Online appendix
Price Selection in the Microdata

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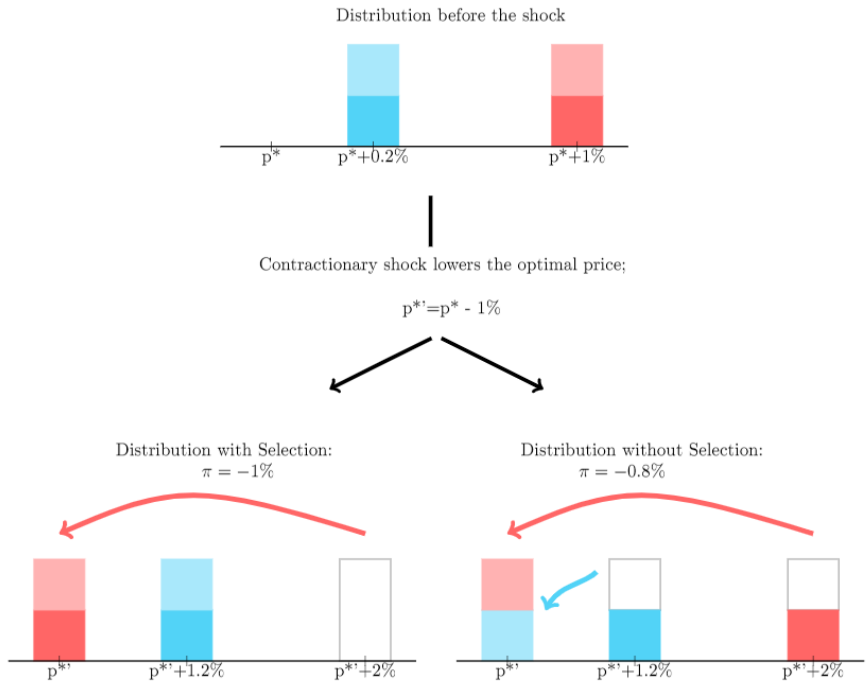
The appendix presents an illustrative example for selection (Section A); shows the fit of the price-gap distribution (Section B.1), and the decomposition of alternative state-dependent models (Section B.2); shows the adjustment of the frequency and the size to the credit shock (B.3). Additionally, it shows that our baseline results are robust to using competitors'-reset price gap (Section C.1.1) and reset-price gaps (Section C.1.2); using an identified monetary policy shock instead of a credit shock (Section C.2); using non-linear specifications (Section C.3); and to cross-category heterogeneity (Section C.4); as well as robust to excluding product-store fixed effects (Table 14); to using posted prices instead of reference prices (Table 15); to using only product-month combinations with at least 50 competitors (Table 16); and to ending the sample in 2007 just before the Great Recession (Table 17). Section D presents the reference-price filtering algorithm.

A An illustrative example for selection

Figure 11 illustrates the idea of selection graphically, with a description in the text under the figure.

Figure 11: An illustrative example



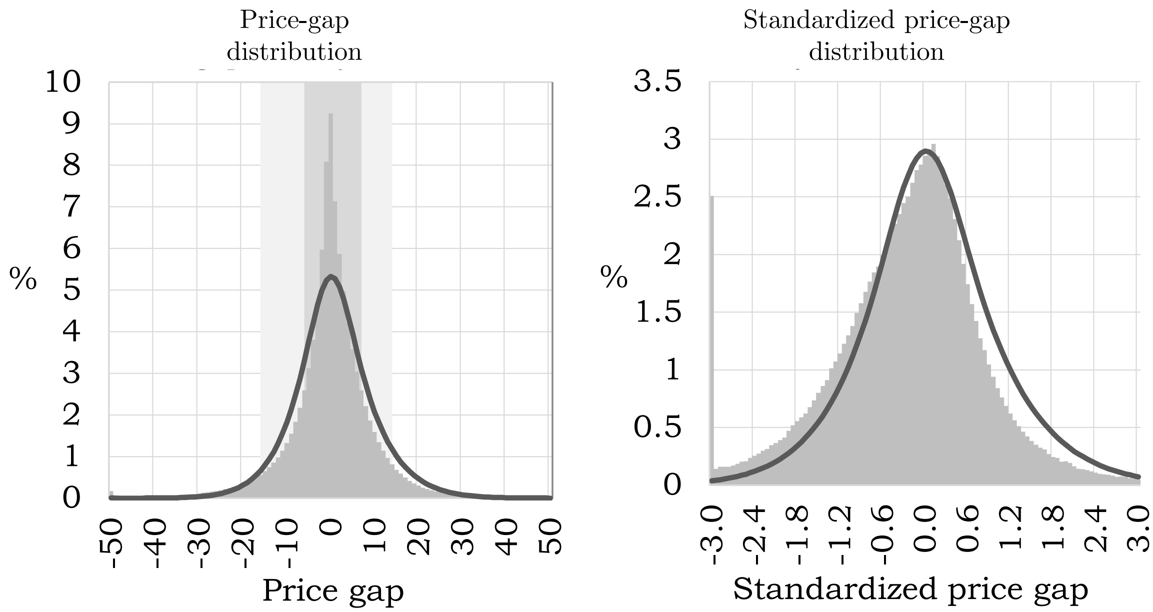
Note: The figure illustrates the mechanism of price selection. Imagine two supermarkets setting the prices of 4 distinct product types. Half of the prices are much higher (+1%) than their optimal price (p^*, price of a dominant competitor), and the other half are only slightly higher (+0.2%). An aggregate shock – such as a uniform price cut by a dominant competitor – reduces the optimal prices of all goods by 1%. Changing prices is costly, so both supermarkets reset half of their prices, but they follow different price-setting rules: one with selection, another without selection. The one with selection (left panel) chooses to reset the prices that are furthest from their optimal prices. This rule generates an interaction between the aggregate shock and the product-level mispricing: the mispricing substantially amplifies the impact of the shock. The price index of that supermarket declines 1:1 with the uniform shock even though only half of its products change prices. Such behavior is typical in state-dependent price-setting models, where selection is high, the aggregate price level is flexible, and monetary policy is close to neutral. The other supermarket without selection (right panel) chooses to adjust its prices according to a predetermined rule that is independent of the mispricing. For example, it resets a certain number of prices in each aisle. Thus, it ends up picking half of the prices with smaller and half of the prices with larger mispricing. This generates a price decline that is strictly smaller than the uniform shock. This behavior is representative of time-dependent price-setting models, with no selection, a sluggish aggregate price level, and non-neutral monetary policy.

B Additional model-matching results

B.1 Fit of the price-gap distribution

Figure 12 shows how our baseline linear hazard model fits the price-gap distribution. The left panel show that the model somewhat underestimates the kurtosis of the price-gap distribution: the empirical price-gap distribution has a sharper peak and fatter tails than the model. However, we argue that this is mostly the result of the model ignoring cross-sectional heterogeneity in the volatility of idiosyncratic shocks. If we control for such heterogeneity in the data by standardizing price gaps at the item level using the standard deviation of reference-price changes, the fit of the model becomes tight, as the right panel shows.

Figure 12: The fit of the price-gap distribution



Note: The figure shows the fit of the baseline linear hazard model of the price-gap distribution (left panel) and standardized price-gap distribution (right panel). The figures show that the model somewhat underestimates the kurtosis of the price-gap distribution, but this is mostly the result of it disregarding some remaining cross-sectional heterogeneity in the volatility of price changes. After standardization controls for this volatility the match of the model is tight.

B.2 Decomposition of alternative state-dependent models

Table 8: Relative strength of adjustment channels

	Empirical moments	Baseline linear hazard	(Woodford, 2009) hazard matched	(Woodford, 2009) kurtosis matched	Uniform random menu cost
Intensive margin (%)	73.4	71.3	76.2	58.1	73.6
Gross extensive margin (%)	26.5	28.7	13.9	24.6	17.1
Narrow selection (%)	0.2	0.0	9.9	17.2	9.2

Note: The table shows the relative strength of the adjustment channels using the empirical moments (hazard and price-gap distributions), in the baseline linear hazard model and a set of alternative state-dependent price-setting models. The results show that the relative strength of narrow selection varies significantly across the models, so it is a useful measure to distinguish between them.

B.3 Adjustment of frequency and size to the credit shock

A purpose of this section is to establish that in response to a contractionary credit shock, reference prices adjust primarily through a shift from price increases to price decreases, rather than through changes in the size of average price increases or decreases. This motivates us to concentrate on the probability of price adjustment in our baseline panel-data regressions rather than its size.

Figure 13 summarizes the results from local-projection regressions of these three cumulative reference-price outcome variables on the credit shock and shows the importance of the frequency responses.[32,] We find the following results.

