Coarse Pricing Policies*

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Abstract
The muted volatility of inflation during the Great Recession and its aftermath has refocused attention on the constraints that firms face when adjusting prices. Using new empirical and theoretical results, I argue that each firm’s choice of how much information to acquire to set prices plays a central role in determining the patterns of pricing at the product-level and the degree of aggregate price rigidity in response to shocks. In support of the information channel, I present product-level evidence that firms price goods using coarse pricing policies that are updated infrequently and consist of a small menu of prices. Firms are heterogeneous in the complexity and duration of their pricing policies, and this heterogeneity is reflected in differential responses to the Great Recession cycle, with firms exhibiting more complex policies responding more aggressively. I develop a theory of information-constrained price setting that generates coarse pricing endogenously, and quantitatively matches the discreteness, duration, and volatility of policies in the data. The information friction dampens the responsiveness of prices to shocks, and, coupled with heightened volatility, induces firms to keep prices relatively high, to protect against losses in an uncertain environment.

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1 Introduction

The behavior of inflation during the Great Recession and its aftermath has challenged conventional models of price adjustment. First, the United States experienced an unexpectedly mild disinflation during the most severe downturn since the Great Depression. Second, inflation was slow to pick up during the subsequent recovery.\footnote{Hall (2011), Ball & Mazumder (2011), Watson (2014), and Del Negro, Giannoni & Schorfheide (2015).} What accounts for these muted inflation dynamics in the midst of such turbulence in economic activity remains an open question. Using data and theory, I argue that information frictions—specifically firms’ choices of how much information to acquire to set prices—played a key role in shaping product-level pricing patterns and in dampening aggregate price dynamics during this period.

In support of the mechanism of endogenous information frictions, I first present evidence that firms set prices using plans that are sticky and coarse. I identify these plans by searching for changes in the distribution of prices charged over time for each individual good. I detect these change points using an adaptation of the Kolmogorov-Smirnov test, which allows for any change in either the shape or the support of a distribution. Applied to weekly scanner price data covering the 2006 to 2015 period, the method identifies pricing policies that change every seven to eight months, and typically consist of a menu of three to four distinct price points, among which the firm alternates roughly every three weeks.

The discreteness of price levels despite the high frequency of price changes suggests that while the timing of price adjustment is quite flexible, the level to which the price adjusts is more constrained. This pattern is at odds with prior models of rigid prices, which assume that the timing of adjustment is constrained—exogenously or due to menu costs—but that once the firm decides to adjust, a new price is chosen optimally.\footnote{An exception is the theory of rigid pricing due to ambiguity aversion by Ilut, Valchev & Vincent (2019).} As I show in the second part of the paper, this pattern arises endogenously in a model of information-constrained pricing, as a cheap way for firms to crudely track the optimal full information price.

As is well-known in the literature, there are large differences across products in the frequency of price changes (Nakamura & Steinsson, 2008). I provide an alternative classification of products, in terms of the types of pricing policies employed. I identify three broad types of policies. Approximately 12% of products feature single price policies (SPP), like the canonical time-dependent or state-dependent pricing models. These products adjust their prices much less frequently and by smaller amounts than average, suggesting that they face a relatively low volatility of their target price. On the other hand, 60% of products exhibit policies with multiple rigid prices (MRP). The volatility of the data is concentrated in these products, which display very frequent and large price changes. However, despite...
this volatility, only three-to-four distinct price levels are typically realized over the life of a policy realization. These products seem to face a high volatility in their desired price, to which they respond by picking a small set of prices among which to alternate, and then occasionally updating this set. The coarseness and volatility of these product prices pose the biggest challenge to existing pricing models, but can be rationalized as a way for firms to economize on information costs. The remaining 28% of products are characterized by one-to-flex policies (OFP), in which one rigid price is accompanied by flexible, short-lived deviations to and from it. This type of pattern has been generated in models that endow firms with different technologies for setting regular versus temporary prices (Kehoe & Midrigan, 2015; Guimaraes & Sheedy, 2011). In the data, these goods feature large and frequent policy shifts, but muted within-policy price volatility. They seem to face more volatility in their desired price than the SPP goods, but also relatively high costs of implementing more complex policies. The theory proposed generates this range of policy types endogenously, as a function of differences in fundamental parameters.

Classifying products by policy type proves useful for understanding inflation dynamics during the Great Recession. Inflation differs significantly across policy types in terms of its volatility and its sensitivity to the state of the economy. While the inflation rates for all product types moved in tandem during the relatively tranquil periods at the beginning and end of the sample, they diverged substantially during the recession and its immediate aftermath. Once inflation started to fall in late 2008, it fell twice as much for the MRP goods as for the SPP goods. Moreover, SPP products continued to raise prices throughout the crisis, while MRP products actually cut prices. During this period, the SPP inflation rate was much less volatile, while the MRP inflation responded much more aggressively to the cycle. The information-based theory presented in this paper predicts precisely these effects, through the information acquisition channel: Firms that generally operate in more volatile markets have incentives to acquire more accurate information, which in turn enables them to choose more complex pricing policies; as a result, they also respond to the aggregate state of the economy more aggressively.

These findings underscore the value of studying pricing data in its entirety, rather than filtering out temporary price changes. Transitory price volatility is crucial to identifying the type of policy of each good, and moreover, the dynamics of different policies during the Great Recession show that transitory price volatility is at least partially responsive to the aggregate state, and does not wash out in the aggregate. This result qualifies the pricing literature’s conclusion that micro price volatility is not relevant to aggregate rigidity. The proposed theory then quantifies the magnitude of this effect.

Distinguishing between policy changes and raw price changes is also useful for evaluating
alternative theories of price setting and identifying potential sources of shocks. The dynamics of price and policy adjustment over time illustrate this point. First, the frequency and size of within-policy price changes are positively correlated over the sample period. This correlation is difficult to reconcile with models of menu costs, which would predict a negative correlation. Instead, it suggests heterogeneity in the volatility of market conditions faced by different firms: The prices of some products rarely change, and even when they do, they change by modest amounts, while others feature the opposite pattern. Second, the rate of policy adjustments rose during the Great Recession, suggesting at least partial state-dependence in the updating of policies over time, ruling out Calvo-like policy adjustment. At the same time, neither the rate nor the size of raw price changes differed significantly. Moreover, the incidence of multi-rigid price policies declined in the recession, while the incidence of single-price policies rose. These patterns point to the role of heightened volatility in shaping price dynamics during this decade. Firms responded to the increase in volatility associated with the Great Recession not by making their pricing plans more complex, but rather by keeping them simple and reviewing them often. This interpretation is further supported by the increase in the rate of policy changes and in the incidence of single price policies that occurred in 2011, which was another period of increased volatility. The theory of information frictions presented in the second part of the paper generates these patterns of policy adjustment in response to heightened volatility.

What drives the large within-policy price volatility? How much of it reflects responding to shocks versus price discriminating (PD) among heterogeneous customers? In practice, these two motives interact, making it hard to isolate the role each plays in generating price volatility. But doing so is important for understanding the magnitude of the micro-macro disconnect in price setting. If most of the micro volatility reflects PD, then it may not be relevant for understanding the aggregate dynamics of inflation. To make progress on this question, I assume that PD products feature policies that mostly consist of price cuts from a high modal price. Roughly one third of the OFP series and one half of MRP series have this property. But it turns out that the volatility of the data is not concentrated in the PD series. PD and non-PD series have similar policies, with two exceptions: PD policies last about twice as long, suggesting less fundamental volatility, and they have somewhat larger within-policy price changes, consistent with having large temporary discounts. Since the theory proposed does not include price discrimination, I only target the non-PD series.

The theory proposed to rationalize the empirical findings embeds costly information in an otherwise standard model of price setting. A continuum of heterogeneous firms set prices in the face of stochastic market conditions. All information about market conditions is available to these price-setters, but at a cost. Firms choose how much information to acquire,
trading off pricing accuracy to save on information costs. Formally, each firm implements an optimal policy that specifies rules for acquiring information and for setting prices based on this information. Moreover, the policy itself can be revised, by paying a fixed cost. If it decides to review its policy, the firm pays a fixed cost which enables it to gather extensive—for simplicity, complete—information about the state of the economy and to reoptimize its policy. These reviews generate breaks in pricing, as seen in the data. In each period, the firm monitors its environment to decide (i) whether or not to pay the fixed cost to update its policy, and (ii) what price to charge in the period. These decisions are based on two imperfect signals, a review signal and a pricing signal. Both signals are modeled following the rational inattention literature (Sims, 2003), using entropy reduction as a measure of the informativeness of a signal (Shannon, 1948), and assuming that the cost of each signal is linear in this measure. The result is stochastic state dependence in both the review and the pricing decisions. How closely prices track the full-information profit-maximizing target price depends on firms’ willingness to pay for more accurate signals, and on the frequency with which they choose to pay the (larger) fixed cost to learn the state and reset their policies.

The setup can be seen as capturing the interaction between headquarters (which chooses the policy) and the local branch (which sets prices day-to-day). Alternatively, it can be seen as a reduced-form representation of the relationship between the producer and the retailer: the overall policy is the result of (relatively infrequent) negotiations between the two parties, while the exact implementation (for instance, when to implement a sale) is up to the retailer.\(^3\)

The theory delivers several novel results. First, it yields coarse prices in an infinite-horizon setting with Gaussian shocks. Even though the target price is continuously distributed, and its distribution is changing continuously, the firm reduces this complex state to a discrete, coarse approximation. The ability to occasionally undertake reviews is key for this result: The reviews prevent the distribution of target prices from becoming too dispersed. And having a manageable distribution of target prices to entertain between reviews means that the firm can afford to pick a pricing policy with a finite number of distinct price points. How many price points are charged with positive probability becomes a numerical question.

Second, the theory can generate heterogeneity in the complexity of pricing policies chosen by firms in different sectors or over time, consistent with the data. The model has a threshold cost of information that determines whether or not the firm acquires any pricing signals between reviews. If the sensitivity of profits to mispricing between reviews is low, relative to the cost of paying for the additional pricing signal, the firm chooses a single-price policy between reviews. It sets a price, and then it only monitors the evolution of market conditions to decide if it is time to change this price. Beyond this threshold, the cardinality of the pricing

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\(^3\)See Anderson, Jaimovich & Simester (2015) for the pricing practices of a U.S. retailer.
policy gradually increases, as does the accuracy with which the firm chooses which price to charge when. Hence, the coexistence of single-price, one-to-flex, and multiple-rigid-prices policies arises naturally if one allows firms to differ in the volatility of idiosyncratic shocks, in the costs of monitoring market conditions, or in the parameters governing the sensitivity of profits to mispricing. Quantitatively, the model matches the duration, coarseness, and volatility of the SPP and MRP policies documented in the empirical part of the paper.

Third, the review decision and pricing decision interact to determine how firms respond to shocks. As a result, matching the micro facts on pricing policies is essential for getting the aggregate dynamics right. In the general equilibrium parameterized to match the characteristics of SPP and MRP policies in the data, the theory predicts that multi-price firms are more responsive to an aggregate shock compared with single-price firms, especially on impact. This is consistent with the inflation dynamics observed in the data during the Great Recession. But is the difference purely reflecting the higher frequency of policy changes of MRP firms? And is the within-policy transitory volatility irrelevant to these firms’ aggregate response? I find that the answer to both of these questions is no. The MRP firms respond differently to the shock not only because they update their policies more frequently, but also because they adjust prices between reviews. Filtering out the within-policy price volatility would overstate the degree of rigidity for the MRP series in the two-to-three months immediately following the shock (before many of the MRP firms have revised their policies), while under-stating it at longer horizons (by underestimating the degree of mistakes in within-policy pricing). Hence, the existence of transitory price volatility changes the impact and persistence of inflation’s response to shocks.

