Journal of Monetary Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jmoneco

Price dispersion and inflation: New facts and theoretical implications[☆]

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A R T I C L E I N F O

Article history:
Received 21 January 2016
Revised 12 March 2019
Accepted 19 March 2019
Available online xxx

JEL classification:
E31
E37
E40
E52
E58

Keywords:
Inflation
Price dispersion
Sales
Sticky prices
Welfare

A B S T R A C T

In workhorse macroeconomic models, price dispersion is a central determinant of welfare, the cost of business cycles, optimal inflation, and the tradeoff between inflation and output stability. While price dispersion increases with inflation in the models, this relationship is negative in the data—due to sales prices. The comovement of price dispersion and inflation for *regular* prices is positive. A model with sales can quantitatively match the comovement in the data, whereas a range of similar models without sales cannot, even for regular prices. These findings have important implications for welfare calculations, optimal inflation, and the effects of monetary shocks.

1. Introduction

The dispersion of prices for homogenous products is a salient feature of micro pricing data. What determines the level and time variation of price dispersion and what does it mean for aggregate analyses? In workhorse macroeconomic models (e.g., Christiano et al., 2005; Smets and Wouters, 2007), inflation is often perceived as an important source of price dispersion. The relation between inflation and price dispersion has significant implications for the dynamic properties of aggregate variables, welfare calculations, and the design of optimal policy.[1] However, different macroeconomic models make conflict-

☆ For detailed comments and suggestions, I thank Urban Jermann (Editor), the associate editor, and the referee, as well as Vladimir Asriyan, Olivier Coibion, Benjamin Faber, Pierre-Olivier Gourinchas, Erik Hurst, Amir Kermani, John Leahy, Maurice Obstfeld, Demian Pouzo, Andrés Rodríguez-Clare, David Romer, and Yury Yatsynovich. I also thank seminar participants at UNC Chapel Hill, the Bank of Canada, the Federal Reserve Bank of Boston, Simon Fraser University, UI Urbana-Champaign, the Federal Reserve Bank of Cleveland, the College of William and Mary, Vanderbilt University, UC Irvine, UH Manoa, and UC Berkeley. I am especially grateful to Yuriy Gorodnichenko for his invaluable advice, guidance, and support during this project. I acknowledge support from the UC Berkeley Graduate Division Summer Grant, which I received while a graduate student there. I also thank Keith Barnatchez and Sandra Spirovska for research assistance and Suzanne Lorant for editorial assistance. The views expressed herein are those of the author and are not necessarily those of the Federal Reserve Bank of Boston or the Federal Reserve System.

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[1] For example, Woodford (2003, Ch. 6) shows a negative effect of price dispersion on welfare in New Keynesian models with time-dependent price rigidity. The welfare loss is also present in models with state-dependent pricing and monetary search (e.g., Benabou, 1992; Diamond, 1993; Head and Kumar, 2005).

https://doi.org/10.1016/j.jmoneco.2019.03.007

ing predictions about the level of price dispersion, as well as about its dynamic properties and sensitivity to inflation. In particular, a higher degree of price rigidity implies a stronger response of price dispersion to inflation. The nature of frictions is important, too: models with time-dependent frictions produce responses of price dispersion to inflation stronger than do models with state-dependent frictions. These contrasting predictions can help us to discriminate across alternative models, which, among other predictions, may substantially differ in their implications for the real effects of nominal shocks (i.e., employment and output responses to monetary policy).[2]

The relationship between price dispersion and inflation is especially important for determining the cost of inflation. Recently, there has been a renewed debate about raising the inflation target, due to secular stagnation and a decrease in the natural rate of interest. In the models employed to study the effects of such policies (e.g., Andrade et al., 2018), inflation reduces the probability of hitting the zero lower bound and allows the real rate to be more negative when the constraint is binding. Importantly, the cost of inflation in these models stems from price dispersion. If price dispersion responds strongly to inflation, raising the target is costly. In fact, many workhorse macro models produce a very large response of dispersion and, therefore, a relatively small optimal inflation rate (e.g., Coibion et al., 2012). However, if price dispersion does not react to inflation strongly, the cost of inflation is low, and the optimal inflation rate is relatively high (e.g., Blanco, 2016; Burstein and Hellwig, 2008). Hence, policymakers can increase welfare by raising the inflation target. Despite the strong link between inflation and price dispersion in these models, empirical evidence on this relationship is scarce.

In this paper, I examine the link between price dispersion and inflation in the data and in the models. First, I compute disaggregated inflation and price dispersion, using scanner data from U.S. grocery and drug stores during the period 2001–2011. These data allow me to measure price dispersion with the variation in prices for an identical product, instead of using indirect proxies such as relative price variability (RPV) or the dispersion of price changes. I then estimate the empirical comovement between price dispersion and inflation at the market–product category level. Disaggregated data enable me to pin down this relationship in the environment of low and stable aggregate inflation, since disaggregated inflation rates vary more than the aggregate inflation rate does. I then use my empirical estimates to discriminate between alternative models of price stickiness.

This paper presents two key findings. Firstly, many workhorse macroeconomic models make predictions about the relationship between inflation and price dispersion that are at odds with the data. A major element that leads to such discrepancy is temporary price changes, or sales. The data feature a weak, positive correlation between price dispersion and inflation when sales are excluded. While workhorse sticky-price models can also produce positive correlation, in the Calvo model without sales, this correlation is an order of magnitude larger than it is in the data, whereas in a standard state-dependent model it is significantly smaller than in the data. A hybrid model that combines various pricing frictions can quantitatively match the positive comovement, but only under counterfactual calibrations. None of these models, however, can match the negative correlation observed in the data with temporary sales. My second key finding is that the Calvo model with sales based on market segmentation can quantitatively match both the positive correlation in the data without sales and the negative correlation in the data with sales. While this model produces a relatively low welfare cost of inflation, it also implies a relatively high degree of monetary non-neutrality. In light of the key role that price dispersion plays in welfare analyses, my results suggest that workhorse models should take sales—which are often ignored even in medium-scale models—seriously.