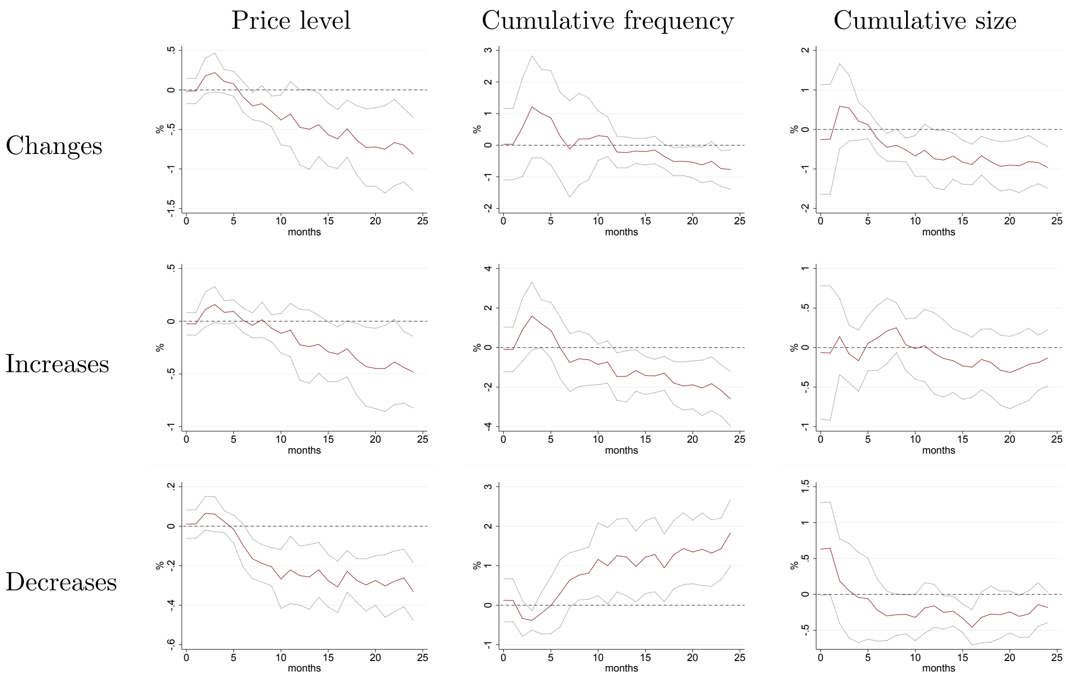
First, as the first panel in the first row of Figure 13 shows, there is a persistent decline in the price level. As the second and the third figures in the first column show, both price increases and price decreases contribute to this decline.

Second, and most importantly, we find a strong shift from price increases to price decreases within a year of the shock. There is a decline in the cumulative frequency of reference-price increases (second panel in the second row), and an increase in the cumulative frequency of price decreases (second panel in the third row). The decline in the cumulative price increases is not much larger than the increase in the cumulative price decreases; so the aggregate frequency declines, but only marginally significantly if at all. Both of these changes contribute to the decline in the price level, and to the reduction in the average size of price changes (third panel in the first row). The average size of price increases stays unchanged and the absolute size of the price decreases increases only marginally. This finding motivates our choice to concentrate on the frequency of reference-price changes in the subsequent analysis.

[32] The local-projection analysis controls for a horizon-dependent constant. Therefore, it effectively assesses the impact of the monetary policy shock on the deviation of the dependent variables from their steady-state value. The decomposition of the deviation of cumulative inflation from its steady state becomes

$$\pi_{t,t+h} - \bar{\pi}_h = \left(\xi^+_{t,t+h} - \bar{\xi}^+_h\right)\bar{\psi}^+_h + \left(\psi^+_{t,t+h} - \bar{\psi}^+_h\right)\bar{\xi}^+_h + \left(\psi^+_{t,t+h} - \bar{\psi}^+_h\right)\left(\xi^+_{t,t+h} - \bar{\xi}^+_h\right) + \left(\xi^-_{t,t+h} - \bar{\xi}^-_h\right)\bar{\psi}^-_h + \left(\psi^-_{t,t+h} - \bar{\psi}^-_h\right)\bar{\xi}^-_h + \left(\psi^-_{t,t+h} - \bar{\psi}^-_h\right)\left(\xi^-_{t,t+h} - \bar{\xi}^-_h\right).$$

Figure 13: Adjustment on the extensive and intensive margins to a credit shock



Note: The figure shows the impulse responses of supermarket reference-price levels and their components to an identified credit shock, and 95% confidence bands using Newey-West standard errors. The panels illustrate how the negative price-level response (first figure in the first row) is predominantly driven by the decline in the price-increase frequency (second panel in the second row) and the increase in the price-decrease frequency (second panel in the third row), while the sizes of price increases and decreases stay mostly constant (third panels in the second and third rows). This adjustment in the gross extensive margin explains the decline in the cumulative size of the price changes (third panel in the first row). The cumulative frequency (net extensive margin) declines, but only marginally significantly (second panel in the first row).

The shift between the price-increase- and price-decrease frequencies per se does not provide sufficient information about the relative importance of various adjustment channels. Notably, such a shift is present in time-dependent models (Calvo, 1983), which do not permit adjustment on the extensive margin. Rather, the shift in these models is the consequence of the adjustment on the intensive margin, as all adjusting firms reduce the size of their price change relative to a counterfactual scenario without the contractionary aggregate shock. The reduction in size necessarily shifts some firms on the margin to decrease their prices, firms that would have increased their prices otherwise. Even though the shift changes the relative share of price increases and price decreases, we should not categorize it as adjustment through the (gross) extensive margin. As we argue in Section 2, extensive-margin adjustments should be assessed within groups determined by the pre-shock size of the price gap. Therefore, to separately identify the channels of adjustment, the analysis needs to explicitly control for the price gap, exactly as we do in our baseline panel-data empirical implementation.

C Additional robustness results

C.1 Alternative price-gap proxies

This section shows that our results are robust to using two alternative gap measures: the competitor reset price and the reset price.

C.1.1 Competitor-reset-price gap

To obtain a proxy for the optimal price, the competitor reset price proxy focuses on the prices of the same product among those competitors that changed their prices in a particular month.

Formally, we formulate the competitor-reset-price gap x^r_{pst} for product p in store s in month t in two steps. First, we calculate an unadjusted gap as $\tilde{x}^r_{pst} = p^f_{pst} - \bar{p}^{*fr}_{pt}$, where p^f_{pst} is the logarithm of the reference price and $\bar{p}^{*fr}_{pt}$ is the average reference-reset-price of the same product across those stores (excluding store s) that changed their prices in month t. Second, analogously to the competitor gap, we deal with persistent heterogeneity across stores (i.e., chains, locations) and categories by subtracting the average store-and-category-level gap α^r_{sc} and reformulating the price gap as $x^r_{pst} = \tilde{x}^r_{pst} - \alpha^r_{sc}$. We restrict attention to those product-months where the number of competing stores that changed their prices in the particular month exceeds 50.

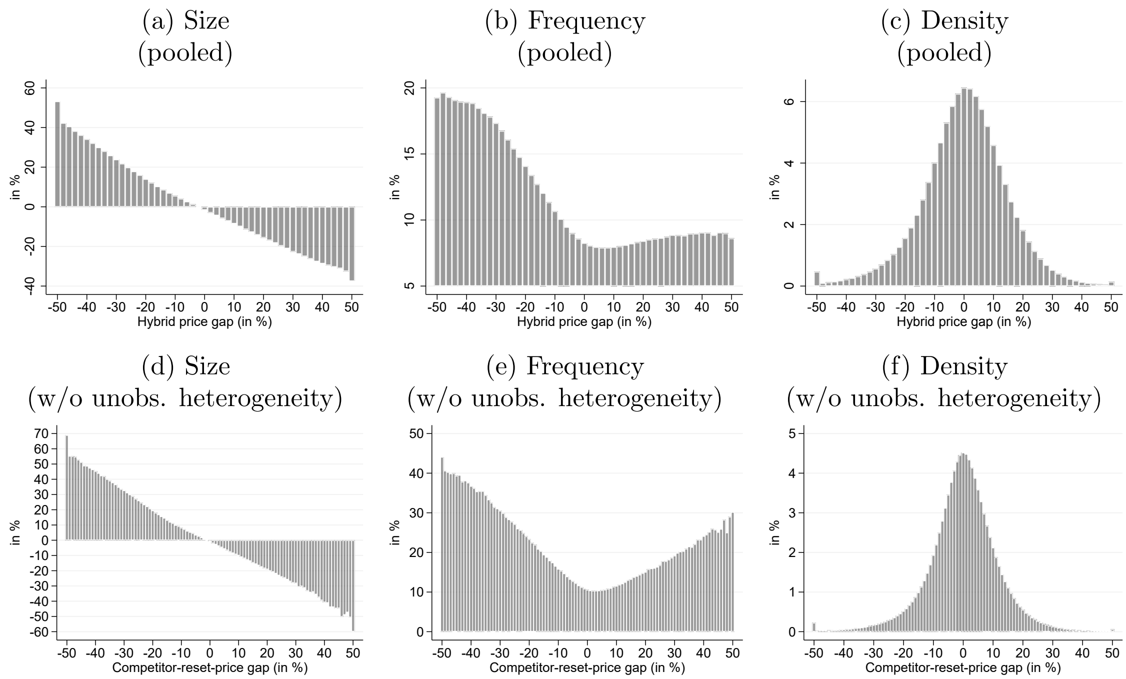
The competitor-reset-price gap is a valid proxy for the theoretical price gap if, for example, the following three mild conditions are satisfied. First, the average price of the same product among price-resetting competitors should track well the evolution of the product's (suitably weighted current and expected future) wholesale price, aggregate demand conditions and competitors' price, which are the primary drivers of the optimal reset price. This symmetry condition is satisfied in most macromodels with price-setting frictions (Calvo, 1983; Dotsey et al., 1999; Golosov and Lucas, 2007). Second, differences in amenities and market power between stores should cause permanent store-and-category-level differences between reset prices (fixed optimal markups). And, third, chains may follow national price-setting strategies (DellaVigna and Gentzkow, 2019), so local demand conditions have an insignificant impact on the optimal reset prices.