Fourth, the severity of the information friction determines the degree of over-pricing relative to the full information benchmark. The profit function is asymmetric, generating larger losses from under-pricing (and having to meet the large resulting demand at high cost) than from over-pricing (and facing limited demand). As a result, information-constrained firms err on the side of over-pricing. Higher uncertainty makes the information problem more severe, generating even more over-pricing. Quantitatively, I estimate over-pricing of between two and five percentage points.

Finally, higher uncertainty also dampens firms’ responses to shocks. This result stands in contrast to the predictions of full-information state-dependent pricing models, and it implies more effective monetary policy during high volatility periods. Intuitively, the result reflects the endogenous response of the firm’s information acquisition strategy: When volatility rises, the firm increases its information expenditure, but it nevertheless faces higher posterior uncertainty. This effect may help explain recent inflation dynamics. The Great Recession was marked by both low aggregate demand and high volatility. These forces push prices in
opposite direction: low aggregate demand induces the firm to reduce its prices, while higher volatility requires setting higher prices. This tension may help rationalize why inflation did not fall more during the Great Recession.

The empirical analysis contributes to a large literature on product-level price patterns (see Klenow & Malin, 2010 for a review).\footnote{See also Bils & Klenow (2004), Klenow & Willis (2007), Klenow & Kryvtsov (2008).} This work has focused attention on transitory sales versus regular prices. I depart from that approach by interpreting both the transitory and the regular price levels as chosen to be jointly optimal, as part of an integrated policy. The resulting evidence of coarse policies is consistent with the simple price plans postulated by Eichenbaum, Jaimovich & Rebelo (2011) and generated here endogenously. Relative to this work, I also present evidence on patterns during the Great Recession.

The theory brings together different features from the costly information literature, primarily Reis (2006), Woodford (2009), and Matějka (2016), combining both lumpy and flow information acquisition, modeling a richer signal structure, and embedding the friction in a general equilibrium economy.\footnote{Other models of price setting with endogenous information acquisition include Maćkowiak & Wiederholt (2009, 2015), Paciello (2012), Paciello & Wiederholt (2014) and Pasten & Schoenle (2016).} Integrating these features is important for reconciling high product-level pricing volatility with aggregate sluggishness. Quantitatively, I build on prior work by targeting a rich set of micro facts and aggregate dynamics. Lastly, I expand the discreteness results of Matějka (2016) beyond the static model with uniform shocks to a dynamic, infinite-horizon model with persistent Gaussian shocks. This shows that the rational inattention framework can generate discrete outcomes in a wide range of environments, which is promising for future work on lumpy adjustment in macroeconomics.

# 2 Empirical Evidence

In this section I discuss two sets of empirical results. First, I characterize the types of pricing policies observed over the entire sample period. Second, I focus on how these policies behaved during the Great Recession and the subsequent recovery, and what they implied for the dynamics of aggregate inflation.

## 2.1 Pricing Policies in Micro Data

**The Data** I use the *Retail Scanner Database* from The Nielsen Company (US), LLC. This database has weekly point-of-sale data on prices and quantities for products sold in stores from 90 retail chains across the United States. Product coverage represents about 27% of the total goods consumption measured by the *Consumer Expenditure Survey* of the Bureau of Labor Statistics (BLS). Categories include health and beauty care, food, beverages,
I limit the sample to the store with the largest number of observations from each chain. Some series have missing observations. I keep only series with at least 52 contiguous observations. The resulting sample has weekly observations on more than one million unique store-UPC pairs, from January 2006 through December 2015.

The advantages of these data are the high frequency of observations, the relatively long time series for individual products, and the large number of products within the categories and across locations. Conversely, the micro data underlying the BLS’s Consumer Price Index (CPI) has monthly or bimonthly sampling, high product turnover rates, and narrower sampling within product groups and across regions. The drawback of the Nielsen data is the narrow coverage of product categories. Nevertheless, it covers products whose prices are highly volatile and exhibit precisely the sharp, transitory price swings that have been at the forefront of the recent price dynamics literature. The median weekly frequency of price changes is 24.6% and the median absolute size of price changes is 11.9%. For comparison, the monthly frequency and the size of price changes for products underlying the CPI average 10.6% and 9.6% over the 2006-2014 period (Nakamura, Steinsson, Sun & Villar, 2018).

The Break Test The empirical method identifies pricing plans at the product level by looking for breaks in individual price series. To identify the break points, I adapt the Kolmogorov-Smirnov test, which tests whether two samples are drawn from the same distribution. I interpret each break as the transition to a new plan, characterized by a new distribution of prices.

Building on work that estimates the location of a single break in a series (Deshayes & Picard, 1986, and Carlstein, 1988), I modify the method to identify an unknown number of breaks at unknown locations in a series. I use an iterative procedure similar to that of Bai & Perron (1998), who sequentially estimate multiple breaks in a linear regression model. I first test the null hypothesis of no break in a series; upon rejection, I estimate the location of the break; I then iterate on the two resulting sub-series until I fail to reject the null of no

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6Data provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business, http://research.chicagobooth.edu/nielsen. The conclusions drawn from the Nielsen data are my own and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The data have also been used by Beraja, Hurst & Ospina (2018) to analyze dynamics in regional price indices.

7DellaVigna & Gentzkow (2017) document near-uniform pricing within chains, so I use one store per chain. As is common in the literature, I exclude the Deli, Packaged Meat, and Fresh Produce departments.

8I exclude price changes less than 1% in absolute value (11% of all changes). In the full sample, the median frequency and size of price changes are 28% and 11%. However, as argued by Eichenbaum, Jaimovich, Rebelo & Smith (2014), very small price changes may reflect measurement error, since in these data, a price observation is the volume-weighted average price of the product in each week. Prices reflect bundling (e.g. 2-for-1 deals) and discounts associated with the retailer’s coupons or loyalty cards. Variation in bundling or in the use of such discounts across weeks may induce spurious small price changes.
break. The critical value used to reject the null of no break is determined via simulations, starting from the asymptotic critical values provided by Deshayes & Picard (1986), which are valid for the test of a single break on i.i.d. data drawn from continuous distributions.\footnote{I simulate data as a mixture of processes that represent commonly observed pricing patterns: sticky prices, sticky prices with transitory deviations of variable sign, size, and duration, and sticky plans with a variable number of prices. The simulation targets the range of frequency and size of price changes observed in the micro data. The critical value is determined by trading off power against false positives in simulated data. The online appendix details the method and its performance across the different processes.}

The test’s usefulness depends on its ability to correctly identify the timing of breaks. I find that the break test correctly identifies breaks 91% of the time in simulated data. It finds the exact location of the break 94% of the time and is off by two periods in the remaining cases. In simulated series restricted to have at least five observations between breaks, the test finds virtually all breaks. It loses power for policies lasting less than five weeks, because there are not enough data points to be confident about the distribution generating them.

Applied to the Nielsen product-level series, this procedure identifies interesting patterns of across-policy and within-policy volatility. Table I reports the key facts.

**Stickiness** The first empirical result is that the identified pricing policies change infrequently. Breaks in the price series typically occur every 7.7 months, and most policies last at least 4.5 months, even though raw prices change every three-to-four weeks. For comparison, papers that seek to filter out transitory price volatility report the duration of regular or reference prices ranging from 7.8 months to 12.7 months in grocery store data, and from 6.7 months to 14 months in the CPI.\footnote{Midrigan (2011), Kehoe & Midrigan (2015) and Eichenbaum et al. (2011) report statistics for grocery store data and Klenow & Kryvtsov (2008), Nakamura & Steinsson (2008), and Kehoe & Midrigan (2015) for CPI data, using different filters. I report the monthly implied duration $= -1/\ln\left(1 - \text{median monthly frequency}\right)$ for all studies, to limit bias due to the censoring of individual price series.} This variation across studies even when using similar data highlights the fact that measures of stickiness are sensitive to the definition of permanent versus transitory price changes and to the filters implemented to identify them.\footnote{In particular, v-shaped filters tend to yield significantly lower duration estimates, because they only allow for transitory price decreases from a rigid mode, whereas I find that transitory price increases from the rigid mode occur in more than a third of the policy realizations in my sample.} An advantage of the break test over the filters is precisely the fact that it sidesteps the need to take a stand on how to define and identify regular versus transitory price changes, which is the source of a big portion of the dispersion in estimates in the existing literature.

**Volatility** Between consecutive breaks, the prices charged are quite volatile. The median weekly frequency of within-policy price changes is 24.6%, consistent with existing work that has identified frequent transitory price volatility accompanying the slower dynamics of regular or reference prices. The data also feature large price changes both within and across
Table I: Characteristics of Pricing Policies

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Single-price</th>
<th>One-to-flex</th>
<th>Multi-rigid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction of series (%)</td>
<td>100</td>
<td>12.0</td>
<td>28.5</td>
<td>59.5</td>
</tr>
<tr>
<td>Monthly frequency of policy changes (%)</td>
<td>12.2</td>
<td>7.8</td>
<td>17.3</td>
<td>12.0</td>
</tr>
<tr>
<td>Implied policy duration (months)</td>
<td>7.7</td>
<td>12.3</td>
<td>5.3</td>
<td>12.0</td>
</tr>
<tr>
<td>Freq. of weekly price changes within (%)</td>
<td>24.6</td>
<td>0.6</td>
<td>15.0</td>
<td>35.8</td>
</tr>
<tr>
<td>Size of price changes within (%)</td>
<td>11.9</td>
<td>5.8</td>
<td>9.9</td>
<td>13.6</td>
</tr>
<tr>
<td>Size of shift across (%)</td>
<td>11.3</td>
<td>8.5</td>
<td>11.7</td>
<td>11.5</td>
</tr>
<tr>
<td>Policy cardinality</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

Note: Nielsen Retail Scanner data, 2006-2015. Implied policy duration is the duration implied by the median monthly frequency of policy changes. Frequency of weekly price changes within is the median weekly frequency with which prices change between breaks. Size of price changes within is the absolute value and is non-zero for SPP because the category allows for rare deviations from the modal price. Size of shift across is the median absolute change in the weighted average price across policy realizations.

Policy changes. The median absolute size of within-policy price changes is 11.9% and the median shift in prices across consecutive policy realizations is 11.3%. These magnitudes are consistent with prior evidence that prices often change by amounts that are much larger than what is needed to keep up with aggregate inflation. Instead, they point to the importance of idiosyncratic drivers of price adjustment (e.g. Golosov & Lucas Jr, 2007, and Klenow & Kryvtsov, 2008). The novelty here is the distinction between within-policy price changes and shifts in the price levels across policies. This distinction is useful, since it can identify the role of different drivers of price variability. Within-policy volatility may be primarily driven by transitory shocks or price discrimination motives, while the shift in prices across policies may be driven by more persistent shocks.

