Price Selection*

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Abstract

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, United States and Canada we find robust evidence of strong price selection across goods and services. At a disaggregate level, price selection accounts for around 36% of inflation variance in the United Kingdom and the United States, and 28% in Canada. Price selection is stronger for goods with less frequent price changes or with more volatile inflation. Aggregation largely washes out price selection for regular price changes, but not for changes associated with price discounts. This evidence favors multi-sector sticky price models with strong price selection at a sector level.

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1 Introduction

The extent to which prices respond to new information—to macroeconomic shocks, in particular—is a fundamental question in economics. In macroeconomic data the correlation between inflation and economic slack is low—also known as a flat Phillips curve—suggesting that prices are relatively insensitive to economy-wide disturbances. Much of the literature has concentrated on reconciling the flat Phillips Curve with evidence of ample price flexibility at a disaggregate level. This usually requires a mechanism that creates large "price contract multiplier" whereby prices do not completely respond to shocks due to implications of market failures in allocating goods, factors or information.[1] This literature, however, has largely abstracted from *price selection*—the mechanism that focuses on the distribution of price adjustments across firms and products, and that works in the direction of amplifying the inflation response. The goal of this paper is to study price selection and its impact inflation dynamics.

Price selection exists when prices that change in response to macroeconomic or monetary disturbances are not representative of the overall population of prices. In theory, adjusting prices tend to have larger gaps relative to their desired levels than other prices; and in response to a common nominal shock the selection of prices with larger gaps may provide an additional impact on inflation. For example, if prices that increase in response to an unanticipated nominal expansion come from below-average levels, the associated individual price increases are larger on average, and the resulting inflation response is greater. While the possibility of price selection is a prominent theoretical insight, the literature provides only a wide range of the degrees of selection, inferred indirectly from applied theoretical models matched to observed micro price behaviour.[2] There is hardly any direct evidence on 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 of measuring price selection and its impact on inflation. We show how price inflation between periods $t-1$ and t can be identically represented as the product of the fraction of prices that change between period $t-1$ and t, and the difference between their average starting and ending levels, which we call *preset* and *reset* price levels. Namely, for the subset of prices that change between periods $t-1$ and t, the preset (reset) price level is their average level before (after) the change, expressed as log deviation from the population average in period $t-1$. When selection is present, upward (downward) movements in inflation would be largely driven by

[1] Important contributions to this voluminous literature include Chari, Kehoe, and McGrattan (2000), Christiano, Eichenbaum, and Evans (2005), and Smets and Wouters (2007). Nakamura and Steinsson (2013) provide a review of empirical evidence used in this literature.

[2] Applied theoretical studies of macroeconomic implications of price selection include Caplin and Spulber (1987), Danziger (1999), Caballero and Engel (2007), Golosov and Lucas (2007), Gertler and Leahy (2008), Nakamura and Steinsson (2010), Costain and Nakov (2011b, a, b), Midrigan (2011), Karadi and Reiff (2012), Head et al. (2012), Carvalho and Schwartzman (2015), Alvarez and Lippi (2014), Alvarez, Le Bihan, and Lippi (2016). There are only a few studies of the price pass-through of firm- or product-level shocks to marginal costs, and they provide a wide range of estimates: from none or very small (Carlsson, 2016) 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, but they do not identify how much of this response is due to price selection.

prices that adjust from below-(above-)average levels, and so the preset price level would correlate negatively with inflation. In the absence of selection, the average starting level of adjusting prices would be close to last period's population average, and so the preset price level would not vary. Since this definition is based on observations of individual price changes, it can be easily applied to micro data for assessing the degree of price selection, and to simulated data generated by sticky price models to gauge plausibility of their predictions.

We employ three detailed micro price datasets to document price selection. For the United Kingdom, we use the dataset underlying construction of the Consumer Prices 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 1100 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 till 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, Symphony 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.

First, we compute the average price change, the fraction of price changes, and reset and preset price levels for each month, product category, and sampling stratum (given by location and store type). In accordance with price measurement methodologies in the United Kingdom, United States, and Canada (ILO, 2004) this level of disaggregation is used for constructing elementary price indices that are then aggregated using consumption expenditure weights to obtain CPI. Price selection hinges on covariation between preset price level and inflation. We measure the extent of price selection by the coefficient in the regression of the preset price level on the average size of price changes (i.e., the intensive margin of inflation fluctuations). For brevity, we refer to this coefficient throughout as "price selection." 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 level, thus providing a convenient metric for gauging economic significance of price selection. By construction, zero price selection means that changes in the preset price level are not correlated with inflation fluctuations. We test this hypothesis in the micro data.

For our baseline case, we exclude price changes associated with price discounts and product substitutions, and we control for stratum and calendar-month fixed effects. The weighted mean price selection across strata is –0.371 for the U.K., –0.360 for the U.S., and –0.285 for Canada, all statistically significant at 1% significance level, and is robust to different empirical specifications. 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 higher inflation volatility: a 5 percentage point increase in the average size of price changes is associated with an additional 1.5 to 2.5 percentage points of inflation variance explained by price selection. In contrast, our evidence does not corroborate the two sufficient statistics that are linked to price selection in standard sticky price models—the kurtosis of price changes (Alvarez, Le Bihan, and Lippi, 2016) and the standard deviation of price spell durations (Carvalho and Schwartzman, 2015).

Finally, we measure the degree of price selection at the *aggregate* level. Stratum-level variables are aggregated using expenditure weights, and aggregate variables are used to compute price selection. We find that regular-price selection is substantially weakened. For the baseline case—no discounts or substitutions—price selection is –0.197 for the U.K., and it is not significantly different from zero for the U.S. and Canada. Similar to the stratum-level evidence, including substitutions in the regression analysis does not change price selection at the aggregate level. By contrast, including price discounts restores a substantial degree of price selection in the U.K. (–0.394) and the U.S. (–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 independent margin of price flexibility, and underscores their role for amplifying cyclical variation of the aggregate price level, recently emphasized for the U.K. and U.S. by Kryvtsov and Vincent (2017). In Canada, aggregate price selection is close to zero for either regular or all posted prices, consistent with less cyclicality in price discounts in the Canadian sample and coarser strata.

In the second part of the paper, we study the implications of the empirical evidence for business cycle models, where price selection is key in determining the inflation-output trade-off. This trade-off has been studied by Caplin and Spulber (1987), Danziger (1999) and Golosov and Lucas (2007) using menu-cost models, where selection arises because firms can choose to incur a menu cost to change their prices. The subset of prices that adjust tend to be the most misaligned, and hence the associated price changes tend to be large. Price selection also arises in models with exogenous (time-dependent) price adjustment, as long as some prices are expected to take longer to adjust after the shock, as, for example, in Taylor (1980) model. This mechanism increases the sensitivity of aggregate inflation to economic slack for a given degree of microeconomic price stickiness. The degree of price selection, however, may be affected by idiosyncratic factors, such as product-level disturbances (Gertler and Leahy, 2008), economies of scale in price-adjustment technology (Midrigan, 2011), the size of aggregate shocks (Alvarez et al., 2017), stochastic volatility of idiosyncratic shocks (Karadi and Reiff, 2012), the number of products per retailer (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 sector heterogeneity in price stickiness (Nakamura and Steinsson,

2008). The most widely used Calvo (1983) sticky price model with random and exogenous timing of price adjustments represents an extreme case with zero price selection. Hence, sticky price models offer a wide range of predictions for the degree of price selection, and the associated size of real effects after monetary shocks.

We demonstrate this range by documenting price selection in standard sticky price models. First, using an analytic example for plain-vanilla Taylor (1980) model, we explain the intuition behind the empirical results. We then quantify price selection in three standard models extended to match micro price dynamics—Taylor (1980), Calvo (1983), and Golosov and Lucas (2007) models. We show that Taylor and Golosov-Lucas models exhibit strong price selection, –0.44 and –0.34 respectively, in line with our evidence at a disaggregate level; conversely, zero price selection in Calvo model is at odds with that evidence. Relative to Taylor model, price selection in Golosov-Lucas model yields a larger response of the aggregate price after an unexpected monetary disturbance because it triggers price changes that close price gaps soon after the disturbance. By contrast, in Taylor model, price gaps close gradually after the shock, as different price cohorts get their turn to adjust.

We then ask whether aggregation weakens price selection by comparing one-sector models to their multi-sector extensions. We study 66-sector versions of Golosov-Lucas and Taylor models calibrated to match the frequency of price changes and the degree of price selection in 66 consumption sectors in the U.K. data. Indeed, in both models, aggregation weakens price selection, albeit by a smaller degree than we observe in the data. Model analysis yields two reasons for weaker aggregate price selection. First, price changes from more flexible sectors are more heavily represented in the cross-section relative to price changes from stickier sectors, and so the aggregate price selection puts larger weight on sectors with relatively weak selection; this mechanism was explained in Kara (2015) and Carvalho and Schwartzman, 2015. Second, price adjustments in different sectors close price gaps of different magnitudes (larger gaps in more inflexible sectors), and so their joint impact on the aggregate price is smaller. Altogether, these multi-sector models account for only one-fifth of sector variation of price selection observed in the data and they generate only a small portion of the aggregation bias observed in the data.

We draw several conclusions for sticky price models. 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. We show that multi-sector models with strong selection at sector level have a better chance of accounting for the evidence on price selection. Nakamura and Steinsson (2010) show that implications of such models for the sources of business cycles and the effectiveness of monetary policy can differ drastically from models without price selection or cross-sector heterogeneity. In a related paper, Bils, Klenow, and Malin (2012) show that workhorse business cycle models, such as Smets and Wouters (2007), are inconsistent with joint dynamics of U.S. inflation and Bils et al's reset price inflation, which we argue is closely related to price selection.