Figure 14 shows the density of the competitor-reset-price gap x_{pst} in our baseline IRi supermarket data set pooled across products and time, and the probability and the size of price adjustment as a function of the price gap. The figures are qualitatively identical and quantitatively close to the analogous figures based on the competitor-price gap (i.e., average of the price in *all* competing stores, not only those that changed their prices).

Table 9 compares the baseline regressions with competitor-price gaps to the same regressions using the competitor-*reset*-price gaps. Results remain robust. The magnitude of the estimated coefficients change somewhat, but neither the sign nor the significance of the estimated impacts changes relative to the baseline.[33]

[33] The sample size is smaller because the competitor-reset-price gap imposes a stronger requirement on the admissible product-months than the baseline regressions. In the baseline, a product-month is admissible if there are at least 50 competitors selling the same product in the particular month. For competitor-reset-price gaps, we require the presence of at least 50 competitors selling the same good *that change their reference prices* in the particular month.

Figure 14: The size and the frequency of subsequent reference-price changes as a function of the competitor-reset-price-gap and its density



Note: The panels show the size and frequency responses of a subsequent price change as a function of the competitor-reset-price gap and its density in the baseline supermarket data set with pooled data (first row) and without unoserved heterogeneity (second row). As with the baseline competitor-price gap (Figure 4), the the size of average subsequent adjustments is close to a (minus) one-on-one relationship with the gap (first column); the frequency of subsequent price adjustment increases with the absolute size of the gap (second column); the relationship is close to linear when unobserved heterogeneity is controlled for (panel e); and density of the competitor-reset-price gaps exhibits fat tails (third column).

C.1.2 Reset-price gap

The second alternative, the reset price is defined as the counterfactual price a firm would charge if price-adjustment frictions were temporarily absent. In a wide class of state-dependent price-setting models, the reset price is the key product-level attractor that drives the probability and the size of price adjustment.

(Bils et al., 2012) offer an iterative algorithm to obtain a proxy for the reset price. The algorithm relies on two key assumptions. First, when a firm adjusts its price, it sets it at the reset price. Second, when the firm does not adjust its price, its reset price evolves with the reset-price inflation of its close competitors, which can be measured from the changes in the reset prices of the adjusting competitors. Formally, the logarithm of the reset price of item i in month t is

$$p^*_{it} = \begin{cases} p_{it} & \text{if } I_{it} = 1 \\ p^*_{it-1} + \pi^*_{ct} & \text{otherwise} \end{cases} \tag{13}$$

Table 9: Robustness to using competitor-reset gap, scanner data, credit shock

	(1)	(2)	(3)	(4)
	Increases $\left(I^{+}_{pst,t+24}\right)$		Decreases $\left(I^{-}_{pst,t+24}\right)$	
	Baseline	Competitor-reset-gap	Baseline	Competitor-reset-gap
Gap (x_{pst-1})	-1.75^{***}	-1.29^{***}	1.55^{***}	1.19^{***}
	(0.06)	(0.04)	(0.06)	(0.06)
Shock (ebp_t)	-0.03^{***}	-0.05^{***}	0.03^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Selection ($x_{pst-1}\widehat{\text{ebp}}_t$)	-0.00	-0.01	0.01	0.00
	(0.04)	(0.05)	(0.05)	(0.06)
Age (T_{pst-1})	0.02^{***}	0.02^{***}	0.00^{**}	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Product x store FE	✓	✓	✓	✓
Calendar-month FE	✓	✓	✓	✓
Time FE	✗	✗	✗	✗
N	$16.1M$	$9.3M$	$16.1M$	$9.3M$
Within R^2	18.5%	15.2%	17.3%	14.5%

Note: The table shows estimation results from the linear-probability panel model using scanner data with the competitor-price gap and the competitor-reset-price gap. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-2) and an indicator with value 1 for price decreases (Columns 3-4). The regressions control for the age (time since last change) of the price and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 3) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities their interaction remains insignificantly different from zero, suggesting narrow selection is absent. The results stay robust to a specification with the competitor-reset-price gap (Columns 2 and 4).
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

where I_{it} is an indicator function that takes the value of 1 if the price of product i changes in month t, and π^*_{ct} is the reset-price inflation in the product's category c. Reset-price inflation, in turn, is given by

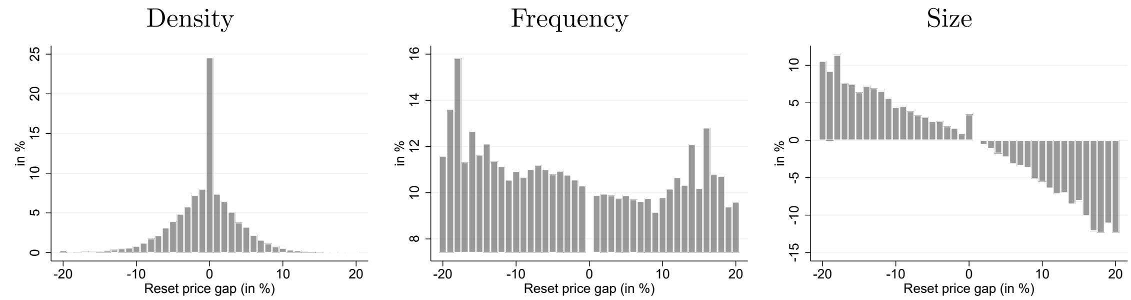
$$\pi^*_{ct} = \sum_{i \in c} \frac{\omega_{it} I_{it} \left(p^*_{it} - p^*_{it-1}\right)}{\sum_{i \in c} \omega_{it} I_{it}}, \tag{14}$$

where ω_{it} denotes the expenditure weight of item i.

The reset-price gap is simply the distance of the logarithm of the price from the logarithm of its reset price $x_{it} = p_{it} - p^*_{it}$. We assess whether these reset price gaps truly proxy actual price gaps by looking at the average size of price changes conditional on the reset-price gap in the previous month. If the proxy is good, there should be a strong correlation between the size of the price change and the lagged reset price gap. The first panel of Figure 15 shows the histogram of the reset-price gaps. The distribution has a negative median, fat tails, and is left-skewed. The third panel of Figure 15 shows the average size of subsequent price adjustment for each reset-price gap bin. The relationship is clearly negative.

Figure 16 presents size and frequency histograms separately for price increases and decreases. The tight

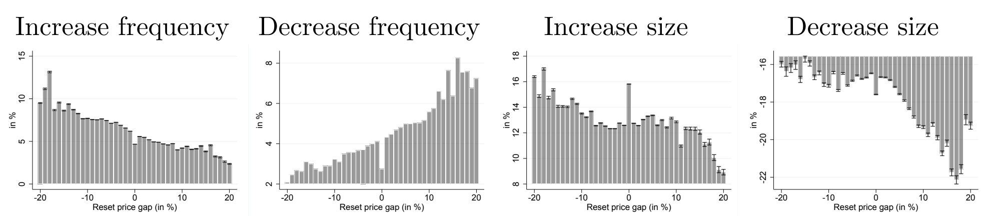
Figure 15: Reset-price-gap density and the subsequent frequency and size of price changes as a function of the gap, scanner data



Note: The figures show the unconditional density of the reset-price gap and frequency and size of subsequent price changes as a function of the gap in the baseline supermarket data set. The figures show that the density of the reset-price gaps has fat tails (first panel); the frequency of subsequent price adjustment increases with the absolute size of the gap (the second panel, see also next figure); and the size of average subsequent adjustments is inversely related to the gap (third panel).

negative relationship between the reset-price gap and the moments are salient in the graphs. At the same time, the panels of the figure reveal that the reset-price gap is not the sole factor driving firms' price-setting decisions, because we see a non-negligible fraction of firms increasing their prices even though their reset-price gap is positive, and conversely, decrease them even though the gap is negative. Furthermore, the probability of price increases drops from its peak after the price gaps become lower than 20% (see the bottom-left panel of Figure 16).

Figure 16: Frequency and size of subsequent price changes as a function of reset-price gap



Note: The figures show the subsequent increase and decrease probabilities and increase and decrease sizes as a function of reset-price gaps. The figures show the negative relationship between gaps and the increase frequency (except for large negative gaps) and the positive relationship between the gaps and the decrease frequency. The figures also confirm a similar relationship with the average size of subsequent price changes, with the relationship losing its monotonicity for positive gaps and increase sizes and negative gaps with decrease sizes.