Specifically, I document five major empirical results as follows: First, the dispersion of prices charged for exactly the same products by retailers within a narrow geographical area is pervasive and cannot be fully explained by transitive price discounts or by differences between store amenities. The average standard deviation of log prices is 9.5 log points. Even if temporary markdowns are excluded, price dispersion remains sizeable: 6.6 log points. Second, I document a negative correlation between price dispersion and inflation at the market-category level, an empirical regularity contrary to predictions of many macro models. Third, I show that this negative relationship is driven entirely by temporary sales: the correlation between inflation and the dispersion of *regular prices* is positive. Fourth, the negative comovement for posted prices and the positive comovement for regular prices are observed not only within market-categories but between them and also at the aggregate level—although the aggregate relationship is somewhat more difficult to pin down statistically. Finally, the state of local labor markets, measured with changes in employment, exhibits only weak comovement with price dispersion and does not alter its relationship with inflation.

I then focus on the implications of these empirical regularities for aggregate models. I find that the best match of empirical findings, for both posted and regular prices, comes from a Calvo model with sales, as in Guimaraes and Sheedy (2011), calibrated to match the observed frequency of sales. In this model, sales enable additional price flexibility that does not interfere with the frequency of regular price changes. Without sales, the Calvo model overstates the comovement of price dispersion with inflation by a factor of 15, while the fixed menu cost (FMC) model (Golosov and Lucas, 2007) understates it by a factor of 4. Intuitively, in time-dependent pricing models, most firms do not change their prices in response to an inflationary shock, while a small fraction of firms may change their prices significantly, thereby yielding a strong response of price dispersion and a small response of inflation. In contrast, in state-dependent pricing models, an inflationary shock moves the firms outside the *Ss* bounds, forcing them to reset their prices and thereby inducing a strong impact on inflation

[2] In particular, in models with time-dependent pricing (e.g., Calvo, 1983), monetary shocks have a nontrivial effect on real variables, whereas in state-dependent models with fixed menu costs (e.g., Golosov and Lucas, 2007), they do not.

and a weak impact on price dispersion. In fact, if menu cost is small, price dispersion may even decrease. The finding that a model with sales matches the properties of regular prices better than a similar model without sales implies that sales have an important interaction with regular prices that is lost when sales are omitted.

To examine the relative role of different pricing frictions, I turn to the smoothly state-dependent pricing (SSDP) model of Costain and Nakov (2011a,b). This model combines state-dependent frictions with time-dependent frictions and is especially useful for my exercise, not only because it produces aggregate dynamics similar to those in other hybrid models (e.g., Dotsey et al., 1999; Woodford, 2009), but because it obtains the purely time- and state-dependent models as limiting cases. The SSDP model comes closer to matching the comovement for regular prices in the data, but, to perform as well as does the model with sales, it requires parameterization inconsistent with other empirical evidence on price-setting. In particular, it requires a higher degree of state-dependence than the one implied by the distribution of price changes.

My results suggest that papers that compute welfare in New Keynesian models (e.g., Coibion et al., 2012) should be more careful about choosing the right measure of price dispersion, because the degree of price dispersion and its comovement with inflation observed in the data are inconsistent with the Calvo model without sales. Because price dispersion affects not only the level of steady-state welfare and the cost of business cycles but the shape of their relationships with trend inflation, using the data-driven measure changes the optimal inflation rate. In my simulations of the Coibion et al. model, the cost of business cycles increases by 40% and the optimal inflation rate decreases by 0.3 percentage points when the level of price dispersion and its sensitivity to inflation are taken from the data.

Overall, my analysis is consistent with the implication of Guimaraes and Sheedy (2011) and Kehoe and Midrigan (2015) that the shape of output responses to monetary shocks in models with sales are similar to that in the corresponding models without sales, even though the models without sales cannot fully match the micro price dynamics observed in the data. If the size of the sales sector is relatively large, however, quantitatively important differences between the models with and without sales exist: When the sales model is calibrated to match the sales sector in the scanner data, the output responses are 20% to 25% smaller than in the model without sales. Hence, my findings also support the literature—in particular, on recent inflation dynamics (e.g., Stevens, 2019)—advocating a more prominent role for sales in macro models.

This paper is closely related to Nakamura et al. (2018), who study the cost of inflation during the Great Inflation of the late 1970s and early ’80s. This paper, instead, focuses on a recent period of low-to-moderate inflation, which is more similar to the economic environment of today. The cost of inflation could differ between such environments, because—as Gagnon (2009) and Alvarez et al. (2019), among others, find in international data—when inflation is high, firms update their prices more often. Thus, it is important to understand the aggregate properties of price dispersion both when inflation is high and when it is low. I extend the analysis in Nakamura et al. further by employing the richness of scanner data, which (1) enable me to measure price dispersion for the same products directly and (2) provide a cross-sectional dimension that helps to overcome insufficient variability in aggregate inflation during this period. As both papers find that the mechanism behind the cost of inflation in workhorse models is likely incomplete, I also examine mechanisms that can bring these models closer to the data.

The studies of price dispersion and inflation include, among others, Van Hoomissen (1988) and Lach and Tsiddon (1992). Due to data availability, these two studies focus on the dispersion of *price changes*. Similarly, many subsequent studies focus on RPV, measured with a standard deviation of inflation rates across sectors (e.g., Choi, 2010; Debelle and Lamont, 1997; Grier and Perry, 1996; Konieczny and Skrzypacz, 2005; Silver and Ioannidis, 2001). Most of these studies find a mildly positive or no relationship between inflation and RPV. In contrast, Reinsdorf (1994) measures price dispersion directly and finds a negative relationship. Yet, his data are limited to nine large metropolitan areas and a relatively short period in the early ’80s.

This paper also contributes to several other strands of literature. On the empirical front, it is related to papers on price dispersion in micro pricing data (e.g., Kaplan and Menzio, 2015; Lach, 2002; Pratt et al., 1979; Sorensen, 2000). While many of those papers focus on the level of price dispersion, this paper also studies its dynamic properties. Next, this paper contributes to the empirical literature on aggregate price flexibility (e.g., Coibion et al., 2015; Kryvtsov and Vincent, 2014; Vavra, 2014), exploiting cross-sectional variation, which has received much attention recently (e.g., Beraja et al., 2016). On the theory front, it contributes to the literature analyzing pricing frictions in macro models (e.g., Alvarez and Lippi, 2014; Benabou, 1988; Caplin and Leahy, 1997; Head et al., 2012; Midrigan, 2011; Sheshinski and Weiss, 1977), by introducing a new testable prediction and using it to discriminate between models.

