, and where the latter is represented as the difference between aggregate reset and preset price levels:

$$\pi_t \equiv Fr_t \cdot \underbrace{[P_t^{res} - P_t^{pre}]}_{DP_t}, \tag{10}$$

where $Fr_t = \sum_s \omega_{st} Fr_{st}$ is the weighted mean fraction of price changes in month t, with stratum expenditure weights ω_{st}, and aggregate reset and preset price levels, $P_t^{res} = \sum_s \omega_{st} \frac{Fr_{st}}{Fr_t} P_{st}^{res}$ and $P_t^{pre} = \sum_s \omega_{st} \frac{Fr_{st}}{Fr_t} P_{st}^{pre}$ are given by the *frequency-weighted* means. Weighting stratum-level price indices by their relative frequency—in addition to expenditure shares—reflects the fact that strata with more frequent price adjustments contribute a relatively larger fraction of price changes in the computation of the average size DP_t, as explained in Klenow and Kryvtsov (2008).

To estimate aggregate selection, we apply the regression of preset price level on the average size of price changes to aggregate variables:

$$P_t^{pre} = \gamma DP_t + \delta_{cal} + error_t, \tag{11}$$

where as before δ_{cal} denotes calendar-month fixed effects.

Table 4 provides the results of this estimation (row "Aggregate"). For regular prices and no substitutions, aggregate price selection is substantially weakened: –0.197 for the United Kingdom (versus –0.371 at a stratum level), 0.061 for the United States (–0.360), and –0.003 for Canada (–0.285); and for the United States and Canada the estimates are not statistically significant. Results are very similar when we include price changes due to product substitutions.

We dissect how aggregation weakens price selection by reporting estimated selection coefficients for two intermediate levels of aggregation using the U.K. data. We aggregate stratum-level variables by 1,044 product categories and by 67 COICOP product classes. We then estimate regression (8) with subscript s now denoting product category or class, with and without fixed effects δ_s. Table 4 reports estimated coefficients. The effects of aggregation depend on whether category fixed effects δ_s are included in the regression. When they are included, selection at product (class) level, –0.385 (–0.361), is similar to –0.371 selection at stratum level. But when fixed effects are not included in the regression, price selection gradually weakens with aggregation. For regular prices and no substitutions, selection decreases from –0.365 at a stratum level, to –0.317 at product category level, to –0.268 at basic class level, and to –0.197 at the aggregate level. Hence, the weakening of price selection is due to product heterogeneity, captured by category/class fixed effects.[24] These results underscore the importance of incorporating sector heterogeneity in sticky-price models. In the next Section, we analyze price selection in a relatively standard multisector model and show that sector heterogeneity in the frequency of price changes can account for roughly half of the attenuation of selection effects induced by aggregation.

When variables in regression (11) are constructed using all prices—both regular and sale prices—a substantial degree of price selection remains at the aggregate level for the United Kingdom: –0.394 (versus –0.371 at a stratum level). For the United States, aggregate selection is also meaningful: –0.140 (versus –0.36 at a stratum level). In both cases, aggregate selection is statistically significant at the 1% level. For Canada, it is still close to zero, –0.039 (versus –0.327 at a stratum level), and it is not statistically significant. Hence, while aggregation of stratum-level regular price changes largely washes out price selection, that is not the case for the United States and the United Kingdom when price discounts are included. This suggests that price discounts represent an important margin of price flexibility in response to macroeconomic shocks.[25]

[24] Aggregation results may also be explained by other factors, such as seasonality or regulated prices. For example, positive selection in *Furniture/Furnishings* is affected by seasonality. When we control for seasonality, this selection coefficient becomes negative, although still statistically near zero. At basic class level, controlling for seasonality reduces selection coefficients for 34 sectors, and lowers the weighted mean across all sectors from –0.289 to –0.322. Because seasonal adjustments are in part pre-determined, seasonal effects are expected to weaken measured price selection. Regulated goods, such as *Tobacco* are also expected to exhibit weaker selection.

[25] This conclusion is consistent with Kryvtsov and Vincent (2021), who use U.K. and U.S. CPI micro data and find that the incidence of price discounts is strongly countercyclical, amplifying fluctuations in the price of aggregate consumption. For the United States, Sheremirov (2020) finds that at a city-category level regular price dispersion is positively correlated with inflation, but when sale prices are included, this correlation is negative. He uses time variation in price dispersion to discriminate across models with different degrees of selection effects. For Canada, price discounts may not have had their

In the United Kingdom, higher inflation is associated with less frequent and smaller price discounts. The change in the frequency and size of price discounts alters the composition of the population of price changes between regular-to-regular and sale-related price changes, creating additional selection effects. Concretely, when retailers want to increase prices, they scale down the frequency and size of price discounts by decreasing the proportion of regular-to-sale (and some sale-to-sale) price changes and increasing the proportion of regular-to-regular price changes. Essentially, retailers appear to replace some large regular-to-sale price decreases with smaller regular-to-regular price increases, resulting in additional inflationary push (see Section A in Supplementary Material).

Table 4: Price selection, aggregate time series

Level of aggregation	Number of groups	Regular prices, excluding subs		All prices		Incl. subs	
		FE	No FE	FE	No FE	FE	No FE
A. U.K.							
Stratum	9030	-0.371***	-0.365***	-0.333***	-0.354***	-0.415***	-0.415***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Product	1044	-0.385***	-0.317***	-0.359***	-0.305***	-0.404***	-0.368***
		(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Basic class	67	-0.361***	-0.268***	-0.357***	-0.273***	-0.330***	-0.275***
		(0.016)	(0.015)	(0.013)	(0.012)	(0.014)	(0.014)
Aggregate	**1**	**-0.197*****		**-0.394*****		**-0.188*****	
		(0.072)		**(0.065)**		**(0.069)**	
B. Canada							
Stratum	9165	-0.285***		-0.327***		-0.268***	
		(0.003)		(0.001)		(0.003)	
Aggregate	**1**	**-0.003**		**-0.039**		**0.013**	
		(0.021)		**(0.028)**		**(0.020)**	
C. U.S.							
Stratum	1550	-0.360***		-0.303***		N/A	
		(0.000)		(0.000)			
Aggregate	**1**	**0.061***		**-0.140*****			
		(0.035)		**(0.021)**			

Notes: Data sources are described in notes for Table 1. For row "Stratum" the entries are price selection coefficients estimated using regression regression (8). "Aggregate" rows provide the estimated values of the coefficient in the time-series regression (11) of aggregate preset price level on the aggregate size of price changes, with calendar-month fixed effects. For the U.K., price selection is computed for two intermediate levels of aggregation, using regression (8) with and without category fixed effects. For row "Product", for each product category, we compute frequency-weighted means of reset and preset price levels across 24 strata in the category. For row "Basic class", we compute the variables by COICOP class. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

full influence on price selection since the sample ends in 2009, before the period when sales had their largest swings in the United States and United Kingdom.

5 Price selection in sticky-price models

In this section, we compare predictions of standard sticky-price models with our empirical findings and perform additional model analyses. First, we calibrate a relatively standard multisector model to the U.K. data and assess the degree to which aggregation weakens price selection in the model. We then show that the degree of monetary non-neutrality is monotone in our measure of price selection, keeping the frequency of price changes constant. We also use the model to gauge potential differences between price selection conditional on particular shocks and unconditional price selection, which is the measure we use in the empirical analysis. In addition, the model provides an assessment of potential small-sample bias in the empirical analysis. We also study whether price selection interacts with real rigidities in the sense of Ball and Romer (1990) and Kimball (1995). Finally, in Supplementary Material (Sections B and C), we provide detailed derivations of price selection in several other models.

5.1 Multisector model

We analyze a multisector model that nests Golosov and Lucas (2007) and Calvo (1983) as limiting cases; we refer to it as the "generalized Golosov-Lucas model." We calibrate the model to match price-setting statistics for 64 basic consumption classes in the U.K. data. Similar models have been analyzed by Nakamura and Steinsson (2010) and Gautier and Le Bihan (2021). For brevity, we provide here a brief description of the model and leave the complete exposition and derivations to Sections B and C of the Supplementary Material.

The economy is populated by a large number of infinitely lived households and monopolistically competitive producers of intermediate goods. The shocks in the baseline case are aggregate shock to the money supply, and idiosyncratic and sectoral productivity shocks. Money supply follows a random walk with drift, with normally distributed i.i.d. innovations. Firm's productivities follow AR(1) processes with two normally distributed innovations: firm- and sector-specific. The demand for product varieties is derived under assumptions of constant elasticity of substitution between consumption goods within and across consumption sectors; we set this elasticity to 3, in line with recent evidence by Hobijn and Nechio (2019) and with studies of retail price behavior (e.g., Midrigan, 2011). Firms usually need to incur a menu cost to change each price, as in Golosov and Lucas (2007). Occasionally, however, they obtain random opportunities to change prices at no cost, as in the Calvo (1983) model. These opportunities are dictated by a parameter that we refer to as the "Calvo weight", which takes on values in the unit interval. Hence, our generalization of the standard menu-cost model is in the tradition of Dotsey, King, and Wolman (1999), who study a sticky-price model with random menu costs.[26] For the baseline case, we also make assumptions on preferences and technology that lead to strategic neutrality of pricing decisions, as often done in the literature (Golosov and Lucas, 2007; Alvarez, Le Bihan, and Lippi, 2016). This significantly reduces computational costs and makes it feasible to calibrate the model.

For each basic consumption class in the data, we calibrate five parameter values—menu cost, Calvo weight, volatility and persistence of idiosyncratic productivity shocks, and volatility of common sectoral productivity innovations—to match five moments in the data—mean fraction of adjusting prices, mean

[26] Menu-cost models with some Calvo price adjustments have also been analyzed by Nakamura and Steinsson (2010) and Alvarez, Le Bihan, and Lippi (2016), among others.

absolute price change, autocorrelation of newly set prices, standard deviation of sectoral inflation, and price selection. We use regular price changes (excluding substitutions) to compute the weighted mean absolute size of price changes. To compute serial correlation of adjusted prices, we compute a linear trend for each regular price quote line and express prices in terms of percent deviations from the trend. For each month, we then compute a weighted AR(1) correlation coefficient between such prices across months in which they changed. Price selection for each consumption class is obtained by estimating specification (11) with class-level data. We set the size of monetary shocks to match the standard deviation of regular-price inflation in the U.K. data, 0.23%. The remaining parameters are assigned as follows: the discount factor is $0.96^{1/12}$, corresponding to a 4% annualized average real rate of interest; mean rate of the money growth is 0.12% to have the model match the mean monthly rate of regular price inflation of 0.12%, or 1.5% per year. To handle sampling error, in our baseline calibration the number of simulated firms in each sector matches the average number of price quote lines in the corresponding consumption class in the data.[27]

5.2 Model results: aggregation and price selection

The model has enough flexibility to fit the moments well, although with some differences across statistics (details provided in Section B, Supplementary Material). The fit for price rigidity (inverse of the mean frequency of price changes), mean absolute price change, and sectoral inflation volatility is almost perfect. The fit for the two remaining statistics—autocorrelation of newly set prices and price selection—is not as tight, but the model still accounts for 84% and 73% of variation across classes, respectively.

Weighted mean price selection across classes in the calibrated model equals –0.275. This compares well with –0.289 in the U.K. data.[28] Recall, aggregate price selection is weaker in the data: for the United Kingdom it equals –0.197 (Table 4). We compute aggregate price selection implied by the calibrated model using model-simulated data, as follows. For each of the 100 simulations, we compute aggregate variables using frequency-weighted sectoral variables, exactly as we did in the empirical analysis explained in Section 4.3. We then measure aggregate price selection by applying regression (11) to these time series. The average across simulations yields aggregate price selection of –0.233. Hence, the calibrated model can account for almost half of the difference between sector-average and aggregate price selection.[29]

[27] We simulate equilibrium dynamics over 235 months and run 100 simulations. Sectors are calibrated separately to make computation feasible. This separation can be exploited because, under strategic neutrality in price setting, firms' marginal costs are exogenous and general-equilibrium feedback effects on firms' optimal policies are small (see Golosov and Lucas, 2007 and Alvarez and Lippi, 2014). Hence, sectors essentially do not interact, and to approximate the general equilibrium we only need to feed the same sequence of monetary shocks for all sectors in a given simulation. Monetary shocks are drawn anew for each simulation. For each simulation, we compute the time series for the components of inflation decomposition (7) and the model counterparts of the empirical moments that we target in the calibration. All moments are computed by applying the same procedure as in Section 3.4 to the model-generated data. For each sector, we take means across the 100 simulations and pick parameters to minimize the distance between these means and data moments.

[28] Mean price selection across classes is virtually identical to the estimated selection coefficient at basic class level in the U.K. data for regular prices and no substitutions, with calendar month fixed effects and not including class fixed effects. In calibrating the model, out of 67 basic classes, we exclude 3 basic classes for which price selection in the data is outside of selection range in the model: *Recreational and Sporting Services* (1.52), *Education* (–3.34), *Canteens* (–1.35).

[29] In Section C in Supplementary Material, we derive the aggregation result analytically for a 2-sector Taylor model.

5.3 Price selection, real rigidities, and monetary non-neutrality

Next, we use the model to study the relationship between price selection and monetary non-neutrality. Due to computational constraints, for this analysis we abstract from cross-sectoral heterogeneity and work with a one-sector version of the model. We exploit the flexibility of the generalized model to generate a range of price selection values. When the Calvo weight is zero, the model coincides with Golosov and Lucas (2007) model with strong price selection; selection is zero when the Calvo weight equals one.

We study a sequence of economies, varying the Calvo weight between zero and one. For each value of the Calvo weight, we re-calibrate the model to match aggregate price-setting statistics for the United Kingdom (Table 5). In particular, we pick the menu cost, volatility and persistence of idiosyncratic productivity shocks to match mean fraction of adjusting prices, mean absolute price change, and auto-correlation of newly set prices. For each economy, we compute price selection and different measures of monetary non-neutrality. Importantly, all economies feature strategic neutrality in price setting and the same frequency of price changes, and thus, differences in the degree of monetary non-neutrality can be traced to selection. We run 100 simulations of each economy and report averages across simulations.