The patterns of volatility can also identify different frictions and sources of heterogeneity in price adjustment. Figure 1a shows a scatter plot the frequency and size of within-policy price changes, and Figure 1b shows a scatter plot of the frequency of policy changes versus the size of shifts across policies, for the different product groups in the sample. The positive correlation between the frequency and the size of adjustment in these panels is difficult to reconcile with theories of price rigidity driven by heterogeneous menu costs, which would be

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12 The policy shift is obtained by computing the average weighted price within each policy realization, and then computing the absolute value of the change in this average across consecutive policies.
Figure 1: Frequency and size of within and across policy price changes across product groups

Note: Nielsen Retail Scanner data, 2006-2015. Panel (a) plots the frequency against the absolute size of within-policy price changes. Panel (b) plots the frequency of policy changes against the absolute size of the shift in the average price across consecutive policies. Points indicate means at the product group level. The expenditure-weighted medians for the full sample are in black.

generate a negative correlation between the size and the frequency of adjustment. Instead, these plots suggest heterogeneity in the volatility of market conditions that firms face. Some products rarely update their prices, and even when they do, they change by modest amounts, while others change prices quite frequently and also by large amounts.

**Coarseness** Although they last a fairly long time and display volatile prices, policy realizations also exhibit coarse pricing. The median number of distinct prices per policy realization is three, and the large majority of policies have less than six price points.\(^{13}\) This finding points to the “disproportionate importance” of a few price points at the policy level, consistent with similar evidence at the series level documented by Klenow & Malin (2010) using the micro data underlying the CPI. This coarseness is also what helps identify break points. What changes systematically across policy realizations is the support of the price distribution; there is no consistent change in the shape or the cardinality of the distribution.

Overall, firms appear to have flexibility in the *timing* of price adjustment, but rigidity in the *level* to which the price adjusts. This combination is at odds with virtually all models of rigid pricing, in which, conditional on deciding to adjust, firms flexibly choose a new price, thus ruling out rigid price levels (insofar as market conditions evolve smoothly). It is also at odds with models in which firms choose deterministic price paths that generate continuous gradual adjustments. The theory proposed in the next section generates the coexistence of

\(^{13}\)These statistics are based on average weekly prices, so they likely understate coarseness.
these two features of the data.

**Policy Heterogeneity** Prior work has documented substantial heterogeneity in the frequency of price changes across goods (e.g., Nakamura & Steinsson, 2008). I find that more generally, there is heterogeneity in the types of pricing policies that products exhibit. Moreover, the different policy types can be matched to some popular models of price setting, while ruling out others.

I classify the policy realizations between consecutive breakpoints in terms of the rigidity in the observed price levels. I then classify each product series in terms of the types of policy realizations observed over the life of the series. Figure 2 shows the incidence of policy types across product groups, and Table I presents key statistics.

**Figure 2** shows the incidence of policy types across product groups, and Table I presents key statistics.

**Single-Price Policies** The workhorse Calvo or menu cost models of rigid price setting generate sequences of *single-price policies* (SPP). Each policy realization consists of a single price, and a break is a shift to a new price. In the data, only about 2% of the series are characterized by such clean single-price plans. Hence, I relax the definition of SPP series to allow for occasional deviations from such rigidity, recognizing that such infrequent deviations are likely not a systematic feature of the firm’s pricing policy and may reflect some degree of measurement error. Specifically, I identify a realization of a single-price policy features as a single sticky price with at most one deviation between two consecutive breaks, and I categorize as effectively single-price products all products for which at least 90% of observations fall inside such policy realizations. Approximately 12.0% of products are SPP products defined in this way.

The prices of SPP goods adjust much less frequently, and by less when they do adjust: the median policy duration is 12.3 months versus 7.7 months for all products, and the median shift in prices is 8.5% versus 11.3% for all products. These goods appear to face a relatively low volatility of their desired price that does not warrant designing complex pricing policies or undertaking large or frequent price changes.

**One-to-Flex Policies** Motivated by the high incidence of transitory price changes in the data, more recent pricing models (Kehoe & Midrigan, 2015 and Guimaraes & Sheedy, 2011) feature a rigid *regular* or *reference* price accompanied by transitory deviations to and from it.

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14For this classification, I assume that the type of policy employed for a particular product does not change over the sample period, and I test this assumption in Section 2.2.

15The online appendix reports statistics at the policy-product level, which are consistent with those at the series level. It also reports statistics based on an alternative series classification method; alternative critical values for the break test; and alternative identification of breakpoints, using the rolling mode filter of Kehoe & Midrigan (2015).
in a one-to-flex pattern.\textsuperscript{16} I identify the OFP series in the data as series for which a plurality of policy realizations feature the OFP pattern.\textsuperscript{17} In the data, 28.5\% of products are OFP series. The median policy duration is much shorter, at 5.3 months, and the median shift in average prices across policy realizations is 11.7\%. However, the policies themselves are not very volatile or complex. They display two or three distinct prices, and the median frequency with which prices adjust inside policies is only 15.0\% (versus 24.6\% for all products). The relatively high across-policy volatility together with the lower within-policy volatility suggest that these products face a higher volatility in their desired price than the SPP goods, but also a high cost of implementing complex policies, which induces them to instead update their policies more frequently.

**Multi-Rigid Policies** Underscoring the rigidity in price levels beyond that of the modal price of each price plan, 59.5\% of products are characterized by policies with multiple rigid prices. These are series for which a plurality of policy realizations feature at least two prices that are revisited over the life of the policy.\textsuperscript{18} The median policy duration for these products

\textsuperscript{16}Kehoe & Midrigan (2015) assume that firms can “rent” a one-period price deviation for free, but must pay a cost to change the price permanently. Alternatively, Guimaraes & Sheedy (2011) develop a price discrimination model that features a two-price distribution in the steady state; with shocks, they assume that the high price changes a la Calvo, while the low price changes freely.

\textsuperscript{17}Since price data are noisy, I allow for some flexibility in categorizing products, by allowing for SPP or MRP policy realizations inside OFP series. In the online appendix, I report results for an alternative classification in which OFP series do not exhibit any MRP realizations. This reduces the incidence of products categorized as OFP and makes these products look very similar to SPP goods.

\textsuperscript{18}A price level is “revisited” if the price returns to that level before a break occurs in the series.
is 7.9 months, but only three to four distinct prices are typically charged over the life of the policy. These products exhibit high volatility: The median shift in prices across policy realizations is 11.5%, the median absolute size of within-policy price changes is 13.6%, and the median frequency of within-policy price changes is 35.8%. These statistics suggest that these products face highly volatile market conditions, and they adjust by choosing more complex — though nevertheless coarse — pricing policies.

The prevalence of MRP goods in the data poses a challenge to existing theories of price rigidity. It is instead consistent with the hypothesis that firms set a small menu of prices which they update relatively infrequently. The theory developed in Section 3 uses costly information to generate such plans endogenously.

**Price Discrimination Policies** Overall, series overwhelmingly feature price changes between policy shifts. What drives this within-policy volatility? The obvious reasons are responding to shocks and attempting to price discriminate among heterogeneous customers. In practice, these motives interact, making it difficult to isolate how important each one is for price volatility. But disentangling these factors is important for quantifying the severity of the disconnect between product-level price volatility and aggregate sluggishness in inflation. If price discrimination is a dominant factor, then the product-level price volatility may be less relevant for the aggregate dynamics of inflation. I estimate the incidence of *price discrimination policies* (PDP) by defining them as policies in which the maximum price is also the mode. Among one-to-flex and multi-rigid series, I label a series as price discriminating if a majority of its policy realizations are PDP. This definition is consistent with models of price discrimination that feature a mass point at the high price of the pricing policy (e.g., Guimaraes & Sheedy, 2011). Roughly one third of the OFP series and one half of MRP series fit this description. Table II reports the statistics for the price discrimination series separately from the non-price discrimination series. PD series feature much longer policy durations (suggesting lower fundamental volatility) and somewhat larger within-policy price changes (consistent with having large discounts to attract bargain hunters). But the remaining non-PD series are also highly volatile, exhibiting frequent and large within-policy price changes. I conclude that the data continue to point to a large micro-macro volatility gap, which requires a model of price setting that divorces product-level volatility from aggregate price flexibility. The information friction modeled in the next section closes this gap by generating noisy pricing that tracks market conditions imperfectly.

**Break Test versus Filters** How much do we gain by allowing for non-parametric changes in the distribution of prices charged? Conceptually, the break test is more flexible in its identification of breaks than filters that identify changes in a particular statistic (such as
<table>
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<tr>
<th>Table II: Price Discrimination Policies</th>
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<td></td>
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<tr>
<td>One-to-flex</td>
</tr>
<tr>
<td>PD</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Fraction of all series (%)</td>
</tr>
<tr>
<td>Monthly frequency of policy changes (%)</td>
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<tr>
<td>Implied policy duration (months)</td>
</tr>
<tr>
<td>Freq. of weekly price changes within (%)</td>
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<tr>
<td>Size of price changes within (%)</td>
</tr>
<tr>
<td>Size of policy shift (%)</td>
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<tr>
<td>Policy cardinality</td>
</tr>
</tbody>
</table>

Note: Nielsen Retail Scanner data. Statistics for one-to-flex and multi-rigid series that are price discrimination (PD) and non-price discrimination (Non-PD) series, where PD series are defined as series in which a majority of policy realizations have the maximum price equal to the modal price.

the modal or the maximum price charged). This flexibility allows me to first identify breaks in price series, and then investigate what aspects of the distribution change across breaks. Simulations suggest that the break test is preferable: while each filter does particularly well on specific data generating processes, the break test does well across different processes, especially when the processes are characterized by random variation in the duration of both regular and transitory prices. By using information about the entire distribution of prices, the break test also has more accuracy in detecting the timing of breaks compared with methods that focus on a single statistic. While the existing literature has focused more on the median duration of regular prices, accurately identifying the timing of breaks is particularly important for characterizing within-policy volatility and the responsiveness to shocks. Statistics such as the number of distinct prices charged, the prevalence of the highest price as the most frequently charged price, or the existence of time-trends between breaks are also sensitive to the estimated location of breaks.

The break test isolates the more persistent changes in pricing patterns from the transitory pricing dynamics. But it itself does not introduce artificial rigidity in the measurement of policy durations, which could be a concern. In simulations in which prices change flexibly

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\[\text{19The online appendix compares the performance of the break test to that of three filters in simulated as well as actual data. The rolling model filter proposed by Kehoe & Midrigan (2015) gives results that are closest to the break test in terms of both accuracy in simulated data and synchronization in actual data.}\]
every three-to-four weeks, the test would conclude that policies last on average six weeks. This duration is much lower than what I find in the data, where the large majority of policies last at least 20 weeks. Hence, the method’s low power for very short-lived policies does not appear to be a constraint for finding break points in the actual data.

2.2 Dynamics During the Great Recession

Making the distinction between different types of policies and between policy changes and raw price changes is useful for disentangling the dynamics of inflation during the Great Recession and its aftermath.

**Inflation** Figure 3a shows the aggregate dynamics, plotting the annualized monthly inflation rate of the Nielsen sample compared with that of the CPI, and with crude oil price inflation. The Nielsen inflation rate closely tracks the Food and Beverages CPI inflation rate (the correlation between the two series is 96%; see also Beraja et al., 2018). Interestingly, these two series started diverging significantly from the overall CPI inflation in October 2008, at the height of the recession. They fell much more slowly and continued to diverge over the sample period, with the exception of a period of more stable oil prices, between early 2012 and early 2014. Much of the gap between these series and the overall CPI inflation rate reflects the fact that CPI inflation has tracked crude oil price inflation much more closely than the Nielsen inflation rate (79% versus only 3% correlation). This is surprising since history would predict Nielsen to be more correlated with oil, not the overall CPI basket. But in this decade, Nielsen prices (and Food CPI more generally) were more rigid during the recession and its immediate aftermath, and also more inflationary starting in 2011. Had oil prices been less volatile, the missing disinflation puzzle of the Great Recession might have been even more severe in the aggregate data.