The paper proceeds as follows: Section 2 describes the data and measurement. Section 3 quantifies price dispersion in the data. Section 4 presents the empirical strategy and results. Section 5 shows that a model with sales can match the empirical comovement of inflation and price dispersion, while Section 6 shows that models without sales are at odds with the data. Section 7 discusses implications for welfare and monetary policy. Section 8 concludes.

2. Data and measurement

I use scanner data provided by IRI, a market research company.[3] The data contain units and total sales of consumer goods at the Universal Product Code (UPC) level and weekly frequency across U.S. grocery and drug stores during the period

[3] I would like to thank IRI for making the data available. All estimates and analysis in this paper, based on data provided by IRI, are by the author and not by IRI. A detailed data description is provided in Bronnenberg et al. (2008) and Kruger and Pagni (2008).

2001–2011. The dataset covers 50 geographical markets, most of which correspond to a single Metropolitan Statistical Area, and 31 product categories, comprising mostly food and personal-care products. About three-quarters of retailers are grocery stores, and the rest are drug stores. This sector covers 10% to 15% of the U.S. economy. I compute the price as a unit value. Information whether a good was on sale is provided; however, no cost information is available. All private-label UPC are masked and therefore excluded from the calculations.

I measure price dispersion for a given product with a standard deviation of log prices across stores in a given market. This measure is motivated by sticky-price models and is standard in the empirical literature (e.g., Gorodnichenko et al., 2018). Specifically, let P_{ist} be the price of product $i \in \mathcal{G}_c$ in store $s \in \mathcal{S}_m$ and month $t \in \mathcal{T}_y$, where $\mathcal{G}_c$ is the set of goods in product category c; $\mathcal{S}_m$ is the set of stores in geographical market m; and $\mathcal{T}_y$ are the months in calendar year y. Price dispersion $\tilde{\sigma}_{imt}$ is computed as the standard deviation of $\log P_{ist}$ across $s \in \mathcal{S}_m$.[4]

I aggregate this measure across products within a given category using annual shares of total sales within markets. That is, if S_{isy} denotes the total annual sales of a given product at the store level, and $\tilde{S}_{imy} \equiv \sum_{s \in \mathcal{S}_m} S_{isy}$ at the market level, the aggregation is as follows:

$$\sigma_{mct} = \frac{\sum_{i \in \mathcal{G}_c} \tilde{S}_{imy} \tilde{\sigma}_{imt}}{\sum_{i \in \mathcal{G}_c} \tilde{S}_{imy}}. \tag{1}$$

My empirical analysis is conducted at the market-category level, but one can use a similar strategy to aggregate price dispersion further to the market or national level.

Next, I construct disaggregated inflation rates using the enhanced Törnqvist index with annual sales as weights:

$$\pi_{mct} = \frac{\sum_{(i,s) \in \mathcal{G}_c \times \mathcal{S}_m} S_{isy} \log (P_{ist}/P_{is,t-1})}{\sum_{(i,s) \in \mathcal{G}_c \times \mathcal{S}_m} S_{isy}}. \tag{2}$$

This method is based on the aggregation of individual price changes, with weights analogous to those used for price dispersion. Therefore, the effect of a change in P_{ist} on price dispersion and inflation is not affected by differences in the aggregation procedures. This is important for the analysis of price-setting mechanisms. The aggregate inflation rate computed using this method is highly correlated with the consumer-price inflation for food obtained from the U.S. Bureau of Labor Statistics (BLS): the correlation coefficient is about 0.8. Online Appendix A provides further details on the disaggregated inflation measure and its robustness to alternative aggregation procedures. For ease of interpretation, I use annualized rates.

Finally, I use the sales flag provided with the data. This indicator is based on a proprietary algorithm that identifies a temporary price reduction of 5% or more, and is comparable to popular alternatives (e.g., Kehoe and Midrigan, 2015; Nakamura and Steinsson, 2008). About 20% of products were on sale in a given week, with an average discount of about 25%.

3. Price dispersion

The average dispersion of prices is reported in column (1) of Table 1. I compute it separately for posted and regular prices, as well as for the sample before and after the onset of the Great Recession. The weekly price dispersion during the entire period is 9.5 log points. Approximately one-third of this measure is due to temporary price reductions: the average dispersion of regular prices is 6.6 log points. Thus, price dispersion is not entirely due to transitory changes (sales). This conclusion holds also when price dispersion is measured across chains (column 2).[5] These estimates are smaller than in Kaplan and Menzio (2015), likely due to differences in the sample composition and data collection (e.g., 34% of their data come from warehouse clubs, discount stores, and dollar stores).

Table 1
Standard deviation of log prices.

	Across stores (1)	Across chains (2)	Net of fixed effects (3)	Grocery stores (4)	Drug stores (5)	Food (6)	Bev. (7)	Beauty (8)	Stockpiling High (9)	Stockpiling Low (10)
Posted price	9.5	12.7	8.6	8.8	9.8	9.7	9.8	9.1	9.1	9.4
2001–2007	9.7	12.4	8.7	9.2	9.5	10.0	10.2	9.2	9.1	9.9
2008–2011	9.1	13.1	8.4	8.1	10.3	9.2	9.1	8.9	9.1	8.6
Regular price	6.6	9.5	4.9	6.0	6.0	6.4	6.6	6.9	6.9	6.2
2001–2007	6.7	9.1	4.8	6.1	5.9	6.4	6.8	7.0	6.9	6.4
2008–2011	6.5	10.3	5.0	5.6	6.3	6.3	6.3	6.8	6.9	5.9

Notes: The table reports the average standard deviation of log prices charged for the same products by retailers in a given market and week. In column (3), fixed effects are removed as in Eq. (3).

[4] In practice, I compute price dispersion at the weekly frequency and then obtain $\tilde{\sigma}_{imt}$ as the average across weeks. I also use unit-weighted standard deviations and obtain similar results.

[5] The chain price is defined as the average log price across stores in a given chain, with the stores' annual sales used as weights.

I also document a decrease in price dispersion across stores between the 2001–2007 and 2008–2011 periods: from 9.7 to 9.1 log points for posted prices and from 6.7 to 6.5 log points for regular prices. While cross-store price dispersion fell during the Great Recession, cross-chain price dispersion rose. A decrease in price dispersion across stores and an increase across chains are consistent with significant mergers and acquisitions in the sector taking place after 2007. They may also result from market segmentation (e.g., see Chevalier and Kashyap, 2019; Kaplan et al., 2016) and from increasing search intensity during the Great Recession.

