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Price-Setting During the Covid Era

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Abstract

Using the micro data underlying the U.S. CPI, we document several findings about firm price-setting behavior during the Covid-19 pandemic, a period with the highest levels of inflation seen in over thirty years. We present three sets of preliminary results: 1) firms primarily adjusted to the pandemic through the intensive margin by altering the size of price changes. In contrast, the frequency of price change changed comparatively little during this period. The dispersion of price changes rose in early 2020, before falling and remaining low throughout 2021. 2) The between-sector variance of price changes rises at various points during the pandemic, which indicates the presence of sectoral shocks. We do not find a relationship between sectoral pre-pandemic flexibility and how quickly firms adjusted to economic shocks during the pandemic. 3) Changes in inflation are substantially driven by changes in the share of price increases relative to the share of price declines. The share of price increases rose in 2021 even as the absolute value of all price changes remained flat. Some of our findings are consistent with time-dependent pricing models, while other patterns are more consistent with state-dependent pricing models in a low inflation environment.

JEL Codes: D40, E31

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1 Introduction

The Covid-19 pandemic has had enormous effects on activity across the economy, particularly with regards to inflation. As economic activity decline during the early portion of the pandemic, the year-on-year change in the CPI-U dropped to 0.24% in May 2020. By 2021, the economic recovery spurred the inflation rate to 7.5% as of January 2022, a rate not seen in the United States since the 1980s. These trends may continue even as the pandemic recedes, a possibility which remains concerning to policy makers.¹ Firms have had to react to almost unprecedented circumstances, which creates circumstances to test various paradigms of firm behavior.

In this paper, we document facts in firm price-setting during the Covid-19 pandemic using the Bureau of Labor Statistics Research Database microdata. We examine whether firms responded to the economic shocks during and after the pandemic in a time-dependent or state-dependent fashion. Our results have significant implications for whether inflation will be persistent into the future and whether monetary policy is effective. Additionally, the Covid-19 pandemic has been characterized by strong sectoral demand shocks throughout the pandemic.² We seek to answer questions about which specific factors were behind the differences in sectoral inflation and how firms responded to sector-specific shocks.

Researchers have extensively studied firm price-setting behavior in the past, but have been restricted to periods of low and stable inflation. In particular, papers such as Bils and Klenow 2004, Klenow and Kryvtsov 2008, and Nakamura and Steinsson 2008 have used BLS data that has predominantly run from the late 1980s to the mid-2000s. However, theoretical work, such as that posed by Nakamura, Steinsson, et al. 2018 and Alvarez, Beraja, et al. 2019, suggests that firms operating under a menu cost model with varying costs may have radically

¹Numerous recent speeches by governors of the Federal Reserve Board and Federal Reserve Bank presidents have highlighted the attention that Federal Reserve leaders are paying to inflation. For one recent example, see Powell 2021 speech at the economic policy symposium in Jackson Hole, WY.

²Much of the increase in inflation in 2021 has been due to large average price increases in certain categories, especially of durable goods. Shifts in the distribution of price changes during this period can shed light on the extent to which this was due to shocks specific to those sectors.

different pricing behaviors in high inflation regimes compared to low inflation regimes.³ We contribute to the literature by studying how U.S. firms react to economic shocks outside of a low, stable inflation environment.

This paper presents three primary empirical findings. First, firms have primarily responded to the pandemic by adjusting the size of price changes rather than the frequency. The size of price adjustments has steadily risen through 2021 with inflation, while the frequency has stayed relatively flat throughout the entire period. We confirm this finding by constructing two counterfactual inflation rate: one with a fixed frequency of price changes and one a fixed size. We show that the former is highly correlated with the actual inflation rate, indicating that firms adjusted through size. A Klenow and Kryvtsov 2008 decomposition confirms that the intensive margin of adjustment comprises a majority of variation in inflation over the time period.

Second, we show that the pandemic induced strong sectoral shocks and that pre-pandemic sectoral characteristics affected how different firms responded to the pandemic.⁴ We show that there are significant differences in the frequency and size of price changes between sectors. Next, we decompose the dispersion of price changes into a within-sector and a between-sector component, and find that both rose with inflation in 2021. Finally, we find a negative relationship between the absolute value of sectoral inflation and the dispersion of price changes within a sector. We conclude this set of results by showing that there is little relationship between pre-pandemic sectoral flexibility and how firms within a sector responds in the pandemic.

Third, we show that the share of price changes that are price increases plays an important role in explaining inflation during the pandemic, particularly the rise of inflation in 2021.⁵

³Alvarez, Beraja, et al. 2019 in particular constructs similar price-setting statistics using Argentinian data that incorporates periods of higher inflation.

⁴Guerrieri et al. 2020 argues that the adjustment of demand between different sectors could lead to temporarily high inflation which the central bank should allow.

⁵Previous work such as Nakamura and Steinsson 2008 and Klenow and Kryvtsov 2008 have acknowledged that price decreases make up a sizable fraction of price changes. Both Alvarez, Beraja, et al. 2019 and Gautier et al. 2022 find that the share of price increases is significant in explaining inflation in their analyses.

Although the frequency of price changes is stable throughout the pandemic period, this aggregation masks changes in the fraction of price changes that are increases compared to decreases. We show that price decreases made up a substantial portion of price changes in the early period of the pandemic, before rapidly falling as inflation rose in 2021. We construct counterfactual inflation rates that emphasize the role of the share of price increases and show that it remains highly correlated with overall inflation. In summary, the share of price increases are a significant margin in firm price adjustment.

This paper contributes to two strands of literature, the first of which studies firm price-setting behavior and its implications for monetary policy. Nakamura and Steinsson 2008, Klenow and Kryvtsov 2008, Vavra 2014, and Nakamura, Steinsson, et al. 2018 show that prices are generally quite flexible and that firms tend to behave in a state-dependent way. However, as far as we are aware, this is the first paper that examines how firms chose to adjust their prices during the Covid pandemic. In particular, we believe that this is the first paper to use BLS pricing microdata, which covers a wide breadth of goods and services, to study the pandemic. We view Gautier et al. 2022 as being similar to our paper in terms of our approach of studying price-setting trends, although their analysis stops before the pandemic.

There is a nascent, burgeoning subfield of papers looking at how households and firms reacted to the pandemic. In particular, papers such as Cavallo 2020, Diewert and Fox 2020, and Cavallo and Kryvtsov 2021 study the implications of the Covid pandemic for U.S. inflation and consumer spending. Our paper is most similar to Cavallo and Kryvtsov 2021, which studies the implications for firm stockouts in pricing models. However, our paper differs by focusing on changes in price-setting behavior.

2 Data

This paper draws upon the Bureau of Labor Statistics Consumer Price Index Research Database. This microdata, which has been extensively studied by earlier researchers, is constructed from the Commodities and Services survey (C&S) that is collected by the Bureau of Labor Statistics to identify price changes. The C&S regularly samples price quotes of about 90,000 products on a regular basis. The C&S includes most types of goods and services, but notably excludes some components such as shelter and medical insurance. This dataset has the advantages of being widely used by researchers as well as containing price quotes for about 70% of the goods and services that consumers regularly purchase. Additionally, the C&S has been collected for a long period of time, which facilitates comparisons between the Covid era and earlier periods of elevated inflation. The most prominent disadvantage of the C&S is that it only samples prices for the three largest statistical areas and for food and energy on a monthly basis. All other goods are sampled on a bi-monthly basis. We do not observe if there are multiple price changes within a month, so our results may indicate a lower bound for price changes.