Figure 3b decomposes the Nielsen inflation rate into the inflation rates for the three types of products — single-price, one-to-flex and multi-rigid. There are stark differences in the degree of state-dependence across the different policy types. All three inflation rates moved largely in tandem at the beginning and the end of the sample, suggesting limited divergence in “tranquil” times. But they diverged significantly in the crisis and its immediate aftermath. During this period, the inflation rate for MRP products fell much more than for SPP products. In fact, single-price products continued to raise prices throughout, while MRP goods cut prices, and MRP inflation fell to a low of −2.7%. Hence, MRP goods, which likely face more volatile market conditions in general, also responded more aggressively to the aggregate shocks during this volatile period.

Table III assesses these differences more formally, exploiting cross-sectional variation at
the national and state levels. First, I compute the monthly inflation rate at the module level, for products of each policy type across all locations, and regress it on monthly national unemployment, using the specification

\[ \pi_{ikt} = \sum_{h=1,2,3} (\alpha_h + \beta_h U_t) D_h + \delta_i + \gamma_t + \lambda_{it} + \epsilon_{ikt}, \] (1)

where \( \pi_{ikt} \) is the inflation rate across products of policy type \( k \) in module \( i \) and month \( t \), \( U_t \) is the unemployment rate, \( D_k \) is a policy type dummy, \( \delta_i, \gamma_t \) and \( \lambda_{it} \) are module, month, and module-by-month fixed effects. The table reports results with and without the time fixed effects. The sensitivity of inflation to unemployment is significantly higher for MRP series than it is for SPP series, and it is not driven by variation in specific modules over time. However, the national data are exploiting essentially a single episode of high unemployment. So I also report results using state-level inflation and state-level unemployment. I expand the sample to include multiple chains in each state, and I keep data from the largest store within each chain and state. This increases the sample size to more than nine million observations, and offers more variation in both inflation and unemployment rates. Using state-level monthly unemployment as a measure of local demand conditions, I regress monthly inflation \( \pi_{sikt} \) — now defined at the state-by-module-by-policy level — on local demand, also adding state, module, and time fixed effects. The specification sweeps out the common variation coming from the Great Recession, but nevertheless, MRP inflation responds significantly to local unemployment, while SPP inflation has no meaningful response.

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20 Nielsen groups products into roughly 1,000 product modules.
Table III: Sensitivity of Inflation to Unemployment by Policy Type

<table>
<thead>
<tr>
<th></th>
<th>National (1)</th>
<th>National (2)</th>
<th>State-level (3)</th>
<th>State-level (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment</td>
<td>-0.046</td>
<td>-</td>
<td>0.015</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(.)</td>
<td>(0.041)</td>
<td>(.)</td>
</tr>
<tr>
<td>Unemployment x OFP</td>
<td>-0.042</td>
<td>-0.089</td>
<td>-0.071**</td>
<td>-0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.049)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Unemployment x MRP</td>
<td>-0.098*</td>
<td>-0.146**</td>
<td>-0.094***</td>
<td>-0.099***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.045)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
</tbody>
</table>

Module FE         | Yes          | -            | -               | -              |
Module x Month FE  | -            | Yes          | Yes             | -              |
State FE          | -            | -            | Yes             | -              |
State x Module x Month FE | -            | -            | -              | Yes            |
Observations      | 254,600      | 244,820      | 9,626,039       | 9,079,654       |
$R^2$             | 0.0608       | 0.5304       | 0.2148          | 0.5669          |

*Note:* Nielsen Retail Scanner Data. The first two columns report regressions of module-policy inflation on national unemployment. Standard errors are in parentheses, clustered at the module level. Two-way clustering by module and month (omitted) reduces significance from the 1% to the 5% level for MRP series. The last two columns report regressions of module-policy inflation by state on state-level unemployment as a proxy for local demand. Standard errors are in parentheses, two-way clustered at the state and month level. All regressions also include policy dummies and fixed effects, as indicated (not reported). **p < 0.01, ***p < 0.001.

The heterogeneous responsiveness to the state of the economy documented here supports the results of Gilchrist, Schoenle, Sim & Zakrajšek (2017), who find that at the peak of the crisis, firms operating in competitive markets lowered their prices significantly, relative to firms operating in less competitive markets. The information-based theory presented in the next section predicts this connection: firms that operate in more volatile or more competitive markets choose more complex pricing policies and respond to shocks more aggressively, while firms that choose simpler policies also adjust more sluggishly to the state of the economy.

Importantly, these findings underscore the value of studying price data in its entirety, without eliminating transitory price volatility. Transitory volatility is crucial to pinning
down the type of pricing policy of different products and, in turn, the type of policy is correlated with how these firms respond to shocks, thereby affecting aggregate inflation dynamics. Splitting the data by frequency of policy reviews — rather than by type of policy — would generate a much less significant relationship between inflation and unemployment across all groups, because it would mix the longer duration single-price series with the longer duration multi-rigid series, which in fact have different cyclical properties.

**Cyclical Policy Choice?** So far, we have seen that MRP products reacted more aggressively to the state of the economy during the recession, while SPP products barely responded. In establishing this result I have assumed that products do not change their policy type over time, so that they can be assigned once and for all to a particular category. However, both the type and the statistics of the policies being realized may vary over time.

How important are changes in the types of policies being realized over time? As shown in Figure 4a, there is some variation in the incidence of different types of policies, with MRP realizations increasing slightly, at the expense of single-price policies. This trend supports the notion that pricing has become more complex in the U.S. in recent decades.\textsuperscript{21} But the increase is not monotonic. Surprisingly, the Great Recession saw a decrease in multi-rigid policy realizations and an increase in single-price policies. The same pattern occurred in 2011, another period of heightened volatility. Over this decade, it seems that firms’ policies have become more complex, except in periods of uncertainty, during which firms seem to

\textsuperscript{21}E.g., Nakamura et al. (2018) document an increase in the incidence of temporary sales over time.
favor implementing simpler, single-price policies.

Nevertheless, the variation in the types of policies realized over time has only a modest effect on inflation dynamics. The main driver of inflation is the volatility of the MRP series. Figure 4b shows the contribution of SPP, OFP, and MRP series to aggregate inflation. The MRP series are the most important not only because they have a large share in the overall number of series, but also because they feature the most volatile inflation. By contrast, SPP series have only a marginal contribution to aggregate inflation dynamics.
Cyclical Policy Adjustment? How do the prices within the different policy types adjust to generate the inflation dynamics seen in the aggregate? For each policy type, I decompose inflation dynamics into the contribution coming from policy adjustments (frequency size of shifts across policies) and from within-policy price changes. During the recession, adjustments overwhelmingly reflect across-policy rather than within-policy changes. As shown in Figure 5, the key adjustment margin is the frequency of policy changes, which rose substantially for all product types. This supports the hypothesis of at least partial state-dependence in policy adjustment. The rate of policy changes increased particularly sharply for single-price products, with a 20 percent increase at the height of the recession. But this increase did not translate into much flexibility in the price index for these firms, which, as we have seen, had a muted response to the Great Recession.

The bottom panels of Figure 5 document the patterns over time for within-policy volatility. The percent changes in the within-policy rates of price adjustment are about an order of magnitude smaller than changes in the rate of policy adjustments. Likewise, the absolute size of within-policy price changes did not change significantly, decreasing by less than five percent. A possible explanation for these patterns is that the heightened uncertainty associated with the Great Recession led firms to keep revising their pricing plans instead of making them more complex. This interpretation is bolstered by the increase in the rate of policy adjustments that took place in 2011, which was another period of increased uncertainty due to the Euro zone crisis, the U.S. fiscal policy crisis, and rising and highly volatile oil prices.22

3 Theory

The empirical evidence supports a theory of price setting that generates coarse, infrequently updated price plans. In this section, I develop a theory of information acquisition that can generate such price plans endogenously.

3.1 The Agents

The economy consists of a fully informed representative household, a continuum of information-constrained producers, and a government that follows an exogenous policy.

22This evidence is also consistent with that of Anderson, Malin, Nakamura, Steinsson & Simester (2017), who find that an increase in oil prices in the 2007-2009 period had a significant effect on the frequency of regular prices posted by a particular retailer. Berger & Vavra (2018) and Nakamura et al. (2018) document countercyclicality in the frequency of regular price changes in the CPI in recent decades; here I emphasize the role of volatility even in the absence of a recession.
Households  The household’s problem is standard. The household has full information and chooses paths for consumption, labor supply, money, and bonds to solve

$$\max_{\{C_t, C_{it}, H_{it}, M_t, B_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left[ \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{1}{1+\nu} \int_0^1 H_{it}^{1+\nu} di \right]$$

$$M_t + B_t \leq M_{t-1} + (1 + i_{t-1}) B_{t-1} + \int_0^1 W_{it} H_{it} di + \int_0^1 \Pi_{it} di + T_t - P_{t-1} C_{t-1}, \quad (2b)$$

$$P_tC_t \leq M_t, \quad (2c)$$

$$C_t \equiv \left[ \int_0^1 [A_{it} C_{it}]^{(\varepsilon-1)/\varepsilon} di \right]^{\varepsilon/\varepsilon(\varepsilon-1)}, \quad (2d)$$

where $A_{it}$ is a good-specific preference shock, $H_{it}$ is the differentiated labor supplied to each firm $i$, $W_{it}$ is the nominal hourly wage of firm $i$, $\Pi_{it}$ is the dividend received from firm $i$, $T_t$ is the net monetary transfer received from the government, $B_t$ is the amount of risk-free nominal bonds held in the period, $i_t$ is the risk-free nominal interest rate on these bonds, $M_t$ is money holdings, $\beta \in (0, 1)$ is the discount factor, $\varepsilon > 1$ is the elasticity of substitution, $\sigma > 1$ is the constant relative risk aversion parameter, $\nu \geq 0$ is the inverse of the Frisch elasticity of labor supply, and $P_t \equiv \left[ \int_0^1 (P_{it}/A_{it})^{1-\varepsilon} di \right]^{1/(1-\varepsilon)}$ is the aggregate price index. The optimality conditions are standard and shown in the online appendix.

Government  For simplicity, the government follows an exogenous policy. The net monetary transfer in each period is equal to the change in money supply, $T_t = M_s^t - M_{s,t-1}$, where the log of money supply evolves according to $\log M_s^t = \log M_{s,t-1} + \eta_t$, $\eta_t \overset{i.i.d.}{\sim} h_\eta$.