More generally, 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. For example, models should exploit additional dimensions of heterogeneity across goods and retailers to match the broad spectrum of price selection in the cross-section and the degree to which price selection dissipates with aggregation. Further, more evidence on whether price selection makes its impact in the wake of the shock, as in menu cost sticky price models, or only gradually, as in time-dependent sticky price models, will be useful for calibrating the degree of monetary non-neutrality in sticky price models. In this regard, combining our measure of price selection with the sufficient statistics approach (Alvarez, Le Bihan, and Lippi, 2016, Carvalho and Schwartzman, 2015) may be helpful for assessing the importance of other drivers of monetary non-neutrality, such as real rigidities or information frictions.

The paper proceeds as follows. We define and explain the concept of price selection in Section 2. Section 3 introduces the data sources and empirical definitions. We then identify and measure price selection in the U.K., U.S. and Canadian micro data in Section 4. Section 5 distils the implications of the empirical findings for sticky price models. Section 6 concludes.

2 Definition of price selection

2.1 Basic intuition

The basic intuition behind price selection can be explained using Calvo and Golosov-Lucas (GL) models as examples. The two panels on Figure 1 provide a stylized representation of the probability of adjustment at a point of time for a log price, p, from a distribution of prices in the population. Let p^* denote a desired log price level at that point of time, common for all price setters. The dispersion of prices at that point of time is the outcome of infrequent price changes; otherwise, all prices would be equal to p^*. Two models considered here differ in the shape of the probability of adjustment function. In the Calvo model (Panel A), that probability for a given price follows an exogenous Poisson process with the arrival rate λ, and therefore the probability of adjustment is a flat function of p. In the GL model (Panel B), firms face fixed cost every time they adjust their prices. Since firm's profit function is concave with respect to the absolute distance between p and 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 $|p - p^*|$, reaching the maximum of 1 when that distance becomes too big.

Now consider the change in the probability of adjustment in response to a common (aggregate or sector-specific) nominal shock: such a shock increases the desired level p^*, say, by 1%. Since the shock increases the distance $|p - p^*|$ 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 pre-shock probability function (blue line) and after-shock function (red line) gives the change in the probability of adjustment for any price on the domain.

Since probability function is flat in the Calvo model, there is no change in how likely a given

price p will adjust in response to the nominal shock. Hence, prices that adjust in response to that shock are representative of the whole population of adjusting prices. This is the example of 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 population of all prices that change. This is the example of price selection.

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 probability of price adjustment monotonically increases with price gap $|p - p^*|$ in common sticky price models, the marginal contribution to the average 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. Our definition below captures price selection regardless of whether or not it is correlated with extensive margin.

2.2 Inflation decomposition

Consider an economy with a continuum of goods, indexed by $i \in [0, 1]$, with $p_t(i)$ denoting log price of good i in period t. Let $G_t(p)$ denote the distribution of log prices in period t. The log of 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 – it 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

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

The first term on the right-hand side is (the negative of) the weighted mean of time-$(t-1)$ level of those log 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 average time-$(t-1)$ level of log prices that adjust between periods $t-1$ and t ("preset price"), and P_t^{res} denote their average time-t level ("reset price"):

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

Then inflation decomposition (3) can be written as

$$P_t - P_{t-1} = Fr_t\,(P_t^{res} - P_t^{pre})\,. \tag{4}$$

Price selection then is identified by movements in P_t^{pre}, the average level of adjusting prices relative to the average level of all prices, P_{t-1}. Co-movement of $P_t^{pre} - P_{t-1}$ with inflation captures the workings of price selection as summarized earlier in this Section.

2.3 Comparisons to alternative inflation decompositions

Decomposition (4) provides a novel spin on 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, $DP_t \equiv P_t^{res} - P_t^{pre}$.[3]

The relationship between inflation and "reset price inflation" was studied in Bils, Klenow and Malin (2012). They define reset price inflation as the estimated rate of change of new prices set by

[3]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.

the subset of price changers. Since the subset of price changers varies from month to month, the reset price inflation depends on both changes in the reset price levels and price selection. Therefore, their approach does not identify price selection and its impact on inflation dynamics. Using simulations of the Smets and Wouters (2007) business cycle model, Bils, Klenow, and Malin (2012) show that it is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. Kara (2015) shows that this issue is less severe if business cycle models incorporate different degree of price flexibility across consumption sectors. Since price selection makes inflation more volatile and less persistent, strong price selection would suggest that Bils et al's reset price inflation may be driven in part by price selection.

In a related approach, Caballero and Engel (2007), and Costain and Nakov (2011a) propose decomposition of inflation response to a monetary shock. This response is due to the cumulative impact of desired log price adjustments (price gaps), $p - p^*$, and can be decomposed into the contributions from changes in the size of adjustments by those prices that are adjusting 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 must rely on model assumptions about the process for the desired price level, p^*, and the conditional probability of adjustment as a function of the price gap, $\Lambda(p - p^*)$. While this approach is well suited for demonstrating theoretical implications of price selection, it is less useful for empirical assessment of price selection because the unobserved desired price level is difficult to measure in the micro data.[4] Caballero and Engel (2007) argue that in theory price selection is neither necessarily 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 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.[5]

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. Decomposition (4) focuses solely on selection of prices that adjust from month to month—summing log price *levels* for those prices that adjust: the average starting and ending price levels of adjusting prices are what we call preset and reset price levels. Their difference, multiplied by the fraction of price adjustments is identically equal to inflation. The contribution of movements in the preset price level deviation, $P_t^{pre} - P_{t-1}$, to inflation dynamics then identifies price selection.

[4]Carlsson (2016) uses the producer price and cost micro data from Sweden to estimate firm-specific marginal cost changes (and therefore p^*); 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 passthrough of cost to prices using scanner data for retail prices.

[5]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.

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

To measure the relationship between inflation and reset and preset price levels we need data on price changes at the level of individual goods and services. We employ three datasets for the United Kingdom, 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 Prices Index (CPI) in these countries. The Symphony 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 developed countries, serving as a compelling source of evidence of price selection, 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 1100 individual goods and services a month, collected across more than 14,000 retail stores across the United Kingdom. The survey excludes housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees. Also expenditures for purposes other than final consumption are excluded, e.g., those for capital and financial transactions, direct taxes, cash gifts. The portion of the data published on 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 includes 236 months, from February 1996 till September 2015. The total number of observations is over 24 million, or about 100,000 per month.[6] 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 based on a probability-proportional-to-size systematic sampling with a size measures 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

[6]Detailed description of the CPI data sampling and collection can be found in the ONS (2014) and Clews, Sanderson, and Ralph (2014). The price quote data are available via 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 (2017), and Chu et al. (2017).

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, availability for purchase throughout the year (except for certain goods that are seasonal). There are currently over 1100 categories in the basket. Examples of categories include: Onions, Edam, Envelopes, Men's Suit (ready made), Electric Heater, Single Bed. 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 22 "strata," given by region and shop type pairing. For each category and stratum, ONS dataset provides sampling weights that reflect that category-stratum's relative importance in households' consumption expenditures. For constructing the CPI, ONS first construct 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.[7]

Throughout the paper, we provide two alternative treatments of price changes at 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 U.K.—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 or as end-of-season reductions. When posted price is discounted, the unobserved regular price equals to the posted price in the month preceding the first month of the sale; and it is equal to the posted price if there is no sale. These definitions are reliable for describing sales behaviour and are commonly used in the literature.[8]

Second, we differentiate price changes associated with product substitutions. When previously collected price-product is no longer available to a field agent, they make a substitution for another product from the same category. Such substitutions—5.6% per month in the U.K.—are more commonly associated with price increases (68% of price changes during substitutions).[9] Symphony IRI data contain prices for uniquely-defined products, and therefore we do not apply this treatment to these data.

[7]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 a calculated based on the Household Final Monetary Consumption Expenditure (HFMCE) and ONS Living Cost 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.

[8]Nakamura and Steinsson (2008) demonstrate that sales affect the measurement of the extent of nominal price stickiness in the U.S. CPI data. Kryvtsov and Vincent (2017) provide evidence of the countercyclical variation in the number of sales in the U.K. and U.S.; they also discuss different definitions of sales in the data.

[9]Klenow and Malin (2010) provide and 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.

3.2 Statistics Canada CPI data

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 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 barbecue, women's gloves, oil filter, 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, 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 to be considered. 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 variation, spanning 13 Canadian provinces and territories.

Like the U.K. dataset, the Canadian dataset provides flags for the months corresponding to a sale (9.0% of monthly observations) or a product substitutions (3.5%). We therefore treat those observations in the same way as we do for the U.K. dataset.

3.3 Symphony IRI Inc. data for the U.S.

Symphony IRI is a marketing and market research dataset that contains scanner data, product description data, store data and household data.[10] The scanner data are provided at a weekly frequency for a panel of 31 grocery products, such beer, coffee, milk, razors, laundry detergents, frozen pizza. To make 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 thousand 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

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

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 only include 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), and products which have less than two observations per week; and we exclude 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.[11]

3.4 Empirical definitions

The micro data used in this paper presents us with two challenges for accurate measurement of price selection: heterogeneity across products, locations and stores, and measurement errors. These issues are known to bias the estimates of price moments in the data, and may as well apply to measurement of price selection.[12]

Heterogeneity of price behaviours 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 incidences of price discounts, product churning, and stockouts.[13] To minimize the effect of heterogeneity on average statistics, we define "elementary" reset and preset price levels for each product category at the level of an elementary price index, stratum (i.e., location and store-type pairing). For each category-stratum preset (reset) price level is defined as the unweighted means of starting (ending) log price levels for all products in the category-stratum in each month. To avoid comparing reset and preset price "dollar" levels across different categories, they are expressed as log deviations from the mean for all log prices in the previous month in the respective category-stratum.

Taking category-stratum averages helps to correct random coding errors, such as, for example, entering a price of 9.99\$ instead of 99.99\$. To account for other rare but volatile month-to-month price movements we exclude observations with log-price changes larger in absolute value than the 99th percentile of absolute log price changes within each category-stratum, similar to the treatment in Alvarez, Le Bihan, and Lippi (2016). We also exclude strata with less than 10 price changes over the sample period.

The empirical counterparts of the four variables entering inflation decomposition (4) are con-

[11] Coibion, Gorodnichenko, and Hong (2015) use the Symphony 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.