We classify the sector of each good or service according to its Elementary Level Index (ELI) as defined by the BLS.⁶⁷ We calculate most statistics through a two-step process. First, we create a statistic for each ELI category (e.g. frequency of price changes for AA011). Second, we aggregate the statistic across ELI's by finding the weighted mean or median. We use the 2018 Consumer Expenditure Survey to construct weights based on the relative importance of different ELI's.

Many ELI's are so narrowly defined that there only a handful of price changes for a

⁶For example, the code AA011 corresponds to men's suits.

⁷The BLS organizes goods and services in the CPI by (in decreasing order of aggregation) Expenditure Class, Item Strata, and Elementary Level Index. We use the Elementary Level Index classification instead of the coarser Item Strata for two reason. First, goods and services belonging to different ELI's within the same Item Stratum may be subject to different economic shocks. Grouping these items together may give an inaccurate picture of how different sectors behave. Second, earlier papers in the literature, such as Bils and Klenow 2004, have calculated statistics at the ELI level. We follow their approach in order to facilitate comparisons with earlier results.

given month. For higher moment statistics, such as variance, skew, or kurtosis, this paucity may make our estimates excessively sensitive. To resolve this constraint, we create a coarser classification for product types from either the first digit or the first two digits of the ELI codes.⁸ We refer to these classifications as the ELI1 and ELI2 categories, respectively. In this case, we would calculate the statistic by ELI1 or ELI2 and then find the weighted mean or median across categories.

There are three challenges to analyzing CPI Research Database, namely bi-monthly observations, substitution, and sales. First, a large fraction of good quotes are only sampled every two months, which poses a difficulty for estimating a monthly time series for price changes. For bi-monthly price quotes, we follow the practice of Nakamura and Steinsson 2008 in assuming that the monthly probability that a price changes is constant between observations. If fraction $f_{j,t}^{bimonthly}$ of prices for ELI j change between date $t-2$ and t , then we assume that the fraction of prices that changed in periods $t-1$ and in period t is

$$(1 - f_{j,t})^2 = 1 - f_{j,t}^{bimonthly}$$

For other statistics, particularly those related to size or dispersion of price changes, we calculate them for monthly and bi-monthly observations separately and then combine them using a weighted average based on the number of observations.

Second, businesses often discontinue or change the quality of goods and services that are sold to consumers and thus sampled by the C&S. The C&S attempts to correct for these changes by finding another version of the good that is similar enough and performing quality adjustments. It's difficult to disentangle pricing effects and quality effects. Additionally, it's unclear if these substitutions are introduced as a result of aggregate economic effects, and what their implications are for monetary policy effectiveness. Thankfully, the BLS tracks product characteristics closely and identifies substitutions effectively.⁹

⁸For example, "AA" corresponds to men's apparel, "A" corresponds to all apparel

⁹The BLS collects this information in order to account for quality changes and the introduction of new goods into its price indices. See Groshen et al. 2017 for more details about the data and methodology.

Third, firms may temporarily reduce a product’s price through a sale or discount, before returning it to the previous level. The research literature on price-setting generally finds that sales are transient and are not a response to aggregate economic shocks.¹⁰ We use the sales flag recorded by the C&S field agents to identify sales. While our primary analysis will exclude any price changes that are due to sales, we conduct a supplemental analysis of whether the prevalence of sales has increased during the pandemic and what its effects may have been. Following Eichenbaum et al. 2014, we drop any price changes less than 1% in magnitude in the ELI sectors they identified. Additionally, we drop any price changes that are smaller than 0.01% or larger than 100% in magnitude as outliers.¹¹

3 Frequency and Size

In this section we analyze how the frequency and the magnitude of price changes have evolved over the course of the pandemic.¹² We then address how much of the variation in the inflation rate can be attributed to the intensive margin of adjustment compared to the extensive margin of adjustment. We conclude by constructing counterfactual inflation rates and studying how the the dispersion of price changes has fluctuated over the course of the pandemic.

3.1 Frequency

One of the major contributions of this paper is testing whether firms have updated prices during the pandemic in a time-dependent or state-dependent fashion. These two pricing models give two quite different predictions about how businesses would set prices during the Covid-era. Given the large supply shocks throughout the pandemic, as well as shifting consumer demand as the economy closed and reopened, it seems likely that firms optimal

¹⁰For example, see Nakamura and Steinsson 2008.

¹¹Several other papers in the price stickiness literature, such as Alvarez, Bihan, and Lippi 2016 and Luo and Villar 2021, also drop small price changes in these sectors.

¹²We use the terms “magnitude” of price change and “absolute value” of price change synonymous.

prices would not be constant. Under a state-dependent model, such as a menu cost model popularized by Golosov and Lucas 2007, firms would predominantly react to these shocks by updating their prices more frequently by roughly the same magnitudes, unless inflation is at a low, stable level.¹³ In contrast, a time-dependent model in the style of Calvo 1983 would predict that firms would respond by adjusting their prices by larger amounts. To test these predictions, we plot the frequency of price changes against the average absolute value of the size of price changes and the average size of price changes.

Figure 1 displays the frequency, size, and magnitude of price changes during the Covid pandemic. We graph a further two years of data before the pandemic for comparison, while still emphasizing the pandemic period. We follow Nakamura and Steinsson 2008 in emphasizing the median frequency of price changes across ELI's, as these are more representative of pricing behavior. We graph the mean size and magnitude of price changes across ELI's. We present the statistics with and without sales for comparison. When price changes due to sales are excluded, we find that the absolute value of price changes rose from about 8.4% in January 2020 before the pandemic to 9.4% in June 2020, before falling back to 8.5% for a majority of 2021. The frequency of price changes likewise rises from 11% in January 2020 to 13% in June 2020. However, the frequency of price changes began rising even before the pandemic became widespread in the United States: from December 2019 until February 2020 the frequency rose by 2 percentage points and continued to rise until April 2020. One possible explanation is that forward-looking firms became aware of the emergence of Covid-19 in early 2020. These businesses could have begun adjusting prices even before the pandemic became widespread in the U.S. Another possibility is that, as Nakamura and Steinsson 2008, the frequency of price adjustment is highly seasonal and highest in the first quarter. In either case, the frequency of price changes (without sales) continued to rise throughout 2021.

The average size and absolute value of price changes tell conflicting stories about how

¹³Nakamura, Steinsson, et al. 2018 and Alvarez, Beraja, et al. 2019 show that the frequency of price changes is relatively insensitive to changes in inflation at low levels of inflation. However, U.S. inflation rose to historic levels in 2021.

firms reacted to the historically large increase in inflation during 2021. In both graphs of 1, the absolute value of price changes is relatively flat during 2021, which indicates that firms are charging their prices by roughly the same amount even as inflation pressures rise. In contrast, the average price change trebles from 1.0% in January to 3.1% in October. This discrepancy can be explained by firms increasing their prices more often in 2021 and decreasing them less often.

To further investigate the significance of the size of price changes, we evaluate whether variations in the frequency of price changes or the size of price changes play a larger role in explaining variation in inflation over the course of the pandemic. As in Klenow and Kryvtsov 2008, we view inflation as being described by $\pi_t = fr_t * dp_t$. We construct the inflation rate over the course the pandemic, which equals the frequency of price changes multiplied by the size of price changes. We calculate an inflation rate for each ELI category separately, and then aggregate the inflation rates together using the 2018 Consumer Expenditure weights. Because of the limitations of the data and differences between the CPI Research Database and official CPI-U,¹⁴ we construct our own inflation metrics from the CPI Research Database.