Table 5: Price selection in the generalized multisector Golosov-Lucas model

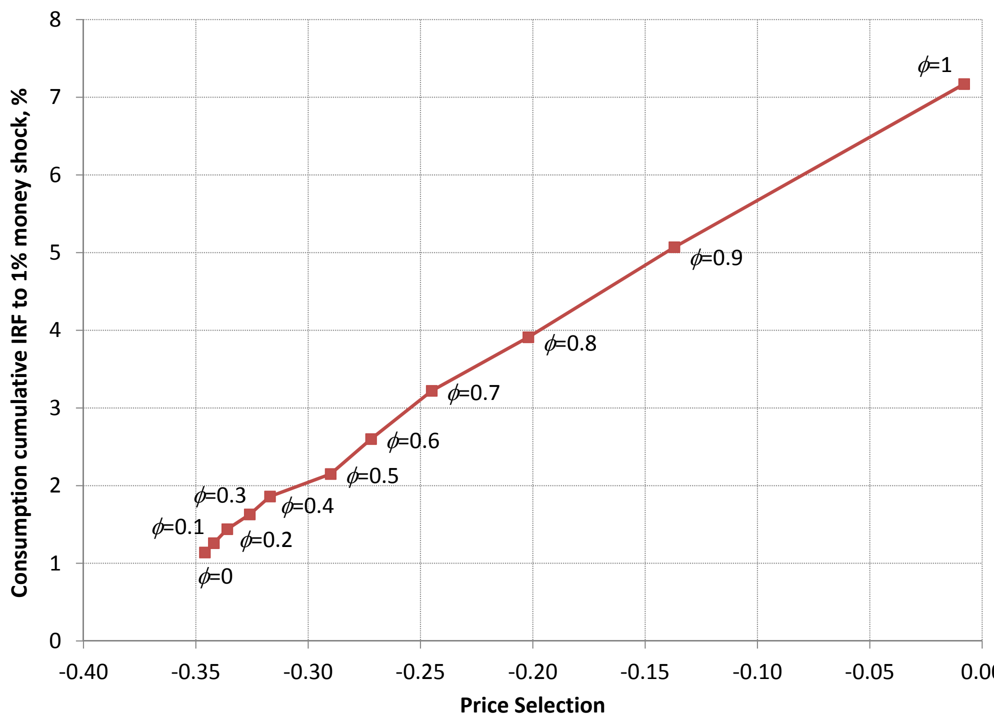
Moments	Data (1)	Multisector model (2)
Fraction of p-changes		
weighted mean	0.121	0.120
min	0.033	0.033
max	0.914	0.921
Sector-level selection		
weighted mean	-0.289	-0.275
min	-0.848	-0.481
max	0.380	-0.005
Aggregate selection	-0.197	-0.233
Aggregation effect	0.092	0.042

Notes: Data entries correspond to statistics from the 64 basic classes in the U.K. data. Price selection entries in Column (1) correspond to estimates obtained by running regression (11) for each basic class. Aggregation effect is the difference between aggregate selection and weighted mean selection. Column (2) reports results from the generalized 64-sector Golosov-Lucas model. We simulate equilibrium dynamics in each sector over 235 months for a given draw of money growth shocks. The number of firms in each sector matches the average number of price quote lines in the corresponding consumption class in the data. For each simulation, we compute the relevant moments by applying the same procedure as in Section 3.4 to the model-generated data. We report means across 100 simulations.

Results are reported in Figure 4 and Table 6. They show that the size of monetary non-neutrality across re-calibrated models varies monotonically with price selection. For each additional 10 percentage points of the share of inflation variance explained by price selection, the cumulative response of consumption to a +1% monetary impulse decreases by about 1 percentage point. Hence, despite its model-free nature, the price selection measure captures the key role of selection effects for the inflation-output trade-off in standard sticky-price models. Price selection is close to –0.35 in the Golosov and Lucas (2007) model, which is close to our panel-based estimates of price selection at the disaggregated level (Table 2). Matching the level of aggregate price selection that we estimate for the United Kingdom (–0.197) requires a Calvo weight of approximately 0.8. This implies larger monetary non-neutralities, but not proportionally: the model with a Calvo weight of 0.8 closes less than 50% of the difference in non-neutrality between the two limiting models. In other words, adding some selection to the Calvo model reduces non-neutrality considerably.

Finally, we ask whether price selection interacts with real rigidities, in the sense of Ball and Romer (1990) and Kimball (1995), in determining monetary non-neutrality. For a given frequency of price changes, real rigidities are known to mute the response of prices to monetary shocks, and thus to increase the degree of monetary non-neutrality. More generally, non-neutrality can be thought of as a function of the frequency of price changes, the degree of selection, and the strength of real rigidities. We show that the effects of real rigidities on monetary non-neutrality are orthogonal to selection effects. For brevity, results are presented in Supplementary Material, Section E.

Figure 4: Price selection and monetary non-neutrality in the generalized Golosov-Lucas model



Notes: Figure provides the mapping between price selection and the extent of monetary non-neutrality in the generalized Golosov-Lucas model. We vary price selection by changing the "Calvo weight" parameter ϕ, from zero (which yields the Golosov-Lucas model) to one (which delivers the Calvo model). All economies feature the same frequency of price changes. Monetary non-neutrality is measured as the consumption cumulative IRF to a 1% permanent impulse to the level of money supply.

Table 6: Price selection and monetary non-neutrality in the generalized Golosov-Lucas model

Moments	**Weight on Calvo adjustment in generalized Golosov-Lucas model**										
	0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Fraction of price changes per month, %	12.0	12.2	12.0	12.1	12.1	12.1	12.1	12.1	12.1	12.1	12.1
Weight on Calvo in nested model	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Price selection	-0.346	-0.342	-0.336	-0.326	-0.317	-0.290	-0.272	-0.245	-0.202	-0.137	-0.008
Consumption st.dev., %	0.27	0.28	0.31	0.33	0.36	0.39	0.44	0.49	0.55	0.62	0.74
Consumption ser. corr	0.52	0.55	0.59	0.61	0.64	0.67	0.71	0.75	0.78	0.82	0.86
Half-life of consumption IRF to 1% shock, months	1.07	1.17	1.30	1.41	1.54	1.74	2.02	2.39	2.80	3.48	4.64
Consumption cumulative IRF to 1% shock	1.14	1.26	1.44	1.63	1.86	2.15	2.60	3.22	3.91	5.07	7.17

Notes: Entries are results of simulations of generalized Golosov-Lucas model, which nests the Calvo model. Columns correspond to simulations for different weight on Calvo pricing. Each economy is simulated over 235 months for a given draw of a money growth shocks and 10000 draws of idiosyncratic productivity shock. For each simulation we compute the time series for each of the variables. We repeat this simulation 100 times and report the means of model moments over these simulations.

5.4 Unconditional versus conditional price selection, and sample size

In this section, we use our calibrated models to study two potential issues associated with our empirical analysis: the use of unconditional data moments and small sample size.

In our analysis, we mainly rely on unconditional moments computed from micro price data. In doing this, we follow essentially all of the literature on price setting, which routinely uses unconditional data moments to calibrate models in which there is typically only one aggregate shock—the monetary shock. While absolutely widespread, this approach may be criticized for the disconnect between empirical targets and their theoretical counterparts. We take a step toward addressing this criticism by analyzing conditional and unconditional price selection in a model with two aggregate shocks—monetary and productivity shocks.[30] For brevity, we leave details of the model and calibration to the Supplementary Material, Section B. The bottom line is that conditional and unconditional price selection are quite similar.

The second issue is a potential small-sample bias in several smaller U.K. consumption classes. Small sample bias may arise because, in a sector with small number of price changes, idiosyncratic shocks might account for a large share of the variation in both the preset price-relative and the average size of price changes. In this case, comovement between the preset price-relative and inflation may be overstated and price selection may appear stronger.[31] In Section 4, we provided empirical evidence that our estimates were not driven by idiosyncratic price changes, by splitting the sample at each stratum and using the time series of the size if price changes estimated with one half of the sample to instrument for the size of price changes in the other sub-sample. In this Section, we address the small sample concern using numeric simulations of the multisector model.

In the baseline calibration of the multisector model, we choose the number of firms in each sector to match the average number of individual price quote lines in the corresponding U.K. consumption class. Because we fit the frequency of price changes in each class, the calibrated model also matches the number of price changes observed for each class. To study small sample bias, we run new simulations of the calibrated model with a large number or firms (fifteen thousand) in *all* sectors. If sample size is indeed an issue, we would obtain different results for sectors with a small number of firms. We find that small samples do induce a bias toward stronger price selection (i.e., more negative estimates). The magnitude of the bias, however, is small. For instance, in the model with a large number of firms in all sectors, weighted average price selection equals –0.249, compared to –0.275 in the baseline model. Aggregate price selection is –0.226 in the model with a large number of firms, compared to –0.233 in the baseline model.

[30] An alternative approach would be to compute conditional empirical moments given some series of identified monetary shocks. Implementing this approach, however, is not straightforward. It usually involves projecting the time series of interest onto the identified monetary shocks and then working with the projected series. This is a sound approach to obtain conditional, counterfactual series in linear models. When the underlying model involves non-linearities and lumpy behavior, however, this approach can be quite problematic. For example, linear methods may yield significantly biased estimates of structural parameters in the presence of lumpy behavior and small samples (Berger, Caballero, and Engel, 2018). In the context of our analysis, however, the problem is even more fundamental because the degree of price selection depends on the identities of prices that do or do not adjust after shocks. Therefore, the construction of the conditional time series would also need to take into account the effect of the shock on the identities of adjusters and non-adjusters.

[31] We thank Peter Karadi—our discussant at the Cleveland Fed's 2019 "Inflation: Drivers and Dynamics" Conference—for raising this issue.

6 Conclusions

We draw several conclusions for sticky-price models. First, multisector models with selection at disaggregated levels have a better chance of accounting for the evidence we provide. Nakamura and Steinsson (2010) and, more recently, Gautier and Le Bihan (2021), show that implications of such models for the sources of business cycles and the effectiveness of monetary policy can differ in important ways from the implications of models without price selection or sectoral heterogeneity.

Second, aggregation can significantly reduce selection. Our calibrated model can account for about half of the drop in price selection that we estimate with the U.K. data when moving from stratum-level selection to aggregate price selection. Making full sense of the effects of aggregation requires uncovering new mechanisms that weaken aggregate price selection beyond the effects of heterogeneity in the frequency of price changes.

In addition, we note that standard sticky-price models can account only for variation of price selection in a range between around 0 and –0.5. This covers approximately 60% of the weight in the empirical distribution of price selection that we estimate at the stratum level. Models that exploit additional dimensions of heterogeneity across goods and retailers might be able to expand that range and better fit the facts we uncover.

Finally, appropriately measuring price selection allows us to more accurately identify the determinants of monetary non-neutrality. For example, we show that real rigidities and price selection essentially do not interact—at least under standard assumptions—and so their effects on non-neutrality can be studied independently. Given the evidence we provide, studying mechanisms that can help reconcile observed micro price flexibility and aggregate price sluggishness becomes an even more important endeavor. Real rigidities and information frictions are two such mechanisms that should benefit from additional empirical research.

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Price Selection
– Supplementary Material*–

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Contents

A Data Appendix

A.1 Price selection and additional category characteristics

Section 4.2 in the main text shows that price selection is stronger for category-strata with less frequent and larger average price changes. To glean further into possible determinants of price selection across sector, we compare price selection by sector groups and by sector characteristics.

Table A.1 provides weighted mean price selection across strata in different groups of sectors. For example, *Services* and *Non-durables* feature the strongest and the weakest price selection, respectively, and *Durables* and *Semi-durables* have intermediate selection values. This ranking of price selection is in line with the ranking of the degree of price rigidity in those sectors: prices in *Services* (*Non-durables*) are *least* (*most*) flexible, and prices in *Durables* and *Semi-durables* are somewhere in between. Hence, price selection across sector groups lines up with price rigidity and volatility, as we show in Section 4.2 in the main text.

Moreover, *Food* and *Fuel* sectors, which exhibit flexible and volatile prices, exhibit price selection below average. Selection coefficient for *Liquid Fuels* is small positive and statistically significant. This is not surprising, since prices are virtually flexible in this sector, and therefore, we would expect selection to be close to zero. High-volume, perishable food products, such as milk, bread, eggs and soda, tend to have flexible and volatile prices as they respond to sector/stratum-specific disturbances or to manufacturer's costs in case of direct-to-store products. It is possible that such disturbance or a combination of disturbances trigger adjustments of prices that adjusted only recently and/or adjustments in the direction opposite to average adjustment in that stratum or sector. We find that 21 out of 45 of strata with positive and significant price selection coefficients are in Food and Beveridge sectors.

Aggregation results may also be explained by other factors affecting price selection, such as seasonality or regulated prices. Price selection will also weaken due to pooling of price changes across different strata of the same sector. For example, positive selection in *Furniture/Furnishings* is affected by seasonality. When we control for seasonality, this selection coefficient becomes negative, although still statistically near zero. Controlling for seasonality reduces selection coefficients for 34 out of 64 sectors, and lowers the weighted mean across all sectors from –0.289 to –0.322. Because seasonal adjustments are time-dependent, seasonal effects are expected to weaken measured price selection. Regulated goods, such as *Tobacco* are also expected to exhibit weaker selection.

Are there other sector characteristics that affect price selection over and above their effect of price rigidity and volatility? We merge the results by sector with four types of sector-specific information. First, we add the data on life expectancy for durable goods, obtained from Bils and Klenow (1998) for the United States (we mapped 18 U.K. basic classes to this measure). Second, we add 5-firm concentration ratios for the United Kingdom in 2004 from Mahajan

(2006) (we mapped 50 U.K. basic classes to this measure). Finally, we add quarterly real consumption expenditures from the Household Final Consumption Expenditures database at the U.K. Office for National Statistics, for the period from 1996Q1 to 2014Q3 (we mapped 65 U.K. sectors). For each sector, we construct the standard deviation of the quarterly change in the log of real consumption and a measure of sector's cyclicality—the regression coefficient of sector's log consumption growth on aggregate log consumption growth (Klenow and Malin, 2010).