[12] For example, Alvarez, Le Bihan, and Lippi (2016) demonstrate how heterogeneity and measurement errors introduce an upward bias in measured kurtosis of price changes.

[13] Klenow and Malin (2010)and Nakamura and Steinsson (2013) provide detailed reviews of microeconomic evidence on price dynamics and the extent of heterogeneity.

structed as follows. Let p_{ist} denote log price of product i in category-stratum s and in month t, and let P_{st} denote the elementary price index for category-stratum s in month t. Index i uniquely identifies an individual product in a particular retail outlet and location. Let ω_{st} denote expenditure weight corresponding to category-stratum s in month t, and N_{st} be the number of observations in stratum s in month t. To control for level- and trend-effects across products, we define month-t log price deviation as the log price level in month t relative to the elementary price level in month $t-1$, $\widehat{p}_{ist} = p_{ist} - P_{st-1}$, and month-$t$ lagged log price deviation as the price level in month $t-1$ relative to the elementary price level in month $t-1$, $\widehat{p}_{-1,ist} = p_{ist-1} - P_{st-1}$. Let I_{ist} be an indicator of a price change for product i in month t, $I_{ist} = 1$ 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 weighted mean of log price changes in that bin and month, and express it identically as follows:

$$\begin{aligned} \pi_{st} \equiv & \quad \tfrac{\sum_i (p_{is,t} - p_{is,t-1})}{N_{st}} \\ \equiv & \quad \underbrace{\frac{\sum_i I_{is,t}}{N_{st}}}_{Fr_{st}} \times \quad \left[\underbrace{\frac{\sum_i I_{is,t}\widehat{p}_{ist}}{\sum_i I_{is,t}}}_{P^{res}_{st}} - \underbrace{\frac{\sum_i I_{is,t}\widehat{p}_{-1,ist}}{\sum_i I_{is,t}}}_{P^{pre}_{st}} \right], \end{aligned} \tag{5}$$

which, takes the same form as (4):

$$\pi_{st} \equiv Fr_{st} \cdot \underbrace{[P^{res}_{st} - P^{pre}_{st}]}_{DP_{st}}, \tag{6}$$

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 prices that changed in month t (relative to the corresponding elementary price level 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 price level in month $t-1$). Expressions (5) and (6) are the empirical counterparts of inflation decomposition (4): inflation is the product of the fraction of price changes and the difference between reset and preset price levels. Note that the latter can be defined as the average size of prices that change in month t, $DP_{st} \equiv P^{res}_{st} - P^{pre}_{st}$. Decomposition (6), therefore, 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 our empirical analysis in the next section, we assess price selection for stratum-level time series, using the variables defined in (6).

Table 1 provides descriptive statistics for the U.K., U.S. and Canadian data for the case which excludes price changes due to sales and substitutions.[14] Regular price inflation in the both U.K. 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,

[14] Tables A.1–A.3 in Supplementary Material compare descriptive statistics across different treatments of sales and substitutions.

or 3.5% per year. In a given month, 12.7% of regular prices change in the U.K., or around once every 8 months. Prices in Canada and grocery prices in the U.S. change 21.7% and 22.3% of time, or once in every 4 months on average. An average magnitude of price changes therefore is 0.96%, 0.84%, and 1.31% in the U.K., Canada, and the U.S, respectively. Reset and preset price levels are expressed as % deviations from the population average, and therefore their averages may vary depending on inflation experiences over the samples in the country datasets. Indeed, both levels are positive for the U.K. (1.12% and 0.76%), and negative for Canada (–0.20% and –0.72%) and the U.S. (–2.19% and –2.90%). The remaining rows in Table 1 provide the 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 category-stratum level

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

$$P_{st}^{pre} = \beta DP_{st} + \delta_{cal} + \delta_s + error \tag{7}$$

where the dependent variable, P_{st}^{pre}, is preset price level for a product category-stratum s in month t, and the independent variable of interest is the average size of 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 β is equal to the estimated fraction of DP_{st} variance accounted for by variation in preset price level P_{st}^{pre} , with the remaining fraction due to reset price level changes. Hence, we adopt the estimated $\hat{\beta}$ as our measure of price selection. Typically, $\hat{\beta}$ is expected to be between –1 and 0, so values of $\hat{\beta}$ that are significantly different (and below) 0 are interpreted as evidence of price selection. Our baseline specification (7) also includes calendar-month fixed effects δ_{cal}, and category fixed effects δ_c. Equation (7) is estimated by a pooled weighted least squares regression.

Table 2 provides the results of this estimation for all three datasets. For our baseline, we consider the case with regular prices, and excluding price changes due to product substitutions. The estimated price selection is –0.371 for the U.K., –0.360 for the U.S., and –0.285 for Canada, all statistically significant at 1% confidence level (column 1).[15] The estimates are largely consistent across three countries; a somewhat lower absolute value for Canada can be attributed to aggregation across locations within a province. The degree of price selection is virtually unchanged when we allow calendar-month fixed effects, add category-specific linear trends, or consider unweighted regressions (columns 2 through 4). To visualize price selection, Figure 2 provides scatter plots for the largest strata in nine selected product categories in the U.K., including oil, milk, hotel, and cigarettes.

[15]Table A.4 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. Furthermore, including a constant in the regression changes the estimated value of the price selection coefficient by only about 0.0003, so it is immaterial for the results below.

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). Hence, each plot demonstrates joint variation of P_{st}^{pre} and DP_{st} across months for a given stratum. The slope of the trend line is equal to $\hat{\beta}_s$, representing the estimated degree of price selection. While there is substantial variation in both variables for each category-stratum and across strata, they tend to correlate negatively for each category-strata, pointing to the prevalence of price selection.[16]

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 U.K. and the U.S., –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 U.K., and slightly weaker in Canada, –0.415 and –0.268; and substitutions are not conducted in the IRI dataset. Hence, price discounts and substitutions do not appear to materially influence price selection at a stratum level.

To what extent does price selection differ across categories? Figure 3 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. To focus on the coefficients that are accurately estimated, we also plot the weights for the coefficients that are statistically different from zero (solid bars). Almost all coefficients (91% of the weight) are included in the theoretical range between –1 and 0. The weighted mean across all price selection values (all non-zero values) is –0.392 (–0.396), and the weighted median is lower at –0.400 (–0.402) since the distribution of price selection is slightly negatively skewed.

4.2 Price selection and price adjustment

How does price selection vary with price behaviour? We explore the richness of the datasets to answer this question and provide more guidance for business cycle models, discussed in Section 5. We modify the panel regression (7) by allowing price selection to vary with price adjustment moments computed at a stratum level, so that $\beta = \beta_1 + \beta_2 \Gamma_{st}$, where Γ_{st} is one of price adjustment moments for category-stratum s in month t. We also focus on cross-section variation since it is larger than variation across time, thus giving us a better chance of detecting the relationship between price selection and price adjustment. This leads us to the following empirical specification:

$$P_{st}^{pre} = \beta_1 DP_{st} + \beta_2 DP_{st} \times \Gamma_{st} + \delta_t + error \tag{8}$$

[16] 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 U.K. 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 stripping the regression variables of high and low frequencies using the Baxter-King (12,96,24) bandpass filter. As a result, price selection remains highly statistically significant, although its magnitude is roughly half of the magnitude for monthly series.

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 five price adjustment moments: the frequency and average size of price changes, Fr_{st} and DP_{st}, the average absolute size of individual price changes, kurtosis of non-zero price changes, and standard deviation of complete price spells.

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 stemming from variation across time reported above: –0.367 for the U.K., –0.373 for the U.S., and –0.295 for Canada, all highly statistically significant. We visualize our cross-section findings in Figure 4, which provides scatter plots for nine selected months in the U.K., for all 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 given month. The slope of the trend line is equal to $\hat{\beta}_s$, representing the estimated degree of price selection. 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 across section.

The other columns in Table 3 provide the results for full specification (8), including all five interaction terms, for the baseline case and for alternative cases incorporating price discounts and product substitutions.[17].

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 $\hat{\beta}_2$ for the interaction term $DP_{st} \times Fr_{st}$. For the baseline case, the estimates imply that in the category-stratum with a 10 percentage point lower fraction of price changes price selection accounts for higher fraction of its inflation variance: by 2.2 percentage points for the U.K. (from –0.367 to –0.389), by 6.7 percentage points for the U.S. (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 points lower price adjustment falls between 1.9 and 6.7 percentage points, with an average around 4.5 percentage points. The empirical relationship between the degree of nominal rigidity and price selection can be further corroborated by comparing price selection across the types of product. For example, we find that Services (the lowest frequency of price changes) and Non-durables (the highest frequency of price changes) feature the strongest and the weakest price selection.

This evidence is consistent with intuition: less frequent price changes imply that a larger fraction of prices is misaligned relative to the desired level, and therefore in response to a shock of the same magnitude, a larger mass of prices will move closer to the desired price. Remarkably, the point estimates are in line with the mainstream sticky price models, as we show in Section 5. For example, in Taylor (1980) model with monthly fraction of price changes Fr price selection accounts for the fraction $\frac{1}{2} - \frac{1}{2}Fr$ of inflation variance, i.e., a 10 percentage point lower fraction of price changes

[17] Estimating interaction coefficients separately, instead of altogether, does not alter the conclusions. The results are available upon request.

strengthens price selection by 5 percentage points.

The second robust finding is that price selection is stronger in category-strata in which price changes are higher on average, given by $\hat{\beta}_2$ for the interaction term $DP_{st} \times DP_{st}$. If the average size is higher by 5 percentage points, price selection strengthens by 1.5 percentage points for the U.K. (from –0.367 to –0.382) and for the U.S. (from –0.373 to –0.388), and by 2.5 percentage points for Canada (from –0.295 to –0.320). This finding implies that price selection amplifies fluctuations in inflation, which 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, in part due to the workings of price selection (Burstein, 2006; Alvarez et al., 2017).