Table 10 shows that we obtain qualitatively similar effects using reset-price gaps. A one standard deviation credit tightening (30 basis points) reduces the probability of price increases by around 1 percentage point and increases the probability of a price decrease by the same amount. The probabilities are less sensitive to the reset-price gaps than to our baseline competitor-price gap. Nevertheless, they are qualitatively similar, since the probability of a price increase for a product at the first quartile relative to the third quartile is 2.25 percentage points lower, and for the price decreases it is 1.6 percentage points higher. The interaction terms remain insignificantly different from zero, continuing to imply the absence of any selection effect.

Table 10: Estimates, scanner data, reset-price gap, credit shock

	(1)	(2)	(3)	(4)	(5)	(6)
	Price increases $\left(I^{+}_{pst,t+24}\right)$			Price decreases $\left(I^{-}_{pst,t+24}\right)$		
Gap (x_{pst-1})	-0.45^{***}	-0.48^{***}		0.34^{***}	0.37^{***}	
	(0.07)	(0.06)		(0.04)	(0.04)	
Shock ($\hat{\text{ebp}}_t$)	-0.04^{***}		-0.04^{***}	0.03^{***}		0.03^{***}
	(0.01)		(0.01)	(0.01)		(0.01)
Selection ($x_{pst-1}\hat{\text{ebp}}_t$)	-0.14	-0.13		0.12	0.14	
	(0.14)	(0.12)		(0.12)	(0.10)	
Age (T_{pst-1})	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.02^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Positive gap (x^{+}_{pst-1})			-0.39^{***}			0.33^{***}
			(0.07)			(0.07)
Negative gap (x^{-}_{pst-1})			-0.49^{***}			0.35^{***}
			(0.13)			(0.07)
Pos. sel. ($x^{+}_{pst-1}\hat{\text{ebp}}_t$)			0.11			-0.03
			(0.15)			(0.13)
Neg. sel. ($x^{-}_{pst-1}\hat{\text{ebp}}_t$)			-0.27^{**}			0.21^{*}
			(0.13)			(0.12)
N	$16.1M$	$16.1M$	$16.1M$	$16.1M$	$16.1M$	$16.1M$
within R^2	2.6%	0.3%	2.6%	1.3%	0.3%	1.3%

Note: The table shows estimation results from the linear-probability panel model using scanner data. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-3) and an indicator with value 1 for pride decreases (Columns 4-6). The regressions include product-store and calendar-month fixed effects, control for the age of the price (months since last change), and calculate standard errors with two-way clustering. The baseline regressions (Columns 1 and 4) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust to a specification with time fixed effects (Columns 2 and 5, without calendar-month FE) and a specification with separate coefficients for positive and negative gaps (Columns 3 and 6).
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

C.2 Response to monetary policy shocks

This section describes the properties of our second identified shock, the monetary policy shock, and price adjustment in response. Again, we find that prices adjust predominantly through the gross extensive margin. Additionally, we also find a response of the size and frequency of price changes that is inconsistent with time-dependent models.

As we have done with the credit shock, we start by characterizing the dynamic impact of a monetary policy shock on inflation and its components using the local projection method (Jordà, 2005). The local projection framework puts minimal structure on the data generating process. As instruments for monetary policy shocks, we use changes in the 3-month-ahead federal funds futures in a 30-minute window around FOMC press statements, as in (Gertler and Karadi, 2015). The identification assumption is that because financial markets incorporate all available information into futures prices before the announcement, the change in the futures price indicates the size of the policy surprise. Furthermore, the narrow window guarantees that no other economic shock systematically contaminates the measure. We restrict our interest to announcements where the interest rate surprise and the S&P blue-chip stock price index moved in the opposite direction over the same time frame. As argued by (Jarociński and Karadi, 2020), such co-movement is indicative of a dominant monetary policy shock, when the impact of the central bank's contemporaneous announcements about the economic outlook played a minor role. We transform these surprises to monthly variables by summing up monetary policy surprises within each calendar month.

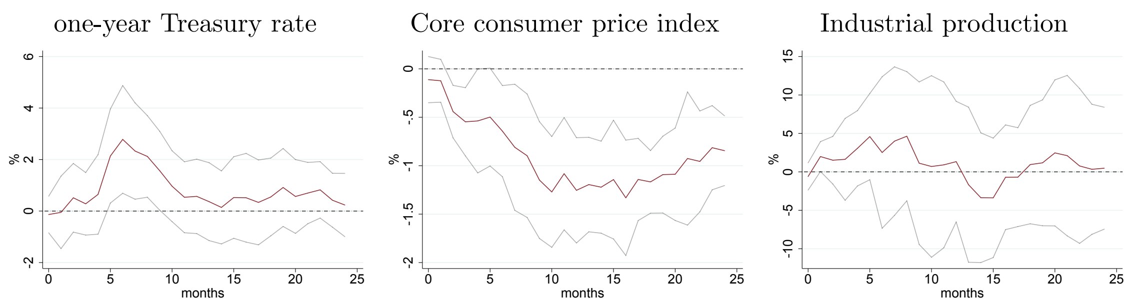
We run a series ($h = 0, \ldots, 24$ months) of regressions of the following form:

$$x_{t+h} - x_t = \alpha_h + \beta_h \Delta i_t + \Gamma_h \Phi(L) X_t + u_{t,h}, \tag{15}$$

where x_t is the variable of interest (for example, the log price level), and Δi_t is our proxy for a monetary policy shock. The local projections also include a set of controls $\Gamma_h \Phi(L) X_t$, where Γ_h is a vector of parameters for each h, X_t is a vector of control variables and $\Phi(L)$ is a lag-polynomial. Unless stated otherwise, the controls we use are the 1- to 6-month lags of the one-year Treasury rate, the consumer price index, industrial production and the excess bond premium (Gilchrist and Zakrajšek, 2012).

Our key object of interest is the coefficient β_h. In the figures below, we plot β_h, $h = 0, 1, \ldots, 24$ along with 95% confidence bands.

Figure 17: Impulse responses of key macroeconomic variables to a monetary policy tightening

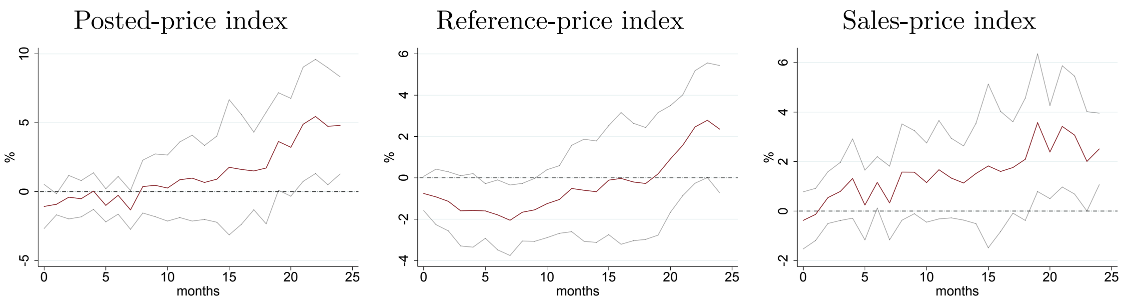


Note: The panels show impulse responses to an identified monetary policy shock in the scanner-data sample between 2001 and 2012 in a local-projection framework, and 95% confidence bands using Newey-West standard errors. The panels show that a monetary policy shock causes a sizable drop in the price index, but no noticeable drop in activity.

First, consumer prices respond as expected to the monetary shock. Figure 17 plots impulse responses to some key macroeconomic variables. In particular, we plot the response to the one-year constant maturity Treasury rate, the response to the logarithm of the consumer price index excluding food and energy, and the response of the logarithm of industrial production. The response of consumer prices is consistent with standard results (Gertler and Karadi, 2015): the interest-rate increase generates a delayed and hump-shaped decline in the core consumer price index. Within the short sample, we observe no noticeable drop in industrial production.

Second, when we consider the response of our supermarket prices, supermarket reference prices exhibit the expected response to a monetary tightening. Figure 18 plots the impulse responses of supermarket prices. Similar to the aggregate price index, supermarket reference prices display a hump-shaped decline with wide confidence bands after a monetary policy tightening (see middle panel). The decomposition of posted prices

Figure 18: Impulse responses of the supermarket-price indices to a monetary policy tightening



Note: The panels show impulse responses to an identified monetary policy shock in the scanner-data sample between 2001 and 2012 in a local-projection framework, and 95% confidence bands using Newey-West standard errors. The figures show that the reference-price index declines significantly at around a 6-month horizon in response to the shock. The posted-price index increases significantly at a two-year horizon contrary to standard theory, but the increase is mostly driven by an increase in the filtered-out sales-price index.

into reference- and sales-price indices also reveals that the supermarkets respond to the shock by actively adjusting their reference prices, and not by modifying their strategy on temporary sales. This finding is consistent with views that argue that temporary-sales strategies are predetermined and not an active adjustment margin at business cycle frequencies (Anderson et al., 2017). Consequently, we concentrate on reference prices in our subsequent analysis.