Table A.2 reports coefficients of cross-section regressions with price selection for each sector as the dependent variable (weighted mean across strata in the sector) and one of the sector's characteristics as the independent variable. To gauge independent influence of that characteristic on price selection, we run two sets of regressions—with and without the sector's average fraction of price changes as another regressor. We find that cyclicality or volatility of the sector's consumption growth, or life expectancy (for durable goods) do not correlate with price selection. By contrast, there is a statistically significant positive correlation between price selection and sectors' 5-firm concentration ratios, i.e., more concentrated sectors tend to exhibit weaker selection, even after controlling for the effect of price rigidity. Examples of sectors with high 5-firm concentration ratios and weak selection are *Tobacco* and *Liquid Fuels*, and sectors with low concentration ratios and strong selection include *Dry-cleaning*, *Repair and Hire of Clothing*, *Tools and Equipment for House and Garden*, *Passenger Transport by Road*, and *Canteens*. This relationship is intuitive: firms with more market power have less need to move their prices in response to changes in market conditions.

We conclude that price rigidity and volatility are the main determinants of price selection and its variation across sectors, as we argue in the paper. The other factors discussed here may include: seasonality, regulated prices, sector's market concentration, and multiple shocks within sector. We leave it to future research to further elaborate on this list.

Table A.1: Price selection by sector groups, United Kingdom

	% of total weight	Fraction of price changes			Price selection		
		Baseline	All prices	Incl. subs	Baseline	All prices	Incl. subs
All categories	100	0.127	0.159	0.157	-0.389	-0.384	-0.412
Durables	12.0	0.097	0.164	0.128	-0.345	-0.348	-0.405
Semi-durables	32.3	0.063	0.136	0.136	-0.412	-0.362	-0.461
Non-durables	43.3	0.208	0.248	0.220	-0.327	-0.333	-0.345
Services	12.4	0.093	0.099	0.125	-0.441	-0.437	-0.449
Food	14.9	0.171	0.216	0.184	-0.362	-0.370	-0.380
Fuel	0.4	0.590	0.592	0.591	-0.155	-0.161	-0.158

Notes: Table provides statistics for each of product groups (first column): total weight, the fraction of price changes, and the weighted mean of price selection coefficients across strata.

Table A.2: Price selection and sector characteristics, United Kingdom

Sector characteristic	Number of sectors	No controls			Control for frac of p-changes		
		Baseline	All prices	Incl. subs	Baseline	All prices	Incl. subs
Cyclicality	65	-0.002	-0.001	0.000	0.000	0.000	0.002
std of consumption growth	65	0.338	0.485	0.302	0.306	0.386	0.286
5-firm concentration ratio	50	0.002***	0.001**	0.002***	0.001**	0.001	0.001**
Durability	18	0.008	-0.001	0.004	0.005	-0.006	0.004

Notes: Table provides estimated coefficients in the regression of sector's characteristic (first column) on the weighted mean of stratum selection in the sector. Data on life expectancy for durable goods are from Bils and Klenow (1998) for the United States. 5-firm concentration ratios for the United Kingdom in 2004 are from Mahajan (2006). Quarterly real consumption expenditures are from the Household Final Consumption Expenditures database at the U.K. Office for National Statistics, for the period from 1996Q1 to 2014Q3. For each sector, we construct the standard deviation of the quarterly change in the log of real consumption and a measure of sector's cyclicality—the regression coefficient of sector's log consumption growth on aggregate log consumption growth. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.2 Price selection and price discounts

In Section 4.3 of the paper, we presented evidence that when all prices are included in the estimation of price selection in the United Kingdom—i.e., regular and sale prices—a substantial degree of price selection remains at the aggregate level: –0.394 (versus –0.371 at a stratum level). In this Section, we clarify how price discounts in the United Kingdom contribute to price selection at the aggregate level.

We distinguish four types of individual price changes in month t: those from a regular price in month $t-1$ to a regular price in month t (R-R changes), from a regular to a sale price changes (R-S changes), from a sale to a regular changes (S-R), and from a sale to a sale price changes (S-S). In all price observations, non-zero price changes constitute 15.8% of observations. Most of them, 11.6% are R-R changes, and the remaining 4.2% are sale-related changes, i.e., R-S (2.4%), S-R (1.4%) and S-S (0.5%), see Table (A.3). Let $P_{st}^{pre,X}$ and FR_{st}^{X} denote the preset price level and the fraction of type-X price changes in stratum s in month t, $X \in \{\text{R-R,R-S,S-R,S-S}\}$. By construction, stratum preset price level is the frequency-weighted mean of preset price levels across four types of price changes:

$$P_{st}^{pre} = \frac{Fr_{st}^{\text{R-R}}}{Fr_{st}} P_{st}^{pre,\text{R-R}} + \frac{Fr_{st}^{\text{R-S}}}{Fr_{st}} P_{st}^{pre,\text{R-S}} + \frac{Fr_{st}^{\text{S-R}}}{Fr_{st}} P_{st}^{pre,\text{S-R}} + \frac{Fr_{st}^{\text{S-S}}}{Fr_{st}} P_{st}^{pre,\text{S-S}}$$

For each type of price changes, we then aggregate the preset price and fraction of price changes the same way we constructed aggregates in Section 4.3, i.e., the aggregate fraction of type-X price changes Fr_t^X is the stratum-weighted mean of the fraction of type-X price changes in month t. Similarly, we construct preset price levels $P_t^{pre,X}$ as the stratum-weighted mean preset price for type-X price changes in month t.

We estimate price selection for each of the four types of price changes using regression (11) in the main text (we constrain the seasonal effects to be the same that we estimate for all price changes). Table (A.3), row 3, reports estimated price selection coefficients. First, aggregate price selection for R-R price changes, –0.234, is weaker than for all price changes, –0.394, in line with the our finding that aggregation weakens price selection for regular price changes. Second, among sale-related price changes, R-S changes exhibit strong price selection, –0.638, and S-R changes exhibit strong selection of the opposite sign, approximately half the magnitude, 0.339, and selection associated with S-S changes is not statistically different from zero. Combined, sale-related price changes fully offset the weakening of price selection associated with R-R price changes.

In the United Kingdom, higher inflation is associated with less frequent and smaller price discounts. Correlation of the fraction of sales with the average size of price changes, DP_t, is –0.638, durations of complete price spells ending with R-S or S-R changes are somewhat longer when inflation is higher, and absolute size of both R-S and S-R changes is negatively correlated with DP_t as well (rows 6–7). Importantly, the change in the frequency and size of price discounts alters the composition of the population of price changes between R-R and sale-related price changes, which results in additional selection effects, despite the fact that most sale-related price changes are temporary.

Concretely, retailers scale down the frequency and size of price discounts by decreasing the proportion of R-S (and some S-S) price changes and increasing the proportion of R-R price changes (row 4). Essentially, retailers appear to substitute some large R-S price decreases into smaller R-R price increases, resulting in additional inflationary push. Furthermore, those fewer sales that do happen, also contribute to selection. For R-S price decreases, preset price level is strongly negatively correlated with DP_t, –0.616, meaning that retailers tend to choose relatively low regular prices when they put the product on discount (row 5). For S-R price increases, correlation of preset price level with DP_t, is positive 0.328, because discounts are smaller (S prices are relatively high). But this correlation is weaker than for R-S changes.

Table A.3: Price selection and price discounts, United Kingdom

		Price changes				
		All	**R-R**	**R-S**	**S-R**	**S-S**
		(1)	(2)	(3)	(4)	(5)
1	**Fraction of price changes**	0.158	0.116	0.024	0.014	0.005
2	**Share in all price changes**	1	0.725	0.151	0.094	0.031
3	**Price selection**	-0.394***	-0.234***	-0.638***	0.339**	0.069
		(0.065)	*(0.064)*	*(0.123)*	*(0.132)*	*(0.144)*
4	**corr (Fr_t^X/Fr_t, DP_t)**	---	0.528***	-0.785***	0.098	-0.307***
5	**corr ($P_t^{pre,X}$, DP_t)**	-0.498***	-0.147***	-0.616***	0.328***	0.159**
6	**corr ($\lvert p\Delta_t\rvert^X$, DP_t)**	-0.188***	-0.177***	-0.151**	-0.139**	-0.188***
7	**corr (Dur_t^X, DP_t)**	0.005	0.011	0.122*	0.128**	0.081

Notes: The table reports statistics for posted prices (excluding substitutions) in column 1, and four sub-samples that include only regular-to-regular price changes (column 2), regular-to-sale changes (column 3), sale-to-regular changes (column 4), and sale-to-sale changes (column 5). Price selection (row 3) for each of the four types of price changes is estimated using regression (11) in the main text. We constrain the seasonal effects to be the same in all five cases. Fr_t^X is the stratum-weighted mean of the fraction of type-X price changes in month t, where X={R-R,R-S,S-R,S-S}. $P_t^{pre,X}$ is the stratum-weighted mean preset price for type-X price changes in month t. $|p\Delta_t|^X$ and Dur_t^X are stratum-weighted means of absolute size and complete-spell durations for type-X price changes. *** p<0.01, ** p<0.05, * p<0.1.

A.3 Price selection and measurement errors

Because variation of prices at the micro level is substantial, one may be concerned that price selection at a stratum level can be measured inaccurately due to potentially small sizes of strata and the dominance of large idiosyncratic shocks. In Section 5.4 in the main text we discuss a theoretical exercise assessing this concern. In this Section, we assess it directly in the data.[1]

For the baseline case (regular prices, no substitutions), we split all price change obser-

[1] We thank Yuriy Gorodnichenko for suggesting the exercise we do in this Section.

vations into two random subsamples of roughly equal sizes. First, for each subsample, we estimate price selection using the same specification as for the full sample, i.e., equation (8) in the main text, with calendar month and stratum fixed effects. Table (A.4), columns (2) and (3), shows that price selection coefficients for subsamples 1 and 2, –0.387 and –0.388, are highly significant and very close to –0.371 estimated for the full sample.

Second, we use DP_t from one subsample as an instrumental variable for DP_t in the other subsample. Such instrumental variable is valid because the (classical) measurement error and idiosyncratic shocks are uncorrelated across two randomly assigned subsamples. Columns (4) and (5) report price selection of –0.341 in both cases, which is close to the baseline for the full sample. We conclude that measurement errors and idiosyncratic shocks are unlikely to drive the results.

Table A.4: Price selection across two random subsamples, United Kingdom

	Baseline	**DP from sample 1**	**DP from sample 2**	**DP from sample 1 IV: DP from sample 2**	**DP from sample 2 IV: DP from sample 1**
	(1)	(2)	(3)	(4)	(5)
Price selection	-0.371***	-0.387***	-0.388***	-0.341***	-0.341***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Number of observations	1,073,186	1,042,782	1,044,255	1,025,767	1,025,767
R^2	0.032	0.035	0.035	0.008	0.008

Notes: The table reports estimated price selection for the baseline case (regular prices, no substitutions) in column (1). We split baseline price change observations into two random subsamples of roughly equal sizes. For each subsample, we estimate price selection using the same specification as for the whole subsample (8, in the main text), with calendar month and stratum fixed effects, results are in columns (2)–(3). We then use DP_t from one subsample as an instrumental variable for DP_t in the other subsample, columns (4) and (5) report the results. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Additional tables and figures

Tables A.5–A.7 provide summary statistics for different treatments of price discounts and product substitutions for the U.K, U.S. and Canada.

Table A.8 provides comparisons with alternative standard errors: Driscoll and Kraay (1998), clustered by strata, and clustered by month.

Figure A.1 Panel A provides monthly time aggregate series for DP_t and P_t^{pre} for the case of regular prices and no substitutions in the U.K.. The series display similar volatility, and are significantly negatively correlated. These correlations indicate that price selection contributes to fluctuations in the size of price changes, since lower preset price pushes up the average size of price changes. Panel B shows bandpass-filtered series for DP_t and P_t^{pre}. The two series lose more than half of volatility, but the negative correlation remains significant.

Therefore, preset prices contribute to the dynamics of the average size of price changes, even when high-frequency fluctuations are filtered out.

Table A.5: Summary statistics for the U.K. CPI Data

	Sample	Regular prices, excl. substitutions	Regular prices, incl. substitutions	Posted prices, excl. substitutions	Posted prices, incl. substitutions
(1)	π	0.121	0.220	-0.161	0.115
(2)	*Fr*	0.127	0.158	0.162	0.191
(3)	adp	12.22	14.11	14.68	15.92
(4)	corr	-0.032	-0.012	-0.072	-0.049

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Sample period: from February 1996 through September 2015.

The entries are weighted means of stratum-level monthly variables. Observations across strata are based on consumption expenditure weights, observations across months are weighted equally. π - inflation, in %; *Fr* - the fraction of items with changing prices; *adp* - the average absolute size of price changes, in %; *corr* - serial correlation of newly set prices for an individual product.

Table A.6: Summary statistics for the Statistics Canada CPI Data

	Sample	Regular prices, excl. substitutions	Regular prices, incl. substitutions	Posted prices, excl. substitutions	Posted prices, incl. substitutions
(1)	π	0.182	0.210	0.168	0.185
(2)	*Fr*	0.217	0.223	0.280	0.290
(3)	adp	8.25	8.48	12.90	12.82
(4)	corr	0.164	0.164	0.110	0.123

Notes: Data are from the Statistics Canada's Consumer Price Research Database. Sample period: from February 1998 to December 2009.

The entries are weighted means of stratum-level monthly variables. Observations across strata are based on consumption expenditure weights, observations across months are weighted equally. π - inflation, in %; *Fr* - the fraction of items with changing prices; *adp* - the average absolute size of price changes, in %; *corr* - serial correlation of newly set prices for an individual product.

Table A.7: Summary statistics for the IRI Inc. Data

	Sample	Regular prices, excl. substitutions	Posted prices, excl. substitutions
(1)	π	0.291	0.021
(2)	Fr	0.223	0.323
(3)	adp	8.43	13.98
(4)	corr	-0.027	-0.136

Notes: Data are from the Symphony IRI Inc.. Sample period: from January 2001 to December 2011.