Price dispersion cannot be fully explained by good, store, or time fixed effects. I account for these effects, as well as time-varying store effects and good-store effects, by estimating the equation

$$\log P_{ist} = \alpha_i + \gamma_s + \delta_t + \zeta_{st} + \eta_{is} + \varepsilon_{ist} \tag{3}$$

and computing the dispersion of ε_{ist}. Hence, this procedure removes the variation due to the stores that charge consistently higher prices, for a given product, than do other stores, as well as due to the stores that are relatively expensive, for all products, in a given month. These effects might be due, among other things, to chain effects, the store location and size, and differences in store amenities and marginal costs. I estimate that these effects account for only 10% of the standard deviation of posted prices and for 25% of the standard deviation of regular prices (column 3). Hence, a substantial portion of price dispersion remains unexplained, pointing to welfare loss due to misallocation.[6]

Microeconomic factors such as the elasticity of demand, market power, product characteristics, and store-specific costs are known to affect the degree of price dispersion (e.g., Gorodnichenko et al., 2018). I find, however, that such factors have a limited effect on its aggregate properties. In particular, the degree of price dispersion across drug stores is similar to that across grocery stores (columns 4 and 5), despite the fact that drug stores charge a convenience premium, indicating greater market power. The level of price dispersion is also roughly similar for food, for beverages, and for personal-care items (columns 6 through 8)—all of which differ in the demand elasticity and the degree of storability—and across the categories of goods that differ in the perceived degree to which they can be stockpiled (columns 9 and 10), defined as in Bronnenberg et al. (2008). These findings suggest that inventory management, often emphasized in the literature (e.g., Anderson et al., 2017; Kryvtsov and Midrigan, 2013), plays only a limited role.

4. Comovement with inflation

As price dispersion is unlikely to completely stem from micro factors examined in the previous section, can it be explained by aggregate variables? To answer this question, I focus on comovement with inflation, emphasized by aggregate models.

4.1. Econometric strategy

I estimate the comovement of price dispersion and inflation at the market–product category level. This specification is supported by multisector models with sticky prices (e.g., Carvalho, 2006). Panel data also enable me to account for the correlation structure of residuals, trends in variables, and potential time breaks. In particular, I estimate the following specification:

$$\sigma_{mct} = \beta\,\pi_{mct} + \gamma_{mc} + \tau_t + \boldsymbol{\delta}'\boldsymbol{z}_{mct} + \varepsilon_{mct}, \tag{4}$$

where σ_{mct} is price dispersion across stores in market m, category c, and month t; π_{mct} is the corresponding disaggregated inflation rate; γ_{mc} and τ_t are market-category and time fixed effects, respectively; $\boldsymbol{z}_{mct}$ is a vector of control variables including local labor-market characteristics or lags of π and σ; and ε_{mct} is the error term. All variables are seasonally adjusted using the U.S. Census X-12-ARIMA filter. Standard errors are computed as in Driscoll and Kraay (1998), to account for serial correlation and correlation across groups.

Macroeconomic models often give rise to a nonlinear relationship between inflation and price dispersion, but numerous tests suggest that a parsimonious linear specification provides a useful summary of the comovement (Online Appendix C). This functional form is also supported by the data (e.g., see Fig. E.1 in Online Appendix E). The linearity implies that the slope coefficient β is a natural measure of comovement, which should not be interpreted in a causal way since both inflation and price dispersion are endogenous variables. The identification of exogenous changes in inflation is beyond the scope of this paper.

4.2. Empirical estimates

Table 2 presents estimates of Eq. (4). The comovement of price dispersion and inflation is negative for posted prices (Panel A) and positive for regular prices (Panel B). Columns (1) through (3) show estimates for various combinations of fixed effects. Cross-sectional fixed effects control for heterogeneity across markets and product categories and allow us to focus on the comovement *within* a given market-category. Time fixed effects control for possible time trends. The baseline

[6] This conclusion holds even when I partial out store-good-year effects.

Table 2
Comovement of price dispersion and inflation in the data.

	Price dispersion					
	(1)	(2)	(3)[b]	(4)	(5)	(6)
Panel A: Posted prices						
Inflation	−0.057***	−0.026***	−0.022***	−0.043**	−0.022***	−0.023***
	(0.010)	(0.010)	(0.008)	(0.019)	(0.008)	(0.008)
Unemployment rate					−0.000	
					(0.000)	
Employment, log						0.025***
						(0.006)
Market–product category effects	N	Y	Y	Y	Y	Y
Time effects	N	N	Y	Y	Y	Y
Lags	N	N	N	Y	N	N
Observations	202,788	202,788	202,788	182,664	202,788	202,788
Panel B: Regular prices						
Inflation	0.050***	0.029***	0.026***	0.052***	0.026***	0.026***
	(0.009)	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)
Unemployment rate					0.001*	
					(0.000)	
Employment, log						−0.000
						(0.004)
Market–product category effects	N	Y	Y	Y	Y	Y
Time effects	N	N	Y	Y	Y	Y
Lags	N	N	N	Y	N	N
Observations	202,264	202,264	202,264	182,192	202,264	202,264

Notes: This tables presents estimates of Eq. (4). The estimation sample is 2001–2011. The series are seasonally adjusted, using the X-12-ARIMA filter. Driscoll and Kraay (1998) standard errors with serial correlation of up to 12 lags are in parentheses. Controls in column (4) include 12 lags of the change in inflation and price dispersion.
[b]denotes the baseline specification; *,**,*** denote the 10%, 5%, and 1% significance levels, respectively.

estimates used for comparison with models include both types (column 3). A 1 percentage point increase in the annualized inflation rate is associated with a 0.022 log point decrease in price dispersion. Once sales are excluded, a 1 percentage point increase in the annualized inflation rate corresponds to a 0.026 log point increase in price dispersion.

I examine sensitivity of the baseline estimates to additional controls. I control for predetermined trends in the variables, using 12 lags of changes in inflation and price dispersion, and find qualitatively similar results (column 4). Next, I control for local business-cycle conditions, using the local unemployment rate and total employment. The former accounts for the flows between employment and unemployment, while the latter also includes migration and the flows out of the labor force, which were particularly important during the Great Recession. I include the two measures separately to avoid collinearity. The slope of the local unemployment rate is insignificant for posted prices and significant, but quantitatively small, for regular prices (column 5). The slope of log employment is positive for posted prices (column 6). Importantly, controlling for the state of local labor markets does not alter the estimates of the comovement of price dispersion and inflation.