Finally, we do not find a robust relationship between price selection and kurtosis of non-zero price changes or standard deviation of price spell durations. Hence, our empirical results do not corroborate the use of these moments as sufficient statistics for the size of monetary neutrality, proposed by Alvarez, Le Bihan, and Lippi (2016) and Carvalho and Schwartzman (2015). We provide some discussion for future work using the sufficient statistic approach in Section 5.

4.3 Evidence from aggregate time series

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 a nominal disturbance that moves the desired price for all products in the elementary stratum, the subset of prices that adjust in the period of the disturbance tend to originate from levels that are differ from the average for all prices. The key question then is to what degree price selection is important for the response to macroeconomic shocks, which affect prices for all products and in all locations?

Similar to inflation identity at a stratum level (5)–(6), 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:

$$\pi_t \equiv Fr_t \cdot \underbrace{[P_t^{res} - P_t^{pre}]}_{DP_t}, \tag{9}$$

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

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

$$P_t^{pre} = \beta DP_t + \delta_{cal} + error \tag{10}$$

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

Table 4 provides the results of this estimation (row "Aggregate"). We find that for regular prices and no substitutions aggregate price selection is substantially weakened: –0.197 for the U.K. (versus –0.371 at a stratum level), 0.061 for the U.S. (–0.360), and –0.003 for Canada (–0.285); and for the U.S. and Canada the estimates are not statistically significant. Results are very similar when we include price changes during product substitutions. This aggregation result is reminiscent of findings in Boivin, Giannoni, and Mihov (2009) who document larger price responsiveness to sector-specific shocks than to macroeconomic and monetary disturbances.

By contrast, when regression variables are constructed using all prices—both regular and sale prices—substantial degree of price selection remains at the aggregate level for the U.K. and the U.S.: –0.394 for the U.K. (versus –0.371 at a stratum level) and –0.140 for the U.S. (–0.360), both statistically significant at 1% level. For Canada, it is still close to zero, –0.039 (versus –0.327 at a stratum level), but 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 U.S. and U.K. when price discounts are included. This suggests that price discounts represent an important margin of price adjustment in response to macroeconomic shocks. This conclusion is consistent with Kryvtsov and Vincent (2017) who use evidence from the 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 Canada, price discounts may not have had their full influence on price selection since the sample ends in 2009, before the period when sales had their largest swings in the U.S. and U.K..

To glean into why price selection may dissipate with aggregation, we estimate regression (10) using weighted means,$\sum_s \omega_s P_{st}^{pre}$ and $\sum_s \omega_s DP_{st}$, instead of frequency-weighted means. The results, reported in Supplementary Material, show that relative frequency weights account for less than a third of the aggregation. This suggests that other sources of cross-section heterogeneity may be responsible for weak price selection at the aggregate level.

We also repeat the estimation for two intermediate levels of aggregation using the U.K. data. At a category level, the variables are aggregated across 12 U.K. regions and two store types (less or more than 10 outlets), using both weighting schemes. This reduces the size of cross-section from 8914 to 1037 groups. Price selection is affected very little. Next, at a coarser level yet, we compute the variables by COICOP class, decreasing the cross-section to 66 classes. Again, class level selection is only slightly weaker, –0.361 versus –0.371 at a stratum level for regular prices and no subs. Hence, most of price selection goes away with aggregation across (as opposed to within) broad product categories. In the next section, we ask whether standard multi-sector sticky price models are consistent with price selection in the data.

5 Price selection in sticky price models

In this section we compare predictions of standard sticky price models with the facts presented in the previous section. We proceed in three steps. First, we explain the intuition behind the empirical results using an analytic example for plain-vanilla Taylor (1980) model. Second, we quantify price selection in three one-sector models that are parameterized to match the key micro price moments—Taylor (1980), Calvo (1983), and Golosov and Lucas (2007) models. We show that Taylor and Golosov-Lucas models exhibit strong price selection in line with our evidence at a disaggregate level; by contrast, zero price selection in Calvo model is at odds with that evidence. Finally, we quantify aggregate price selection in multi-sector versions of calibrated Taylor and Golosov-Lucas models.

5.1 Analytical example

We first provide intuition behind price selection using a simple version of Taylor (1980) model, which exhibits strong price selection as documented in Carvalho and Schwartzman (2015). 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. draws ε_t. In the simplest case with no strategic complementaries and no front-loading effects, firms that can adjust their price set it to the desired price level, which is equal to the level of the money supply. 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 :

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

so the average size of price changes is the sum of the shocks in the last T periods.

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

$$P_t^{pre} = M_{t-T} - P_{t-1} = -\frac{\varepsilon_{t-1} + 2\varepsilon_{t-2} + ... + (T-1)\varepsilon_{t-(T-1)}}{T}\,, \tag{11}$$

so it is the weighted mean of the past shocks, with higher weight on older shocks. This example is useful for highlighting the difference of price selection in time-dependent models versus state-dependent models, e.g., Golosov and Lucas (2007). In Taylor model, the subset of price adjusters does not change at the time of the shock ε_t, and so preset price does not immediately respond to the change in M_t. By contrast, in menu cost models, the shock triggers or prevents the adjustments of those prices that are affected by the shock as we illustrated in Section 2.1 and Figure 1. Second, according to (11), prices become increasingly more misalighned after a shock with the largest price gap for prices at the end of the price spell; i.e., the impact of price selection is backloaded over the

duration of the response. This is unlike menu cost models, where price selection responds the most soon after the shock. These differences lead to a bigger impact of price selection on the response of the aggregate price in menu cost models, as we illustrate below.

The price selection statistic is :

$$\beta \quad = \frac{cov\left(P_t^{pre}, DP_t\right)}{var(DP_t)} = \frac{\sum_{j=0}^{T-1} \frac{j}{T}}{T} = \quad -\frac{1}{2} + \frac{1}{2T}\,, \tag{12}$$

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 Taylor model explains half of inflation variance. In Supplementary Material (Section C) we provide detailed derivations of price selection in the Taylor model, and models due to Calvo (1983), where selection is zero, Caplin and Spulber (1987) where selection is $-\infty$, and Head et al. (2012) where selection is –0.33.

This analytical example demonstrates that the projection of P_t^{pre} on DP_t—our measure of price selection—summarizes the degree to which price adjustment in period t reallocates the weight from prices based on "old" shocks toward prices that have responded to recent shocks. Non-zero price selection ($\beta < 0$) implies that after the shock the population-average price level assigns larger weight on prices informed by more recent shocks than prior to the shock. Zero price selection ($\beta = 0$), as in Calvo model, means that there is no change in the distribution of shocks incorporated in the cross-section of prices. Finally, *reverse* price selection ($\beta > 0$) implies that the relative weight on older prices is higher after adjustment to a shock in t. Reverse price selection can happen in models in which the frequency of price adjustment decreases with the time since last adjustment, for example, in one-sector models with decreasing hazard rate of price changes.

Reverse price selection is the main reason why price selection weakens with aggregation. Consider, for example, the Taylor model with two equally weighted sectors with different degree of price flexibility: $T_1 = 2$ and $T_2 = 4$. According to (12), selection in the two sectors is: $\beta_1 = -\frac{1}{4}$, $\beta_2 = -\frac{3}{8}$, so that on average selection at a sector level is $-\frac{5}{16}$. It is straightforward to derive aggregate selection, $-\frac{10}{40}$, which is by 20 percentage points weaker than sector-average selection. 40% of the aggregation bias is due to two out of each three price changes coming from sector with weaker selection; this mechanism was explained in Kara (2015) and Carvalho and Schwartzman, 2015. The remaining bias is due to the fact that price adjustments in different sectors close price gaps of different magnitudes (larger gaps in more inflexible sectors), and so their joint impact on the aggregate price is smaller. The aggregation result in the model is consistent with empirical results in Section (4.3) where aggregate price selection is weaker than average sector-level selection, in part due to heterogeneity in the frequency of price changes across sectors.

5.2 One-sector models

In our analytical example, we abstracted from fitting the characteristics of the observed price behaviour at a micro level, which may be important for assessing the implications of our empirical findings for applied macroeconomic models of business cycles. In this section, we parameterize

three one-sector models to match the key micro price moments—Taylor (1980), Calvo (1983), and Golosov and Lucas (2007) models—and compare their predictions to the evidence on price selection at a stratum level in Section 4.1.

Each model represents an economy populated by a large number of infinitely lived households and monopolistically competitive producers of intermediate goods. The shocks in this economy are aggregate shocks to the money supply and idiosyncratic productivity shocks. The idiosyncratic shocks follow an AR(1) process normally distributed i.i.d. innovations, and money supply follows random walk with drift, also with normally distributed i.i.d. innovations. Model details are provided in Section B of the Supplementary Material.

Each model is parameterized to match three moments regarding micro-level price behaviour: the average fraction of price changes in a given month, their average absolute size, and serial correlation of newly adjusted prices (Panel A in Table 5). For concreteness, we use the moments for the U.K. reported in Table 1, but we note that the takeaways we develop in this Section are not sensitive to the particular combination of moments we use. In the U.K. data, we use regular price changes (excluding substitutions) to compute the weighted mean fraction and absolute size of price changes; their across-time means are 0.121 and 12.2%, respectively. 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. The mean correlation across months is –0.03. We also pick the size of the monetary shocks to match the standard deviation of regular-price inflation in the 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 rate of regular price inflation of 0.12, or 1.5% per year.

The demand for product varieties is derived under assumptions of constant elasticity of substitution between consumption goods, which we choose to equal to 3, in line with studies of retail price behaviour (Midrigan, 2011), and strategic neutrality of pricing decisions, as usually assumed in menu cost models (Golosov and Lucas, 2007).

We simulate equilibrium dynamics in each model over 235 months for a given draw of a money growth shocks and 10000 draws of idiosyncratic productivity shock.[18] For each simulation we compute the time series for the components of the inflation decomposition (6) and the model counterparts of the empirical moments reported in Table 2. All moments are computed by applying the same definitions as in Section 3.4 to the artificial model-generated data. We repeat this simulation 100 times and report the means and standard deviations of model moments over these simulations in Table 5.