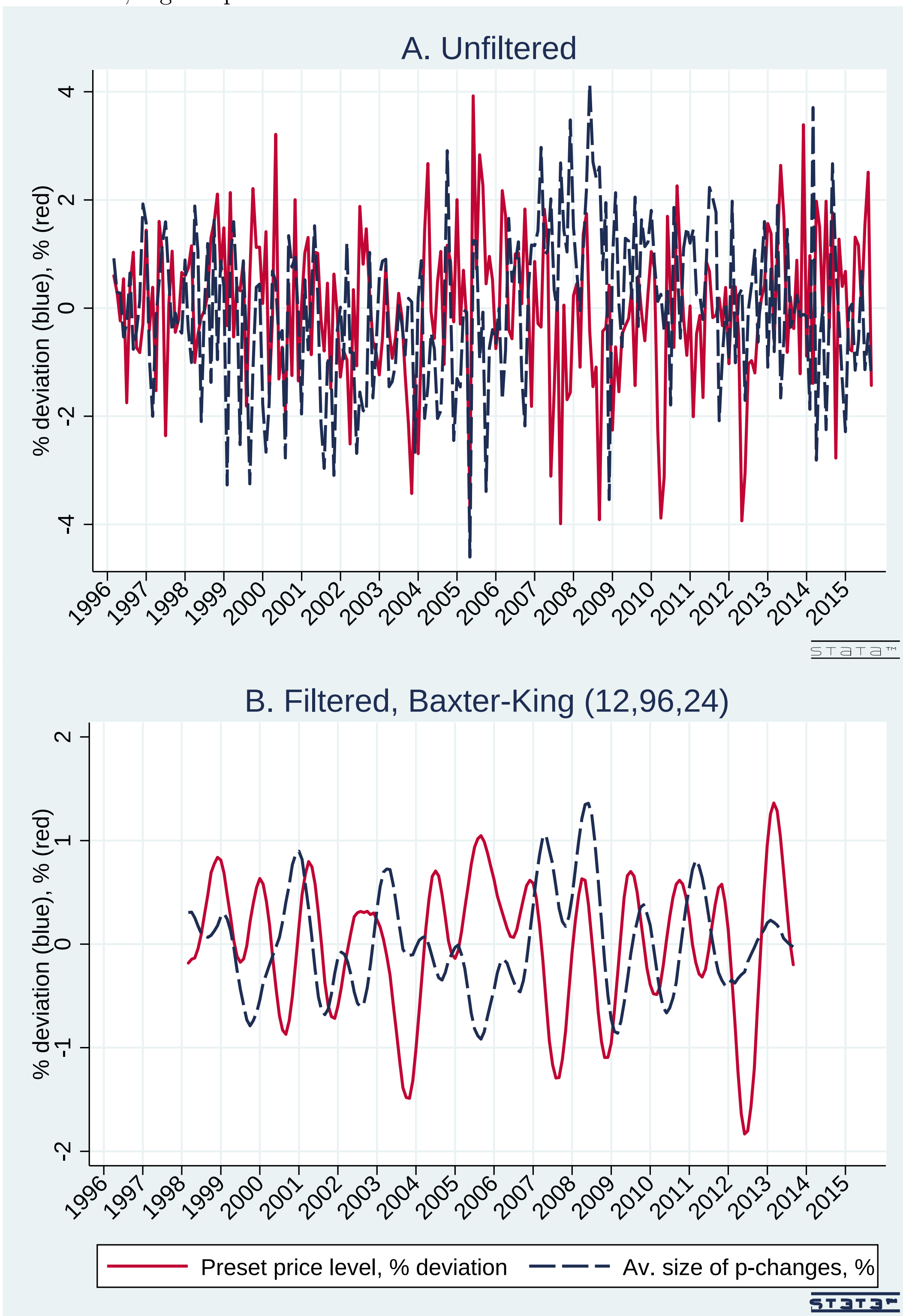
The entries are weighted means of stratum-level monthly variables. Observations across strata are based on consumption expenditure weights, observations across months are weighted equally. π - inflation, in %; Fr - the fraction of items with changing prices; *adp* - the average absolute size of price changes, in %; *corr* - serial correlation of newly set prices for an individual product.

Table A.8: Alternative standard errors, U.K. CPI data

Coefficient	Point estimate	Standard errors			
		Pooled WLS	Driscoll-Kraay	Cluster by strata	Cluster by month
	(1)	(2)	(3)	(4)	(5)
Price selection	-0.373	0.002***	0.010***	0.008***	0.011***

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Sample period is from February 1996 through September 2015. Point estimate in Column (1) is the estimated coefficient γ in the following empirical specification: $P_{ct}^{pre} = \gamma DP_{ct} + \delta_t + \delta_c + error$, where δ_t and δ_c are month and category fixed effects. The number of observations is 1,073,089. Column (1) presents the estimates, Column (2) provides baseline standard errors (pooled WLS), Column (3) provides Driscoll-Kraay standard errors, Column (4) clusters standard errors by strata (8,941 clusters) which allows for arbitrary correlation of errors across time, and Column (5) clusters standard errors by month (235 clusters) which allow for arbitrary cross-sectional correlation of errors. *** – denotes statistical significance at 1% confidence level.

Figure A.1: Preset price level and average size of price changes in the United Kingdom, aggregate time series, regular prices and no substitutions



B Sticky-price models

Here we present the Golosov and Lucas (2007) and Calvo (1983) models, and the generalized version that nests them. For expositional simplicity, we present one-sector versions of the models. The multisector versions simply assume that firms are distributed into sectors that differ in terms of some of the model's structural parameters, and whose measures pin down average consumption expenditure shares.

The economy is populated by a large number of infinitely lived households and monopolistically competitive producers. The shocks in these baseline economies are aggregate shocks to the money supply, and idiosyncratic and sectoral productivity shocks. We describe productivity shocks below and later also consider a version with aggregate productivity shocks. We assume that money supply, M_t, follows random walk with drift

$$\log M_t = \log \mu + \log M_{t-1} + \varepsilon_{mt}, \tag{B.1}$$

where μ is mean growth rate of money supply, and ε_{mt} is a normally distributed i.i.d. random variable with mean 0 and standard deviation σ_m.

B.1 Representative household

The problem of the representative household is identical in all models. Households buy a continuum of consumption varieties, indexed by i, trade money and state-contingent nominal bonds, and supply labor in a competitive market. The problem of the household is to choose sequences of money holdings, $\left\{M_t^d\right\}$, consumption varieties, $\left\{c_t\left(i\right)\right\}$, state-contingent bonds, $\{B_{t+1}\}$, and hours worked $\{h_t\}$ to maximize utility:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln c_t - \psi h_t\right] ,$$

subject to an aggregate consumption aggregator

$$1 = \int_0^1 \Gamma\left(\frac{c_t\left(i\right)}{c_t}\right) di \, , \tag{B.2}$$

the budget constraint

$$M_t^d + E_t\left[\mathbf{Q}_{t+1|t}\cdot \mathbf{B}_{t+1}\right] \leqslant M_{t-1}^d - \int_0^1 p_{t-1}\left(i\right) c_{t-1}\left(i\right) di + W_t h_t + B_t + \int_0^1 \Pi_t\left(i\right) di + T_t \, , \tag{B.3}$$

and a cash-in-advance constraint,

$$\sum_{j=0}^{\infty} p_t(i)\, c_t(i) \leq M_t^d \,. \tag{B.4}$$

Here c_t is aggregate consumption given by a homothetic function (B.2), and where the curvature of function Γ determines the degree of real rigidities; M_t^d are money holdings, $\mathbf{B}_{t+1}$ is a vector of state-contingent bonds, B_{t+1}, where one unit of each bond pays one dollar in date $t+1$ if a particular state is realized, and it pays zero otherwise; $\mathbf{Q}_{t+1|t}$ is a vector of bond prices, $Q_{t+1|t}$, in each state in date t. $p_t(i)$ is the price of consumption good j, $\Pi_t(i)$ are firms' dividends, and T_t are lump-sum transfers from the government. The budget constraint (B.3) says that the household's beginning-of-period balances combine unspent money from the previous period, $M_{t-1}^d - \int_0^1 p_{t-1}(i)\, c_{t-1}(i)\, di$, labor income, returns from bond holdings, dividends, and government transfers. The household divides these balances into money holdings and purchases of state-contingent bonds. Money is used to buy consumption subject to cash-in-advance constraint (B.4). Household starts period 0 with initial money and bond holdings M_0^d and $\mathbf{B}_1$.

First-order conditions for household's problem yield a standard expression for household's stochastic discount factor and for the demand for consumption of variety i:

$$c_t(i) = c_t \left(\Gamma'\right)^{-1} \left(\frac{P_t(i)}{P_t}\right) , \tag{B.5}$$

where P_t is the price of aggregate consumption

$$1 = \int_0^1 \Gamma\left(\left(\Gamma'\right)^{-1}\left(\frac{P(i)}{P_t}\right)\right) di \,,$$

and a condition for the optimal allocation of working hours:

$$\psi P_t c_t = W_t \,.$$

B.2 Firms in Golosov and Lucas (GL) model

A monopolistically competitive firm producing variety i is endowed with a constant returns to scale technology that converts $l(i)$ units of labor input into $a(i)\, l(i)$ units of output in each period, where $a(i)$ represents a firm's productivity level in that period. We assume $\ln a(i)$ follows an AR(1) process:

$$\ln a(i) = \rho_a \ln a_{-1}(i) + \varepsilon_a \,,$$

where $a_{-1}(i)$ is the previous period's productivity level, and ε_a is a mean zero, normally distributed error with standard deviation σ_a. We introduce sectoral shocks in the multisector versions of the models by adding a common component to the productivity innovations ε_a for all firms that belong to the same sector. This adds a single parameter for each sector (the standard deviation of those innovations), which allows us to target the standard deviation of sectoral inflation rates in our calibrations. Due to symmetry of the firm's problem across varieties, we omit index i to avoid cluttering notation.

Let κ denote a fixed cost of changing a price ("menu cost") expressed in units of labor. The firm begins the current period with price p_{-1}, inherited from the previous period. After realizing its current productivity level a, the firm chooses whether to adjust its price. If it changes its price, the firm pays the fixed labor cost at wage W, and chooses the new relative price p. Otherwise, the firm keeps its previous price. Since at price p the demand for firm's output is given by (B.5), the firm will produce $c\left(\Gamma'\right)^{-1}\left(\frac{p}{P}\right)$ units of consumption good of its variety. The problem of the firm therefore can be written as follows:

$$V^a(p_{-1}, a;\, f) = \max_{p \geq 0}\ \frac{1}{Pc}\left[\left(p - \frac{W}{a}\right) c\left(\Gamma'\right)^{-1}\left(\frac{p}{P}\right) - \kappa W\right] + \beta \int V(p'_{-1}, a';\, f') F\left(da'|a\right)\ , \tag{B.6}$$

$$V^n(p_{-1}, a;\, f) = \frac{1}{Pc}\left[\left(p_{-1} - \frac{W}{a}\right) c\left(\Gamma'\right)^{-1}\left(\frac{p_{-1}}{P}\right)\right] + \beta \int V(p'_{-1}, a';\, f') F\left(da'|a\right)\ , \tag{B.7}$$

$$V = \max\left\{V^a, V^n\right\}\ , \tag{B.8}$$

where function V^a is the value of adjusting its price, V^n is the value of not adjusting its price, and V is the value before the adjustment decision. Firm's state before price adjustment consists of its price p_{-1}, realized productivity a, and aggregate state variable f that gives the measure of firms over (p_{-1}, a). Function F denotes the c.d.f. of future productivity shocks a' conditional on the current realization a.

The firm's problem is completed by specifying the laws of motion for the firm's endogenous state variables p'_{-1} and f'. Its price is set to its optimal level in case of price adjustment, and it remains at p_{-1} otherwise. Price and productivity realizations for all firms determine the new measure f'.

B.3 Firms in Calvo model

The only difference from firm's problem in GL model is the price adjustment decision. In GL model the firm chooses optimally whether or not to adjust its price in each period. In Calvo model that decision is exogenous: with probability λ, $0 < \lambda < 1$, the firm does not adjust its price, and with probability $1 - \lambda$ it sets its price optimally. Formally, in the firm's problem, equations (B.6) and (B.7) will stay the same, and equation (B.8) is replaced with

$$V = \begin{cases} V^a + \kappa W, \text{ w/prob } 1 - \lambda \\ V^n, \text{ w/prob } \lambda \end{cases}.$$

B.4 Firms in generalized model

This is the generalized model we calibrate to the U.K. basic consumption class data. Given the beginning-of-period price p_{-1} and the realization of productivity a, the firm becomes a GL firm (receiving value $V^{GL}(p_{-1}, a, ; f)$) with probability $1-\phi$ and a Calvo firm (receiving value $V^{Calvo}(p_{-1}, a, ; f)$) with probability ϕ. Hence, the value function for a firm in this generalized model is the expected value of the two possible values V^{GL} and V^{Calvo}:

$$V(p_{-1}, a; f) = (1 - \phi)V^{GL}(p_{-1}, a; f) + \phi V^{Calvo}(p_{-1}, a; f). \tag{B.9}$$

When taking this model to the data, for each sector, we partially tie our hands and set the probability of a price change conditional on the firm being in "Calvo mode" $(1 - \lambda)$, equal to the empirical frequency of price changes for the associated consumption class. Hence, relative to the GL model, the generalized model adds only one free parameter for each sector: the probability that the firm becomes a Calvo firm in each period, ϕ. We use this parameter to target price selection in each sector.