We construct two counterfactual inflation rates to illustrate the role of frequency and size in determining aggregate inflation. The first counterfactual inflation is the case where the frequency of price changes is held constant at the January 2020 level, while the size of price changes varies. The second counterfactual inflation is where the size of price changes is held constant at the January 2020 level while frequency is permitted to vary. We refer to these two measures as the fixed frequency inflation and the fixed size inflation, respectively. The equations for these are

$$\begin{aligned}\pi_t^{freq} &= \bar{f}r \cdot dp_t \\ \pi_t^{size} &= fr_t \cdot \bar{d}p\end{aligned}$$

¹⁴Among other differences, the CPI-U contains shelter, while our dataset does not.

Figure 2 plots our inflation rate and the two counterfactual inflation rates against each other. Our measure of month-on-month inflation is quite volatile, particularly in mid-2020 as the economy contracts in the face of Covid-19. The fixed-frequency counterfactual inflation, where the size of price changes fluctuates, tracks the inflation rate quite closely. In contrast, the fixed size inflation rate varies insignificantly over the entire course of the pandemic, even during the high-inflation period of 2021.

To further test the result, table 1 calculates the correlation between all three inflation series from March 2020 onward. The fixed frequency inflation rate is highly correlated with the overall inflation rate, while the fixed size inflation rate actually has a negative correlation. State-dependent models, where firms select when to change prices, would have difficulty explaining variation in the inflation rate over the course of the pandemic. While some menu cost models (Nakamura, Steinsson, et al. 2018, Alvarez, Beraja, et al. 2019) mainly adjust inflation through the size of price changes, these results hold mainly in a low-inflation environment with weak aggregate shocks. However, the U.S. economy during the pandemic has been characterized by dramatic aggregate shocks and an elevated rate of inflation, particularly in 2021.

We confirm our results regarding the relevance of the extensive margin of adjustment compared to the intensive margin by conducting the Klenow and Kryvtsov 2008 decomposition of inflation variation into the two components. We limit our analysis to the post-March 2020 period in order to focus on how firms responded during the pandemic. The analysis is

$$var(\pi_t) = \underbrace{var(dp_t) \cdot \bar{f}r^2}_{\text{Intensive Margin}} + \underbrace{var(fr_t) \cdot \bar{d}p^2 + 2\bar{f}r \cdot \bar{d}p \cdot cov(fr_t, dp_t)}_{\text{Extensive Margin}}.$$

Table 2 displays the decomposition of inflation variance between intensive and extensive. As in Klenow and Kryvtsov 2008, the intensive margin of adjustment explains a lion's share of the inflation variance, with the extensive margin playing a minor role. The extensive margin is slightly more significant if we include sales. This fact can be explained by the fact

that firms can adjust their prices more frequently if we incorporate sales. We interpret these results as supporting a time-dependent model of pricing.

3.2 Dispersion

Higher order moments can be informative for determining firm behavior and the effectiveness of monetary policy. Alvarez, Bihan, and Lippi 2016 and Alvarez, Borovičková, and Shimer 2021 derive measures of real cumulative effects of monetary policy from the variance and kurtosis of firm price changes. In contrast, Luo and Villar 2021 focuses on how the skew of price changes can be informative for describing a complicated menu cost model. If the dispersion of price changes falls in a particular period, then that fact would suggest that firms are adjusting their prices in the same manner in response to an aggregate shock. In contrast, a rise in price change dispersion could either reflect firms reacting to private information about the nature of the pandemic, or the role of sector-specific shocks.

We construct two measures of dispersion: the standard deviation of price changes and the interquartile range. In both cases we construct the price change statistic at the ELI2 level, and then find the weighted means across ELI2's. These measures thus reflect the within-ELI dispersion in price changes. We smooth the resulting time series using a three month moving average and plot the result in graph 3. We find that the dispersion of price changes began rising sharply in March 2020, likely as a response to the pandemic, and remained high for much of 2020. However, even in late 2020 before the economy fully reopened, the dispersion of price changes began trending down and remained flat throughout 2021. These results indicate that firm-specific shocks played its most significant role early in the pandemic, and that the elevated inflation period of 2021 can best be represented as specific sectoral or aggregate shocks. Additionally, the decline in dispersion supports a state-dependent model of firm price-changing. In this scenario, a rise in inflation pushes more firms to make positive price changes and fewer firms to make negative price changes. As a result, dispersion within each ELI2 falls even as prices rise.

4 Sectors

This section investigates how sectoral differences can affect firm price-setting decisions by addressing two research questions. First, we study the role of sectoral shocks compared to aggregate shocks. Second, we test whether more flexible sectors have reacted more quickly to the pandemic and subsequent elevated inflation.

4.1 Sectoral Shocks

Sectoral shocks and frictions can have macroeconomic effects. Guerrieri et al. 2020, in particular, argue that an adjustment of demand between different sectors, in an economy subject to wage, price, and labor reallocation frictions, can lead to temporarily high inflation that the central bank should optimally allow. Whether the current increase in inflation is due to a sectoral reallocation or an aggregate rise in demand is therefore crucial to determine the appropriate stance of monetary policy.

We begin by presenting statistics on broad sectors over the course of the pandemic. For the purpose of legibility, we aggregate all ELI categories to the first digit of their ELI code.¹⁵ These ELI1 codes cover general categories of consumer expenditure such as food and beverages, housing, and transportation. We begin by calculating the frequency, size, and absolute value of price changes for each individual ELI category and data. As before, we disregard any price changes due to sales. Following that, we use the ELI1 2018 CE weights to calculate the median frequency of price changes and mean sizes and absolute values of price changes. Figure 4 presents the statistics by ELI1 side by side from 2019 until the present.

Firms in different sectors have disparate price-setting behaviors, both during the pandemic and prior to it. The prices of apparel goods, for instance, were frequently updated even before the pandemic. The price change frequency rose from 30% in February 2020 to a peak of 39% in August 2020, before declining afterwards. In contrast, the size of price adjustment

¹⁵For example, the Elementary Level Index for Men’s Suits (AA011) is mapped onto the ELI1 category “A”, which contains all apparel goods.

wildly fluctuates between price increases and price decreases while the absolute value of the changes stays relatively flat. These facts suggest that firms that sell apparel goods make most of their adjustment through deciding whether to increase or decrease prices.¹⁶

In the transportation sector, firms selling goods and services¹⁷ adjust their prices quite frequently, even before the pandemic. However, there the size and absolute value of price change is quite small and steady. In early 2021 firms reacted to the supply shocks by updating their prices by larger amounts, which could reflect a negative supply shock. These contrasts with the apparel sector suggest not only that different sectors face different frictions in how they set prices, but that sector-specific shocks may have played a significant role. Given how little variation there is in the absolute value of price changes¹⁸, a menu cost model with large sectoral shocks may be able to explain this graph the best.

The rise and fall of the dispersion of price changes in figure 3 reflect a mix of sectoral and idiosyncratic shocks. If the dispersion of price changes was primarily due to strong sectoral shocks, such as a decline in demand for services in 2020, then we would expect to see the within-sector dispersion decline and the between-sector dispersion rise. In order to measure the role of sectoral forces as opposed to idiosyncratic shocks more carefully, we decompose the variance in price changes into a between-sector and within-sector component for each date. The equation for this breakdown is

$$var(dp_{i,j,t}) = \sum_j^J \sum_i^{I_j} (dp_{i,j,t} - \bar{dp}_t)^2 = \underbrace{\sum_{j=1}^J \omega_j Var(\hat{dp}_{i,j,t})}_{\text{Within-Sector}} + \underbrace{\sum_{j=1}^J \omega_j (dp_{j,t} - \bar{dp}_t)^2}_{\text{Between-Sector}}$$

where i corresponds to a specific good or service, j corresponds to an ELI2 category, t denotes a time period, and $dp_{i,j,t}$ is the change in log prices for product i in sector j at time

¹⁶The fluctuates in the size of price changes could be explained by a simple menu cost model with a small region of in action due to insignificant updating costs.