As before, we find that adjustment of the reference-price level happens through the extensive margin (by modifying the number of price changes) rather than through the intensive margin (by changing the average size of price changes). To show this result, we decompose the cumulative reference-price inflation into the frequency ($\xi_{t,t+h}$) and the size ($\psi_{t,t+h}$) of price increases and price decreases as follows:

$$p_{t+h} - p_{t-1} = \pi_{t,t+h} = \xi^{+}_{t,t+h}\psi^{+}_{t,t+h} + \xi^{-}_{t,t+h}\psi^{-}_{t,t+h}. \tag{16}$$

The frequency of reference-price[34] increases and decreases is defined as

$$\xi^{\pm}_{t,t+h} = \sum_i \bar{\omega}_{it,t+h} I^{\pm}_{it,t+h}, \tag{17}$$

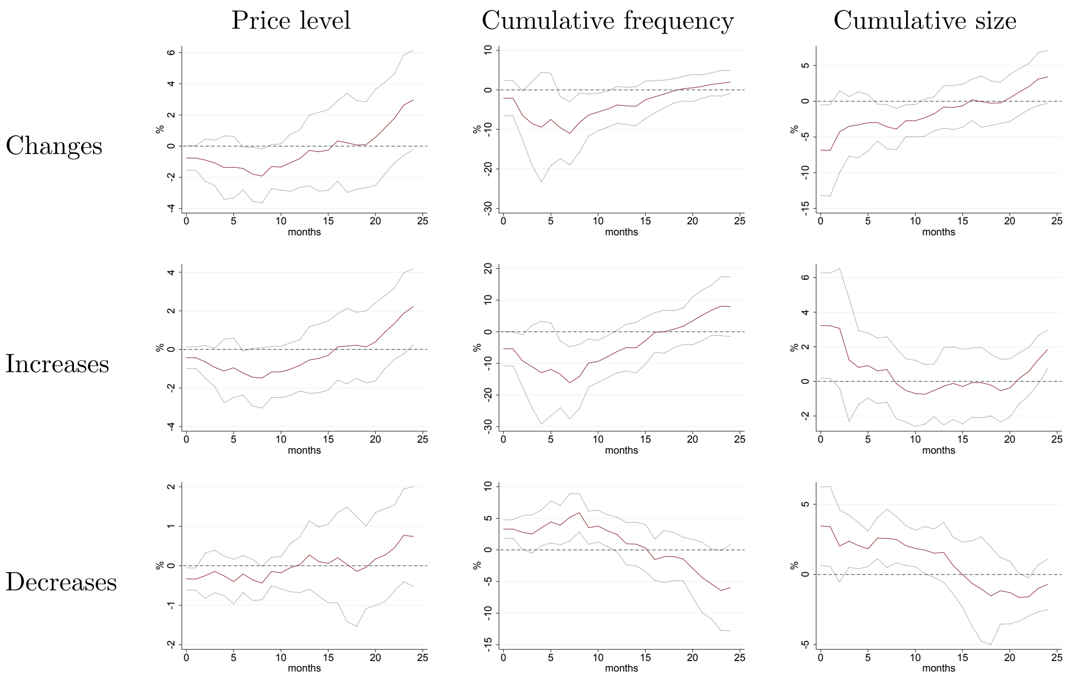
where $I^{+}_{it,t+h}$ and $I^{-}_{it,t+h}$ are indicators that take the value 1 if the reference price of item i (a product in a particular store) increased or decreased between months $t-1$ and $t+h$, respectively, and 0 otherwise. The weight $\bar{\omega}_{it,t+h}$ is measured as the average weight of the product between t and $t+h$. The average size of price increases and decreases is defined as

$$\psi^{\pm}_{t,t+h} = \frac{\sum_i \bar{\omega}_{it,t+h} I^{\pm}_{it,t+h}(p_{it+h} - p_{it-1})}{\xi^{\pm}_{t,t+h}}. \tag{18}$$

Following a monetary shock, we find that there is a strong adjustment on the extensive margin within a year of the policy shock: the cumulative frequency of reference-price increases declines, and the cumulative

[34] We suppress the superscript f for notational convenience.

Figure 19: Adjustment on the extensive and intensive margins to a monetary policy tightening



Note: The figures show the impulse responses of supermarket reference-price levels and their components to an identified monetary policy shock, and 95% confidence bands using Newey-West standard errors. The figures show that the negative price-level response (first figure in the first row) is predominantly driven by the decline in the price-increase frequency (second panel in the second row) and the increase in the price-decrease frequency (second panel in the third row). This adjustment in the gross extensive margin explains the decline in the cumulative size of the price changes (third panel in the first row). The cumulative frequency (net extensive margin) also declines (second panel in the first row).

frequency of price decreases rises. The decline in the cumulative price increases is larger (around 15% at its peak) than the increase in the cumulative price decreases (around 5% at its peak), so the aggregate frequency declines. Both of these changes contribute to the decline in the price level, and to the reduction in the average size of price changes. Figure 19 illustrates the decomposition of the response to a monetary policy shock into these adjustment margins.

By contrast, the average size of price increases rises and the absolute size of the price decreases declines. Both of them mitigate the impact of the shock on the price level rate. Such evidence is inconsistent with the underlying assumptions in time-dependent models (Calvo, 1983), which assume a constant frequency of price changes and attribute the adjustment after a monetary policy shock to the intensive margin. Our evidence instead points to the importance of the extensive margin, as the frequency of price increases and decreases adjusts significantly. It challenges the predominance of the intensive-margin adjustment, which would predict *smaller* price increases and *larger* price decreases. The increase in the frequency and the decline in the average absolute size of price adjustment have been documented after large (e.g., value-added tax, exchange rate) shocks by (Karadi and Reiff, 2019) and (Auer et al., 2021), who also showed that menu cost pricing models with leptokurtic idiosyncratic productivity shocks (Midrigan, 2011) are consistent with this pattern. To our knowledge, we are the first to document the same pattern after regular monetary policy shocks in US data. In contemporaneous work, a similar pattern has been documented by Balleer and Zorn (2019) using German PPI data.

Table 11: Estimates, scanner data, competitor-price gap, monetary policy shock

	(1)	(2)	(3)	(4)	(5)	(6)
	Price increases $\left(I^{+}_{pst,t+12}\right)$			Price decreases $\left(I^{-}_{pst,t+12}\right)$		
Gap (x_{pst-1})	-1.71^{***}	-1.71^{***}		1.36^{***}	1.36^{***}	
	(0.06)	(0.06)		(0.05)	(0.05)	
Shock (Δi_t)	-0.03^{*}		-0.03	0.01^{*}		0.01^{*}
	(0.01)		(0.02)	(0.01)		(0.01)
Selection ($x_{pst-1}\Delta i_t$)	-0.07	-0.07		0.07	0.07	
	(0.06)	(0.05)		(0.06)	(0.05)	
Age (T_{pst-1})	0.03^{***}	0.03^{***}	0.03^{***}	0.01^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Positive gap (x^{+}_{pst-1})			-1.92^{***}			1.93^{***}
			(0.10)			(0.09)
Negative gap (x^{-}_{pst-1})			-1.58^{***}			1.01^{***}
			(0.06)			(0.05)
Pos. selection ($x^{+}_{pst-1}\Delta i_t$)			-0.05			0.05
			(0.09)			(0.05)
Neg. selection ($x^{-}_{pst-1}\Delta i_t$)			-0.08			0.08
			(0.12)			(0.08)
Product x store FE	✓	✓	✓	✓	✓	✓
Calendar-month FE	✓	✗	✓	✓	✗	✓
Time FE	✗	✓	✗	✗	✓	✗
N	$23.7M$	$23.7M$	$23.7M$	$23.7M$	$23.7M$	$23.7M$
Within R^2	16.4%	14.7%	16.5%	13.3%	12.7%	13.8%

Note: The table shows estimation results from the linear-probability panel model using scanner data and a monetary policy shock. The regressions are run separately on an indicator with value 1 for reference-price increases (Columns 1-3) and an indicator with value 1 for reference-price decreases (Columns 4-6). The regressions include product-store and calendar-month fixed effects, control for the age of the price (time since last change), and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 4) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities, which is evidence for state-dependence, their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust to a specification with time fixed effects (Columns 2 and 5) and a specification with separate coefficients for positive and negative gaps (Columns 3 and 6).
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

Table 11 shows that the estimated coefficients are similar to those from our specification using the credit shock and tell the same story. There is evidence for the state-dependence of price changes as the price gaps and the monetary policy shock significantly impact the probability of price changes, but there is no evidence for selection as they do not interact.

C.3 Non-linear specifications

Our baseline results rely on a linear-probability specification. The framework is suitable to assess the average impact of explanatory variables on binary dependent variables (Wooldridge, 2010), especially if the actual relationship for common values of the dependent variables is indeed close to linear as our evidence above indicates.

First, Table 12 reports the coefficients of a specification analogous to that described in Section 5.4.1 with 5 equal-sized bins instead of 15. The regression results compare the price-setting behavior of the reference small-price change bin to two bins with medium sized negative ($-4\% \leq x_{pst-1} < -1\%$) and positive ($1\% \leq x_{pst-1} < 4\%$) gaps and two bins with large negative ($x_{pst-1} < 4\%$) and positive ($4\% \leq x_{pst-1}$) gaps.