Due to space constraints, many other robustness checks are relegated to Online Appendix E. For example, measurement choices related to data aggregation and composition do not have qualitatively relevant effects (Table E.2). Next, as Nakamura et al. (2018) use the absolute size of price changes as a measure of dispersion, I examine that measure's comovement with inflation. I confirm their finding that there is little response of the size of price changes to inflation: Once the baseline sets of fixed effects are included, the coefficients are small and insignificant (Table E.3, column 3). Hence, this exercise suggests that the price dispersion measured directly from the distribution of product prices has properties different from those of proxies motivated by the models.[7] Next, results for inflation measured with the Laspeyres index, as in Beraja et al. (2016), can be found in Table E.4. The estimates are quantitatively similar to the baseline for regular prices; for posted prices, the correlation is still negative but significantly less pronounced. This discrepancy highlights the importance of applying the same aggregation scheme to both inflation and price dispersion. As further checks, I report estimates of weighted regressions in Table E.7 and estimates of the comovement *between* markets and categories in Table E.8. Fig. E.2 shows that the comovement results hold both in cross-sectional and in time-series analyses. In addition, I do not find that instances of negative inflation affect its relationship with price dispersion in a material way (Table E.10).

To summarize, the data reveal robust comovement of price dispersion and inflation, negative for posted prices and positive for regular prices. These results hold across a range of econometric specifications, sample periods, aggregation procedures, and measures. Aggregate variables other than inflation do not seem to have a strong association with price dispersion or to alter its relationship with inflation. Are these findings consistent with aggregate models? This question is addressed next.

[7] Nakamura et al. (2018) emphasize product heterogeneity observed within a narrow category (e.g., organic vs. regular milk) as a major obstacle to measuring price dispersion directly. In scanner data, however, we can measure price dispersion for *exactly the same* product (e.g., half-gallon of organic, low-fat milk of a given brand).

5. A model with sticky prices and flexible sales

In this section, I show that a workhorse macroeconomic model with Calvo pricing and sales can match the empirical comovement of price dispersion and inflation. Sales are modeled as in Guimaraes and Sheedy (2011, henceforth, GS). Following their approach, the sales sector is introduced into the general equilibrium model of Erceg et al. (2000). Since this model is well documented, here I overview only the key mechanism that generates sales. I refer the reader to the original publication for full details.

In the GS model, a variety of product brands is embedded into a variety of product types, with each household having a preferred brand for some products but perceiving brands of other products as close substitutes. Specifically, let $\mathscr{T}$ be a measure-one continuum of product types τ, and let $\mathscr{B}$ be a measure-one continuum of brands b for each product $\tau \in \mathscr{T}$. For a given household and a set of goods $\Lambda \subset \mathscr{T}$ of measure $\lambda \in (0, 1)$, the household is *loyal* to a particular brand of each product $\mathcal{B}(\tau) \in \mathscr{B},\ \tau \in \Lambda$. For all other goods $\tau \in \mathscr{T} \setminus \Lambda$, the household is a *bargain hunter* (i.e., the brands are highly substitutable). The Dixit–Stiglitz consumption aggregator over products and brands is as follows:

$$C = \left(\int_{\Lambda} c(\tau, \mathcal{B}(\tau))^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}\tau + \int_{\mathscr{T} \setminus \Lambda} \left(\int_{\mathscr{B}} c(\tau, b)^{\frac{\eta-1}{\eta}} \mathrm{d}b \right)^{\frac{\eta(\epsilon-1)}{\epsilon(\eta-1)}} \mathrm{d}\tau \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{5}$$

where $c(\tau, b)$ is consumption of brand b of product τ; ϵ is the elasticity of substitution between product types; and η is the elasticity of substitution between brands of the same product type for a bargain hunter, with $\eta > \epsilon$. The elasticity of substitution across brands for a loyal customer is zero. The continuum of households with heterogenous preferences over the brands to which they are loyal ensures that households' idiosyncratic preferences do not matter for aggregate consumption of each product and brand. The relative size of the sales sector is $\sigma \in (0, 1]$.

For each firm producing a given brand, the equilibrium price is a mixed strategy between a regular price and a sales price. The regular price allows the firm to extract consumer surplus from loyal customers, whereas sales are conducted to attract bargain hunters. Because firms compete for the same pool of bargain hunters, sales are strategic substitutes. That is, firms have more incentives to have sales when other firms' products are not on sale. Regular prices are sticky à la Calvo, while sales are flexible: given the sticky regular price, a firm chooses the frequency and size of sales.

In this model, the relation between inflation and regular-price dispersion is positive since it is driven largely by the Calvo process. As in the standard model, an increase in inflation implies that the firms that do not change their regular price fall further behind from the firms that do and from the aggregate price level. However, the relation between inflation and posted-price dispersion is more nuanced. With sticky prices and flexible sales, the firms whose regular price falls behind the optimal reset price have an incentive to increase the frequency of sales. With more firms having sales, price dispersion across firms may decrease. Thus, the model with sales has a potential to explain the negative comovement between inflation and price dispersion of posted prices observed in the data. Whether the comovement is negative under a plausible parameterization is a quantitative question.

Note that the sensitivity of observed regular-price dispersion to inflation is smaller than in the model without sales because firms lagging behind the optimal price are more likely to have sales. Market segmentation lies at the heart of this selection mechanism: When the relative price of selling to loyal customers, due to regular-price stickiness, falls behind the optimum, the relative price of selling to bargain hunters remains to be chosen optimally, and therefore the market of bargain hunters becomes relatively more attractive than the market of loyals precisely for the firms that have not adjusted their regular prices in a long time. This selection mechanism—*who* chooses to conduct sales for bargain hunters and who chooses not to—gives the sales model a state-dependent flavor.

Following Guimaraes and Sheedy (2011), I calibrate the sales sector to match the average frequency and size of sales in my data. Because the frequency of sales is higher in the scanner data than in the BLS data (20% and 7%, respectively), the calibrated elasticity of substitution across product types ϵ is slightly higher than in that paper (3.15 vs. 3.01), and the elasticity of substitution across brands η is somewhat lower (16.45 vs. 19.70). Note that the sales sector does not affect the frequency of price changes for regular prices, which is exogenous. I use the same macro parameters as in the GS paper, which also relies on the previous literature for calibration. Table 3 summarizes parameter values, using exactly the same notation as in the original paper.