¹⁷Examples of Elementary Level Indices in the transportation ELI1 category are new vehicles and gasoline

¹⁸With the exception of the Education and Communications (“E”) ELI1 category, which saw large fluctuations in the magnitude of price changes as workers shifted towards working from home in greater numbers.

t . ω_j is the weight on ELI2 category j , and $Var(\hat{d}p_{i,j,t})$ denotes the variance of prices within ELI2 sector j . We define ELI2 categories as the first two characters of an ELI¹⁹. We perform this analysis by ELI2 instead of ELI because ELI’s are defined as rather narrow categories. Many ELI’s only contain a couple dozen price observations per month, and only a small minority of those may reflect price changes. In these cases, there may not be a sufficient number of price changes to accurately estimate the variance. ELI2 categories are sufficiently broad to contain enough price changes each period to estimate the variance, while also being fine enough to permit meaningful comparisons between sectors. Because the terms in the decomposition contain the size of price changes in percent and squares, the within-sector and between-sector components are described in units of percent-squared. We calculate the within-sector and between-sector dispersion as defined above for each period and display the results in figure 5.

The within-sector dispersion of price changes is an order of magnitude larger than the between-sector dispersion, which indicates that idiosyncratic shocks play a markedly larger role than sectoral.²⁰ To the extent that ELI2 categories are broadly defined and that firms throughout the U.S. in the same sector nevertheless face a variety of different incentives, the importance of within-ELI2 dispersion is not surprising. Additionally, both dispersion components regularly fluctuate even pre-pandemic, possibly as a result of seasonal forces.²¹

Both components of dispersion rise suddenly in two periods: the early portion of the pandemic in Spring 2020 and the second half of 2021 as inflation began to rise. In the former case, the sudden impact of the pandemic and lockdowns could have pushed some sectors to sharply cut prices (e.g. such as airlines), while others found themselves suddenly in high demand. In the latter case, a rise in between-ELI2 variance could reflect the fact that some

¹⁹For example, the Elementary Level Index for Men’s Suits (AA011) is mapped onto the ELI1 category “AA”, which contains all men’s apparel goods.

²⁰We have rerun this decomposition defined at the ELI level instead of the ELI2, and obtained a similar magnitude of difference.

²¹Nakamura and Steinsson 2008 documents that the frequency of price changes is highly seasonal, particularly in sectors such as Apparel that regularly introduce new products. Seasonal price-dispersion could represent differential demand shocks over the course of the year.

sectors of the economy were more constrained by supply shocks than others, and that early inflation was uneven. These results further support the work of authors such as Guerrieri et al. 2021, who are concerned with how monetary policy should react if there are asymmetric shock son sectors. However, the fact that the within-ELI2 component of dispersion rose runs counter to the prediction of many menu cost models,²² which prediction the dispersion of price changes to fall as inflation rises. If all firms within a sector are jointly hit by a negative sectoral shock, then there should be impetus on them to rise their prices in tandem. As a result, all firms that choose to change their prices choose to increase their prices by similar amounts, and the dispersion of price changes falls.

4.2 Sectoral Regressions

Time-dependent and state-dependent models make different predictions about the dispersion of price changes after a shock to demand. The Calvo model, for instance, predicts that the dispersion of price changes will rise following such a shock, while a menu cost model predicts that the dispersion will fall. We test these two models by regressing dispersion on sectoral inflation. On the left-hand side is the dispersion of price changes for a specific ELI2 sector and date, and the right hand-side contains the inflation rate for that specific ELI2 sector.²³ We calculate the ELI2-specific inflation rates from the CPI-research database using the frequency of price changes and the size of price changes. Our approach mimics the decomposition of inflation put forth in Klenow and Kryvtsov 2008. The regression specification is

$$\sigma_{j,t} = \alpha + \beta\pi_{j,t} + \delta_j + \varepsilon_{j,t}$$

where j refers to an ELI category, $\sigma_{j,t}$ is standard deviation of price changes within an ELI-date, $\pi_{j,t}$ refers to the month-on-month inflation rate for ELI j , and δ_j refers to ELI fixed effects. We smooth the regressions variables over several months, in order to reduce

²²See papers such as Luo and Villar 2021 for more detail.

²³We conduct our analysis using ELI2 categories, instead of ELI, to ensure that have a sufficient number of observations each period to reliably estimate the standard deviaiton of price changes.

the influence of noise coming from sampling variation.

Table 3 displays the result. In columns (1) and (2) we find no relationship between the ELI2-specific inflation rate and the dispersion of price changes during the Covid pandemic. One possibility is that the limited time-span of our analysis means that our regression is underpowered.²⁴ However, a simple menu cost model predicts that the dispersion of price changes falls if inflation is high or if there is deflation. In the former case, firms move out of the inaction region on the right and almost uniformly increase prices. In the latter case, firms move out of the inaction region on the left and decrease prices instead. In both cases the dispersion of price changes falls. The Covid pandemic has been characterized by unusually low and high inflation in different periods, so our results may capture both effects. Therefore, we rerun the analysis above by regression the standard deviation of price changes (within an ELI2-date) on the absolute value of sectoral inflation and present the result in columns (3)-(5). Contrary to the menu cost predictions, we find that the dispersion of price changes rises as the absolute value of inflation rises, not declines. Adding ELI fixed effects or the official CPI-U inflation rate weakens but does not eliminate this relationship. For robustness, we rerun our analysis on the pre-Covid period, which runs from January 1988 to February 2020 and display the results in table 4. We confirm that there is a positive relationship between the absolute value of inflation and the dispersion of price changes, which provides support for a time-dependent, Calvo-style model of firm pricing.²⁵ Further work will need to be done to investigate the implications of this result for menu cost models.

Next, we turn to the role of price flexibility during the pandemic. As Nakamura and Steinsson 2010 note, there is considerable variation in sectoral price setting flexibility, and thereby pricing frictions. Given that the Covid pandemic and subsequent recovery has been characterized by large aggregate shocks, we study whether flexible firms have reacted more quickly to changes in aggregate inflation. Our regression specification is

²⁴We rerun our analysis on a longer span of data below in order to increase the power.

²⁵The coefficient on inflation becomes statistically significant and negative, which offers further evidence that our analysis on the Covid period was underpowered.

$$fr_{j,t} = \alpha + \beta \cdot fr_j^{2019} + \gamma \cdot fr_j^{2019} \cdot \pi_t + \varepsilon_{j,t}$$

where j corresponds to an ELI and fr_j^{2019} is the average frequency of price changes before February 2020 by ELI. Our prediction is that as inflation rose in 2021, firms in flexible sectors adjusted more quickly than others, so that $\gamma > 0$. Table 5 present our results.

We find that firms in flexible sectors did not react to an uptick in the inflation rate more quickly. Sectors that were flexible pre-pandemic maintain their flexibility during the pandemic. These results follow the low inflation environment described by Alvarez, Beraja, et al. 2019, which demonstrate that the frequency of price adjustments is unresponsive to inflation at low inflation rates. However, given the elevated level of inflation in 2021, it is unclear whether the low inflation regime describes our timeframe.

5 Price Increases Share

Firms not only face decisions of whether to update prices and the magnitude of updates, but whether they should increase prices or decrease prices. The Covid pandemic has been characterized by large negative and positive economic shocks at different periods, which have placed different pressures on firms to change their prices.²⁶ We presented results earlier in this paper that demonstrated that the magnitude of price changes and the average price change generally do not co-move, which suggests that the increase/decrease margin is significant for explaining how firms reacted to the pandemic. This section delves further into decomposing price changes between price increases and price decreases.