The results are robust to this non-parametric specification as Table 12 shows. In particular, the probability of price change increases with the average absolute size of the price gaps in the bin in line with broad selection, but the interaction terms are not significantly different from the interaction term of the reference bin, implying no detectable narrow selection.

The linear-probability specification does not take into account some fundamental aspects of probabilities, most notably that (a) the sum of the probabilities of price increases, price decreases and no price changes equals one and (b) that probabilities are non-negative.

We show that those concerns do not affect our results by also estimating both a multinomial- and an ordered-probit model, which explicitly take into account the discrete and interlinked nature of our dependent variables. The multinomial version assumes that the firm compares the relative advantages of a price increase, no price change, and a price decrease. It allows for different coefficients in the price increase and decrease parts of the model. We interpret each coefficient as relative to the no-change scenario.

In contrast, the ordered probit specification assumes the three decisions are ordered on a single line. The coefficients then relate changes in variables to movement along this line and the position on the line determines the likelihood of each outcome. As a result, there is just one set of coefficients determining the probability of each outcome, whereas the multinomial model has outcome-specific coefficients.

We cannot include fixed effects in either specification due to the incidental parameters problem of non-linear models (Hahn and Newey, 2004), nor can we turn to conditional maximum likelihood models (Chamberlain, 1980; Pforr, 2014) as current implementations are computationally infeasible beyond a few thousand observations and our sample contains millions. Instead, we control for cross-sectional heterogeneity in the probability of price adjustments by including the average frequency of price increases and price decreases of close substitutes (see below),[35] and standardize price gaps at the product-store level (i.e. we subtract the mean and divide by the standard deviation).

We define these close substitutes as the same product p in a particular (geographic) market M and calculate the average frequency of reference-price increases and decreases per market, excluding the changes in store s itself. Formally, the average frequency of increases (decreases are analogous) is

$$\xi^{+}_{psM} = \sum_{t=1}^{T} \frac{\sum_{z \in M \setminus s} \omega_{pzt} I^{+}_{pzt}}{\sum_{z \in M \setminus s} \omega_{pzt}}, \tag{19}$$

where $M \setminus s$ is the set of stores in market M except store s, ω_{pzt} is the annual expenditure weights of product

[35] These variables would be crowded out by the item fixed effects in our baseline specifications.

Table 12: Non-linear specification, 5 groups

	(1) $I^{+}_{pst,t+24}$	(2) $I^{-}_{pst,t+24}$
Large negative gap ($x_{pst-1} << 0$)	0.35***	−0.28***
	(0.01)	(0.01)
Medium negative gap ($x_{pst-1} < 0$)	0.15***	−0.13***
	(0.01)	(0.01)
Medium positive gap ($x_{pst-1} > 0$)	−0.15***	0.13***
	(0.01)	(0.01)
Large positive gap ($x_{pst-1} >> 0$)	−0.33***	0.32***
	(0.01)	(0.01)
Large negative selection ($x_{pst-1} << 0) * \widehat{\text{ebp}}_t$	0.01	−0.01
	(0.01)	(0.01)
Medium negative selection ($x_{pst-1} < 0) * \widehat{\text{ebp}}_t$	0.00	−0.00
	(0.01)	(0.00)
Medium positive selection ($x_{pst-1} > 0) * \widehat{\text{ebp}}_t$	0.00	−0.00
	(0.00)	(0.00)
Large positive selection ($x_{pst-1} >> 0) * \widehat{\text{ebp}}_t$	0.01	−0.01
	(0.01)	(0.01)
Age (T_{pst-1})	0.02***	0.01***
	(0.00)	(0.00)
Product x store FE	✓	✓
Time FE	✓	✓
N	$16.1M$	$16.1M$
within R^2	16.6%	16.5%

Note: The table shows estimation results from the linear-probability panel model using scanner data. The regressions are run separately on an indicator with value 1 for price increases (Column 1) and an indicator with value 1 for pride decreases (Column 2). The regressions include product-store and time fixed effects and calculates standard errors with two-way clustering. The table shows that even though groups with larger absolute gaps increase the price-change probability, the interaction term with the aggregate shock always stays insignificantly different from zero. The results confirm that narrow selection is undetectable in the data.
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

p in store z in month t, and I^{+}_{pzt} is an indicator function taking the value 1 if there is a price increase for product p in store z at month t.

Regressions results align with our baseline findings: the price gap and the aggregate shock significantly influence the price-change probabilities, but their interaction is never consistent with a significant selection effect. The interaction term is mostly insignificant, except for price decreases in the multinomial-probit model. In this case, while the interaction term is significantly different from zero, it has a counterintuitive sign: a higher positive gap and aggregate credit tightening imply fewer (not more) price decreases. Con-

Table 13: Multinomial- and ordered-probit estimates, scanner data, competitors' price gap, credit shock

	(1)	(2)	(3)
	Multinomial probit		Ordered probit
	Incr. $\left(I^{+}_{pst,t+24}\right)$	Decr. $\left(I^{-}_{pst,t+24}\right)$	Change $(I_{pst,t+24})$
Gap (x_{pst-1})	-3.15^{***}	3.37^{***}	-4.24^{***}
	(0.02)	(0.04)	(0.04)
Shock (ebp_t)	-0.11^{***}	0.05^{***}	-0.10^{***}
	(0.03)	(0.01)	(0.02)
Selection $(x_{pst-1}\widehat{\text{ebp}}_t)$	-0.05	-0.21^{**}	0.04
	(0.06)	(0.11)	(0.12)
Age (T_{pst-1})	0.01^{*}	-0.03^{***}	0.02^{***}
	(0.00)	(0.00)	(0.00)
Freq. incr. (ξ^{+}_{psM})	5.17^{***}	2.91^{***}	1.79^{***}
	(0.03)	(0.02)	(0.03)
Freq. decr. (ξ^{-}_{psM})	3.02^{***}	5.84^{***}	-1.33^{***}
	(0.03)	(0.05)	(0.04)
Product x store FE	✗	✗	✗
Calendar-month FE	✓	✓	✓
Time FE	✗	✗	✗
N	$16.1M$	$16.1M$	$14.3M$

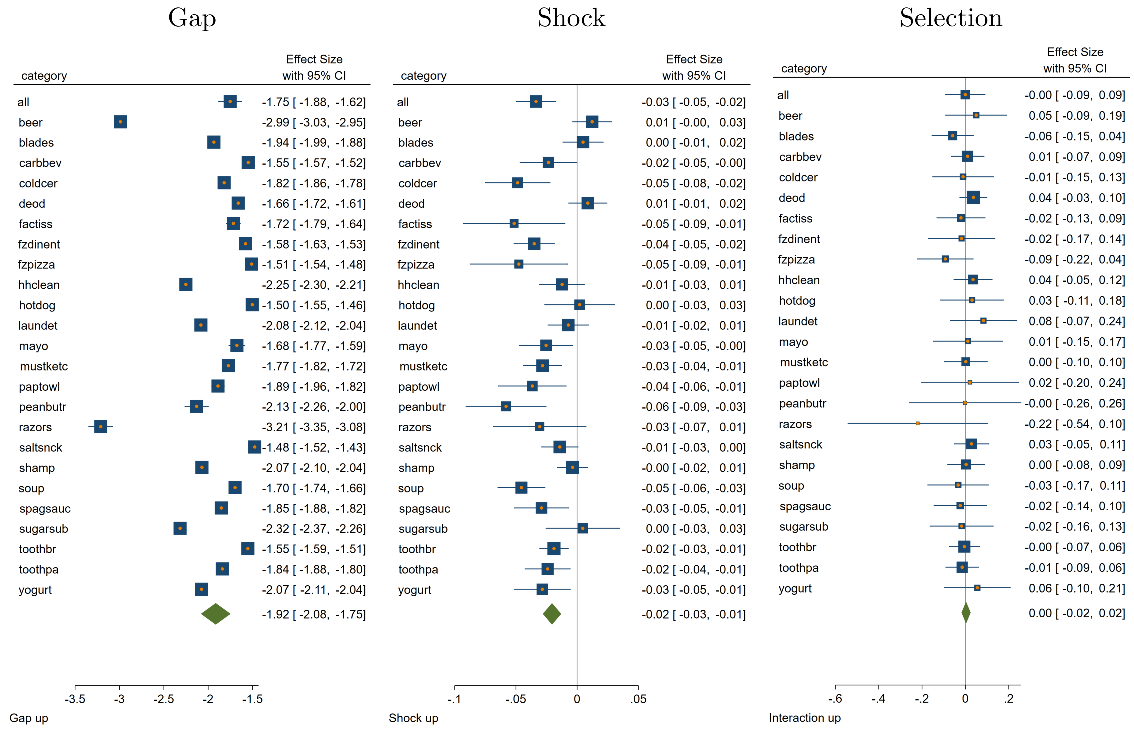
Note: The table shows estimation results from multinomial-probit and ordered-probit models using scanner data. The regressions consider 3 choices (price increase, no change, decrease). The regressions control for the age (time since last change) of the price and the average frequency of price increases and price decreases among competitor prices in the market (excluding own change), and use standard errors with clustering across product-stores. The results are robust: the price gap and the aggregate shock significantly influence the price-change probabilities, but their interaction is never consistent with a significant selection effect. The interaction term is mostly insignificant, except for price decreases in the multinomial-probit model. In this case, the interaction term is significantly different from 0, but has a counterintuitive sign: a higher positive gap and aggregate credit tightening imply fewer (not more) price decreases. Consequently, this estimate is also inconsistent with selection.
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

sequently, this estimate is also inconsistent with selection. Table 13 presents these findings. Columns 1 and 2 show the estimated coefficients from the multinomial-probit specification and Column 3 the estimated coefficients from the ordered-probit specification.