I then simulate the paths for price dispersion and inflation in this model and estimate a time-series analog of Eq. (4).[8] The results are presented in Table 4. Under the baseline calibration, the model comes reasonably close to matching the comovement both for posted prices and for regular prices—not only qualitatively but quantitatively. Although this result holds for specific parameter values, the direction of the effect is stable for a wide range of parameters. There are two interesting observations, however. First, the comovement is sensitive to the degree of price stickiness but not of wage stickiness. Intuitively, price stickiness is directly related to the benefits from sales; if regular prices are flexible, sales provide little advantage over regular price changes. Second, if monetary shocks are volatile, the relationship between price dispersion and inflation is positive for posted prices, too. This happens because the absolute size of price changes by the adjusters is

[8] To account for seasonal adjustment in the data, I run the MA(12) filter on both series. I also estimate the same regressions without the filter and obtain similar results.

Table 3
Sales-model calibration.

	GS notation (1)	Value (2)
Sales sector		
Elasticity of substitution between product types	ϵ	3.15
Elasticity of substitution between brands	η	16.45
Fraction of loyals	λ	0.735
Size of sales sector	σ	0.255
Nonsales parameters		
Discount factor	β	$1.03^{-\frac{1}{12}}$
Intertemporal elasticity of substitution	θ_c	0.333
Frisch elasticity of labor supply	θ_h	0.7
Elasticity of output to hours	α	0.667
Elasticity of substitution between differentiated labor units	ς	20
Price stickiness	ϕ_p	0.889
Wage stickiness	ϕ_w	0.889
Monetary-policy shocks		
Persistence	$\mathfrak{p}$	0.536
Volatility	Ω_m	0.02

Notes: The model is calibrated as in Guimaraes and Sheedy (2011), except for two parameters that determine the frequency and size of sales. In the GS original calibration, $\epsilon = 3.01$ and $\eta = 19.70$, leading to a significantly lower frequency of sales than the one observed in the scanner data.

Table 4
Price dispersion–inflation comovement in the sales model.

		Alternate value (1)	Baseline value (2)	Regular prices (3)	Posted prices (4)
Data				0.026	−0.022
Baseline calibration				0.033	−0.033
Sensitivity to parameter values:					
Price stickiness	ϕ_p	0.650	0.889	0.001	−0.008
Wage stickiness	ϕ_w	0.650	0.889	0.029	−0.037
Monetary-shock persistence	$\mathfrak{p}$	0	0.536	0.033	−0.035
Monetary-shock volatility	Ω_m	0.20	0.02	0.182	0.056
Elasticity of substitution between product types	ϵ	3.01	3.15	0.012	−0.127
Elasticity of substitution between brands	η	19.70	16.45	0.002	−0.138
Fraction of loyals	λ	0.950	0.735	0.014	−0.110
Size of sales sector	σ	1	0.255	0.027	−0.019
Calibration to infrequent sales:					
$\epsilon = 3.01,\ \eta = 19.70$ (GS)				−0.000	−0.135
and $\sigma = 1$				−0.003	−0.095
and $\Omega_m = 0.20$				0.047	−0.022

Notes: This table presents the comovement of price dispersion and inflation for regular prices (column 3) and posted prices (column 4) in the Guimaraes and Sheedy (2011) model. The alternate parameter values used in the sensitivity exercises are in column (1), along with the corresponding baseline values in column (2).

increasing with inflation, leading to more dispersion of regular prices. If the volatility is sufficiently large, this effect can dominate the effect of sales, working in the opposite direction.

6. Sales and state-dependent pricing

In this section, I examine sticky-price models that do not allow for sales. I focus on two questions: (1) Can a Calvo model without sales match the regular-price comovement for a plausible degree of aggregate price rigidity? (2) Can a model with state-dependent pricing match the data under a plausible calibration? To address these questions in a unified framework, I present simulations of a hybrid model that allows for time- and state-dependent frictions: the SSDP model. Since this model is analyzed extensively in Costain and Nakov (2011a,b), I relegate the model details to Online Appendix G.

To provide intuition on the key mechanism, I overview the price-adjustment process. Under purely time-dependent pricing, such as in Calvo (1983), the probability of price-adjustment $\lambda(\cdot)$ is constant and independent of the loss from inaction L: $\lambda(L) = \bar{\lambda} \in (0, 1)$. In the FMC model, this probability is characterized by the indicator function of the loss being above some fixed cost $\alpha > 0$: $\lambda(L) = \mathbb{1}\{L > \alpha\}$. Under SSDP, $\lambda(L)$ is a smooth, increasing function, such that $\lim_{L\to 0} \lambda(L) = 0$,

Table 5
Comovement coefficient across the models.

	Regular prices (1)	Posted prices (2)
Data	0.026	−0.022
Calvo with sales	0.033	−0.033
Calvo without sales	0.385	–
Fixed menu cost	0.006	–
Smoothly state-dependent pricing	0.137	–

Notes: This table compares the comovement of price dispersion and inflation in the Calvo model with sales (Guimaraes and Sheedy, 2011) with that in the models without sales. The Calvo model without sales overstates the comovement for regular prices, whereas the fixed menu cost model (Golosov and Lucas, 2007) understates it. The hybrid smoothly state-dependent pricing model (Costain and Nakov, 2011a) is qualitatively closer to the Calvo model without sales and also overstates the comovement.