An equilibrium consists of prices and allocations $p_t(i)$, P_t, W_t, $c_t(i)$, c_t and l_t that, given prices, solve households' and firms' decision problems, and markets for consumption goods, labor, money and bonds clear. The model is solved by a non-linear projection method explained in Miranda and Fackler (2012) using approach developed in Krusell and Smith (1998).[2]

B.5 Model with two aggregate shocks

To analyze conditional and unconditional price selection, we resort to two GL models that differ only in the number of aggregate shocks. One model features monetary shocks only, and the other adds aggregate productivity shocks. Aggregate productivity shocks are introduced by adding a common innovation to all firms' productivity innovations. In the model

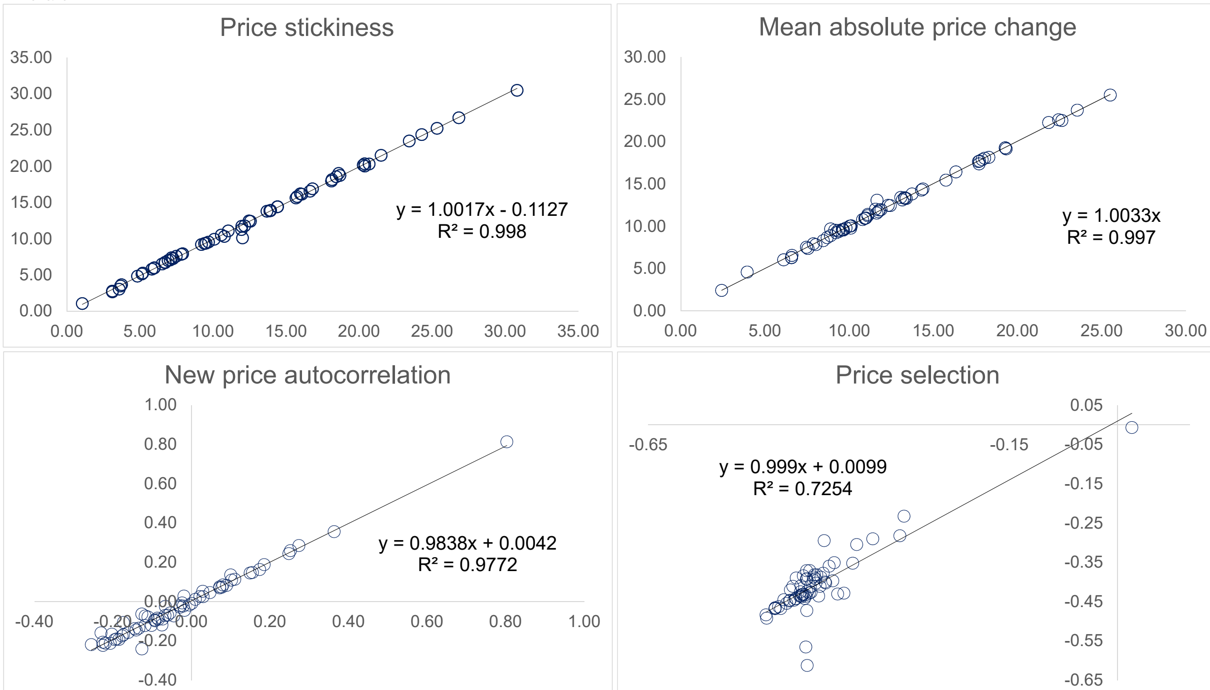
[2]See Klenow and Willis (2007) and Midrigan (2011) for application of this approach to solving models with non-convex price adjustment problems.

with monetary shocks only, we calibrate menu cost, volatility and persistence of idiosyncratic productivity shocks to match mean fraction of adjusting prices, mean absolute price changes, and autocorrelation of newly set prices. In the model with two aggregate shocks, we also calibrate the standard deviation of common productivity innovations to match the standard deviation of inflation. Calibrations are done as in our previous analyses, matching the mean of simulated moments across 100 simulations to targeted moments. With the two calibrated models, we can compute unconditional price selection in the model with two aggregate shocks and compare it with (conditional) price selection in the model with monetary shocks only.

To enrich our analysis, we consider different sets of targeted moments. To that end, we exploit the 64 basic consumption classes in the U.K. data, which we use to calibrate our multisector model. We treat the moments of each sector as targeted moments of a hypothetical aggregate economy, to which we calibrate the two models. This allows us to compare conditional and unconditional price selection in a range of environments—in particular, in environments in which the relative importance of the two aggregate shocks varies significantly. The number of firms in each economy matches the average number of price quote lines in the corresponding consumption class in the data.

Our findings are reported in Figure B.1. Each circle in a scatter plot reports the simulated moment in the economy with monetary shocks only (vertical axis) against the simulated moment in the economy with both aggregate shocks. Scatter plots for price stickiness (inverse mean fraction of price changes), mean absolute price change, and new price autocorrelation show that the two models produce very similar targeted moments. The plot for price selection—an untargeted moment—shows some differences between the two economies. In most cases, however, price selection conditional on monetary shocks is quite similar to unconditional price selection in the model with two aggregate shocks.

Figure B.1: Conditional and unconditional price selection in the Golosov and Lucas (2007) model

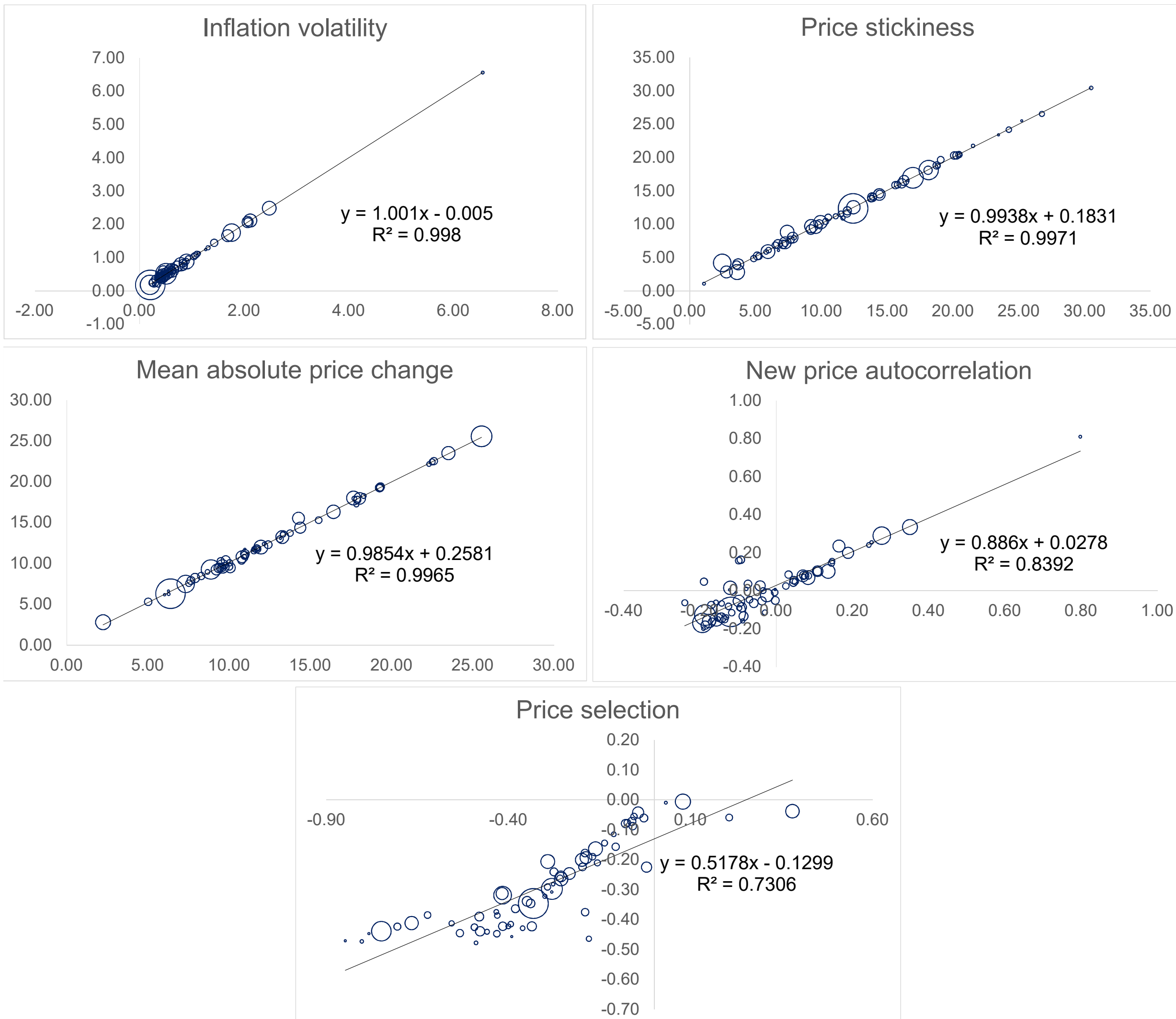


Notes: In each figure, each circle reports the simulated moment in the economy with monetary shocks only (vertical axis) against the simulated moment in the economy with both aggregate shocks. Black solid lines represent fitted OLS regressions.

B.6 Fit of the multisector model

Figure B.2 summarizes the fit of the model used for . For each targeted statistic, a scatter plot shows empirical moments on the horizontal axis and moments produced by the calibrated model on the vertical axis. Each circle corresponds to a basic consumption class, and its size is proportional to the associated expenditure share. Black solid lines represent fitted OLS regressions. It is clear that the model has enough flexibility to fit the moments well, although with some differences across statistics. The fit for price rigidity (inverse of the mean frequency of price changes), mean absolute price change, and sectoral inflation volatility is almost perfect. The fit for the two remaining statistics—autocorrelation of newly set prices and price selection—is not as tight, but the model still accounts for 84% and 73% of variation across classes, respectively.

Figure B.2: Fit of calibrated multisector model



Notes: Scatter plots illustrate model fit. In each figure, empirical moments are in horizontal axis and moments produced by the calibrated model are in vertical axis. Each dot corresponds to a basic consumption class in the U.K. data, and its size is proportional to the associated expenditure share. Black solid lines represent fitted OLS regression.

C The analytics of price selection in sticky-price models

C.1 Equilibrium in a sticky-price model

Let $\Gamma(S)$ be the numeraire for nominal variables in state S—it could be the money supply or the aggregate price level. All nominal variables will be normalized by one-period lag of the numeraire, $\Gamma(S_{-1})$. Denote by $\gamma(S)$ the growth rate of the numeraire, $\gamma(S) = \Gamma(S)/\Gamma(S_{-1})$.

A monopolistically competitive firm is endowed with production technology that implies cost function $W(s,S)$, where s denotes firm-specific exogenous state variables and S denotes aggregate state in the economy. The firm uses this technology to produce its own variety of differentiated good that is used for consumption. The firm also faces fixed (menu) cost of changing its price, $\kappa(S)$. A firm that decides to change its price p faces the following problem:

$$\begin{aligned} V^a(p_{-1},s;S) &= \max_p \frac{U_c(S)}{P(S)}\left[\left(p-W'(s,S)\right)\left(\frac{p}{P(S)}\right)^{-\theta} C(S)-\kappa(S)\right] \\ &+\beta\int V\left(p,s';S'\right)F_s\left(ds'|s\right)F_S\left(dS'|S\right), \end{aligned}$$

where $V^a(p_{-1},s;S)$ is the value of adjusting price, $P(S), C(S), U_c(S)$ are aggregate price, consumption, marginal utility, and $F_s(s'|s,S)$, $F_S(S'|S)$ are the laws of motion of individual and aggregate state. The notational convention for $V^a(p_{-1},s;S)$ is that p_{-1} is the price normalized by $\Gamma(S_{-1})$.

The value function of the firm that does not change its price is

$$\begin{aligned} V^n(p_{-1},s;S) &= \frac{U_c(S)}{P(S)}\left[\left(p_{-1}\gamma(S)^{-1}-W'(s,S)\right)\left(\frac{p_{-1}\gamma(S)^{-1}}{P(S)}\right)^{-\theta} C(S)-\kappa W\right] \\ &+\beta\int V\left(p_{-1}\gamma(S)^{-1},s';S'\right)F_s\left(ds'|s\right)F_S\left(dS'|S\right). \end{aligned}$$

Finally, continuation value is

$$V\left(p,s';S'\right)=\lambda\left(p,s';S'\right)V^a\left(p,s';S'\right)+\left(1-\lambda\left(p,s';S'\right)\right)V^n\left(p,s';S'\right),$$

where function $\lambda(p_{-1},s';S')$ is the probability of adjustment. For example, in the standard menu cost model

$$\lambda\left(p_{-1},s';S'\right)=\begin{cases}1, & \text{if } V^a\geq V^n\\ 0, & \text{if otherwise}\end{cases},$$

and in the Calvo model

$$\lambda\left(p_{-1},s';S'\right)=\lambda.$$

The new price

$$p(p_{-1},s;S)=\begin{cases}p^*(p_{-1},s;S), & \text{if adjust}\\ p_{-1}\gamma(S)^{-1} & \text{if not adjust}\end{cases}$$

and accordingly the conditional distribution of new prices

$$h(p\mid p_{-1},s;S).$$

Firm's decision functions can be aggregated to give the functions $P(S), C(S), U_c(S), W(S)$, and the laws of motion for $F\left(p_{-1}, s \mid S\right)$ and $F_S\left(S' \mid S\right)$. Assuming "cash-in-advance" aggregate demand gives

$$P\left(S\right) C\left(S\right) = 1.$$

Next, log-linear utility gives

$$W\left(S\right) = \frac{\theta - 1}{\theta},$$

where wage is normalized such that the average price level is unity.

The end-of-period distribution of price-state pairs is

$$G(p, s \mid S) = \int_{p_{-1}} h\left(p \mid p_{-1}, s; S\right) F(dp_{-1}, s \mid S).$$

Note again the notation convention: in $G(p, s \mid S)$ prices p are normalized by $\Gamma\left(S\right)$, whereas in $F(p_{-1}, s \mid S)$ prices p_{-1} are normalized by $\Gamma\left(S_{-1}\right)$.