We find significant differences in the degree of price selection across the models (Panel B in Table 5). In Calvo model price selection is zero, since the timing of price changes is independent of the state of the economy. By contrast, in Golosov-Lucas and Taylor models price selection is

[18] We simulate the dynamics for 255 months and discount the first 20 months to remove the effect of initial conditions.

significant, –0.34 and –0.44, respectively, and in line with the analysis in Golosov and Lucas (2007) and Carvalho and Schwartzman (2015). Golosov-Lucas model's prediction falls right in the middle of the range of empirical values that we document at a disaggregate level for the U.S. (between –0.30 and –0.36), U.K. (–0.37 and –0.42), and Canada (–0.27 and –0.33); and Taylor model puts price selection a bit above this range. Hence, models with strong selection mechanisms, and in particular, Golosov-Lucas model, find support in micro price data.

To further clarify the implications of price selection in sticky price models, Figure 5 shows the responses to a +1% impulse to money growth. The bottom panel shows the responses of DP_t, P_t^{res}, and P_t^{pre}. In Calvo model (left panels) preset price does not move after the shock and the aggregate price response is due to the increase in the reset price level. In Golosov-Lucas model, the shock triggers more adjustments of prices below population average and prevents adjustments of prices above it, leading to a decrease of the preset price level on impact by 1.2 percentage points. This decrease amplifies the response of the average size of price changes on impact to around 3.8% versus 1% in Calvo model. As a result of quicker aggregate price response, monetary non-neutrality in Golosov-Lucas model, measured by the response of aggregate consumption, is smaller than in Calvo model: consumption responds by 0.54% on impact (0.88% in Calvo) with half-life of the response of 1.1 month (4.9 months in Calvo), as shown in the top panels.

Stronger price selection in Taylor model relative to Golosov-Lucas model, however, does not imply smaller monetary non-neutrality as consumption responds as much as in Calvo model and lasts three times longer than in Golosov-Lucas model. The key difference is that, unlike in Golosov-Lucas model, price selection in Taylor model unravels only gradually after the shock, with most of its impact at the end of the response. The middle bottom panel shows that the response of preset price gradually builds from zero on impact to –0.39% on month 11 after the shock, returning to zero on month 12 as all prices respond to the shock. Since most of the reset-price response occurs only late after the impulse, its impact on aggregate price response is reduced relative to Golosov-Lucas model. Hence, price selection in state-depenent sticky price models—by way of triggering price changes that are commensurate with the disturbance—yields a larger response of the aggregate price after the shock, and therefore, a smaller monetary non-neutrality.

These results are not influenced by the response of the fraction of price changes in Golosov-Lucas model, which moves very little, increasing by only 0.2 percentage points after the shock. We also explored the sensitivity of predicted price selection to the change in the degree of real rigidities, modeled as strategic complementarity and substitutability, which influence the extent to which price-setters synchronize their price changes with competitors. We find that over a wide range of the degree of strategic substitutability and complementarity—while matching the same moments in the data—the values of price selection are virtually unchanged.[19] This suggests that price selection—as captured by the statistic we propose—is a *distinct* mechanism that affects aggregate price dynamics via selection of price adjusters among all prices, and therefore applied research of monetary non-neutrality should incorporate it in the analysis.

[19]The numerical results are available upon request.

5.3 Multi-sector models

While some one-sector models can match strong selection at a disaggregate level, we need to study multi-sector models to gain insights about why price selection is weaker at the aggregate level. We extend Golosov-Lucas and Taylor models to a multi-sector setup in which we match price selection at a sector level. Namely, we augment price adjustment cost with an assumption that with some probability a firm will set its price according to a Calvo pricing whereby a fraction of time it is able to reset its price, and otherwise, it is not.[20] Since Calvo pricing is associated with zero price selection, the nesting parameter that assigns the fraction of time the firms uses Calvo pricing, instead of Taylor or Golosov-Lucas pricing, also determines the degree of price selection in that sector.

The empirical range of sector-level price selection coefficients (91% of them falling between 0 and –1) is much wider than the range spanned by these nested Taylor and Golosov-Lucas models (which fall between 0 and –0.5). Therefore, for our empirical targets we use only the portion of price selection due to variation in the fraction of price changes across sectors, as explained in Section 4.1. We associate sectors in the model with 66 basic classes in the U.K. data. Assuming a coarser 66-sector cross-section instead of all 8941 strata helps to keep the quantitative burden manageable, while leaving the empirical targets very much the same, since in the data, price selection at a class level is quite close to stratum-level selection (see Table 4 Panel A). This gives us sector-level price selection that is on average –0.255, ranging between –0.130 and -0.298, while the fraction of price changes varies between 0.033 and 0.404. In each model, we parameterize the nesting and price adjustment parameters to match price selection and the frequency of price changes for each class in the data.

Table 6 provides the results for 66-sector Taylor and Golosov-Lucas models; for reference, the table also provides the results for 66-sector Calvo model, in which selection in each sector is zero. Panel B shows that aggregate price selection is –0.195 in Taylor model and –0.193 in Golosov-Lucas model; and it remains zero in Calvo model. Hence, in line with empirical evidence in Section 4.3 aggregation weakens price selection. There are two reasons for this result. First, selection is weaker in sectors with more frequent price changes; and since price changes from more flexible sectors are represented more in the cross-section relative to price changes from stickier sectors, the aggregate price selection puts larger weight on sectors with relatively weak selection. Second, concurrent price adjustments in different sectors are imperfectly correlated as they close price gaps of different magnitudes; such smoothing of price selection across sectors lowers its impact on the aggregate price. We estimate that about 40% of the weakening in price selection is due to such demand spillovers in Golosov-Lucas model, and 53% in Taylor model. In the data, however, most of aggregation bias stems from the lack of correlation of preset prices across sectors.

[20]Such assumption is commonly made in menu cost models to generate a realistic mass of relatively small price changes, a robust feature in the micro data, documented in Klenow and Kryvtsov (2008). See Gertler and Leahy (2008), Nakamura and Steinsson (2010), and Midrigan (2011), among others. For simplicity, we also assume the demand elasiticty for goods to be the same within and across sectors, as done in Nakamura and Steinsson (2010) and Gautier and Le Bihan (2017).

While aggregate price selection is similar in magnitude in both Taylor and Golosov-Lucas models, it has different impact on the aggregate price level response for the same reasons as it did in one-sector models. As Figure 6 shows, in Golosov-Lucas model the response of preset price is the largest at the time of the shock, while in Taylor model it only gradually builds up after the shock and has its impact only when a bulk of price response has already occurred. As a consequence, the aggregate price response is quicker in Golosov-Lucas model than in Taylor model, albeit the two responses are closer than in one-sector versions.

6 Conclusions

We draw several conclusions for sticky price models. First, multi-sector models with strong selection at sector level have a better chance of accounting for the evidence on price selection. Nakamura and Steinsson (2010), and more recently, Gautier and Le Bihan (2017), show that implications of such models for the sources of business cycles and the effectiveness of monetary policy can differ drastically from models without price selection or cross-sector heterogeneity. We note that predictions of standard sticky price models can only account for sector variation of price selection between around –0.1 and –0.3, which is approximately one-fifth of the weight in the empirical range shown in Figure 3. Furthermore, the degree to which aggregation weakens selection at a sector level is very modest, taking it from –0.25 to –0.19. Models that exploit additional dimensions of heterogeneity across goods and retailers should have a better chance of fitting the facts.

Second, price selection contributes significantly to how quickly prices adjust to an aggregate nominal shock. When the bulk of price adjustments occurs at the onset of the shock, as in Golosov-Lucas model, price selection is most effective for amplifying the response of the aggregate price to the shock. Alternatively, when most price adjustments are delayed till later after the shock, as in Taylor model, the impact of price selection is muted and so is the aggregate price response. Although pervasive Taylor price adjustment is clearly rejected in the data—for example, the standard deviation of price spell durations in multi-sector Taylor model is too low relative to the data, as shown in Supplementary Material—it may capture the features of more complex adjustment by multi-product retailers (as shown in Alvarez and Lippi, 2014) or the responses to seasonal variations in demand (see evidence in Warner and Barsky, 1995).

Third, our findings are complimentary to the "sufficient statistic" approach in this literature that explores the theoretical mapping between particular moments in the price data and the size of monetary non-neutrality. According to this approach, conditional on matching the sufficient statistic—available in the micro data—sticky price models provide an accurate prediction for the size of monetary non-neutrality, regardless of the mechanisms behind it. The two most recently proposed sufficient statistics are based on the kurtosis of price changes (Alvarez, Le Bihan, and Lippi, 2016) and the standard deviation of price spell durations (Carvalho and Schwartzman, 2015). Unlike the sufficient-statistic approach that relies on theory, we provide a direct measure of one of the mechanisms linking micro moments with monetary non-neutrality. Evidence from cross-

section regressions in Section 4.2 is not conclusive for the relationship between price selection and either of the two sufficient statistics. Since we show that price selection is associated with both frequency and size of price changes, and that its degree varies across sectors, we hypothesize that one sufficient statistic cannot capture the degree of price selection. Hence, combining our measure of price selection with the sufficient statistics approach may help to assess the importance of other drivers of monetary non-neutrality, such as real rigidities or information frictions.

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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	1152	705	31
	# of strata/category	22	13	50
(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)	P^{pre}	1.116	-0.198	-2.191
(5)	P^{pre}	0.761	-0.718	-2.904
(6)	adp	12.22	8.25	8.43
(7)	corr	-0.032	0.164	-0.027
(8)	sd_delta	15.74	10.00	11.21
(9)	kurt	5.73	4.70	5.11
(10)	meandur	5.62	6.94	3.56
(11)	sd_dur	5.33	6.28	4.11
(12)	frac of sales	5.6	9.0	9.0
(13)	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 through 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)-(11), 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 %; Ppre (Pres) - preset (reset) price level defined as the unweighted means of starting (ending) log price levels for all products in the stratum in each month, expressed as % deviations from the average for all log prices in the stratum; adp - the average absolute size of price changes, in %; corr - serial correlation of newly set prices for an individual product; sd_delta - standard deviation of non-zero price changes for a given stratum, in %; kurt - kurtosis of non-zero price changes for a given stratum; meandur - mean price spell duration (for complete spells), in months; sd_dur - standard deviation of price spell durations for a given stratum (for complete spells), in months; frac of sales - fractions of observations with discounted price; mean frac of subs - mean fraction of observations with product substitutions.