Firms  A continuum of monopolistically competitive firms produce differentiated goods using the production function $Y_{it} = H_{it}^{1/\gamma}/A_{it}$, where $H_{it}$ is the differentiated labor input, $A_{it}$ is the firm-specific inverse of productivity, and $\gamma \geq 1$ captures the returns to scale in production. The stochastic variable $A_{it}$ represents the effort required to produce the good and also increases the utility from consuming it.\textsuperscript{23} The law of motion for this quality term is $\log A_{it} = \log A_{i,t-1} + \xi_{it}$, with $\xi_{it} \overset{i.i.d.}{\sim} h_\xi$. Excluding information costs, nominal profit is $\Pi_{it} = P_{it} Y_{it} - W_{it} H_{it}$. The profit maximizing full information flexible price is $X_{it} \equiv A_{it} M_t/Y^*$, where $Y^*$ is the associated equilibrium output, $Y^* \equiv [(\varepsilon - 1)/(\varepsilon \gamma (1 + \nu))]^{1/(\sigma + \gamma (1+\nu)-1)}$.\textsuperscript{24}

\textsuperscript{23}The assumption that this term enters both the household’s demand and the firm’s cost implies that the firm’s profit is shifted in the same way by the aggregate nominal shock and by this idiosyncratic shock, which enables a reduction in the state space of the problem. See also Midrigan (2011) and Woodford (2009).

\textsuperscript{24}The online appendix derives this and all subsequent results that are omitted here for brevity.
3.2 The Firms’ Information Problem

Monitoring the state of the economy is costly for firms, but they can choose how much attention to pay to market conditions. Each firm chooses a policy that specifies a menu of prices and a rule that determines which price to charge in each period and state of the world. How many prices are on the menu and how sensitive the rule is to market conditions depend on the firm’s willingness to acquire more information in order to make its prices track the full information target price more closely. Moreover, motivated by the evidence of breaks in product-level price series, I assume that firms can revise their policies, subject to a fixed cost. This means that in addition to deciding which price to charge in each period, firms must also decide whether or not to undertake a policy review. How much information about market conditions to acquire in order to make this decision is also their choice, depending on how valuable it is to have accurately-timed policy reviews.

Objective Each firm maximizes its discounted expected profits net of the monitoring and policy review costs. The fixed cost of policy reviews makes the firm’s problem dynamic. Let \( \pi_{it} \) denote a firm’s per-period profit in units of marginal utility, excluding information costs. Profit in the economy with costly information can be written as a function of the gap between a firm’s actual price and the frictionless target \( X_{it} \), and of the gap between actual output and the frictionless level of output \( Y^* \):

\[
\pi_{it} = (Y^*)^{1-\sigma} \left[ \left( \frac{P_{it}}{X_{it}} \right)^{1-\varepsilon} \left( \frac{Y_t}{Y^*} \right)^{2-\varepsilon-\sigma} - \frac{\varepsilon - 1}{\varepsilon(1+\nu)} \left( \frac{P_{it}}{X_{it}} \right)^{-\varepsilon\gamma(1+\nu)} \left( \frac{Y_t}{Y^*} \right)^{\gamma(1+\nu)(1-\varepsilon)} \right],
\]

where aggregate output relative to frictionless output depends only on the joint distribution of prices and targets in each period, after firms have made all their decisions:

\[
Y_t = Y^* \left[ \int_0^1 \left( \frac{P_{it}}{X_{it}} \right)^{1-\varepsilon} dt \right]^{-1/(1-\varepsilon)}.
\]

The information-constrained firm chooses a pricing and reviewing policy that solves

\[
\max_{\{P_{it}, I_{it}^p, I_{it}^r, \delta_{it}^r\}} \sum_{t=0}^{\infty} \beta^t \left[ \pi_{it} - \theta^p I_{it}^p - \theta^r I_{it}^r - \kappa \delta_{it}^r \right],
\]

where \( I_{it}^p \) is the quantity of information acquired in period \( t \) in order to make the pricing decision, with unit cost \( \theta^p > 0 \), \( I_{it}^r \) is the quantity of information acquired to decide whether or not to review the policy, at a unit cost \( \theta^r > 0 \), \( \delta_{it}^r \) is equal to 1 if the firm reviews its policy in period \( t \) and 0 otherwise, and \( \kappa > 0 \) is the fixed cost associated with a policy review. Payment of this fixed cost enables the firm to obtain complete information about
the economy at the time of the review, as in Reis (2006) and Woodford (2009).  

**Monitoring Market Conditions** Figure 6 presents the timeline in each period. The firm monitors the evolution of market conditions using two costly signals that it observes in each period: a review signal, which is used to decide if the policy has become obsolete such that it is worthwhile to pay the fixed cost to redesign it, and a price signal, which is used to decide which price, from the menu of prices specified by the current policy, the firm should charge in the period. We can interpret these two signals as the information acquired by two different managers in the firm: a manager at headquarters, monitoring the overall performance of the firm’s policy, and a “floor” manager, monitoring the day-to-day fluctuations that might warrant temporary price adjustments. The cost of each signal is linear in Shannon’s (1948) mutual information between the signal and the state of the economy. Mutual information measures the reduction in uncertainty about the state of the economy achieved by an optimally designed signal. Uncertainty is measured by entropy, and the signal is optimal for the decision that is based on its information content. More informative signals—which reduce uncertainty about the optimal decisions more—are more costly. Hence, for each of its two decisions, the firm faces a trade-off between closely tracking the action warranted by current market conditions and economizing on information expenditure.

For tractability, there is no free memory—including regarding the passage of time—and all information, including that about past events or actions, is subject to the unit costs \( \theta_r \) and \( \theta_p \) for the review and pricing signals respectively. There is also no free transmission of information between the managers who make the two decisions.  

**The Firm’s Choices** Given this specification, I now formalize each firm’s choice of signals and define the information cost of each choice. Consider a firm undertaking a policy review in an arbitrary period \( t \). Let \( \tilde{\omega}_t \) denote the state of the economy at the time of the review,

---

25The assumption that the review cost is fixed and yields complete information simplifies the model and may be rationalized via economies of scale in the review technology.

26The assumptions that information from memory is as costly to process as new information, and that keeping track of time is also just as costly simplify the firm’s problem and the resulting optimal policy considerably. The implications of this equal-cost assumption are discussed in more detail in the appendix.
after the realization of that period’s shocks. This “pre-review” state includes the current target prices as well as the history of shocks, signals and decisions through period \( t - 1 \), for all firms in the economy. Let \( \overline{V}_t (\tilde{\omega}_t) \) be the firm’s maximum attainable value, upon conducting a review, and let \( V_t (\tilde{\omega}_t) \) be the continuation value under the policy in effect at the beginning of the period. The firm’s decision of whether or not to undertake a review depends on information about the difference between these two values. Extending the results of Woodford (2009), information about this difference is acquired in the form of a binary signal indicating whether or not to review the policy. Such a signal that directly indicates the action to be taken ensures that the firm does not spend resources on any extraneous information that is not directly used in its decision.

Formally, the firm’s review policy can be recast as the choice of (\( i \)) a sequence of hazard functions \( \{\Lambda_{t+\tau} (\tilde{\omega}_{t+\tau})\}_{\tau \geq 1} \), indicating the probability of a review in each future period and state of the world, and (\( ii \)) an unconditional frequency \( \Lambda_t \) with which the firm anticipates undertaking reviews over the expected life of the policy. The cost of this review policy each period is expected to be \( \theta r I_{r_{t+\tau}} \). Using the definition of mutual information,\(^{27}\)

\[
I_{r_{t+\tau}} = E_t \left\{ I \left( \Lambda_{t+\tau} (\tilde{\omega}_{t+\tau}), \Lambda_t \right) \right\}, \quad \forall \tau > 0, \tag{6a}
\]

\[
I \left( \Lambda, \Lambda \right) = \Lambda \left[ \log \Lambda - \log \Lambda \right] + (1 - \Lambda) \left[ \log(1 - \Lambda) - \log(1 - \Lambda) \right]. \tag{6b}
\]

At the time of its review, the firm also chooses its pricing policy, which determines how prices are set between reviews. The firm does not have to choose a single price to charge until the next review, as in Calvo or menu cost models; nor does it have to choose a pre-determined path, as in Reis (2006) or Burstein (2006). Rather, it can choose a menu of prices and a state-dependent rule for deciding which price to charge when. Let \( \omega_{t+\tau} \) indicate the state that is relevant for the firm’s pricing decision in period \( t + \tau \), after firms have made their review decisions. This “post-review” state consists of the pre-review state \( \tilde{\omega}_{t+\tau} \) and the review decisions of all firms in the economy. As in the case of the review policy, the signal structure directly indicates the action to be taken, which in this case is the price to be charged. Hence, the price setting policy consists of three objects: \( P_t, \tilde{f}_t (p) \), and \( \{f_{t+\tau} (p|\omega_{t+\tau})\}_{\tau \geq 0} \), namely (\( i \)) the set of log prices in the menu, (\( ii \)) the unconditional discounted frequency with which the firm expects to charge the prices in this set until the next review, and (\( iii \)) the sequence of state-dependent distributions from which a price is

\(^{27}\)It is convenient to exploit the symmetry of the mutual information function to write the amount of information acquired in terms of the relative entropy between the conditional and the unconditional probabilities that characterize the review policy, rather than in terms of the relative entropy between the prior and posterior state of the world, conditional on receiving the signal.
drawn in each period, conditional on the state. These conditional distributions govern how closely prices track market conditions in real time. The expected cost of the information needed to implement this pricing policy is $\theta P_{t+\tau}$ in each period, where, again using the definition of mutual information, this cost is linear in the distance between the conditional and the unconditional frequencies,

$$I_{t+\tau} = E_t \left\{ I \left( f_{t+\tau}(p|\omega_{t+\tau}), \overline{f}_{t}(p) \right) \right\}, \forall \tau \geq 0,$$

(7a)

$$I(f, \overline{f}) = \sum_{p \in \mathcal{P}} f(p|\omega) \left[ \log f(p|\omega) - \log \overline{f}(p) \right].$$

(7b)

**The Firm’s Policy** The policy chosen at the time of a review in some period $t$ attains the maximum continuation value

$$V_{t}(\overline{\omega}_{t}) = E_t \left\{ \Pi_{t}(\omega_{t}) + \sum_{\tau=1}^{\infty} \beta^\tau \Gamma_{t+\tau}(\overline{\omega}_{t+\tau-1}) W_{t+\tau}(\overline{\omega}_{t+\tau}) \right\},$$

(8)

$$W_{t+\tau}(\overline{\omega}_{t+\tau}) \equiv [1 - \Lambda_{t+\tau}(\overline{\omega}_{t+\tau})] \Pi_{t+\tau}(\omega_{t+\tau}) + \Lambda_{t+\tau}(\overline{\omega}_{t+\tau}) \left[ V_{t+\tau}(\overline{\omega}_{t+\tau}) - \kappa \right] - \theta^\tau I(\Lambda_{t+\tau}(\overline{\omega}_{t+\tau}), \overline{\Lambda}_{t}),$$

(9)

where $E_t \Pi_{t+\tau}(\omega_{t+\tau})$ denotes the average profit that the firm expects in $t + \tau$ given its pricing policy, net of the cost of the price signal, and where, if the policy survives to period $t + \tau$, the firm pays for the review signal in that period, and then either keeps its policy unchanged, or pays the fixed cost to review its policy and obtain the new maximum continuation value. The average per-period profit net of the cost of the pricing signal is given by

$$\Pi_{t+\tau}(\omega_{t+\tau}) \equiv \sum_{p \in \mathcal{P}_t} f_{t+\tau}(p|\omega_{t+\tau}) \left\{ \pi(p; x_{t+\tau}; Y_{t+\tau}) - \theta^p [\log f_{t+\tau}(p|\omega_{t+\tau}) - \log \overline{f}_{t}(p)] \right\},$$

(10)

and the survival probability is given by

$$\Gamma_{t+\tau}(\overline{\omega}_{t}) \equiv 1 \text{ and, for } \tau > 1,$$

$$\Gamma_{t+\tau}(\overline{\omega}_{t+\tau-1}) \equiv \prod_{k=1}^{\tau-1} [1 - \Lambda_{t+k}(\overline{\omega}_{t+k})].$$

(11)

---

28 For expositional purposes and foreshadowing later results, the set of prices is countable, although nothing in the specification rules out policies featuring continuous price distributions. Note that since knowledge regarding the passage of time is assumed to be available only through the signals themselves, both the pricing decision and the review decision are defined relative to two single discounted frequencies $\overline{f}_{t}(p)$ and $\overline{\Lambda}_{t}$, indexed by the time of the review and applicable in all periods until the next review.