$\lim_{L\to\infty}\lambda(L)=1$, and the first derivative $\lambda_L>0$. The following functional form satisfies these conditions:

$$\lambda(L)=\frac{\bar{\lambda}}{\bar{\lambda}+\left(1-\bar{\lambda}\right)\left(\frac{\alpha}{L}\right)^{\xi}}, \tag{6}$$

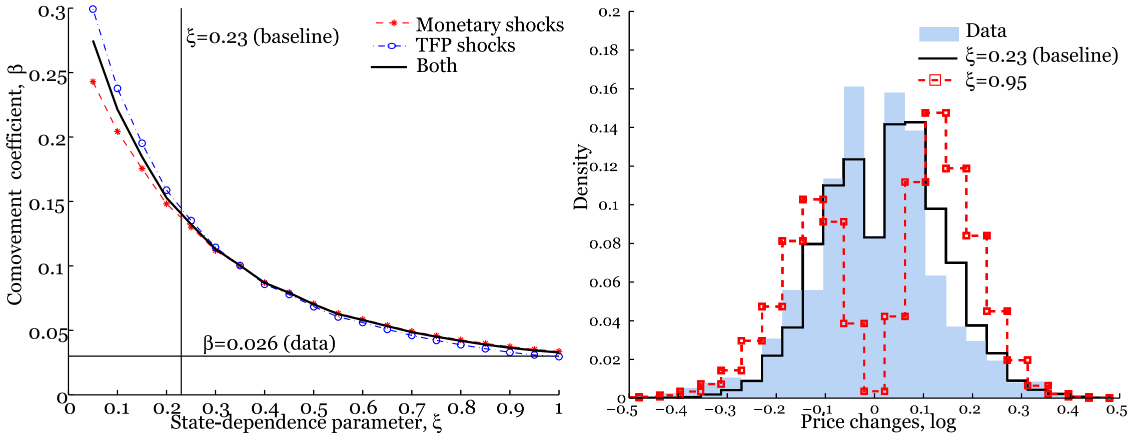
where $\xi>0$ controls for the degree of state-dependence, with larger ξ corresponding to more state-dependence. The SSDP model converges to the Calvo model as $\xi\to 0$ and to the FMC model as $\xi\to\infty$. This pricing assumption is embedded into a general equilibrium model similar to the one studied before, the details of which, including calibration, can be found in Online Appendix G.[9]

Table 5 compares the comovement of price dispersion and inflation in the SSDP model and the two limiting cases with that in the data. The comovement in the Calvo model without sales is about 15 times greater (for the baseline calibration) than in the data for regular prices, and the negative comovement for posted prices is elusive, even in alternative calibrations (see Online Appendix Table G.2). In the baseline FMC model without sales, the comovement coefficient is small: more than 4 times smaller than in the data. The SSDP model produces the comovement about 5 times greater than in the data, between those in the Calvo and FMC models. The Calvo model with sales performs better than any of these models without sales.

What is the role of pricing frictions in these results? In the standard Calvo model, the size of nominal shocks does not affect the number of firms that adjust their prices. If the frequency of price adjustment is small, few firms change their prices, with only a small effect on the aggregate price level. Still, firms that reset their prices change them proportionally to the shock, thereby increasing price dispersion. Hence, nominal shocks have a relatively small effect on inflation and a relatively large effect on price dispersion. As small changes in inflation are associated with large changes in price dispersion, the comovement coefficient is relatively large. To match the data, a larger fraction of firms would have to adjust their prices, to amplify the response of inflation and to dampen the response of price dispersion. In the FMC model, instead, the comovement is weak. Firms set their prices according to the *Ss* rule, with a strong selection effect: firms that are further away from the optimal price are more likely to adjust, with a relatively large effect on inflation and a relatively small effect on price dispersion. If the menu cost is very small, most firms adjust their prices to exactly the same price, and price dispersion may decrease.

The comovement in the SSDP model is in between those in the Calvo and FMC models and depends strongly on the smoothness parameter ξ. Under the baseline calibration, the comovement is larger than in the data, implying that, to match the data, the model should allow for more state-dependence (i.e., ξ should be larger). Since the baseline value of this parameter is estimated to match the empirical distribution of price changes (Costain and Nakov, 2011a), a larger ξ makes the distribution more like that in state-dependent models, with fewer small price changes. A practical question is whether the increase in ξ needed to match the data is sufficiently small not to affect the distribution of price changes. Fig. 1 suggests that this is not the case. Panel A shows the comovement of price dispersion and inflation for different values of ξ. To match the comovement, ξ should be set to approximately 0.95, above its baseline value of 0.23. Note that the nature of shocks in this model is not particularly important because the comovement is determined largely by the degree of aggregate price stickiness. Panel B compares the distribution of price changes under the two values of ξ with that in the data and shows that the distribution is bimodal under the larger ξ, with almost no price changes around zero. This discrepancy constitutes a major criticism of state-dependent models in the literature (e.g., Midrigan, 2011). Thus, plausibly calibrated models without sales do not match the comovement of price dispersion and inflation in the data, even if they allow for some state-dependence.

[9] Note that while the SSDP model features flexible wages, wage stickiness plays only a quantitatively minor role for the dynamics of price dispersion in the GS model. This discrepancy between the two models, therefore, is not substantial for the comovement.



Panel A: Comovement coefficient *Panel B: Distribution of price changes*

Fig. 1. State-dependence, comovement, and price changes. Panel A shows that, to match price-dispersion dynamics in the data, the smoothly state-dependent pricing model needs more state-dependence than in the baseline calibration. Panel B shows that such a degree of state-dependence implies a counterfactual distribution of price changes (cf. Costain and Nakov, 2011a, Fig. 1).

7. Implications for welfare and monetary policy

Why are price dispersion and its comovement with inflation important in practice? One reason is that this comovement is used for the calculations of welfare, the cost of business cycles, and the optimal inflation rate. The other reason is that the impulse-response functions of output to monetary shocks may differ across models, and therefore one can use the comovement to discriminate between models with different degrees of monetary non-neutrality. In this section, I quantify these effects.

7.1. Welfare cost of inflation

The welfare analysis is based on Coibion et al. (2012), who derive a microfounded welfare function in a Calvo model with trend inflation (and no sales). For zero trend inflation, the limiting case of this model is similar to Guimaraes and Sheedy (2011), with the size of the sales sector being zero, and to Costain and Nakov (2011a,b) with $\xi \to 0$. The advantage of studying this model is that, due to the lower-bound constraint, it gives rise to a nonzero optimal inflation target; thus, I can measure the effect of price dispersion on the optimal inflation rate.

The second-order approximation of the utility function is

$$U_t = \Theta_0 + \Theta_1 \mathbb{V}\mathrm{ar}\big(\hat{y}_t\big) + \Theta_2 \mathbb{V}\mathrm{ar}\big(\hat{\pi}_t\big) + \text{h.o.t.}, \tag{7}$$

where y is the output gap; π is inflation; $\Theta_i,\ i = 0, 1, 2,$ are functions of the model parameters; and h.o.t. stands for higher-order terms. Notation $\hat{x}$ represents the log-deviation of variable x from its steady-state. Price dispersion affects welfare through the steady-state channel (Θ_0) and through the variability of inflation (Θ_2). This functional form holds across a range of models, while the exact definitions of the parameters Θ are specific to the model. The first-order approximation of steady-state price dispersion gives rise to a linear relationship with steady-state inflation: $\bar{\sigma} \simeq \sqrt{\alpha}/(1-\alpha)\ \bar{\pi}$, where α is the Calvo parameter.