We begin by displaying figure 6, which displays the median frequency of price changes, price increases, and price decreases against the year-on-year change of the CPI-U. As before, we disregard any price changes due to sales. We find that the the frequency of price increases

²⁶As earlier work such as Nakamura and Steinsson 2008 has noted, a substantial fraction of price changes are actually price decreases. Researchers such as Nakamura, Steinsson, et al. 2018, Alvarez, Beraja, et al. 2019, and Gautier et al. 2022 have further demonstrated that in low inflation environments, firms primarily adjust to inflation by shifting the fraction of price changes that are price increases relative to decreases.

and price decreases rises in 2020. The fraction of price changes that are increases falls from 63% in January 2020 to 47% in November 2020. However, as inflation begins to pick up in 2021, the frequency of price decreases drops from 4.7% in January 2021 to 4.0% in January 2022, a decrease of 20%. In contrast, the frequency of price increases surges from 8% to 12.5%. Our results suggest that one of the big drivers of inflation, particularly in 2021, has been firms shifting their price changes from price decreases to increases.²⁷

Next, we investigate the role that the intensive margin plays in price increases and decreases. We explore this possibility by graphing the magnitude of price increases and decreases against the CPI-U over the course of the pandemic. Figure 7 displays the the median magnitude of price increases and decreases across ELIs. We find that the magnitude of price decreases is substantially larger than price increases prior to the pandemic, but that this gap has narrowed recently. One possible explanation for this behavior is that the menu cost of adjusting prices downward are substantially larger than the cost of increasing it. Alternatively, demand shocks that affect firms could be non-symmetric in some fashion that encourages large price decreases.

The magnitudes of both increases and decreases have risen over the course of the pandemic. During 2020, the magnitude of price decreases rose rapidly, from 7.0% in January 2020 to 8.8% in May 2020. Price increases followed soon after, beginning their rise in April 2020 by a similar amount. These magnitudes began falling throughout the rest of 2020, before rising slightly with inflation. These results could be explained by a menu cost model with large aggregate shocks in early 2020 which push the optimal prices far away from the current prices, necessitating large price resets and fewer small price changes. After the initial impact of the pandemic, firms return to only making moderate price changes when they find the optimal price to be outside of the inaction region.

We quantify the significance of the share of price increases through a series of inflation

²⁷Because we are displaying the median frequency of price changes across-ELI's instead of means, adding two time series together does not necessarily yield its aggregate. Results about the fraction of price changes that are price increases comes from the author's own calculations.

counterfactuals and decompositions. The inflation rate can be decomposed into a price increase component and price decrease component, as in Gautier et al. 2022, which is

$$\pi_t = f_t^+ \cdot dp_t^+ - f_t^- \cdot dp_t^-$$

where f_t^+ denotes the mean frequency of price increases across ELI's, f_t^- the frequency of price decreases, dp_t^+ is the mean magnitude of price increases across ELI's, and dp_t^- the magnitude of price decreases across ELI's.

Using the frequencies and magnitudes of price increases and decreases, we create a series of inflation counterfactuals in order to study the significance of increases and decreases during the pandemic. We follow the approach of Gautier et al. 2022 in running three counterfactuals. In the first case, we hold the frequencies of price increases and decreases constant at the January 2020, while allowing the size of increases and decreases to vary. In the second case, we do the reverse by holding the magnitudes of increases and decreases fixed while allowing the frequencies to vary. In the third and final counterfactual, we fix the overall frequency of price changes as well as the magnitude of price increases and price decreases, while allowing the fraction of price changes that are increases to vary. The equations for these counterfactual inflation rates are

$$\begin{aligned}\pi_t^{\bar{f}^+, \bar{f}^-} &= \bar{f}^+ dp_t^+ - \bar{f}^- dp_t^- \\ \pi_t^{\bar{d}p^+, \bar{d}p^-} &= f_t^+ \bar{d}p^+ - f_t^- \bar{d}p^- \\ \pi_t^\alpha &= \alpha_t \bar{f}^+ \bar{d}p^+ - (1 - \alpha_t) \bar{f}^- \bar{d}p^-.\end{aligned}$$

We refer to the first case as the fixed frequency inflation, the second case as the fixed size, and the third case as the varying fraction.

Figure 8 plots all three inflation counterfactuals against the month-on-month inflation rate calculated from the CPI Research Database. The overall inflation rate is considerably

more volatile than the counterfactual inflation series, since each counterfactual shuts down at least one source of variation. For the most part, the counterfactual inflation series agree with each other, with the fixed size and fixed frequency scenarios being particularly close.

Next, we calculate the correlations between the four time series and display the results in table 6. We find fixing the size of price increases and decreases results in an inflation rate that is correlated with the overall inflation rate. If we further fix variables and only allow the fraction of price changes that are increases to vary, the correlation drops from 0.658 to 0.373. However, even the varying fraction counterfactual has a higher correlation with actual inflation than the fixed frequency scenario. We interpret these results as indicating that the extensive margin is quite important for determining how firms adjust prices, and that at least a component of this is the decision about whether to increase or decrease prices.

6 Conclusion

In this paper, we have documented how firms have adjusted prices during one of the most economically disruptive periods of recent history, the Covid-19 pandemic. We use these results to test predictions made by different models of firm price setting and study the role of sectoral shocks.

We have presented three main findings. First, the frequency of price changes has been relatively constant and the intensive margin of adjustment has played a predominant role in how firms have reacted. Second, there are large sectoral differences in price-setting behavior. Firms were affected by large sectoral and idiosyncratic shocks. Additionally, we find that the dispersion of price changes has a positive relationship to the magnitude of inflation, which stands in contrast to typical menu cost predictions. Third, and finally, we show that the allocation of price changes between increases and decreases has been dynamic over the course of the pandemic, and that this margin plays a role in explaining firm responses and overall inflation.

At the moment of this paper's authorship, the year-on-year CPI-U inflation rate remains at an historically elevated level. A typical menu cost model makes two predictions when inflation is elevated: in response to a positive inflation shock, firms respond by increasing the frequency of price adjustments and the dispersion of price changes falls. This paper presents results contrary to both predictions, which raises questions about the suitability of menu cost models in these environments.

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Tables

Table 1: Counterfactual Inflation Correlations

	Inflation	Fixed Size	Fixed Frequency
Inflation	1		
Fixed Size	-0.031	1	
Fixed Frequency	0.943	-0.063	1

Notes: All three time series in this graph are constructed with data from the BLS CPI research database. Inflation is defined as the fraction of prices that change multiplied by the average price change. The fixed size time series is the counterfactual inflation rate where the size of price changes is fixed at the January 2020 level, while allowing frequency to vary over time. The fixed frequency counterfactual inflation rate is the case where frequency is fixed at the January 2020 level, and size is allowed to vary. All time series are defined as month-on-month changes. All price changes due to sales are excluded.

Table 2: Klenow-Kryvtsov (2008) Decomposition

Sample	Intensive Margin	Extensive Margin
No Sales	93.1%	6.9 %
With Sales	97.4 %	2.5 %

Notes: This table replicates the Klenow and Kryvtsov 2008 decomposition of inflation variation into an extensive margin and intensive margin component. The analysis is conducted on data from March 2020 onwards.