29 The flow profit $\pi$ defined in (3) is now redefined in terms of the log price $p$ and the log target price $x$. 

25
3.3 The Optimal Policy

Consider a firm that reviews its policy in period $t$. I shall index the firm’s policy objects by $t$ to indicate dependence on the aggregate state at the time the policy was reviewed. Let $\Phi$ and $\Phi$ denote the relevant parts of the aggregate state—namely the joint distributions of normalized prices and targets—at the time of some subsequent review decision and pricing decision respectively. The implementation of the firm’s policy depends on both idiosyncratic conditions (summarized by the firm’s normalized target price) and on these distributions.

Each time it reviews its policy, the firm learns the complete state of the economy. Therefore, its decisions can be expressed as a function of the aggregate state and of idiosyncratic variables that are normalized by the state at the time of its last review. Specifically, for a firm that last reviewed its policy in period $t$, I define its normalized pre-review target in period $t + \tau$ as $\tilde{y}_t + \tau ≡ x_{t+\tau} - x_t$. If the firm undertakes a review in period $t + \tau$, its normalized target is reset to 0; otherwise, its normalized post-review target is $y_{t+\tau} = \tilde{y}_{t+\tau}$.

Finally, I denote by $q_{t+\tau} ≡ p_{t+\tau} - x_t$ the firm’s normalized price.

The Optimal Pricing Policy. The probability that a firm that reviewed its policy in period $t$ will charge normalized price $q$ in aggregate state $\Phi$ when facing a normalized target $y$ is

$$f_t(q|y, \Phi) = \frac{\overline{f}_t(q) \exp \left\{ \frac{\pi(q, y, Y(\Phi))}{\theta_p} \right\}}{\sum_{\tilde{q} \in Q_t} \overline{f}_t(\tilde{q}) \exp \left\{ \frac{\pi(\tilde{q}, y, Y(\Phi))}{\theta_p} \right\}},$$

where $Q_t$ is the set of prices in the menu (possibly a singleton) and $\overline{f}_t$ is the unconditional discounted frequency with which the firm expects to charge these prices until the next review.

The Optimal Review Policy. The probability of a policy review in aggregate state $\tilde{\Phi}$, given a normalized pre-review target $\tilde{y}$, satisfies

$${\Lambda}_t(\tilde{y}; \tilde{\Phi}) = \frac{{\Lambda}_t(\tilde{y}; \Phi)}{1 - {\Lambda}_t(\tilde{y}; \Phi)} \exp \left\{ \frac{1}{\theta_p} \left[ \nabla(\tilde{\Phi}) - \kappa - V_t\left(\tilde{y}; \tilde{\Phi}\right) \right] \right\},$$

where $\Lambda_t$ is the unconditional discounted frequency of reviews, $V_t$ is the continuation value under the current policy, and $\nabla$ is the maximum continuation value upon review.

The Frequency of Reviews. The optimal discounted frequency of policy reviews is

$$\overline{\Lambda}_t = \frac{E_t \left\{ \sum_{\tau=1}^{\infty} \beta^\tau \Gamma_t \left( \tilde{y}^\tau - 1; \tilde{\Phi}_{t+\tau-1} \right) {\Lambda}_t(\tilde{y}_\tau; \tilde{\Phi}_{t+\tau}) \right\}}{E_t \left\{ \sum_{\tau=1}^{\infty} \beta^\tau \Gamma_t \left( \tilde{y}^\tau - 1; \tilde{\Phi}_{t+\tau-1} \right) \right\}},$$

where $\Gamma_t(\tilde{y}; \tilde{\Phi}_{t+\tau})$ is the probability that the policy chosen in period $t$ continues to apply $\tau + 1$
periods later, as a function of the sequences of targets and aggregate states, with \( \Gamma_t(0; \tilde{\Phi}_0) \equiv 1 \) (the policy lasts at least one period), and, for \( \tau > 0 \),

\[
\Gamma_t(\tilde{y}; \tilde{\Phi}_{t+\tau}) \equiv \prod_{k=1}^{\tau-1} \left[ 1 - \Lambda_t(\tilde{y}_k; \tilde{\Phi}_{t+k}) \right].
\]  

(15)

The Frequency of Prices. The discounted frequency with which the firm expects to set the normalized price \( q \) is a discounted average of the conditional probabilities of charging this price under different states, weighted by the probability of reaching these states:

\[
\bar{f}_t(q) = \frac{\mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \Gamma_t(\tilde{y}; \tilde{\Phi}_{t+\tau}) f_t(q|y_\tau, \Phi_{t+\tau}) \right\}}{\mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \Gamma_t(\tilde{y}; \tilde{\Phi}_{t+\tau}) \right\}}.
\]  

(16)

The Optimal Pricing Support. The set \( Q_t \) is the optimal support of the pricing policy if and only if \( Z_t(q) \leq 1 \) for all \( q \) and \( Z_t(q) = 1 \) for all \( q \) such that \( \bar{f}_t(q) > 0 \), with

\[
Z_t(q) \equiv E_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \Gamma_t(\tilde{y}; \tilde{\Phi}_{t+\tau}) \frac{\exp \left\{ \frac{1}{\theta_p} \pi(q; y_\tau; Y(\Phi_{t+\tau})) \right\}}{\sum_{q' \in Q_t} \bar{f}_t(q') \exp \left\{ \frac{1}{\theta_p} \pi(q'; y_\tau; Y(\Phi_{t+\tau})) \right\}} \right\}.
\]  

(17)

where the pricing policy satisfies equations (12) and (16). The associated probability distribution satisfies the fixed point \( \bar{f}_t(q) = \bar{f}_t(q) Z_t(q) \), \( \forall q \in Q_t \).

Discussion  The firm’s pricing policy is defined by equations (12), (16), and (17). Since all information about the state is equally costly, the firm chooses a signalling mechanism that directly conditions on its target and on the expected output level, which are sufficient statistics for idiosyncratic and aggregate conditions. Moreover, since the firm can revise its policy, the pricing problem becomes a static problem over the distribution of states that it expects to face until the next review. This means that the solution inherits the properties of solutions from the static rational inattention literature. In particular, it is worth recalling three important features of an equation of the form (12): First, it exhibits partial state-dependence in that the probability of setting a particular price in a particular state is high, relative to the average probability of charging other prices in that state, if the profit from doing so is high relative to the average profit that the firm can expect in this state across all the prices on the menu. Second, the state-dependence is stochastic. Regardless of the target price, there is positive mass on all prices for which \( \bar{f}_t(q) > 0 \). This implies not only that the firm can make considerable mistakes in pricing, but also that the price may change from one period to the next even if there is no change in the fundamentals. Third, the information

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cost $\theta^p$ governs the degree of noise in the solution. The higher the cost, the flatter is the conditional distribution in equation (12), reducing pricing accuracy.

Equation (16) differs from the static rational inattention solution. It represents the discounted frequency with which the firm anticipates that it will charge different prices from its current policy, with future states mattering less for the firm’s choice of a policy today.

The condition for the optimality of the support defined in equation (17) is crucial in the context of a potentially discrete solution. The value $Z_t(q)$ represents the value of charging the price $q$ relative to the value of charging other prices $q' \in Q_t$, on average, across all possible targets $y$ that the firm expects to encounter until its next review. The optimal support is chosen so as to equate this value across all prices in the support. Moreover, it requires that charging any other price would yield a weakly lower average value. If one can find a set of prices that satisfy the conditions in (17), then this set characterizes the uniquely optimal solution at the information cost $\theta^p$.

The firm’s review policy is defined by equations (13) and (14). The conditional probability of a policy review has the same form as the probability of a price change derived by Woodford (2009), generalizing it to the general equilibrium model with pricing policies consisting of more than one price between reviews. The review decision depends on the firm’s own pre-review normalized target, and also on expected aggregate dynamics. When deciding whether or not to review its policy, the firm considers the gain from undertaking a review relative to the cost of the review $\kappa$. The dependence of the review decision on the state is imperfect: In order to economize on information costs, the optimal review signal neither rules out a review nor indicates it with certainty. When the cost of information $\theta^r$ is low, the firm can afford to acquire more information in order to make its review decision, and hence this decision becomes increasingly precise.

**Equilibrium** A stationary equilibrium is a set of stochastic processes $\Lambda_t(\tilde{y}; \tilde{\Phi})$, $\overline{V}_t(\tilde{y}; \tilde{\Phi})$, $\overline{f}_t(q)$, $f_t(q|y, \Phi)$, $Q_t$ that satisfy optimal firm behavior, where the relevant aggregate states are the joint distributions of pre-review and post-review prices and targets.

The steady state with idiosyncratic shocks is characterized by a set of time-invariant objects $\Lambda(\tilde{y})$, $\overline{V}(\tilde{y})$, $\overline{Q}$, $\overline{f}(q)$, and $f(q|y)$ that satisfy the conditions above for the case of zero aggregate shocks in each period, and stationary joint distributions of normalized targets and prices, pre- and post-reviews. The steady-state algorithm solves the firm’s pricing policy between reviews by incorporating algorithms based on the information theory literature, namely Arimoto (1972), Blahut (1972), Csiszár (1974), and Rose (1994). Given the steady state solution, dynamics are obtained using a linear approximation to the dynamic equations of the model around the steady state, for the case of small aggregate shocks. I use the
method of Reiter (2009) with Klein (2000) numerical Jacobians code. For tractability, I restrict the degree to which firms’ choices of a review policy and a pricing support depend on the aggregate state and the number of firm cohorts in the equilibrium distributions.\footnote{Costain & Nakov (2011) also use this approach to solve a general equilibrium monetary model with heterogeneous firms and state-dependent price setting. As they note, the advantage of this method is that it allows for a solution that is non-linear in the idiosyncratic shocks, while maintaining linearity in the (small) aggregate shocks.}

4 Numerical Results

The model is parameterized at the weekly frequency, targeting the duration, discreteness, and volatility of pricing policies identified in micro data.

4.1 Pricing Policies in the Model

Table IV shows the parameterization of the baseline single-price and multiple-price models. Most parameters are common. The parameters that determine the preferences of the representative consumer and the properties of the production function are set to values commonly used in the literature. The elasticity of substitution is $\varepsilon = 5$. The elasticity of inter-temporal substitution is $\sigma = 2.7$. The production function features decreasing returns to scale ($\gamma = 1.5$). These parameters determine the curvature and asymmetry of the profit function, which in turn affect the losses associated with mispricing. The volatility of idiosyncratic shocks and the information costs are chosen to target the frequency of policy reviews, the median shift in prices across policies, the cardinality of pricing policies, the frequency of the modal price per policy, and the frequency and size of within-policy price changes. Although these parameters are jointly optimized to target the pricing moments, I indicate in the table the statistics that are relatively more sensitive to variations in each parameter. All parameters play a role in influencing firms’ incentives to acquire information, but the volatility of the shocks plays the biggest role, with small changes in the size of shocks affecting both how much the firm spends on signals and how frequently it resets its policy.