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***** (0.002)	**-0.371***** (0.002)	**-0.369***** (0.002)	**-0.357***** (0.002)	**-0.333***** (0.002)	**-0.415***** (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***** (0.003)	**-0.284***** (0.003)	**-0.283***** (0.002)	**-0.310***** (0.002)	**-0.327***** (0.001)	**-0.268***** (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***** (0.000)	**-0.363***** (0.000)	**-0.361***** (0.000)	**-0.369***** (0.000)	**-0.303***** (0.000)	**N/A**
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 (7) of monthly stratum preset price levels on the monthly average stratum size of price changes, with stratum fixed effects. Columns (1)--(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.

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)
DP_{st} x Kurt p-$chgs_s$		-0.006***	-0.005***	-0.004***		0.004**	0.000	0.006***		0.001***	0.002***
		(0.001)	(0.001)	(0.000)		(0.002)	(0.002)	(0.001)		(0.000)	(0.000)
DP_{st} x Std p-$spells_s$		-0.005***	-0.012***	-0.001		0.005***	0.009***	-0.000		0.003***	0.001***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(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 (8) of monthly stratum preset price levels on independent variables, with month fixed effects. 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, $Kurt_s$ -- kurtosis of non-zero price changes in stratum s, Std p-$spells_s$ -- the standard deviation of complete price spell durations in stratum s. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Price selection, aggregate time series

Level of aggregation	Number of groups	Regular prices, excluding subs	All prices	Incl. subs
A. U.K.				
Stratum	8941	-0.371***	-0.333***	-0.415***
		(0.002)	(0.002)	(0.002)
Category	1037	-0.385***	-0.359***	-0.404***
		(0.006)	(0.005)	(0.005)
Basic class	66	-0.361***	-0.357***	-0.330***
		(0.016)	(0.013)	(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 selectiton coefficients at a stratum level replicated from Table 2. Other rows provide price selection for aggregated groups (category, basic class, and aggregate). For the U.K., basic class corresponds to Classification of Individual Consumption by Purpose (COICOP). "Aggregate" rows provide the estimated values of the coefficient in the time-series regression (10) of aggregate preset price level on the aggregate size of price changes, with calendar-month fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Price selection in one-sector sticky price models

Moments	Data	One-sector models		
		Calvo	Taylor	GL
A. Calibration targets				
Fraction of p-changes	0.12	0.125	0.125	0.121
		(0.000)	(0.000)	(0.000)
Abs size of p-changes, %	12.2	12.4	12.3	12.2
		(0.1)	(0.0)	(0.1)
Serr corr of reset prices	-0.03	-0.03	-0.03	-0.05
		(0.05)	(0.02)	(0.02)
Inflation mean, %	0.12	0.12	0.14	0.12
		(0.06)	(0.06)	(0.02)
Inflation stdev, %	0.23	0.23	0.23	0.23
		(0.03)	(0.03)	(0.01)
B. Price selection	-0.37	-0.01	-0.44	-0.34
		(0.01)	(0.01)	(0.01)
C. Predicted moments				
Consumption stdev, %		1.60	0.98	1.27
		(0.20)	(0.10)	(0.02)
Consumption ser. corr		0.86	0.79	0.84
		(0.04)	(0.04)	(0.06)
Half-life of C, months		4.88	2.96	1.07
		(3.54, 6.31)	(2.40, 3.51)	(0.90, 1.28)
Std of price spells	5.3	7.21	0.00	7.92
		(0.08)	(0.00)	(0.07)
Kurtosis of p-changes	5.7	4.79	3.00	1.23
		(0.02)	(0.00)	(0.02)

Notes: Table provides the results from simulations of three one-sector models: Calvo (1983), Taylor (1980), Golosov and Lucas (2007). We simulate equilibrium dynamics in each model 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 and standard deviations of model moments over these simulations. Column "Data" refers to statistics for the U.K. data from Tables 1 and 2 for regular prices and no substitutions.

Table 6: Price selection in multi-sector sticky price models

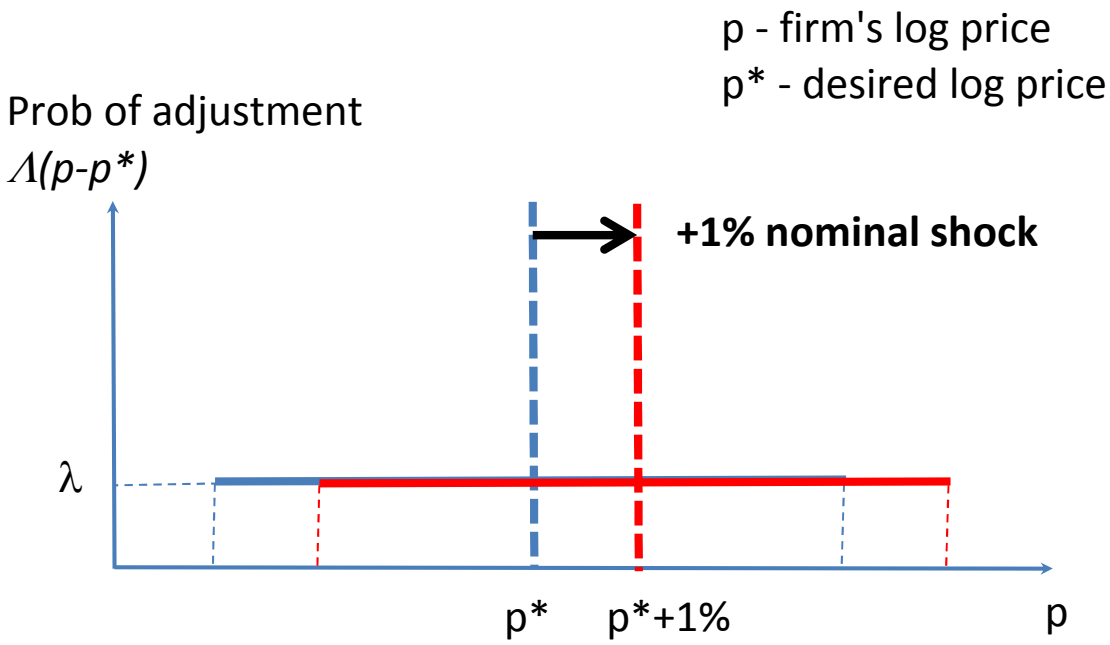
	Data	Calvo	Taylor	GL
A. Calibration targets				
Fraction of p-changes				
weighted mean	0.121	0.124	0.124	0.121
min	0.033	0.034	0.040	0.034
max	0.404	0.404	0.392	0.407
Sector-level selection				
weighted mean	-0.255	0.000	-0.255	-0.254
min	-0.296	0.000	-0.298	-0.327
max	-0.130	0.000	-0.120	-0.094
B. Price selection				
Aggregate	-0.197	0.000	-0.195	-0.193
C. Predicted moments				
Consumption ser. corr		0.91	0.88	0.83
Half-life of C, months		7.00	5.22	3.70

Notes: Table provides the results from simulations of three models: Calvo (1983), Taylor (1980), Golosov and Lucas (2007). Number of sectors is 66. We estimate the cross-section regression (8) for variables at a basic class level in the U.K.. In each model, we parameterize the nesting and price adjustment parameters to match price selection and the frequency of price changes for each class. We simulate equilibrium dynamics in each model 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.

Figure 1: Price selection in sticky price models, stylized example

A. Time-dependent adjustment (Calvo, 1983)

Conditional on aggregate nominal shock,
probability of adjustment is the same for all prices



B. State-dependent adjustment (Golosov-Lucas, 2007)

Conditional on aggregate nominal shock,
probability higher for low prices, and lower for high prices