C.4 Heterogeneity across product categories

Finally, our results are robust to heterogeneity across product categories when we run our baseline regression separately for the 31 different product categories available in the IRi data set. This is reassuring because our baseline regression does not differentiate between potentially heterogeneous responses to idiosyncratic and aggregate volatility across product categories. The heterogeneity in demand elasticities due to different product characteristics and market structure (e.g., alcohol vs. milk) might potentially bias our estimates.

Figure 20: Estimated coefficients across product categories, price increases



Note: The figure shows estimates across product categories for price increases with 95% confidence bands for our baseline specification that uses the scanner data, the competitor-price-gap measure, and credit shocks. The panels show that the results are robust across product categories: the higher gap significantly decreases the price-increase probability; credit tightening decreases the price-increase probability in the majority of categories; and their interaction is never significant, indicating narrow selection is absent.

We show in Figures 20 and 21 that indeed the results are robust across product categories. Figure 20 shows the estimated coefficients and the uncertainty surrounding them for price increases and Figure 21 for price decreases. We find that in the majority of categories a higher gap (price too high) and a credit tightening both significantly decrease the probability of a price increase and increase the probability of a price decrease. The interaction of gap and shock is never significant, again indicating that selection is absent.

Figure 21: Estimated coefficients across product categories, price decreases

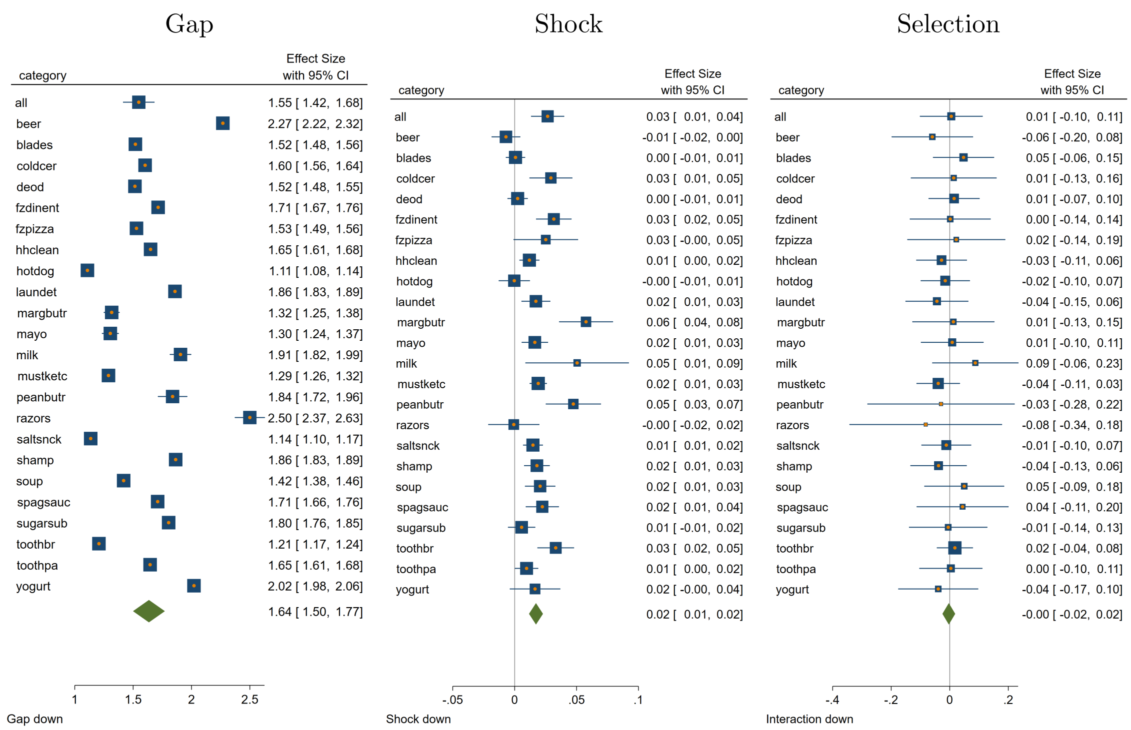


Table 14: Robustness to dropping item fixed effects, scanner data, competitors' price gap, credit shock

	(1)	(2)	(3)	(4)
	Increases $\left(I^{+}_{pst,t+24}\right)$		Decreases $\left(I^{-}_{pst,t+24}\right)$	
Gap (x_{pst-1})	-1.75^{***}	-0.99^{***}	1.55^{***}	0.90^{***}
	(0.06)	(0.10)	(0.06)	(0.10)
Shock (ebp_t)	-0.03^{***}	-0.04^{***}	0.03^{***}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)
Selection ($x_{pst-1}\hat{\text{ebp}}_t$)	-0.00	-0.01	0.01	0.02
	(0.04)	(0.02)	(0.05)	(0.03)
Age (T_{pst-1})	0.02^{***}	-0.01^{**}	0.00^{**}	-0.03^{***}
	(0.00)	(0.01)	(0.00)	(0.00)
Product x store FE	✓	✗	✓	✗
Calendar-month FE	✓	✓	✓	✓
Time FE	✗	✗	✗	✗
N	$16.1M$	$16.1M$	$16.1M$	$16.1M$
Within R^2	18.5%	8.9%	17.3%	9.3%

Note: The table shows estimation results from the linear-probability panel model using scanner data with and without product-store fixed effects. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-2) and an indicator with value 1 for pride decreases (Columns 3-4). The regressions control for the age (time since last change) of the price and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 3) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust to a specification without product-store fixed effects (Columns 2 and 4).
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

Table 15: Robustness using posted prices, scanner data, competitor-price gap, credit shock

	(1)	(2)	(3)	(4)
	Increases $\left(I^{+}_{pst,t+24}\right)$		Decreases $\left(I^{-}_{pst,t+24}\right)$	
	Reference	Posted	Reference	Posted
Gap (x_{pst-1})	-1.75^{***}	-1.46^{***}	1.55^{***}	1.25^{***}
	(0.06)	(0.05)	(0.06)	(0.05)
Shock (ebp_t)	-0.03^{***}	-0.04^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Selection ($x_{pst-1}\hat{\text{ebp}}_t$)	-0.00	-0.01	0.01	0.02
	(0.04)	(0.03)	(0.05)	(0.04)
Age (T_{pst-1})	0.02^{***}	0.01^{***}	0.00^{**}	-0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Product x store FE	✓	✓	✓	✓
Calendar-month FE	✓	✓	✓	✓
Time FE	✗	✗	✗	✗
N	$16.1M$	$18.6M$	$16.1M$	$18.6M$
Within R^2	18.5%	17.6%	17.3%	14.8%

Note: The table shows estimation results from the linear-probability panel model using scanner data with reference and posted prices. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-2) and an indicator with value 1 for pride decreases (Columns 3-4). The regressions include product-store and calendar-month fixed effects, control for the age (time since last change) of the price and aggregate variables, and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 3) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities, their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust using posted prices.
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

Table 16: Robustness using product-months with at least 50 competitors, scanner data, competitor-price gap, credit shock

	(1)	(2)	(3)	(4)
	Increases $\left(I^{+}_{pst,t+24}\right)$		Decreases $\left(I^{-}_{pst,t+24}\right)$	
	Baseline	50+ competitors	Baseline	50+ competitors
Gap (x_{pst-1})	-1.75^{***}	-1.76^{***}	1.55^{***}	1.56^{***}
	(0.06)	(0.06)	(0.06)	(0.06)
Shock (ebp_t)	-0.03^{***}	-0.03^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Selection ($x_{pst-1}\hat{\text{ebp}}_t$)	-0.00	-0.00	0.01	0.01
	(0.04)	(0.05)	(0.05)	(0.05)
Age (T_{pst-1})	0.02^{***}	0.02^{***}	0.00^{**}	0.00^{**}
	(0.00)	(0.00)	(0.00)	(0.00)
Product x store FE	✓	✓	✓	✓
Calendar-month FE	✓	✓	✓	✓
Time FE	✗	✗	✗	✗
N	$16.1M$	$15.3M$	$16.1M$	$15.3M$
Within R^2	18.5%	18.9%	17.3%	17.7%

Note: The table shows estimation results from the linear-probability panel model using scanner data with product-month with at least 1 (baseline) and at least 50 competitors. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-2) and an indicator with value 1 for pride decreases (Columns 3-4). The regressions include product-store and calendar-month fixed effects control for the age (time since last change) of the price and aggregate variables, and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 3) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust if we restrict our analysis to product-store combinations with at least 50 competitors.
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