The first key numerical result is that pricing policies feature discrete prices. The solution is discrete even though the model is infinite-horizon and with Gaussian shocks. Figure 7 shows a sample price series, along with the target price that would be charged in the full information, flexible price benchmark. The shading marks the timing of policy reviews as identified by the break test. Consistent with the data, the theory generates large, transitory volatility among a small number of infrequently updated price levels. The firm’s actual price tracks the target price well, especially in the medium-run, although in the short run the firm often makes large mistakes, reflecting noise in both its reviewing and pricing decisions.
Table IV: Baseline Parameterization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Values</th>
<th>Explanation/Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor</td>
<td>$\beta$</td>
<td>0.9994</td>
<td>Annual discount rate of 3%</td>
</tr>
<tr>
<td>Elasticity of substitution</td>
<td>$\varepsilon$</td>
<td>5</td>
<td>Full info markup of 25%</td>
</tr>
<tr>
<td>Elast. of inter-temporal subst.</td>
<td>$\sigma$</td>
<td>2.7</td>
<td>Strategic complementarities</td>
</tr>
<tr>
<td>Inverse Frisch elasticity</td>
<td>$\nu$</td>
<td>0</td>
<td>Indivisible labor</td>
</tr>
<tr>
<td>Inverse production fn. exponent</td>
<td>$\gamma$</td>
<td>1.5</td>
<td>Decreasing returns to scale</td>
</tr>
<tr>
<td>Fixed cost of policy review</td>
<td>$\kappa$</td>
<td>1.65; 1.8</td>
<td>Frequency of policy reviews</td>
</tr>
<tr>
<td>Cost of review signal</td>
<td>$\theta^c$</td>
<td>4</td>
<td>Price shift across policies</td>
</tr>
<tr>
<td>Cost of price signal</td>
<td>$\theta^p$</td>
<td>&gt; 0.13; 0.1</td>
<td>Cardinality of policy</td>
</tr>
<tr>
<td>Std. dev. of idio. quality shock</td>
<td>$\sigma_\xi$</td>
<td>0.016; 0.028</td>
<td>Size of price changes</td>
</tr>
</tbody>
</table>

Note: Where there are two values, the first indicates the SPP parameterization, and the second indicates the MRP parameterization.

The second key numerical result is that the model can generate both single-price policies and multiple-price policies, depending on parameter values. In particular, there exists a finite threshold $\bar{\theta}^p$ such that for costs of the price signal below this level, the firm always chooses to acquire the pricing signal and to implement a policy with multiple prices between reviews. The level of this threshold depends on the distribution of target prices that the firm expects will be realized between reviews. This distribution is shaped by the distribution of exogenous shocks and by how quickly the chosen review policy triggers a review when the target price deviates too much from the current policy. Larger exogenous shocks or less frequent reviews that allow shocks to accumulate both result in a higher threshold and make complex pricing policies more likely.

Table V shows the model’s ability to match statistics from the micro data for both SPP and MRP series.\(^3\) For the MRP data, large shock volatility generates policies with four distinct price levels, and large price changes both within and across policies. I target more moments than there are free parameters, so the match is imperfect. Nevertheless, the model captures very well the volatility and discreteness seen in the data. The discrete solution for the firm’s pricing policy yields a moderate frequency of price changes between reviews of

\[^3\]I target statistics for the multi-rigid series excluding the price discrimination series, since the model does not feature a price discrimination motive. In the interest of space, I omit results for OFP series, whose properties are between those of SPP and MRP series; OFP pricing patterns are generated by changing the cost $\theta^p$ so as to generate a disproportionate mass at a single price in the distribution.
39.4% versus 38.6% in the data. As in the data, policies feature one dominant rigid price, with the frequency of the modal price reaching 66% on average, versus 58% in the data.

How well do the information-constrained firms do, relative to a hypothetical firm that faces no information frictions in this economy? In the model, MRP firms achieve about 90% of the profits they would achieve if they had full information. They spend approximately 5.2% of their revenues on monitoring market conditions and updating their policies, most of which is spent on the fixed cost of policy reviews.

Since they are quite uncertain about their target price, MRP firms set prices that are 4.5 percentage points higher than the prices that would be set by fully informed firms in the same environment. Overpricing—as insurance against mistakes—reflects the fact that the firm stands ready to meet whatever demand it faces at its current price. This makes having prices that are too low much more costly than having prices that are too high, relative to the full information optimum.

For the single-price firms, I lower the volatility of idiosyncratic shocks to match the smaller size and frequency of price changes. I also assume that redesigning single-price policies is slightly cheaper ($\kappa = 1.65$ versus 1.80 for MRP firms). Since they face less volatility in their target price, SPP firms have lower incentives to acquire information between reviews. As a result, the threshold unit cost for the price signal $\theta^p$, which determines the desirability of having a multiple price policy, is much lower (0.13 versus 0.42 for the MRP parameterization). Overpricing is also less severe for these firms: Prices are on average 2.9 percentage points higher than the prices that would be set by fully informed firms. Lastly, profits are quite high (91% of the profits they would achieve if they had full information) even though information expenditure is less than half than that of the MRP firms.
Table V: Pricing Policies in the Model

<table>
<thead>
<tr>
<th></th>
<th>Single-price</th>
<th>Multi-rigid (non-PD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td><strong>Targets</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cardinality of the pricing policy</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Weekly frequency of policy reviews (%)</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>Shift in prices across policies (%)</td>
<td>8.5</td>
<td>8.5</td>
</tr>
<tr>
<td>Weekly freq. of modal price (%)</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Weekly frequency of price changes within (%)</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Size of price changes within (%)</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Information expenditure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(% of revenues)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>On reviews</td>
<td>1.8</td>
<td>3.0</td>
</tr>
<tr>
<td>On review signal</td>
<td>0.7</td>
<td>0.6</td>
</tr>
<tr>
<td>On price signal</td>
<td>0.0</td>
<td>1.6</td>
</tr>
<tr>
<td>Total info expenditure</td>
<td>2.5</td>
<td>5.2</td>
</tr>
<tr>
<td>Profits, excluding info costs (% FI)</td>
<td>91.2</td>
<td>90.0</td>
</tr>
<tr>
<td>Threshold cost $\theta_p$ for acquiring price signal</td>
<td>0.13</td>
<td>0.42</td>
</tr>
<tr>
<td>Amount by which prices exceed FI price (%)</td>
<td>2.9</td>
<td>4.5</td>
</tr>
</tbody>
</table>

*Note:* Data versus baseline model results.

Figure 8 shows the steady state hazard functions for policy reviews for the MRP and SPP firms, and the associated steady state distributions of pre-review and post-review normalized target prices. Overall, the data favor a parameterization in which both types of firms spend relatively little on making an accurate review decision. Both hazard functions are very flat for much of the relevant state space. This implies that, all else equal, firms are slow to reset their pricing policies. Nevertheless, mispricing becomes increasingly costly when prices fall too far below the optimum. As a result, the hazard functions steepen much faster when prices fall behind, so that firms are quicker to raise prices than to cut them. The SPP hazard function displays a particularly strong steepening, since these firms cannot respond by adjusting prices between reviews.
Cost of Price Signal  First, consider the case of a high cost of the price signal, $\theta^p$, keeping all other parameters at the values of the MRP parameterization. The firm reduces the amount of information obtained to make its pricing decision, and instead it acquires a more precise review signal. For a high enough value of $\theta^p$, it eliminates the price signal altogether and charges a single price between reviews. Having a more accurate timing of reviews allows the firm to undertake reviews less frequently ($\bar{\Lambda}$ declines). Hence, the firm partially makes up for its more costly price signal by spending more resources on its review policy. Nevertheless, it achieves lower profits and overprices more, since its choice of policy is more constrained.

Cost of Review Signal  Next, consider an increase in $\theta^r$, the cost of monitoring market conditions to decide whether or not to undertake a policy review. The firm now chooses a less informative review signal, which implies a flatter hazard for policy adjustment. To compensate for the increased inaccuracy in making this decision, the frequency of reviews increases, and the threshold $\theta^p$ below which multiple-price policies are chosen also increases, making MRP policies more likely. Overall, the firm can compensate such that profits are not significantly affected.

Cost of a Review  Finally, consider an increase in $\kappa$, the fixed cost of policy reviews. The firm undertakes reviews less frequently, and instead acquires more informative signals,
Table VI: Alternative Parameterizations for MRP Series

| Policies                                      | Base | High $\theta_p$ | High $\theta_r$ | High $\kappa$
|-----------------------------------------------|------|-----------------|-----------------|----------------
| Cardinarity of the pricing policy             | 4    | 1               | 5               | 5              |
| Weekly frequency of policy reviews (%)        | 3.4  | 2.8             | 4.4             | 2.8            |
| Shift in prices across policies (%)           | 10.8 | 12.9            | 9.3             | 11.4           |
| Information expenditure (% of revenues)       |      |                 |                 |                |
| On reviews                                   | 3.0  | 3.3             | 4.7             | 3.2            |
| On review signal                             | 0.6  | 1.4             | 1.7             | 0.9            |
| On price signal                              | 1.6  | –               | 1.5             | 2.8            |
| Total info expenditure                       | 5.2  | 4.6             | 6.4             | 6.9            |
| Profits, excluding info costs (% FI)          | 90.0 | 85.2            | 90.0            | 89.1           |
| Amount by which prices exceed FI price (%)    | 4.5  | 4.9             | 4.5             | 5.0            |

*Note:* The first column shows the baseline MRP parameterization. Each subsequent column considers a single parameter change: $\theta_p = 0.42$, which is the threshold information cost for multiple-price policies; $\theta_r = 20$, which generates a near-constant probability of policy reviews; and $\kappa = 3.6$, which also generates a very flat hazard function for policy reviews.

especially on pricing. It makes its review decision slightly more precise, and it designs a more complex and more accurate pricing policy. Overall, the level of spending on information increases. Profits (excluding information costs) decline, but not as much as they would if the firm had exogenously given signals. Overpricing also increases, since the firm now resets its policy less frequently, and hence there is more risk of prices becoming more stale between reviews.

Overall, the results suggest that constraints on firms’ ability to design complex pricing policies may be more costly (generating lower profits and higher average prices for consumers) than having higher costs associated with the review policy, which the firm can counteract by adjusting its pricing policy between reviews. This suggests that within-policy price flexibility is a valuable way for firms to respond to shocks, a point I return to in the next section.
4.3 Discreteness

Central to obtaining a discrete solution is the shape of the distribution of target prices that the firm expects to encounter until the next review. This distribution is the key object of attention for the firm. Importantly, unlike in other rational inattention models, it is endogenous, since it is shaped by the firm’s review policy which determines in which states of the world the current policy continues to apply. The review policy is more likely to trigger a review when the firm’s target price has drifted far from the current menu of prices. Hence, the firm can afford to pick a small menu of prices, and then occasionally reset it. Since the profit function is asymmetric, the probability of a policy review is also asymmetric. This makes the firm more likely to reset its policy when its prices have become too low. This yields a distribution of post-review target prices whose support—while unbounded—is skewed and has negative excess kurtosis. I find numerically that these effects are strong enough to generate a discrete support for a finite cost of the price signal.