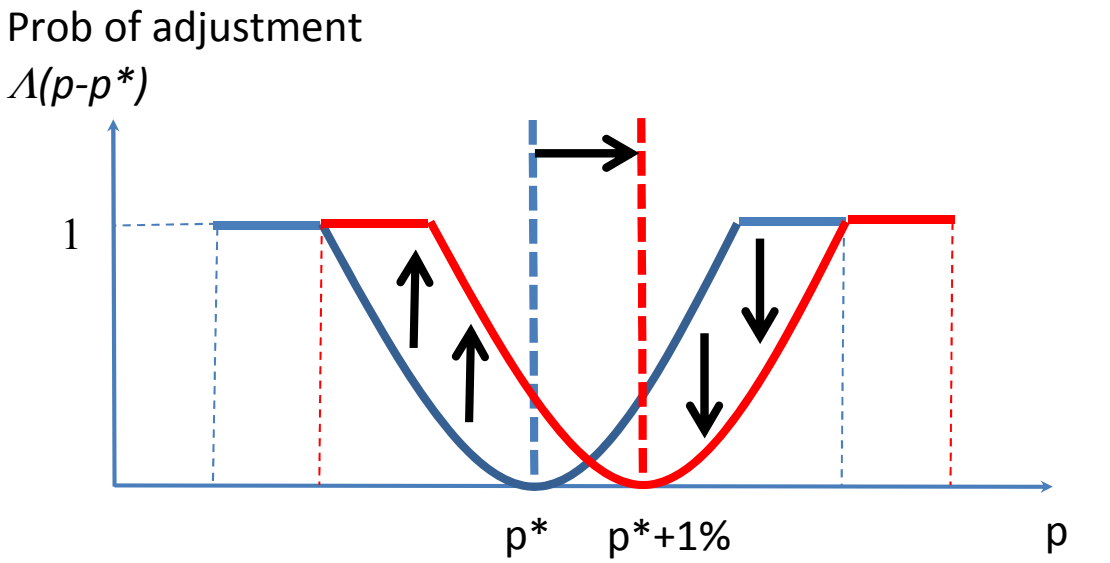
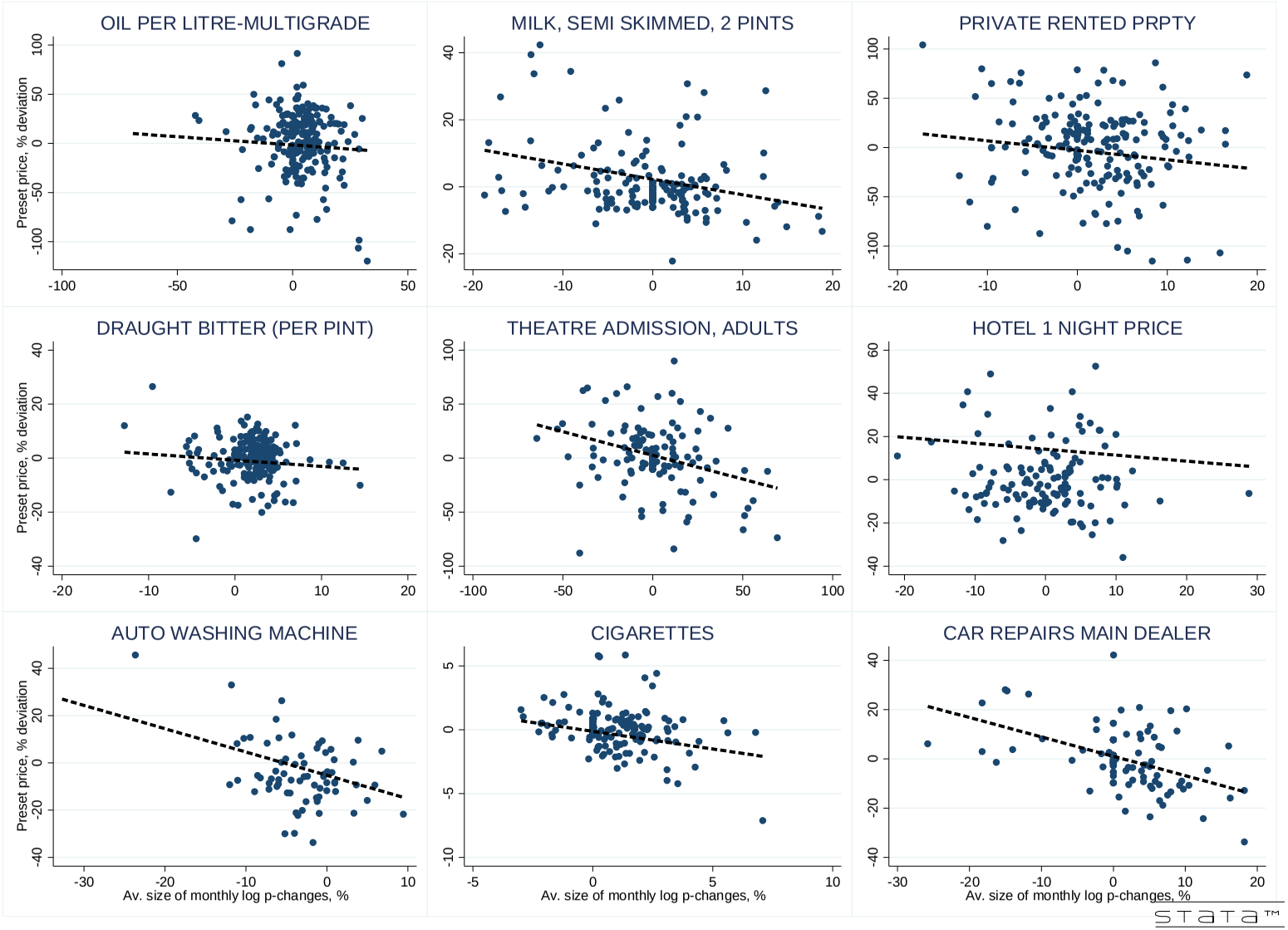
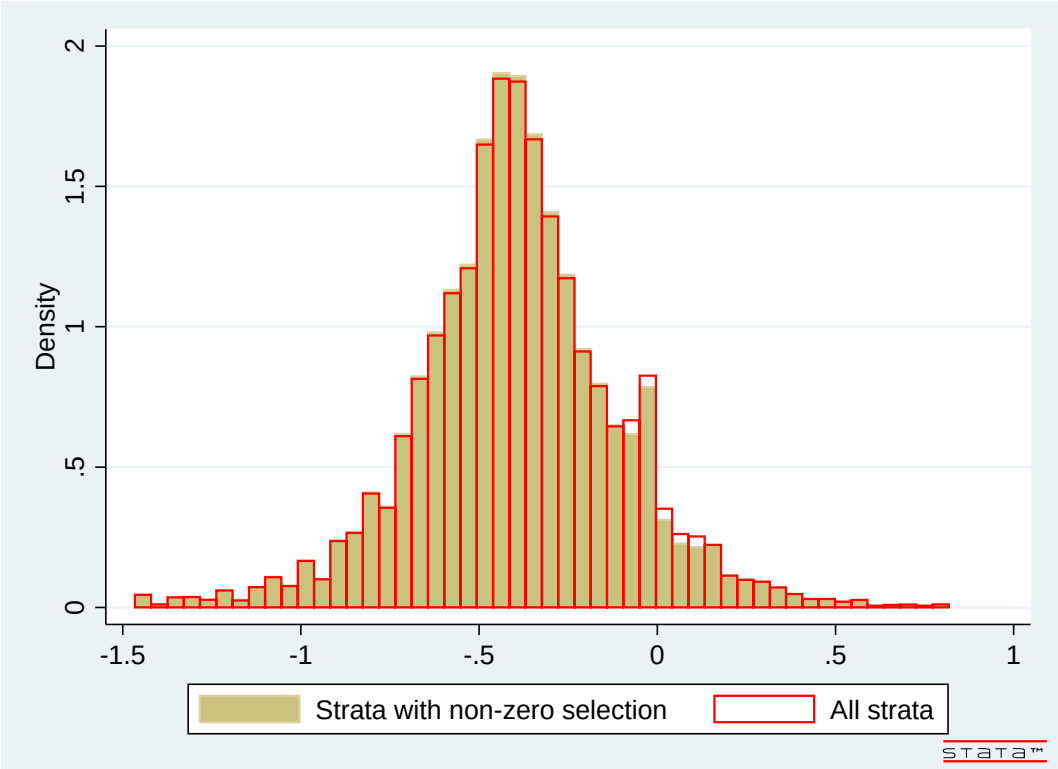


Figure 2: Preset price level and average size of price changes, variation over time for largest strata in selected product categories, U.K. CPI data



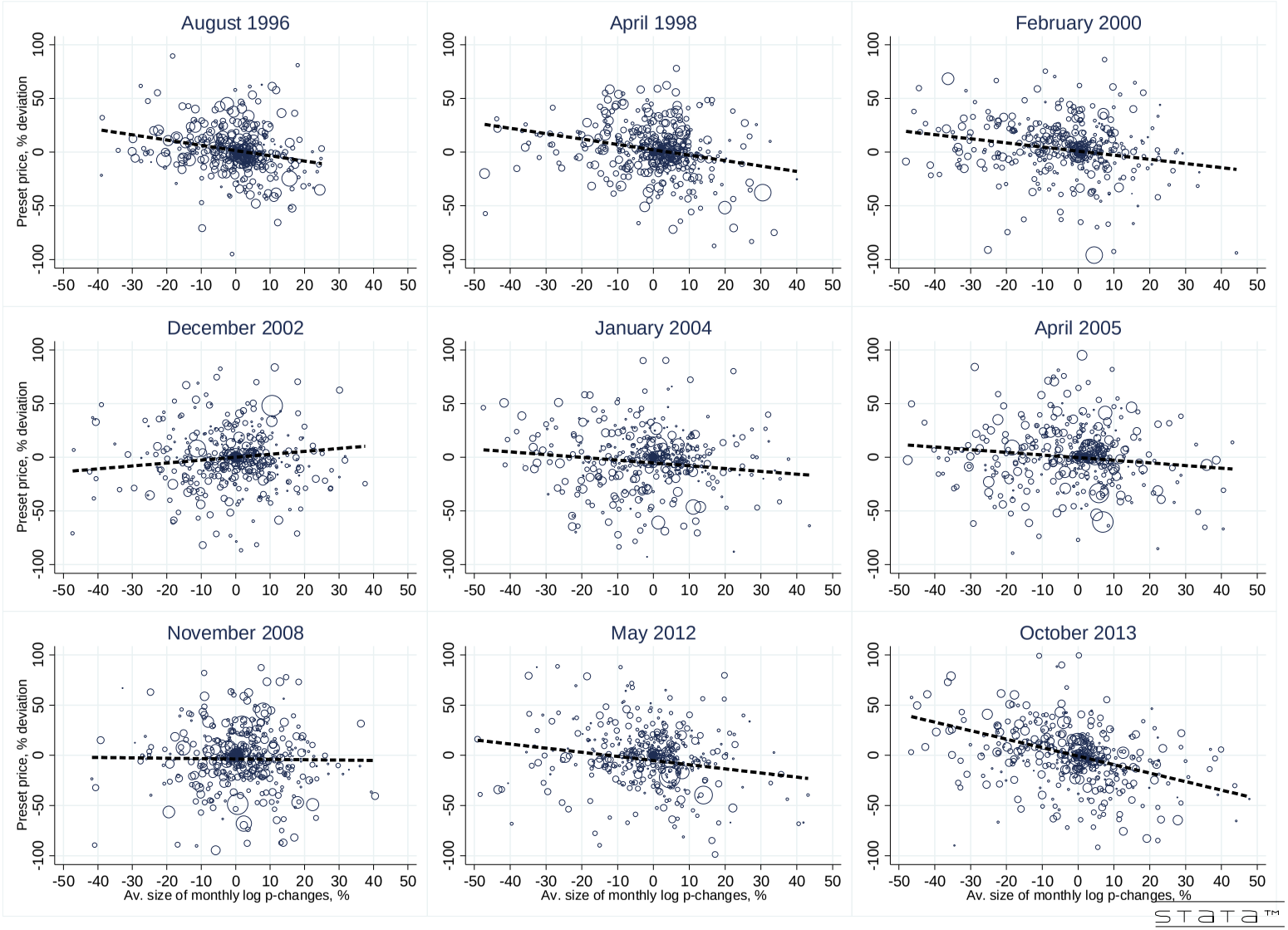
Notes: Figure provides scatter plots for largest strata in nine selected product categories in the U.K., including oil, milk, hotel, and cigarettes. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). 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 $\hat{\beta}_s$, representing the estimated degree of price selection corresponding to the statum.