As the relationship between price dispersion and inflation in the model differs from that in the data, I compare welfare under the model-based first-order approximation and under the relationship estimated in the data: $\bar{\sigma}^{\text{data}} = \hat{\gamma} + \hat{\beta}\ \bar{\pi}$, where $\hat{\gamma}$ and $\hat{\beta}$ are the estimates from Section 4. The constant γ is added in order to match the level of price dispersion in the data when steady-state inflation in the model equals trend inflation observed in the data.[10] In comparison with the approximation used in the model, $\bar{\sigma}^{\text{data}} > \bar{\sigma}^{\text{model}}$ and $\beta^{\text{data}} \ll \beta^{\text{model}}$. Table 6 compares welfare U_t and the cost of business cycles, $\Theta_1 \mathbb{V}\mathrm{ar}\big(\hat{y}_t\big) + \Theta_2 \mathbb{V}\mathrm{ar}\big(\hat{\pi}_t\big)$, obtained using $\bar{\sigma}^{\text{data}}$ and $\bar{\sigma}^{\text{model}}$. There are large differences between the welfare estimates; the cost of business cycles is 40% larger than the one based on the model-based approximation (−0.007 vs. −0.005). As $\bar{\sigma}^{\text{data}} > \bar{\sigma}^{\text{model}}$, inflation is relatively more costly, and the optimal rate of inflation goes down from 1.3% to 1%.

This example suggests that the mismatch in the key relationship between inflation and price dispersion used to calculate welfare, its components, and the optimal inflation rate can have a quantitatively large effect on the calculations. Therefore, welfare calculations that rely on the relationship between inflation and price dispersion should be based on a model that matches it or, otherwise, should use a direct measure of price dispersion obtained from the data.

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[10] In the presence of time-invariant product-store effects, this measure of price dispersion may overstate the steady-steady welfare loss but not the cost of business cycles.

Please cite this article as: V. Sheremirov, Price dispersion and inflation: New facts and theoretical implications, Journal of Monetary Economics, https://doi.org/10.1016/j.jmoneco.2019.03.007

Table 6
Welfare cost of inflation.

		Data (1)	Calvo model (2)
Output-gap variability	(a)	−0.000	−0.000
Inflation variability	(b)	−0.007	−0.005
Cost of business cycle	$(c) = (a) + (b)$	−0.007	−0.005
Steady-state loss	(d)	−0.238	−0.009
Total welfare loss	$(e) = (c) + (d)$	−0.245	−0.014
Optimal inflation rate, %		1.0	1.3

Notes: This table compares the welfare cost of inflation based on price dispersion–inflation comovement in the data (column 1) with that based on the Calvo model without sales (column 2). The welfare function follows the derivations in Coibion et al. (2012).

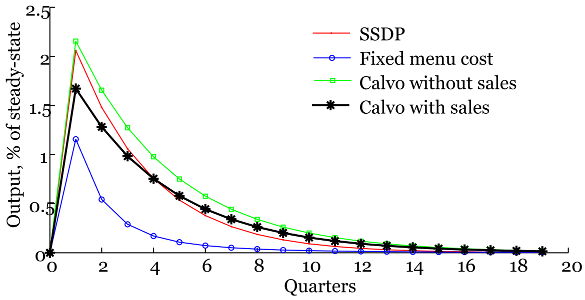

Fig. 2. Output response to monetary shocks. The shock is a 1 percentage point increase in money growth. To allow for comparison across the setups, the response in the Calvo model with sales is obtained by multiplying, at each horizon, the corresponding response in the Calvo model without sales, as in Costain and Nakov (2011a), by the ratio of the responses in the Guimaraes and Sheedy (2011) models with and without sales.

7.2. Output response to monetary shocks

I compare the output responses to monetary shocks between the Calvo, FMC, SSDP, and GS models. As the SSDP model encompasses the Calvo and FMC cases, the comparison of the first three models is studied extensively in Costain and Nakov (2011a). Therefore, the value-added of this exercise is in the comparison of the three models that do not allow for sales—and cannot match the comovement of price dispersion and inflation—with the Calvo model *with sales*.

To make sure that sales are the only difference between the models, I apply a scale adjustment to the GS model. To do this, I first generate output responses to a 1 percentage point increase in money-supply growth in the Guimaraes and Sheedy (2011) versions of the Calvo model with and without sales. For each time horizon, I compute the ratio of the responses in the two versions (i.e., by how much sales attenuate the output response). I then multiply these ratios by the responses, at the corresponding horizon, in the Calvo model without sales from the SSDP setup. The resulting series represents the output response to a monetary shock in the Calvo model with sales, set up as in Costain and Nakov (2011a).

As Fig. 2 demonstrates, the Calvo model with sales is characterized by a high degree of monetary non-neutrality, consistent with the results in the previous literature. Although sales add to aggregate price flexibility, resulting in a decrease of 20% to 25% in the output response, the persistence of the response is similar to that in the Calvo model without sales. The output response in the Calvo model with sales is smaller than in the SSDP model at short horizons but larger at longer horizons. I conclude that (1) the sales model that matches the properties of price dispersion in the data is close to workhorse models without sales featuring a significant degree of time-dependence; and (2) when the sales sector is large, the quantitative differences between the output responses in the models with and without sales can be important in practice.

8. Conclusion

Price dispersion is a central determinant of welfare, the cost of business cycles, the optimal rate of inflation, and the tradeoff between inflation and output stability. Many workhorse macroeconomic models give rise to dynamic properties of price dispersion that are inconsistent with the data. To get the models closer to the data, it is important to have a more realistic mechanism for the pricing decisions of firms. In particular, it is important to model a mechanism that gives rise to temporary price discounts. As this paper shows, a workhorse model that allows for sales matches price-dispersion dynamics better than do the alternative models without sales. Although many dynamic properties of the sales model are qualitatively similar to those of the analogous model without sales, the quantitative differences between them can be important in practice. Welfare analyses are particularly sensitive to price-dispersion properties. Overall, this paper makes the case for sales to be included in aggregate models, especially those employed by central banks for quantitative predictions.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2019.03.007.

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