Given the optimality of a discrete support, the cost of the price signal \( \theta^p \) then determines how many prices the firm chooses to charge between reviews, and how closely the probability of charging each price is tied to market conditions. Figure 9 illustrates how the pricing policy evolves in partial equilibrium, as a function of the cost of the price signal \( \theta^p \), keeping the review policy fixed. The panels plot the evolution of \( Z(q) \) defined in equation (17) as a function of \( q \), for decreasing levels of the information cost. For a high information cost, the solution yields a singleton, \( Q = \{\bar{q}\} \). The function \( Z \) is below 1 everywhere except at \( \bar{q} \). As the information cost falls, the function \( Z \) increases for all points around \( \bar{q} \). However, the growth occurs at a much faster rate in the range that will contain the new mass point. Eventually, \( Z > 1 \), triggering the addition of a new mass point to the optimal support. Moreover, there is no other fast-growing area over the entire range of \( q \), such that the transition from the single-price to the multiple-price policy occurs with the growth of a single new mass point. This is due to the asymmetry of the problem: new mass points are added one by one to the support, spreading out over a wider and wider range of possible prices. In a setup that retains the skinny tails of the distribution of states relative to the objective function (such that discreteness remains optimal) but instead employs a symmetric objective and a symmetric distribution of states, the singleton price would “break” into two and be replaced by a price below \( \bar{q} \) and a price above \( \bar{q} \) simultaneously. As the cost of information is further reduced, a low price and a high price would continue to be added symmetrically. In the quadratic-normal setup, for any finite information cost, \( Z(q) = 1 \) for all \( q \in \mathbb{R} \), as the optimal price support “breaks” to the entire real line immediately.\(^{33}\)

\(^{33}\)A setup in which the state is drawn from a distribution with bounded support yields a signal with a
Lastly, the signal endogenously allocates more attention to the regions of the state space with the potential to generate larger losses from inaccuracy. Asymmetry in the objective function implies that more attention needs to be allocated to the steeper part of the objective, since that part generates larger losses from deviating from the full-information optimum. Furthermore, depending on the distribution of shocks, attention is allocated first to the areas with more mass, and negative excess kurtosis requires less attention in the tails.

Note: The panels plot the function $Z(q) - 1$ as the cost of information $\theta^p$ is reduced. The points of support are shown as multiples of $\overline{q}$, the price that would be charged under the single-price policy.

Figure 9: Growth of new mass points in the price distribution.

discrete support, regardless of the shape of the objective function, as discussed by Fix (1978), Matějka (2016) and Matějka & Sims (2010). The analysis in this paper is complementary to this work, in that I demonstrate how discreteness can arise in an infinite horizon model with Gaussian shocks.

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5  Implications

What does the theory imply for the responsiveness of prices to shocks, and how does this responsiveness change if the environment becomes more volatile? In this section, I address these questions, connecting the model’s micro predictions to implications for the dynamics of aggregate inflation.

5.1  Adjustment to Aggregate Shocks

Figure 10a shows how the MRP and SPP price indices respond to a contraction in aggregate nominal spending. Both series decline gradually, reflecting imprecision in pricing decisions. But MRP prices adjust faster. Since they face a higher idiosyncratic volatility, they acquire more information about market conditions and, as a result, they are also more responsive to the aggregate shock. This divergence is consistent with the patterns seen in the data during the Great Recession, when the MRP series adjusted prices more aggressively.

How much of the difference between the MRP and the SPP responses comes from the fact that MRP goods update their policies more frequently, and how much from the fact that they adjust prices between policy reviews? This split informs the question of the relevance of transitory price volatility for aggregate flexibility. The consensus that has emerged in the recent pricing literature is that such volatility does not meaningfully contribute to aggregate price flexibility. Consider filtering out the within-policy price volatility of the MRP series, and targeting only the frequency of policy reviews and the shift in prices across policies. The resulting impulse response function, labeled ‘Filtered’ in the figure, is initially less responsive than the benchmark MRP index. But over time, it reaches and then overshoots the MRP line. The area between the two lines shows the role that within-policy price adjustment plays in responding to the aggregate shock. This dimension of adjustment is an important source of flexibility on impact and soon after the shock is realized. Most MRP firms have not yet updated their policies, but they are getting signals that they should charge the lower prices on their menus. Since these signals are partially informative, the overall MRP price index falls more than the Filtered index. But eventually, this transitory volatility actually slows down adjustment. Even after updating their policies, MRP firms continue to make mistakes in their pricing, since their price signal is imperfect. Hence, transitory price volatility has subtle effects on aggregate flexibility, flattening the IRF, and hence changing both the impact response and its subsequent persistence. I conclude that getting a truly accurate picture of how the degree of flexibility evolves over time in response

\[ \sigma_\xi = 0.025 \]

This filtering out of transitory price changes requires a reparameterization of the MRP model to feature a lower volatility of idiosyncratic shocks. The cost of undertaking policy reviews is imperfect. Hence, transitory price volatility has subtle effects on aggregate flexibility, flattening the IRF, and hence changing both the impact response and its subsequent persistence. I conclude that getting a truly accurate picture of how the degree of flexibility evolves over time in response

\[ \kappa = 1.2. \]
Figure 10: Impulse response functions across model specifications

Note: Model results. Panel (a) shows the impulse response functions of the price index to a negative nominal demand shock for the baseline SPP and MRP series, as well as for three alternative parameterizations: ‘Filtered’ shows the response of the SPP model calibrated to match the frequency of policy reviews and the shift across policies seen in the MRP data; ‘Calvo-low’ is the response of the standard Calvo model calibrated to match these same statistics; and ‘Calvo-high’ is the response of the standard Calvo model calibrated to match the frequency and size of all price changes in the MRP data. In all cases the MRP statistics are for the non-price discrimination series. Panel (b) shows the impulse response functions of the price index to the same shock in a low versus high volatility environment, for both the SPP and MRP models.

to shocks seems to require getting the dynamics of transitory price volatility right.

To put in context the responsiveness to shocks of the information-constrained firms, I consider some alternative parameterizations of the standard single-price Calvo model. First, consider a Calvo model calibrated to match the MRP frequency of policy reviews and shift in prices across policies. The resulting impulse response function is labeled ‘Calvo - low’ in the figure. The area between this line and the ‘Filtered’ line shows that the review decision of the information-constrained firm is moderately state-dependent. Alternatively, the impulse response function labeled ‘Calvo - high’ corresponds to a Calvo model calibrated to match the MRP frequency and size of all price changes. This line shows virtually no rigidity. The difference between the MRP line and this line underscores the weak relationship between the raw frequency of price changes and the degree of aggregate flexibility. This outcome reflects the noise in the firm’s pricing decisions and the constraint that having a sparse menu of prices places on firms’ ability to respond to shocks in real time.  

35For clarity, the figure omits the Calvo parameterization that matches the SPP frequency and size of policy adjustment. That response function is very similar to the SPP response function, highlighting the low degree of state dependence implied by the SPP hazard function. The fact that high price volatility does not necessarily imply fast adjustment to shocks has been discussed in prior work seeking to match patterns in the micro data, with prominent examples being Kehoe & Midrigan (2015) and Eichenbaum et al. (2011). However, this paper generates this result in the context of a model in which the firm chooses its policy...
Table VII: The Effects of An Increase in Fundamental Volatility

<table>
<thead>
<tr>
<th></th>
<th>MRP series</th>
<th>SPP series</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in frequency of policy reviews (%)</td>
<td>7.8</td>
<td>9.1</td>
</tr>
<tr>
<td>Change in shift across policies (%)</td>
<td>6.6</td>
<td>4.3</td>
</tr>
<tr>
<td>Change in frequency of price changes within (%)</td>
<td>3.0</td>
<td></td>
</tr>
<tr>
<td>Change in size of price changes within (%)</td>
<td>1.1</td>
<td></td>
</tr>
<tr>
<td>Change in total spending on information (%)</td>
<td>10.3</td>
<td>10.8</td>
</tr>
<tr>
<td>Change in profits relative to FI (ex-info) (%)</td>
<td>-0.7</td>
<td>-0.8</td>
</tr>
<tr>
<td>Change in average prices charged (%)</td>
<td>0.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Note: Model results. The table shows changes in key statistics as a result of a 10% increase in volatility relative to the baseline parameterizations.

5.2 The Relationship between Volatility and Inflation

Variations in the volatility of fundamental shocks have become of increasing interest in light of the large volatility in outcomes experienced during the Great Recession. The model makes strong predictions about how volatility affects pricing policies, the aggregate price level, and its responsiveness to shocks. Table VII summarizes with a numerical illustration how the MRP and SPP policies change. Higher volatility increases the losses from having imprecise information about market conditions. As a result, it affects both the firm’s review policy and its pricing policy. In a more volatile environment, spending increases on all ways of acquiring information to offset the negative effects of facing a more volatile environment. The increased uncertainty results in a large increase in the frequency of policy reviews. Conversely, the within-policy frequency and size of price changes do not change significantly. These patterns are consistent with the changes in policies that took place in the data during the Great Recession. One area where the model does not match the data concerns the shift in prices across policies. In the data, the size of the shift does not meaningfully change, whereas in the model part of the adjustment is reflected in higher shifts across policies, for both SPP and MRP series. Lastly, although the firms respond by acquiring more information, this is not enough to completely offset the negative expected effects of higher volatility, and as an additional precautionary measure, the price level also rises by half a percent.

The Great Recession was an episode market by low aggregate demand as well as heightened volatility. These forces push the firm in different directions: on the one hand, low optimally, thereby endogenously generating the price plans postulated by Eichenbaum et al. (2011).
demand pushes the firm to reduce its prices; on the other hand, higher volatility requires setting higher prices. This tension can rationalize why inflation did not fall more during the Crisis. At the same time, it has implications for the effectiveness of monetary policy in combatting the recession. Consider the IRFs of prices to a negative demand shock when volatility is 10% higher. The model predicts that the degree of price flexibility is similar in the two economies, for both SPP and MRP series, as shown in Figure 10b. This reflects the endogenous response of information acquisition. Faced with a more uncertain environment, firms increase their information acquisition just enough to offset the higher volatility. These results contrast existing theoretical results from the menu cost model literature, where aggregate flexibility increases when volatility rises. For example, Vavra (2014) shows this result in a menu cost model with stochastic volatility.\textsuperscript{36}

6 Conclusion

This paper argues that firms’ choice of how much information to acquire to set prices determines aggregate price dynamics through the patterns of pricing at the micro level, and through the large heterogeneity in pricing policies across firms. Information frictions generate coarse, volatile prices that quantitatively match the patterns of price setting seen at the product level in micro data. These prices respond slowly to shocks, even though they change often. The transitory price volatility seen in the data affects the response of the price index to aggregate shocks, both in terms of the magnitude of the effect on impact and in terms of its sluggishness, though the effect is fairly modest. Finally, an increase in volatility results in a precautionary overpricing, as firms seek to protect themselves against the losses from underpricing in a more volatile environment. This rigidity in the face of a risky environment implies high monetary policy effectiveness in uncertain times. I leave for future work the question of whether cyclicalitiy in the acquisition of information can further dampen the dynamics of inflation in response to large shocks, such as the Great Recession.

\textsuperscript{36}The firm’s ability to resolve the increased uncertainty depends on the cost function for information. In keeping with the existing rational inattention literature, I have assumed that this cost is linear in entropy reduction, but recent experimental evidence (Dean & Neligh (2017)) that the cost function for information processing might not be linear in entropy reduction. I leave this for future work.
References