Table 3: Price Change Dispersion on Inflation

	(1)	(2)	(3)	(4)	(5)
ELI Inflation	-0.256*** (0.067)	-0.099* (0.044)			
Abs. Val. of ELI Inflation			0.582*** (0.075)	0.196** (0.064)	0.258*** (0.067)
CPI-U					-0.001* (0.000)
Constant	0.127*** (0.001)	0.137*** (0.007)	0.121*** (0.002)	0.132*** (0.007)	0.134*** (0.008)
ELI2 Dummies	No	Yes	No	Yes	Yes
R^2	0.010	0.616	0.037	0.617	0.619
Observations	1537	1537	1537	1537	1336

Notes: The dependent variable for these regressions is the dispersion of price changes, measure by the standard deviation, for each ELI2 and date. ELI2-Inflation refers to the ELI2-specific month-on-month inflation rate for a given monthly date. An observation in this table corresponds to an ELI by date. Dates are monthly and restricted to post-March 2020. Price changes due to sales are not included.

Table 4: Price Change Dispersion on Inflation, Pre-pandemic

	(1)	(2)	(3)	(4)	(5)
ELI Inflation	-0.132*** (0.028)	-0.145*** (0.020)			
Abs. Val. of ELI Inflation			0.620*** (0.031)	0.300*** (0.026)	0.316*** (0.026)
CPI-U					-0.003*** (0.000)
Constant	0.120*** (0.000)	0.097*** (0.002)	0.116*** (0.000)	0.096*** (0.002)	0.103*** (0.002)
ELI2 Dummies	No	Yes	No	Yes	Yes
R^2	0.001	0.535	0.016	0.536	0.540
Observations	24280	24280	24280	24280	24280

Notes: The dependent variable for these regressions is the dispersion of price changes, measure by the standard deviation, for each ELI2 and date. ELI2-Inflation refers to the ELI2-specific month-on-month inflation rate for a given monthly date. An observation in this table corresponds to an ELI2 by date. Dates are monthly and restricted to pre-March 2020. Price changes due to sales are not included.

Table 5: Price Frequency on Pre-Pandemic Frequency

	(1)	(2)	(3)	(4)
Pre-Pandemic Freq.	0.909*** (0.012)	0.914*** (0.019)	0.914*** (0.022)	0.914*** (0.022)
Pre-Pandemic Freq. X CPI-U		-0.000 (0.005)	-0.000 (0.007)	-0.000 (0.007)
CPI-U			-0.000 (0.001)	
Constant	0.087*** (0.002)	0.083*** (0.003)	0.083*** (0.004)	0.076*** (0.009)
Time Dummies	No	No	No	Yes
R^2	0.470	0.471	0.471	0.474
Observations	5982	5203	5203	5203

Notes: This table regresses the frequency of price changes for each ELI and date on the flexibility of prices pre-pandemic. The variable pre-pandemic freq is defined as the average frequency of price changes for an ELI between January 1988 and January 2020. An observation in this table corresponds to an ELI by date. Dates are monthly and restricted to post-March 2020. Price changes due to sales are not included.

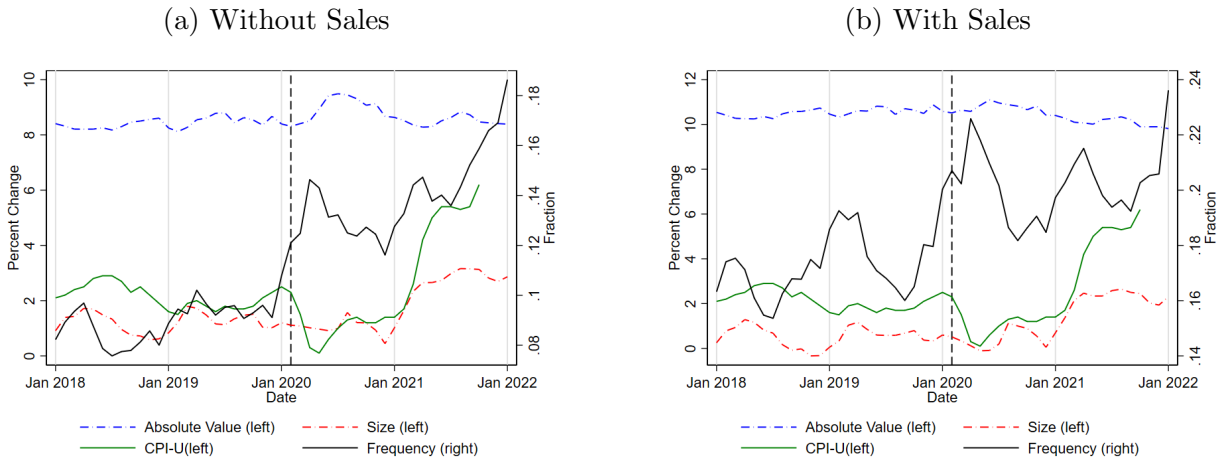
Table 6: Counterfactual Inflation Increase/Decrease Correlations

	Inflation	Fixed Size	Fixed Frequency	Varying Fraction
Inflation	1			
Fixed Size	0.658	1		
Fixed Frequency	0.231	0.154	1	
Varying Fraction	0.375	0.617	0.102	1

Notes: All four time series in this correlation matrix are constructed with data from the BLS CPI research database. All time series are defined as month-on-month changes. All price changes due to sales are excluded.

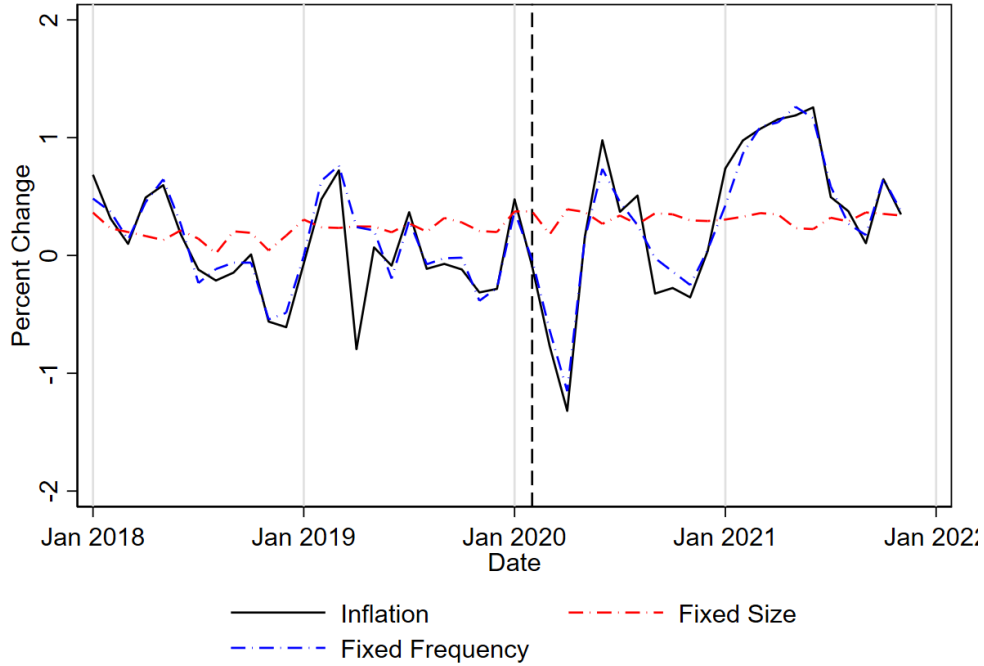
Graphs

Figure 1: Median Frequency and Magnitude of Price Changes



Notes: These graphs are constructed with the BLS CPI research database. The frequency time series is the weighted median of the frequency of price changes for each month across all ELI categories. The size and absolute value series are the weighted mean of the respective statistics across ELI categories. The vertical dashed line corresponds to February 2020. With sales refers to all price changes, including those where the BLS field agent recorded a temporary sale. The year-on-year change in the BLS CPI-U is provided for comparison. Frequency, size, and absolute value of price change time series are smoothed with a 3-month moving average.