Figure 3: Price selection across product strata, U.K. CPI data



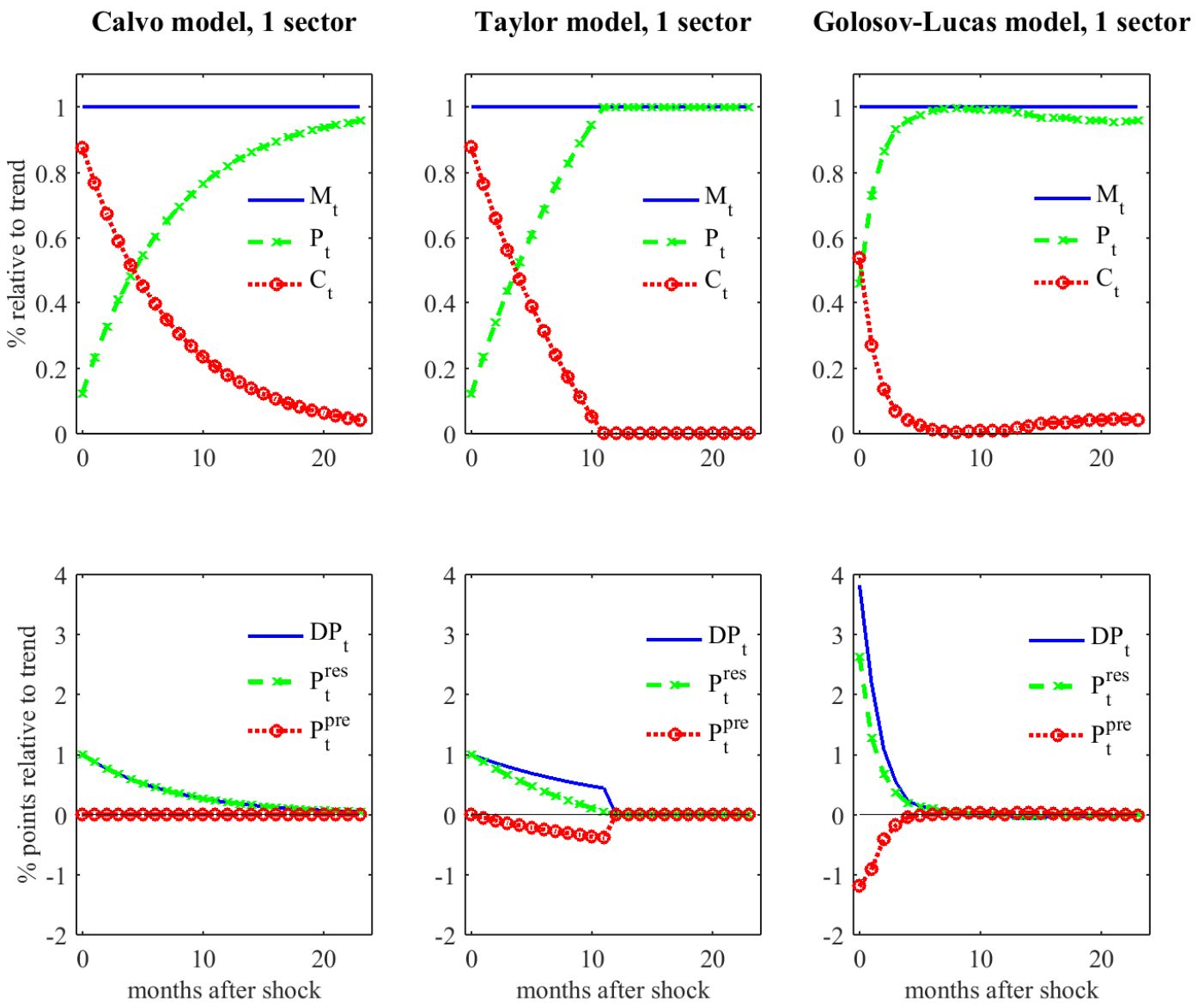
Notes: Figure shows the weighted histogram of price selection coefficients estimated for each category-stratum using regression (10), in the United Kingdom, for the case with regular prices and no substitutions, not controlling for calendar-month effects. The empty red bars show the weights for all estimated coefficients. Solid bars show the weights for coefficients that are statistically different from zero.

Figure 4: Preset price level and average size of price changes, variation over product categories for selected months, U.K. CPI data



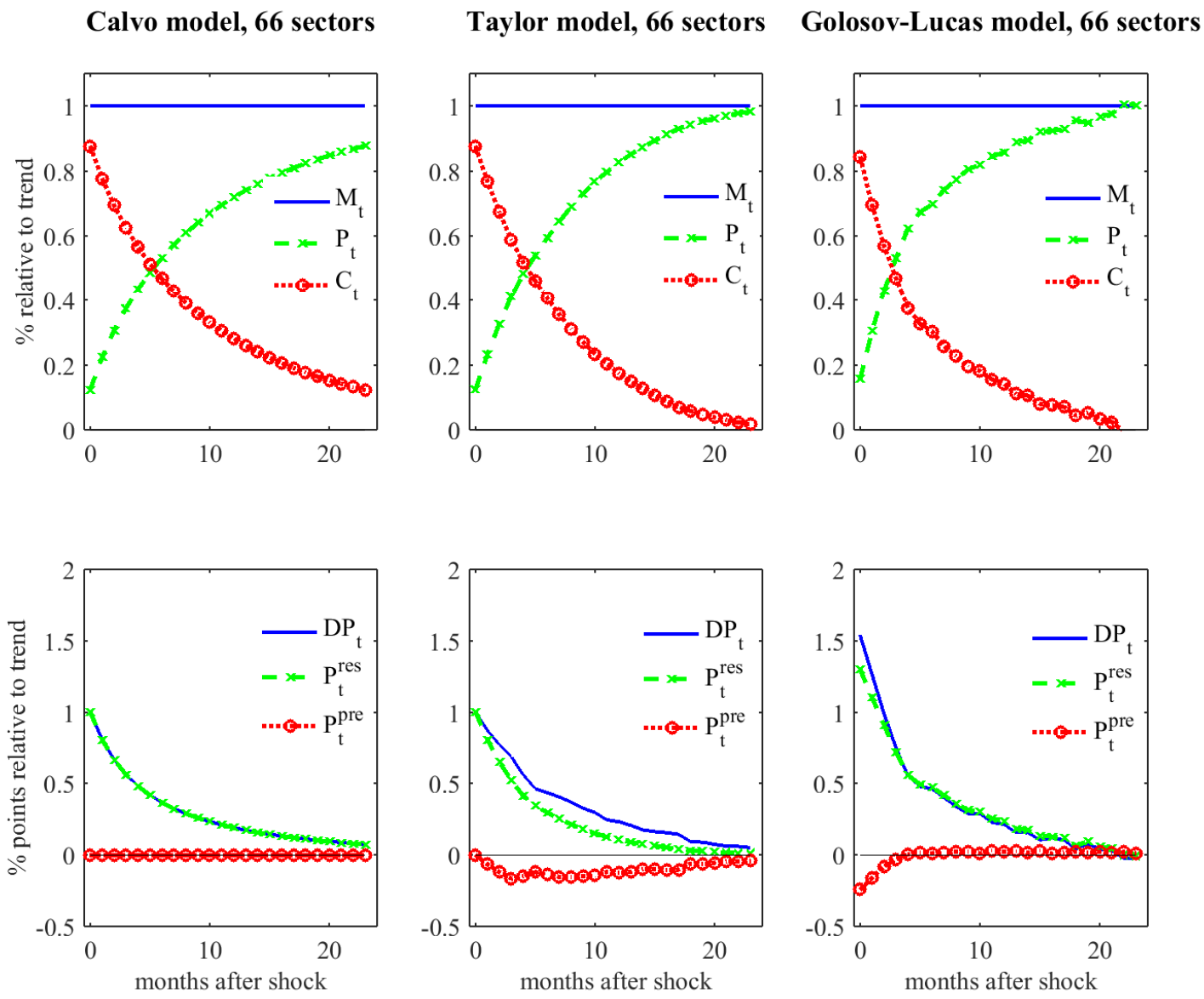
Notes: Figure provides scatter plots for nine selected months in the U.K. for all prices and excluding substitutinos. For each month, each point on the plot represents a observation for the largest stratum in a particular category, giving the average size of price changes (x-axis) and preset price level (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 given month. The slope of the trend line is equal to $\hat{\beta}_s$, representing the estimated degree of price selection.

Figure 5: Impulse responses in one-sector sticky price models



Notes: Figure provides responses to a +1% impulse to money supply growth. Columns correspond to responses in one-sector Calvo model (1st column), Taylor model (2nd column), Golosov-Lucas model (3rd column). Top panel provides responses for money supply (M_t), aggregate price level (P_t), and aggregate consumption (C_t). Bottom panel provides responses for the average size of price changes (DP_t), reset price level (P_t^{res}), and preset price level (P_t^{pre}).

Figure 6: Impulse responses in 66-sector sticky price models



Notes: Figure provides responses to a +1% impulse to money supply growth. Columns correspond to responses in 66-sector Calvo model (1st column), Taylor model (2nd column), Golosov-Lucas model (3rd column). Top panel provides responses for money supply (M_t), aggregate price level (P_t), and aggregate consumption (C_t). Bottom panel provides responses for the average size of price changes (DP_t), reset price level (P_t^{res}), and preset price level (P_t^{pre}).