The end-of-period distribution of prices is

$$G(p \mid S) = \int_{s} G(p, ds \mid S),$$

so the aggregate price is

$$P(S) = \int_{p} p \; dG(p \mid S).$$

The law of motion for the distribution of price-state pairs is

$$\begin{aligned} F'\left(p, s' \mid S'\right) &= G(p, s \mid S) F_s\left(s'|s\right) F_S\left(S'|S\right) \\ &= \left\{ \int_{p_{-1}} h\left(p \mid p_{-1}, s; S\right) F(dp_{-1}, s \mid S) \right\} \cdot F_s\left(s'|s\right) F_S\left(S'|S\right). \end{aligned}$$

Finally, the law of motion for $F_S\left(S' \mid S\right)$ is such that

$$\begin{aligned} P(S') &= \int_{p} p \; dG'(p \mid S') \\ G'(p \mid S') &= \int_{s} G'(p, ds \mid S') \\ G'(p, s \mid S') &= \int_{p_{-1}} h\left(p \mid p_{-1}, s; S'\right) F'(dp_{-1}, s \mid S'). \end{aligned}$$

C.2 Calvo (1983) model

Firms change their price with probability that is independent of the state:

$$\lambda\left(p_{-1}, s; S\right) = \lambda.$$

Conditional on changing price in period t, firms set price as a markup over the average (discounted) marginal cost the firm expects to face over the duration of time the price remains in effect. The natural log of this price (up to a constant) is (assuming no inflation trend)

$$P_t^{res}(i) = (1 - (1-\lambda)\beta)^{-1} \sum_{\tau=0}^{\infty} (1-\lambda)^{\tau} \beta^{\tau} E_t \left[W_{t+\tau}'(i) \right],$$

where $W_t'(i)$ is the log of firm i's nominal marginal cost. Consider a special case with log linear preferences, cash-in-advance constraint and labor-only constant returns technology. In this case, firm's nominal marginal cost is

$$W_t'(i) = M_t - a_t(i).$$

where M_t is the log of money stock and $a_t(i)$ is the log of firm-level productivity. Assume for simplicity that both M_t and $a_t(i)$ follow a random walk. Then firm i's log reset price is

$$P_t^{res}(i) = M_t - a_t(i),$$

and the average reset price is

$$P_t^{res} = M_t.$$

and the average preset price is

$$\begin{aligned} P^{pre}(S) &= \overline{\Lambda}(S)^{-1} \int_p p\ \Lambda(p; S)\, dG(p \mid S_{-1}) \\ &= P(S_{-1}), \end{aligned}$$

which implies that the decomposition is

$$P_t - P_{t-1} = \lambda \left[M_t - P_{t-1} \right].$$

That is, all of the inflation variance is explained by the reset price and price selection is zero.

C.3 Taylor (1980) model

We first illustrate the workings of price selection using a simple version of the Taylor (1980) model.[3] Prices are fixed for T periods and price changes are spread over time so that the fraction of adjusting prices is the same in each period t, $Fr_t = \frac{1}{T}$. Log money supply follows a random walk $M_t = M_{t-1} + \varepsilon_t$, with i.i.d. innovations ε_t with variance σ_ε^2. In the simplest

[3] The Taylor model exhibits the strongest selection effects within the class of time-dependent pricing models, as shown by Carvalho and Schwartzman (2015).

case with no strategic complementarities, firms that adjust their price set it to the desired price level, which is equal to the level of the money supply.[4] The aggregate price is simply the mean of the last T realizations of the money supply, $P_t = \frac{M_t + M_{t-1} + ... + M_{t-(T-1)}}{T}$, and inflation is $\pi_t = \frac{M_t - M_{t-T}}{T}$.

In this simple setup, adjusting prices change from the level of money supply T periods ago, M_{t-T}, to the level of money supply in the current period, M_t, so the average size of price changes is the sum of the last T monetary shocks:

$$DP_t = M_t - M_{t-T} = \varepsilon_t + \varepsilon_{t-1} + ... + \varepsilon_{t-(T-1)}.$$

The preset price level measures the distance between the initial level of adjusting prices, M_{t-T}, and the population average price level P_{t-1}:

$$P_t^{pre} = M_{t-T} - P_{t-1} = -\frac{\varepsilon_{t-1} + 2\varepsilon_{t-2} + ... + (T-1)\varepsilon_{t-(T-1)}}{T}, \tag{C.1}$$

so it is an aggregate of past shocks, with higher weight on older shocks.

The price selection measure is

$$\gamma = \frac{cov\left(P_t^{pre}, DP_t\right)}{var(DP_t)} = \frac{\sigma_\varepsilon^2 \sum_{j=0}^{T-1} \frac{j}{T}}{\sigma_\varepsilon^2 T} = -\frac{1}{2} + \frac{1}{2T}, \tag{C.2}$$

and so price selection is stronger with price stickiness T, in line with empirical results in Section 4.2. For large T, price selection in the Taylor model explains half of inflation variance.

C.4 The nature of the residual term in the regression of P_t^{pre} on DP_t

In the paper, price selection statistic γ is given by $\frac{cov\left(P_t^{pre}, DP_t\right)}{var(DP_t)}$, which is value of the estimated coefficient in regression (5, main text):

$$P_t^{pre} = \gamma DP_t + error_t.$$

In general, selection effects—captured by how P_t^{pre} and DP_t respond to a sequence of shocks—vary over time. For example, in a state-dependent pricing model, very large shocks will drive almost all firms to change prices, making selection to be virtually zero. But for smaller shocks, selection is stronger and may depend on the distribution of price gaps at the time of such shocks. The price selection statistic captures the average relationship between P_t^{pre} and DP_t. Therefore, the error term picks up variations in selection effects around the average. We illustrate this explanation using the analytical example of the Taylor model.

Consider the case with two adjusting cohorts, $T = 2$. In period t, the adjusting cohort

[4] Idiosyncratic shocks that make firms' desired prices heterogeneous have no aggregate effects in the Taylor (1980) model and do not affect our measure of price selection. Hence, we omit them for clarity of exposition.

changes prices by the sum of the shocks over the last two period, i.e., by $DP_t = \varepsilon_t + \varepsilon_{t-1}$. Since price selection in this case is $\gamma = -\frac{1}{4}$,the fitted value in the regression is $\gamma DP_t = -\frac{1}{4}\varepsilon_t - \frac{1}{4}\varepsilon_{t-1}$, i.e., selection effects are split equally across all shocks that contribute to the variance of DP_t.

By contrast, actual selection effects load unevenly across shocks. In the example with $T = 2$, the preset price level is the difference between the starting price level of that cohort, i.e., M_{t-2} and the average price in population at $t-1$, i.e., P_{t-1}. Because $P_{t-1} = \frac{M_{t-1}+M_{t-2}}{2}$, this implies that $P_t^{pre} = M_{t-2} - P_{t-1} = -\frac{\varepsilon_{t-1}}{2}$. Consequently, preset price puts no weight on ε_t because it is measurable with respect to information up to $t-1$, and it puts weight $-\frac{1}{2}$ on ε_{t-1} reflecting the adjustment of prices set in period $t-2$ (half of all prices). This gives the residual term $error_t = \left(0 + \frac{1}{4}\right)\varepsilon_t + \left(-\frac{1}{2} + \frac{1}{4}\right)\varepsilon_{t-1} = \frac{\varepsilon_t}{4} - \frac{\varepsilon_{t-1}}{4}$.

For any T, this residual is

$$\begin{aligned} error_t &= P_t^{pre} - \gamma DP_t \\ &= \frac{T-1}{2T}\varepsilon_t + \frac{(T-1)-2}{2T}\varepsilon_{t-1} + ... + \frac{(T-1)-2\,(T-1)}{2T}\varepsilon_{t-(T-1)} \end{aligned} \tag{C.3}$$

Hence, the error term reflects different degrees of selection effects in the response of DP_t to aggregate shocks at t,$t-1$,$t-2$,.... This distribution of selection effects is determined by the price adjustment mechanism, namely, the sizes of adjusting cohorts and probabilities of adjustments over cohorts (the hazard rate). We leave further clarification of the nature of the residual term to future research.

Interestingly, in this Taylor model, the error terms is uncorrelated with the regressor, DP_t :

$$cov(error_t, DP_t) = \sigma_\varepsilon^2 \left(\frac{T-1}{2T} + \frac{(T-1)-2}{2T} + ... + \frac{(T-1)-2\,(T-1)}{2T}\right) = 0$$

We conjecture that this property does not hold in general, for example, due to correlation between the number of adjusting prices and the size of the shock in state-dependent models. Since we do not a test a relationship between P_t^{pre} and DP_t and use the regression coefficient γ only as a statistic, the nature and statistical properties of the error term are not crucial for our results.

C.5 Aggregation and price selection in two-sector Taylor model

Suppose now that the Taylor model has two equally weighted sectors with different degree of price flexibility: $T_1 = 2$ and $T_2 = 4$. Using the formula for price selection (C.2) gives us price selection in each sector: $\gamma_1 = -\frac{1}{4}$, $\gamma_2 = -\frac{3}{8}$. The average selection is $\frac{\gamma_1+\gamma_2}{2} = -\frac{5}{16}$.

The aggregate price index as $P_t = \frac{1}{2}\left(\frac{M_t+M_{t-1}}{2} + \frac{M_t+M_{t-1}+M_{t-2}+M_{t-3}}{4}\right)$, and the inflation identity can be written as $P_t - P_{t-1} = \frac{1}{2}\left(\frac{M_t-M_{t-2}}{2} + \frac{M_t-M_{t-4}}{4}\right) = \frac{3}{8}\left(\frac{2M_t+M_t}{3} - \frac{2M_{t-2}+M_{t-4}}{3}\right)$, where in the last equation $\frac{3}{8}$ is the average frequency of price adjustment, and the term in parentheses is the frequency-weighted average size of price changes $DP_t^{fr} = P_t^{res} - P_t^{pre} = \varepsilon_t + \varepsilon_{t-1} + \frac{\varepsilon_{t-2}+\varepsilon_{t-3}}{3}$. The weighted mean size of price changes is $DP_t^w = \varepsilon_t + \varepsilon_{t-1} + \frac{\varepsilon_{t-2}+\varepsilon_{t-3}}{2}$.

The frequency-weighted preset price level is

$$\begin{aligned} P_t^{pre,fr} &= \frac{2M_{t-2}+M_{t-4}}{3} - \frac{2}{3}\frac{M_{t-1}+M_{t-2}}{2} - \frac{1}{3}\frac{M_{t-1}+M_{t-2}+M_{t-3}+M_{t-4}}{4} \\ &= -\frac{5\varepsilon_{t-1}+2\varepsilon_{t-2}+3\varepsilon_{t-3}}{12} \end{aligned}$$

and the weighted preset price level is $P_t^{pre,w} = -\frac{3\varepsilon_{t-1}+2\varepsilon_{t-2}+3\varepsilon_{t-3}}{8}$.

Price selection is given by the regression of preset price on the difference of reset and preset prices:

$$\gamma^{fr} = -\frac{cov\left(P_t^{pre,fr}, DP_t^{fr}\right)}{var\left(DP_t^{fr}\right)} = -\frac{5/12+2/36+3/36}{1+1+1/9+1/9} = -\frac{1}{4},$$

$$\gamma^{w} = -\frac{cov\left(P_t^{pre,w}, DP_t^{w}\right)}{var\left(DP_t^{w}\right)} = -\frac{3/8+1/8+3/16}{1+1+1/4+1/4} = -\frac{11}{40}.$$

Note that aggregate selection is weaker than the average of sector-level price selections, and frequency-weighted selection is weaker than weighted selection:

$$\left|\gamma^{fr}\right| < \left|\gamma^{w}\right| < \left|\frac{\gamma_1+\gamma_2}{2}\right|.$$

Hence, aggregation weakens price selection. 40% of this aggregation effect is due to a higher proportion of price changes (two out of each three price changes) coming from the sector with more frequent price changes and weaker selection, i.e., Sector 1; this mechanism stemming from dispersion in frequencies of price changes across sectors was explained in Kara (2015) and Carvalho and Schwartzman (2015). The remaining aggregation effect is due to the fact that price adjustments in different sectors are less mutually correlated than in the model with identical sectors, so their joint impact on the aggregate price is smaller. The aggregation result in the model is consistent with empirical results reported in the paper, where aggregate price selection is weaker than average sector-level selection, in part due to heterogeneity in the frequency of price changes across sectors.

C.6 N-sector nested Taylor-Calvo model

Consider N sectors in a truncated Calvo price setting, where sectors are indexed by j. Let T_j denote the total price cohorts (ages) in sector j. Let $T = \max\{T_j\}$. Then any price at age $\tau < T_j$ adjusts with probability λ_j, and prices adjust for sure after T_j periods. The fraction of prices with duration $\tau = 1$ in sector j is $\lambda_j(1-(1-\lambda_j)^{T_j})^{-1}$.

Define auxiliary vectors: let $\mathbf{A}$ be a $N-$vector with j's entry $\lambda_j(1-(1-\lambda_j)^{T_j})^{-1}$, $\mathbf{\Lambda}$ be a $N-$vector with j's entry λ_j, $\mathbf{\Gamma}$ be a $(N \times T)-$matrix with j's row corresponding to the vector of sector j pricing cohorts equal to $A_j(1-\lambda_j)^{\tau-1}$ for $\tau = 1, ..., T_j$, and zero for $\tau = T - T_j + 1, ..., T$. And let$\omega$be the vector with weights ω_j denoting consumption weight of sector j. The frequency of price changes in sector j is $Fr_j = \frac{\lambda_j}{1-(1-\lambda_j)^{T_j}} = A_j$.

Denote the following vectors:

$$\begin{aligned}
\mathbf{M_{t,t-(T-1)}} &= \left[M_t, M_{t-1}, ...M_{t-(T-1)}\right]' \;\; (T \times 1)\,, \\
\varepsilon_{\mathbf{t-1,t-T}} &= \left[\varepsilon_t, \varepsilon_{t-1}, ...\varepsilon_{t-(T-1)}\right]' \;\; (T \times 1)\,.
\end{aligned}$$

The vector of price indexes $\mathbf{\Gamma} \cdot \mathbf{M_{t,t-(T-1)}}$, and so the aggregate price index is

$$P_t = \omega' \mathbf{\Gamma} \mathbf{M_{t,t-(T-1)}}\,.$$

The reset and preset price levels

$$\begin{aligned}
P_t^{res} &= \delta' \left[\varepsilon_t \mathbf{I_{N\times 1}} + \left(\mathbf{I_{N\times T}} - \mathbf{\Gamma L'}\right) \varepsilon_{\mathbf{t-1,t-T}}\right] \\
P_t^{pre} &= \delta' \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right) \varepsilon_{\mathbf{t-1,t-T}} \\
P_t^{res} - P_t^{pre} &= \delta' \left[\varepsilon_t \mathbf{I_{N\times 1}} + \left(\mathbf{I_{N\times T}} - \mathbf{\Gamma L'}\right) \varepsilon_{\mathbf{t-1,t-T}} - \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right) \varepsilon_{\mathbf{t-1,t-T}}\right],
\end{aligned}$$

where δ is the $(N \times 1)$ vector with entries $\frac{\omega_j A_j}{\omega' \mathbf{A}}$ (or ω_j) for the frequency-weighted (weighted) aggregation, and κ is a $(N \times N)$ diagonal matrix with diagonal element in row j equalling λ_j / A_j, $\mathbf{L}$ is lower triangular $(T \times T)$ matrix, $\mathbf{I_N}$ is the diagonal $(N \times N)$ matrix, $\mathbf{I_{T\times N}}$ is the $(T \times N)$ matrix of 1's, and $\mathbf{I^0_{N\times T}}$ is an $(N \times T)$ matrix in which the entries of row j are 0's for $\tau = 1, ..., T_j$, and 1's for $\tau = T - T_j + 1, ..., T$.