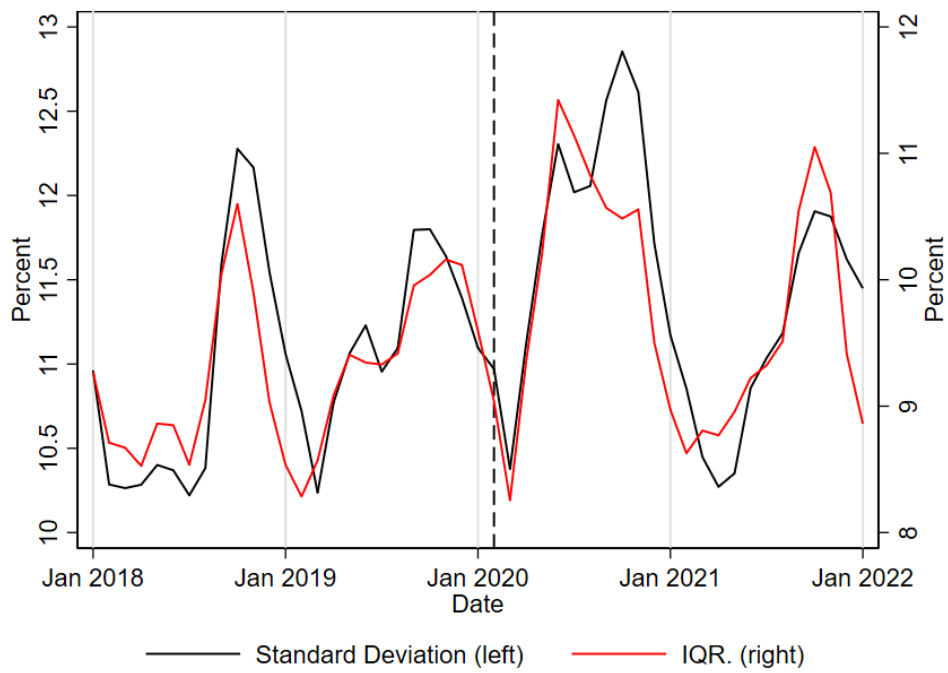
Figure 2: Inflation Counterfactuals



Notes: All three time series in this graph are constructed with data from the BLS CPI research database. Inflation is defined as the fraction of prices that change multiplied by the average price change. The fixed size time series is the counterfactual inflation rate where the size of price changes is fixed at the January 2020 level, while allowing frequency to vary over time. The fixed frequency counterfactual inflation rate is the case where frequency is fixed at the January 2020 level, and size is allowed to vary. All time series are defined as month-on-month changes. The vertical dashed line corresponds to February 2020. All price changes due to sales are excluded.

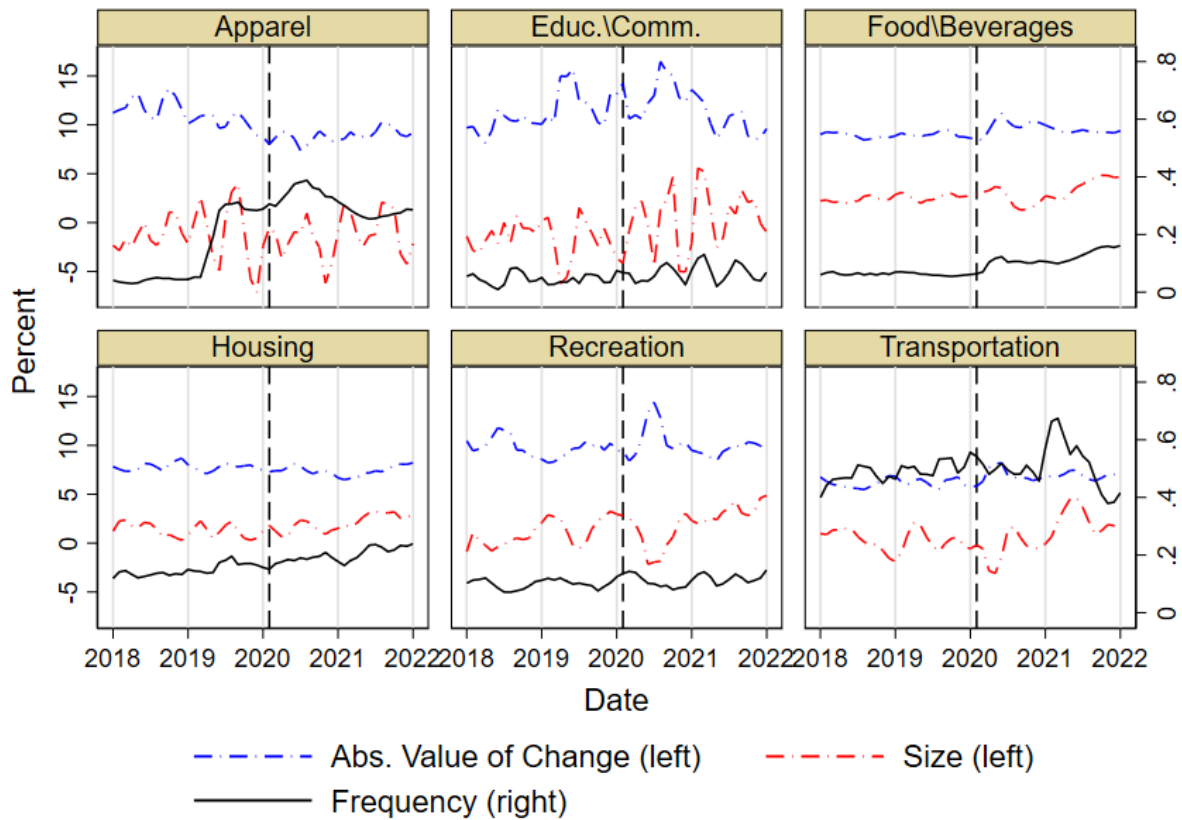
The inflation time series may not match the CPI-U because of sectors not included in the Commodities and Services Survey and observations dropped during the authors calculations. Time series are smoothed with a 3-month moving average.

Figure 3: Price Change Dispersion



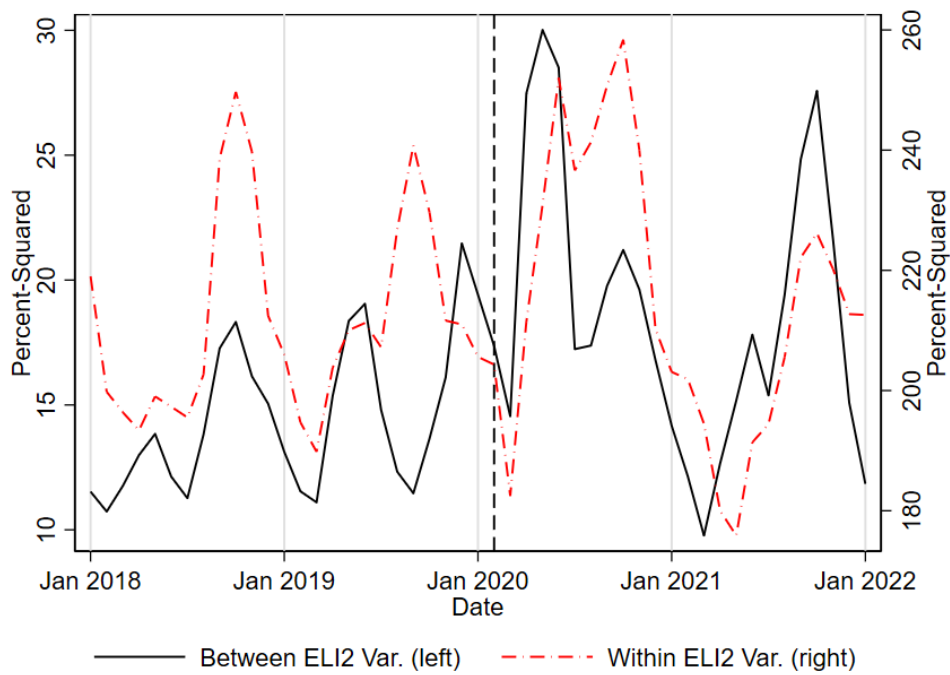
Notes: Both time series are constructed from the BLS CPI research database. They refer to the weighted median standard deviation or iqr across ELI2. Both time series have been smoothed with a three month moving average.