Table 17: Robustness to excluding the Great Recession, scanner data, competitor-price gap, credit shock

	(1)	(2)	(3)	(4)
	Increases $\left(I^{+}_{pst,t+24}\right)$		Decreases $\left(I^{-}_{pst,t+24}\right)$	
	2001-2012	2001-2007	2001-2012	2001-2007
Gap (x_{pst-1})	-1.75^{***}	-1.74^{***}	1.55^{***}	1.50^{***}
	(0.06)	(0.07)	(0.06)	(0.06)
Shock (ebp_t)	-0.03^{***}	-0.03^{***}	0.03^{***}	0.02^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
Selection ($x_{pst-1}\hat{\text{ebp}}_t$)	-0.00	0.06	0.01	-0.06
	(0.04)	(0.07)	(0.05)	(0.07)
Age (T_{pst-1})	0.02^{***}	0.02^{***}	0.00^{**}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Product x store FE	✓	✓	✓	✓
Calendar-month FE	✓	✓	✓	✓
Time FE	✗	✗	✗	✗
N	$16.1M$	$9.9M$	$16.1M$	$9.9M$
Within R^2	18.5%	17.7%	17.3%	16.5%

Note: The table shows estimation results from the linear-probability panel model using scanner data with reference and posted prices. The regressions are run separately on an indicator with value 1 for price increases (Columns 1-2) and an indicator with value 1 for pride decreases (Columns 3-4). The regressions include product-store and calendar-month fixed effects, control for the age (time since last change) of the price and aggregate variables, and use standard errors with two-way clustering. The baseline regressions (Columns 1 and 3) show that even though the price gap and the aggregate shock significantly influence the price-change probabilities, their interaction remains insignificantly different from zero, suggesting selection is absent. The results stay robust using posted prices.
*Standard errors in parentheses; *: significant at 10%, **: significant at 5%, ***: significant at 1%.*

D Reference-price filtering algorithm - Stata implementation

The (Kehoe and Midrigan, 2015) (KM) algorithm calculates regular prices as the mode of a rolling window. The mode is accepted as regular price if at least 50% of the observation in the window is non-missing (the acc parameter) and more than 33% of prices are at the mode (the cutoff parameter). We use a window of one quarter (13 weeks). Due to the nature of the algorithm, a change to a new regular price is sometimes picked up with a delay. The KM algorithm corrects for this by adjusting the current regular price to the subsequent one if the current price is equal to it (and the regular price in the next period equals the actual price).

If the accuracy or cutoff conditions are not met, the regular price is set to the previous one. In the first window, the actual price is taken as regular price if no suitable mode can be found.

We extend the KM algorithm by improving the correction for the delay in the change of the regular price in the presence of missing values. If the current price equals the regular price in two/three/four/five weeks and in between no transactions took place, the regular price is adjusted to the subsequent one.

The remainder of this appendix is dedicated to explaining the stata do-file that runs the algorithm.

```
global number_of_years = 11
global duration = $number_of_years * 52 + 1
global wind = 13
global cutoff = 1/3
global acc = 0.5
global max_cycles = $duration/$wind
```

First, we define the parameters. Number_of_years is the number of years used in the dataset, duration the number of weeks, wind the size of the rolling window, cutoff the minimum fraction of prices at the mode, acc the required amount of nonmissing observations and the use of max_cycles will become clearer later on.

```
cd "<path>"
use <filename>, clear
keep id_nr week price
gen oldprice = price
replace price = round(price, 0.01)
gen int obs_number = 1
gen modalprice = 0
gen fraction = 0
```

Then, we open the database file, which should contain a unique identifier id_nr, a date week and the price. We retain the oldprice just in case and round the actual price to the nearest cent to avoid numerical errors. Obs_number shows the position of each observation within the sequence of weeks for each product-store combination. Modalprice will be the mode of each window, fraction the fraction of prices at the mode.

```
tsset id_nr week
tsfill
```

We tell stata the dataset is a panel with panel variable id_nr and time variable week. Tsfill fills in the missing weeks (as missing).

```
bysort id_nr (week): egen int obs_count = count(week)
drop if obs_count < $wind
replace obs_number = obs_number[_n-1] + 1 if id_nr[_n] == id_nr[_n-1]
```

For each product-store combination, obs_count indicates the length of the time series. We remove product-store combinations that are present shorter than the specified window. The last line of code creates the observation number.

```
qui foreach roll of numlist 1/$wind {
gen byte roll`roll'_cycle = 0
foreach cycle of numlist 1/$max_cycles {
replace roll`roll'_cycle = `cycle'
if obs_number-(`roll'-1) <= `cycle' * $wind
& obs_number-(`roll'-1) > (`cycle'-1) * $wind
}
bysort id_nr roll`roll'_cycle (week):
egen mode`roll' = mode(price), maxmode
gen byte equal_to_mode`roll' = 1 if mode`roll' == price
gen byte is_missing`roll' = missing(price)
bysort id_nr roll`roll'_cycle (week):
egen sum_missing`roll' = total(is_missing`roll')
bysort id_nr roll`roll'_cycle (week):
egen sum_equal`roll' = total(equal_to_mode`roll')
replace mode`roll' = 0 if sum_missing`roll' > $acc * $wind
drop equal_to_mode`roll' is_missing`roll'
}
```

This part of the code calculates the mode over the rolling windows and stores the fraction of prices that are at the mode. The rolling windows are created using the roll`roll_cycle variables. There are 13 of them (roll1_cycle to roll13_cycle), which corresponds to the length of the window. Roll1_cycle starts with thirteen observations of 1, then thirteen of 2, thirteen of 3 and so on until it reaches $max_cycles, which is just the maximum length divided by the window size. After the loop that identifies the cycles, we calculate the mode at each cycle for each product-store combination. If there are multiple modes, we retain the largest one as this is more likely to be the regular price (the lower price is relatively more likely be a long running sale). Finally, we count how many prices within the window are missing and how many equal the mode. We set the mode to 0 (missing) if there are insufficient nonmissing prices ($acc * $wind). The number of prices equal to the mode is used later.

```
qui foreach roll of numlist 1/$wind {
foreach cycle of numlist 1/$max_cycles {
replace modalprice = mode`roll'
if obs_number == roll`roll'_cycle * $wind
+ `roll' - ($wind/2 + 0.5)
replace fraction = sum_equal`roll'/$wind
```

```
if obs_number == roll`roll'_cycle * $wind
+ `roll' - ($wind/2 + 0.5)
}
drop sum_equal`roll'
```

The next step is to link the rolling windows to the right observation. There is a relationship between the observation number (i.e. the position of the observation within the sequence), the number of the roll'roll_cycle variable and the cycle number. You can make this clear for yourself by writing out the sequence and you should find the following formula: Obs_number = cycle * window + roll_nr ($wind/2 + 0.5) Where roll_nr is the number in the name of the roll'roll_cycle variable and the cycle is the value of that variable. The two replace commands assign the mode and the fraction of prices at the mode to the observation.

```
gen regprice = 0
bysort id_nr (week): replace regprice = modalprice
if _n == 1
bysort id_nr (week): replace regprice = modalprice
if fraction > $cutoff & modalprice == price
bysort id_nr (week): replace regprice = regprice[_n-1]
  if (fraction < $cutoff | modalprice != price) & _n != 1
```

The next block deals with regular prices. We set the regular price of the first transaction to the actual price. Then, the regular price is set to the modal price if it passes the cutoff criterion (sufficient number of prices within the window at mode) and the price is equal to the mode. If the price is not at the mode, or the modal price is not accepted, the regular price equals the previous regular price.

```
foreach i in 1/($wind / 2 - 0.5) {
bysort id_nr (week): replace regprice = regprice[_n+1]  if regprice != regprice[_n+1]
& regprice[_n+1] == price
& _n != obs_count
& _n != 1
}
```

Sometimes the algorithm misses the timing of the change in regular price. This loop adjusts the regular price to that of next weeks transaction if the current price equals that regular price and the price in the next period equals the regular price. replace regprice = . if missing(price) Due to the nature of the algorithm, there is always a regular price, even if there are no transactions. This line sets the regular price to missing if there is no transaction that week.

```
bysort id_nr (week): replace regprice = regprice[_n+2]
if  price == regprice[_n+2]
& price[_n+2] == regprice[_n+2]
& missing(regprice[_n+1])
& _n < (obs_count - 2)
```

Sometimes, the algorithm is slow to update the regular price due to missing weeks. If the current price equals the regular and actual price of the first transaction after the missing weeks, the regular price is updated.

This block does that for one missing week, the code for two-five is very similar (and rarely ever makes a change). Afterwards, we run the previous block again (which updates the regular price when there are no missing weeks in between).

```
drop roll* mode* sum_missing*
label var regprice "Kehoe & Midrigan Regular Price"
label var fraction "Fraction of transactions within window at modal price"

label data "KM algorithm with correction for missing weeks in between price changes."
save <filename>_KM.dta, replace
```

Finally, we drop the intermediate variables, label the variables and dataset and save.

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