Price selection is given by the regression of preset price on the difference of reset and preset prices:

$$\begin{aligned}
\gamma &= \frac{cov\left(P_t^{pre}, P_t^{res} - P_t^{pre}\right)}{var\left(P_t^{res} - P_t^{pre}\right)} \\
&= \frac{\delta' \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right) \left[\mathbf{I_{N\times T}} - \mathbf{\Gamma L'} - \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right)\right]' \delta}{\mathbf{1} + \delta' \left[\mathbf{I_{N\times T}} - \mathbf{\Gamma L'} - \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right)\right] \left[\mathbf{I_{N\times T}} - \mathbf{\Gamma L'} - \left(\kappa - \mathbf{I_N}\right) \left(\mathbf{\Gamma L'} - \mathbf{I^0_{N\times T}}\right)\right]' \delta}
\end{aligned}$$

We can check that selection goes to zero as $T \to \infty$ (Calvo model). And it goes to $-\frac{T-1}{2T}$ as $\lambda \to 0$ (Taylor mode).

Consumption response is

$$C_t \quad = \quad M_t - P_t = \omega' \left(\mathbf{I_{T\times N}} - \mathbf{L\Gamma'} \right)' \varepsilon_{\mathbf{t,t-(T-1)}} \,,$$

and serial correlation of consumption is

$$\rho_C \quad = \quad \frac{cov(C_t, C_{t-1})}{var(C_t)} = \frac{\omega' (\mathbf{I_{T\times N}} - \mathbf{L\Gamma'})' \, \mathbf{U_1} \, (\mathbf{I_{T\times N}} - \mathbf{L\Gamma'}) \, \omega}{\omega' (\mathbf{I_{T\times N}} - \mathbf{L\Gamma'})' \, (\mathbf{I_{T\times N}} - \mathbf{L\Gamma'}) \, \omega} \,,$$

where $\mathbf{U_1}$ is the $(T \times T)$ matrix that gives the lag of vector $\varepsilon_{\mathbf{t,t-(T-1)}}$: $\varepsilon_{\mathbf{t-1,t-T}} = \mathbf{U_1} \varepsilon_{\mathbf{t,t-(T-1)}}$.

Monetary non-neutrality can be measured as the half-life of consumption response: $\Psi = \frac{ln(0.5)}{ln \rho_C}$.

C.7 Caplin and Spulber (1987) model

In a monetary equilibrium log prices are uniformly distributed on $[b, B]$ with distribution

$$G\left(p \mid S\right) = \begin{cases} 1 & \text{if } p \in (B, \infty) \\ \frac{p-b}{B-b} & \text{if } p \in [b, B] \\ 0 & \text{if } p \in (-\infty, b) \end{cases}$$

Recalling that money supply follows a one-sided process, the hazard function is :

$$\Lambda\left(p_{-1}; S\right) = \begin{cases} 1 & \text{if } p_{-1} \in (-\infty, b + \omega) \\ 0 & \text{if } p_{-1} \in [b + \omega, \infty] \end{cases}$$

which gives the average fraction of adjusting prices

$$\overline{\Lambda}\left(S\right) = G\left(b + \omega \mid S_{-1}\right) = \frac{\omega}{B - b}$$

To find distribution of reset prices, write the law of motion

$$G\left(p \mid S\right) = G(p + \omega \mid S_{-1}) - G(b + \omega \mid S_{-1}) + H\left(p \mid S\right) G\left(b + \omega \mid S_{-1}\right)$$

so that

$$H\left(p \mid S\right) = \frac{G\left(p \mid S\right) - G(p + \omega \mid S_{-1}) + \overline{\Lambda}\left(S\right)}{\overline{\Lambda}\left(S\right)}$$

The reset price is

$$
\begin{aligned}
P^{res}(S) &= \int_p p \; dH(p \mid S) \\
&= \int_{[b,B-\omega]} pd\left(\frac{G(p \mid S) - G(p+\omega \mid S_{-1}) + \overline{\Lambda}(S)}{\overline{\Lambda}(S)}\right) + \int_{[B-\omega,B]} pd\left(\frac{G(p \mid S) - 1 + \overline{\Lambda}(S)}{\overline{\Lambda}(S)}\right) \\
&= \overline{\Lambda}(S)^{-1}\left(\int_{[b,B-\omega]} pdG(p \mid S) - \int_{[b,B-\omega]} pdG(p+\omega \mid S_{-1}) + \int_{[B-\omega,B]} pdG(p \mid S)\right) \\
&= \overline{\Lambda}(S)^{-1}\left(\int_{[b,B]} pd\frac{p-b}{B-b} - \int_{[b,B-\omega]} pd\frac{p+\omega-b}{B-b}\right) \\
&= \frac{1}{2\omega}\left(B^2 - b^2 - \left((B-\omega)^2 - b^2\right)\right) = B - \omega/2
\end{aligned}
$$

So

$$
\begin{aligned}
\pi^{res}(S) &= P^{res}(S) - P(S_{-1}) + \omega \\
&= B - \omega/2 - \int_{[b,B]} pd\frac{p-b}{B-b} + \omega \\
&= B - \omega/2 - \frac{B+b}{2} + \omega \\
&= \frac{B-b+\omega}{2}
\end{aligned}
$$

The preset price is

$$
\begin{aligned}
P^{pre}(S) &= \overline{\Lambda}(S)^{-1}\int_p p \; \Lambda(p;S)\, dG(p \mid S_{-1}) \\
&= \frac{B-b}{\omega}\int_b^{b+\omega} pd\left(\frac{p-b}{B-b}\right) = b + \omega/2
\end{aligned}
$$

so

$$
\pi^{pre}(S) = P(S_{-1}) - P^{pre}(S) = \frac{B+b}{2} - b - \omega/2 = \frac{B-b-\omega}{2}
$$

Overall, this gives us the following decomposition

$$
P(S) - P(S_{-1}) + \omega = \left[\frac{B-b+\omega}{2} + \frac{B-b-\omega}{2}\right] \; \frac{\omega}{B-b} = \omega
$$

So inflation is equal to the rate of money growth, i.e., there is full monetary neutrality. Price selection is ill-defined, since preset price level relative to the aggregate price is moving with money supply, $\frac{\omega-(B-b)}{2}$, but the average size of price changes is constant, $B-b$.

C.8 Head-Liu-Menzio-Wright model

Head et al. (2012) (HLMW) study a model in which price dispersion arises due to decentralized trade and search frictions in the goods market. An equilibrium pins down a unique relative price distribution $G(p_{-1} \mid S_{-1})$ but does not pin down price changes. This distribution is invariant to monetary shocks. Hence there is full monetary neutrality despite arbitrary price stickiness for a nontrivial measure of goods at a micro level.

Hazard function in HLMW model:

$$\Lambda(p_{-1}; S) = \begin{cases} 1 & \text{if } p_{-1} \in (-\infty, b+\omega) \cap (B+\omega, \infty) \\ 1-\rho & \text{if } p_{-1} \in [b+\omega, B+\omega] \end{cases}$$

which gives the average fraction of adjusting prices

$$\begin{aligned} \overline{\Lambda}(S) &= \int_{p_{-1}} \Lambda(p_{-1}; S)\, dG(p_{-1} \mid S_{-1}) \\ &= G(b+\omega \mid S_{-1}) + (1-\rho)\left[1 - G(b+\omega \mid S_{-1})\right] \\ &= 1 - \rho + \rho G(b+\omega \mid S_{-1}) \end{aligned}$$

To find H write the law of motion for G:

$$G(p \mid S) = \rho\left[G(p+\omega \mid S_{-1}) - G(b+\omega \mid S_{-1})\right] + H(p \mid p_{-1}; S)\left[1 - \rho + \rho G(b+\omega \mid S_{-1})\right]$$

HLMW show that there exists a monetary equilibrium in which this distribution is invariant to changes in the money supply, i.e., there is monetary neutrality. In this case, $G(p \mid S) = G(p|S_{-1}) = G(p)$, and so

$$H(p \mid S) = \begin{cases} \frac{G(p) - \rho[G(p+\omega) - G(b+\omega)]}{1-\rho+\rho G(b+\omega)} & \text{if } p \in [b, B-\omega] \\ \frac{G(p) - \rho[1 - G(b+\omega)]}{1-\rho+\rho G(b+\omega)} & \text{if } p \in [B-\omega, B] \end{cases}$$

Check that H is indeed a distribution function:

$$\begin{aligned} & \int dH(p \mid p_{-1}; S) \\ =\ & \int_{[b, B-\omega]} d\frac{G(p) - \rho\left[G(p+\omega) - G(b+\omega)\right]}{1-\rho+\rho G(b+\omega)} + \int_{[B-\omega, B]} d\frac{G(p) - \rho\left[1 - G(b+\omega)\right]}{1-\rho+\rho G(b+\omega)} \\ =\ & \frac{1 - \rho\left[1 - G(b+\omega)\right]}{1-\rho+\rho G(b+\omega)} = 1 \end{aligned}$$

The reset price is

$$\begin{aligned}
P^{res}(S) &= \int_p p \; dH(p \mid S) \\
&= \int_{[b,B-\omega]} p \; d\frac{G(p) - \rho\left[G(p+\omega) - G(b+\omega)\right]}{1-\rho+\rho G(b+\omega)} + \int_{[B-\omega,B]} p \; d\frac{G(p) - \rho\left[1 - G(b+\omega)\right]}{1-\rho+\rho G(b+\omega)} \\
&= \overline{\Lambda}(S)^{-1}\left[\int_{[b,B]} p \; dG(p) - \rho \int_{[b,B-\omega]} p \; dG(p+\omega)\right] \\
&= \overline{\Lambda}(S)^{-1}\left[\int_{[b,B]} p \; dG(p) - \rho \int_{[b+\omega,B]} p \; dG(p) + \rho\omega\left(1 - G(b+\omega)\right)\right]
\end{aligned}$$

So

$$\begin{aligned}
\pi^{res}(S) &= P^{res}(S) - P(S_{-1}) + \omega \\
&= \overline{\Lambda}(S)^{-1}\left[\int_{[b,B]} p \; dG(p) - \rho \int_{[b+\omega,B]} p \; dG(p) + \rho\omega\left(1 - G(b+\omega)\right)\right] - \int_{[b,B]} p \; dG(p) + \omega \\
&= \overline{\Lambda}(S)^{-1}\left[\left(1 - \overline{\Lambda}(S)\right)\int_{[b,B]} p \; dG(p) - \rho \int_{[b+\omega,B]} p \; dG(p) + \omega\right]
\end{aligned}$$

The preset price is

$$\begin{aligned}
P^{pre}(S) &= \overline{\Lambda}(S)^{-1} \int_p p \; \Lambda(p; S)\, dG(p) \\
&= \overline{\Lambda}(S)^{-1}\left[\int_{[b,b+\omega]} p \; dG(p) + (1-\rho)\int_{[b+\omega,B]} p \; dG(p)\right] \\
&= \overline{\Lambda}(S)^{-1}\left[\int_{[b,B]} p \; dG(p) - \rho \int_{[b+\omega,B]} p \; dG(p)\right]
\end{aligned}$$

so that

$$\begin{aligned}
\pi^{pre}(S) &= P(S_{-1}) - P^{pre}(S) \\
&= \overline{\Lambda}(S)^{-1}\left[-\left(1 - \overline{\Lambda}(S)\right)\int_{[b,B]} p \; dG(p) + \rho \int_{[b+\omega,B]} p \; dG(p)\right]
\end{aligned}$$

Finally,

$$\begin{aligned}
P(S) - P(S_{-1}) + \omega &= \left\{ \overline{\Lambda}(S)^{-1} \left[\left(1 - \overline{\Lambda}(S)\right) \int_{[b,B]} p \; dG(p) - \rho \int_{[b+\omega,B]} p \; dG(p) + \omega \right] \right. \\
&\quad \left. + \overline{\Lambda}(S)^{-1} \left[- \left(1 - \overline{\Lambda}(S)\right) \int_{[b,B]} p \; dG(p) + \rho \int_{[b+\omega,B]} p \; dG(p) \right] \right\} \overline{\Lambda}(S) \\
&= \omega
\end{aligned}$$

Note that this model nests Caplin-Spulber's case for $\rho = 1$ and $G(p)$ as in their baseline choice. As in Caplin-Spulber's case, reset-price inflation and selection effect co-move in offsetting fashion. Unlike Caplin-Spulber's case, for $\rho > 0$, the sum of the two effects *does* move around, so that some of the inflation variance is due to intensive margin.

HLMW solve for G :

$$G(p, n^*) = \begin{cases} 1 - \frac{\alpha_1}{2\alpha_2} \left\{ \frac{\overline{p}(n^*)^{-\frac{1}{\sigma}} [\overline{p}(n^*) - c]}{p^{-\frac{1}{\sigma}} (p - c)} - 1 \right\}, & \text{if} \quad p \in [\widehat{p}(n^*), \overline{p}(n^*)] \\ 1 - \frac{\alpha_1}{2\alpha_2} \left\{ \frac{\overline{p}(n^*)^{-\frac{1}{\sigma}} [\overline{p}(n^*) - c]}{p^{-1} n^* (p - c)} - 1 \right\}, & \text{if} \quad p \in [\underline{p}(n^*), \widehat{p}(n^*)] \end{cases}$$

where n^* is the equilibrium real balances and p is the real price, and

$$\begin{aligned}
\widehat{p}(n^*) &= (n^*)^{\frac{\sigma}{\sigma-1}} \\
\overline{p}(n^*) &= \max\left\{ \frac{c}{1-\sigma}, (n^*)^{\frac{\sigma}{\sigma-1}} \right\} \\
\underline{p}(n^*) &= \frac{c\overline{p}(n^*)(\alpha_1 + 2\alpha_2)}{\alpha_1 c + 2\alpha_2 \overline{p}(n^*)}
\end{aligned}$$

with

$$\begin{aligned}
\lambda &= 0.401 \\
\sigma &= 0.45 \\
\rho &= 0.937 \\
\alpha_1 &= 2(1-\lambda)\lambda \\
\alpha_2 &= \lambda^2
\end{aligned}$$

We recalibrate ρ to 0.792 so that the model matches the frequency of 0.22, a typical value in CPI data. Numerical simulations show that in HLMW model reset price inflation accounts for about two thirds of inflation variance and price selection is responsible for about one third. Increasing ρ to 1, so that the frequency of price changes not triggered by the monetary shock is zero, brings the model's predictions close to those in the Caplin-Spulber model, with fraction of price changes accounting for all inflation fluctuations.

D Selection effects and price selection

Although our measure of price selection is model-free, it is instructive to see how it behaves in standard sticky-models. In this section we use the Calvo and Golosov-Lucas models to provide intuition on selection effects, and to illustrate how they relate to our model-free measure of price selection. The two panels in Figure D.1 provide a stylized representation of the probability of adjustment at a point of time for a log price, p_i, from a distribution of prices in the population. Let p^* denote the common component of the desired log price level at that point in time (each firm's desired price also depends on idiosyncratic components that we omit for clarity of exposition). The dispersion of prices at that point in time is the outcome of infrequent price changes; otherwise, all prices would be equal to p^*. The two models considered here differ in the shape of the function that gives the probability of adjustment as a function of the firm's "price gap", $|p_i - p^*|$. In the Calvo model (Panel B), that probability is a flat function of the price gap $|p_i - p^*|$. In the GL model (Panel A), firms face a fixed cost every time they adjust their prices. Since a firm's profit function is concave with respect to the price gap $|p_i - p^*|$, they are more likely to adjust their price the bigger that distance. Hence, the probability of adjustment Λ is a convex function with respect to $|p_i - p^*|$, reaching the maximum of 1 when that distance becomes big enough that the benefits of adjusting outweigh the fixed cost.

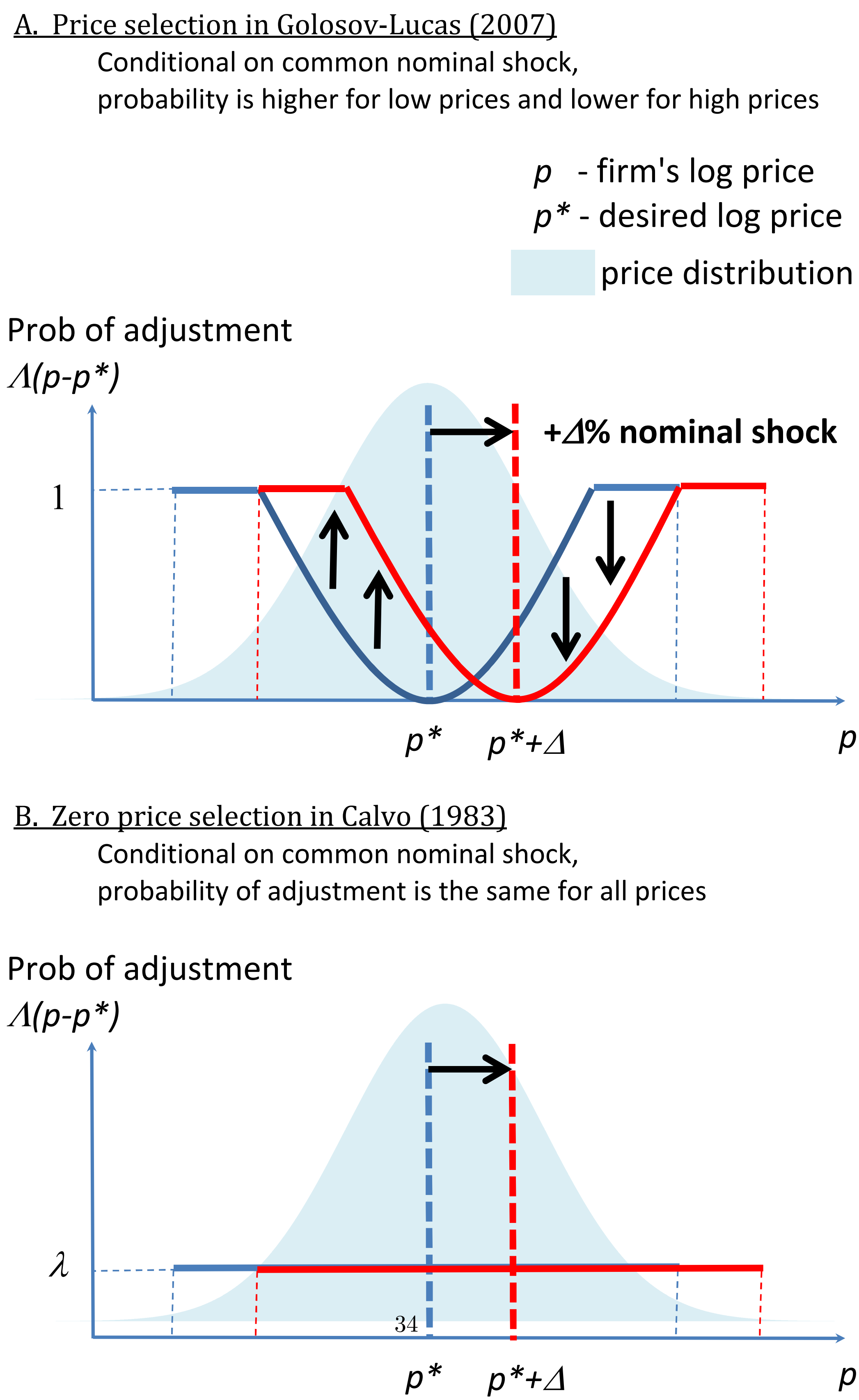
Now consider the change in the probability of adjustment in response to a common shock that increases the desired level p^*, say, by 1%. Since the shock increases the distance $|p_i - p^*|$ for low prices and decreases it for high prices, it affects the probability of their adjustments. Graphically, this is captured by the shift of the probability function to the right by 1%. The distance between the the pre-shock probability function (blue line) and the after-shock function (red line) gives the change in the probability of adjustment for any price in the domain.

Since the probability function is flat in the Calvo model, there is no change in how likely a given price p_i will adjust in response to the shock. Hence, prices that adjust in response to that shock are representative of the whole population of adjusting prices and there is no price selection. In the GL model, lower prices are more likely to adjust, and higher prices are less likely to change. Hence, in response to a positive nominal shock, the average level of prices that adjust is lower than the average over the population of all prices. This is an example of price selection that amplifies the response of aggregate inflation to the shock.

Golosov and Lucas (2007) give an informal explanation of the selection effect along these lines. Caballero and Engel (2007) provide a formal treatment. They clarify that although the probability of price adjustment monotonically increases with the price gap $|p_i - p^*|$ in some sticky-price models, the marginal contribution to the aggregate price response after a monetary shock does not always monotonically increase with the price gap. Note that in our example, the extensive margin complements price selection to amplify fluctuations of the average price level in response to common nominal shocks: both price increases (more frequent) and price decreases (less frequent) push the average price level up.

Finally, it is important to emphasize that our measure of price selection does not depend on any of the objects that are material for price selection in these models, e.g., price gaps. It also does not require firms' desired prices to be identical.

Figure D.1: Selection effects and price selection in sticky-price models, stylized example



E Price selection, real rigidities and monetary non-neutrality

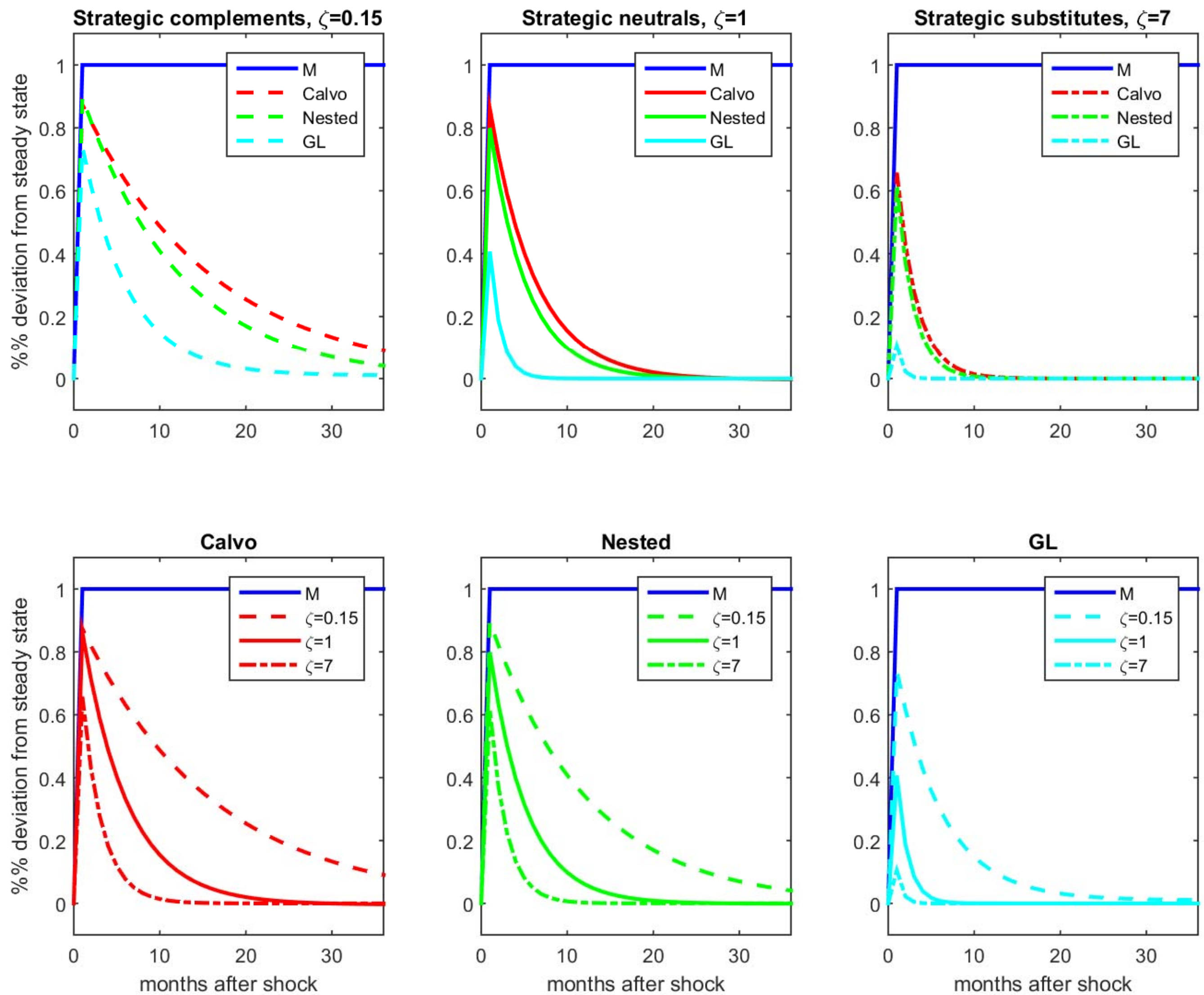
Here we analyze whether price selection and real rigidities interact in generating monetary non-neutrality. We change assumptions on preferences and technologies in the baseline models and parametrize them to obtain different degrees of real rigidity as measured by the Ball and Romer (1990) index of real rigidities (ζ). In addition to the baseline parametrization, which yields strategic neutrality in price setting ($\zeta = 1$), we also study parametrizations that yield strong strategic complementarity ($\zeta = 0.15$) or substitutability ($\zeta = 7$) in pricing decisions. Moreover, we also study this interaction in the generalized version of the Golosov-Lucas model that introduces the possibility of some random price changes as in the Calvo model. Results are presented in Table E.1 and in Figure E.1. They show that real rigidities have an independent effect on monetary non-neutrality.

Table E.1: Price selection, real rigiditites and monetary non-neutrality in Calvo, Golosov-Lucas and Golosov-Lucas+ models

	Targeted moments	Calvo			GL			GL-Calvo		
Ball-Romer index of real rigidities		ζ=0.15	ζ=1	ζ=7	ζ=0.15	ζ=1	ζ=7	ζ=0.15	ζ=1	ζ=7
Calvo weight		1	1	1	0	0	0	0.92	0.92	0.92
A. Calibration targets										
Fraction of pch, %	**16.0**	16.0	16.0	16.0	16.2	16.0	16.0	16.1	16.3	16.2
Abs size of pch, %	**14.7**	14.7	14.7	14.7	14.7	14.7	14.7	14.8	14.7	14.7
Serr corr of reset prices	**0.13**	0.12	0.12	0.13	0.12	0.14	0.13	0.10	0.11	0.13
Inflation mean, %	**0.25**	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Inflation stdev, %	**0.29**	0.28	0.28	0.28	0.28	0.29	0.29	0.27	0.28	0.28
B. Price selection	**-0.14**	-0.06	-0.06	-0.06	-0.36	-0.34	-0.36	-0.15	-0.14	-0.15
C. Predicted moments		.								
Consumption stdev, %		3.39	1.43	0.54	1.06	0.21	0.03	2.79	1.08	0.45
Consumption ser. corr		0.91	0.81	0.65	0.81	0.46	0.22	0.90	0.78	0.60
Half-life of C, months		7.77	3.34	1.59	3.38	0.90	0.46	6.30	2.79	1.35

Notes: We simulate each model with 10000 firms over 235 months for a given sequence of money growth shocks and compute the time series for each of the variables. We repeat this simulation 100 times, drawing new sequences of monetary and idiosyncratic shocks for each simulation, and report the means of model moments across these simulations. Targeted moments selected to be representative of our empirical findings for the three countries. Price selection differs from zero in the Calvo model due to sample size.

Figure E.1: Price selection and real rigiditites in Calvo, Golosov-Lucas and Nested (generalized Golosov-Lucas) models



Notes: Figure provides consumption responses to a +1% impulse to money supply in Calvo, Golosov-Lucas and Nested (generalized Golosov-Lucas) models with strategic complementarity in pricing decisions ($\zeta = 0.15$), strategic substitutability ($\zeta = 7$), and strategic neutrality ($\zeta = 1$). Solid blue line indicates the money supply.

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