Figure 4: Frequency and Size by Sector



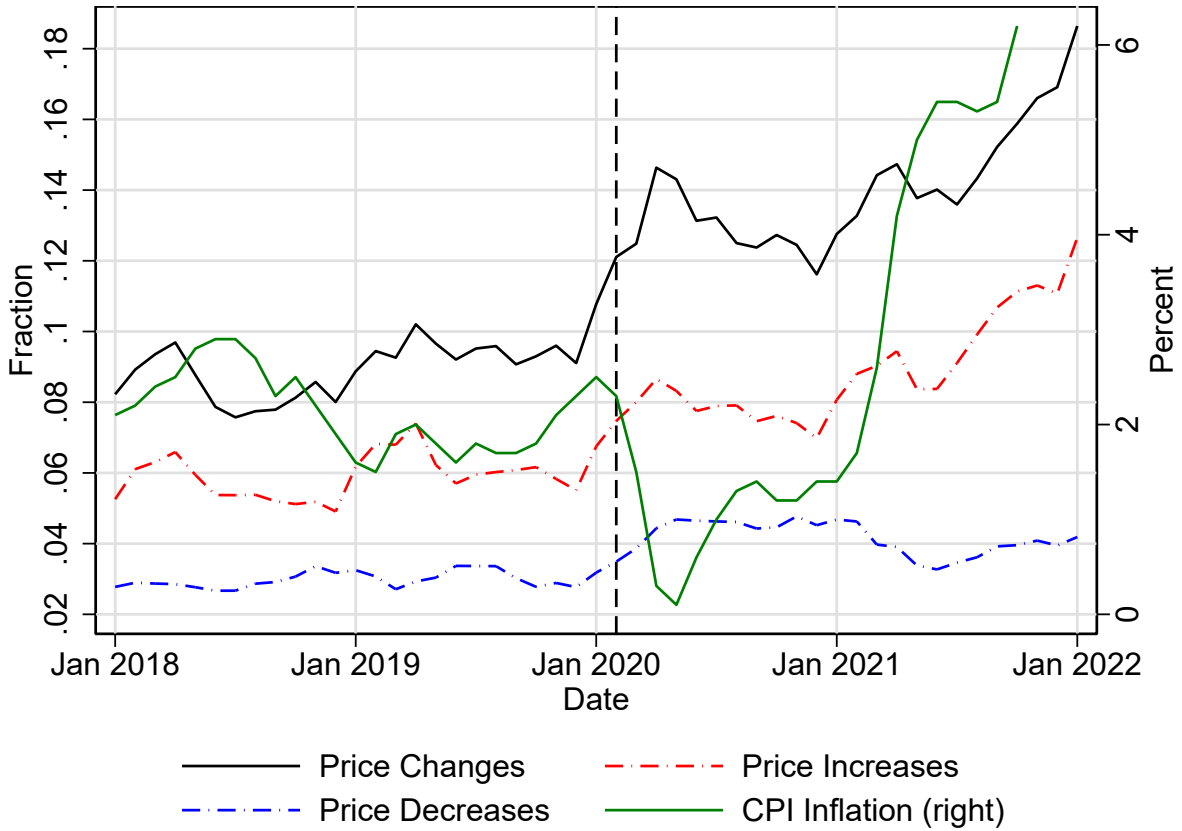
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series is the median value for each month across ELI1 categories, while the size and absolute value time series are the means. The vertical dashed line corresponds to February 2020. Price changes due to sales are excluded from this sample. Time series are smoothed with a 3-month moving average.

Figure 5: Price Change Dispersion Decomposition



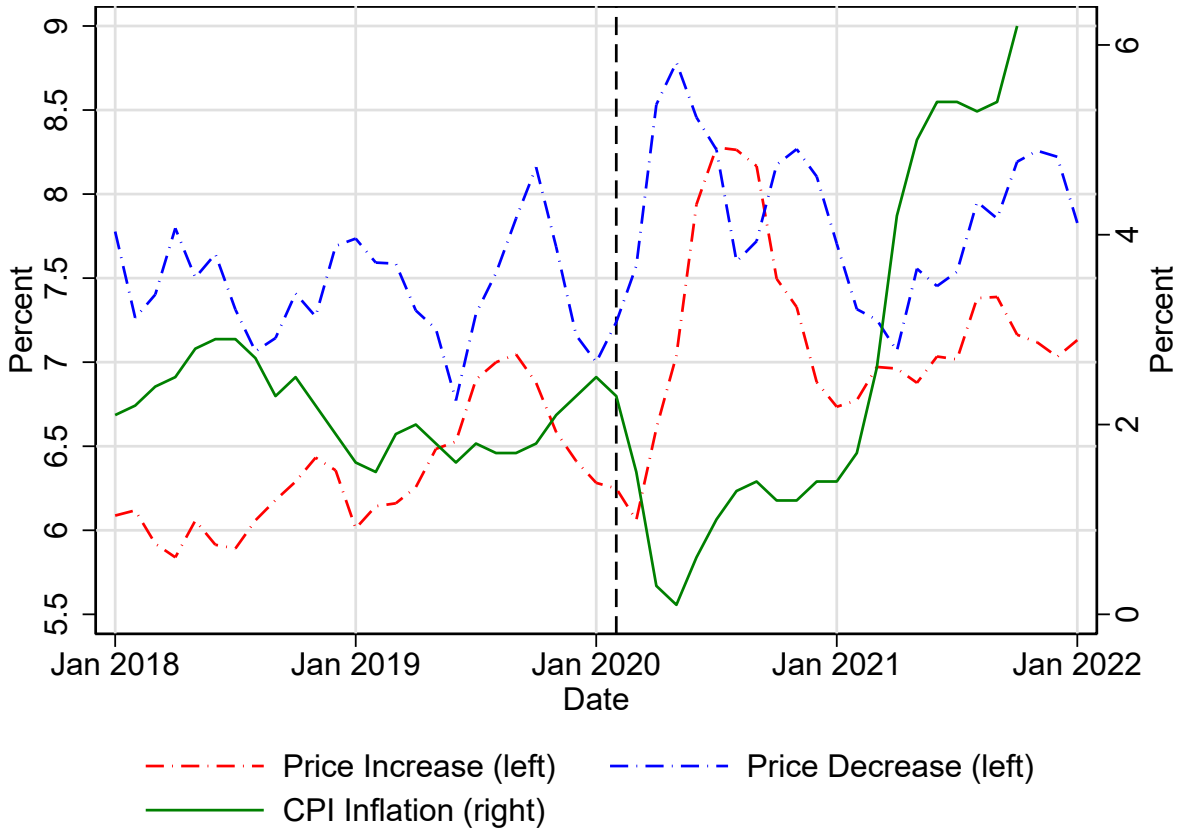
Notes: These graphs are constructed with the BLS CPI research database. The variance of price changes for each date are decomposed into between-ELI2 and within-ELI2 components. Price changes due to sales are excluded from this sample. The vertical dashed line corresponds to February 2020. Time series are smoothed with a 3-month moving average.

Figure 6: Frequency, Increases and Decreases



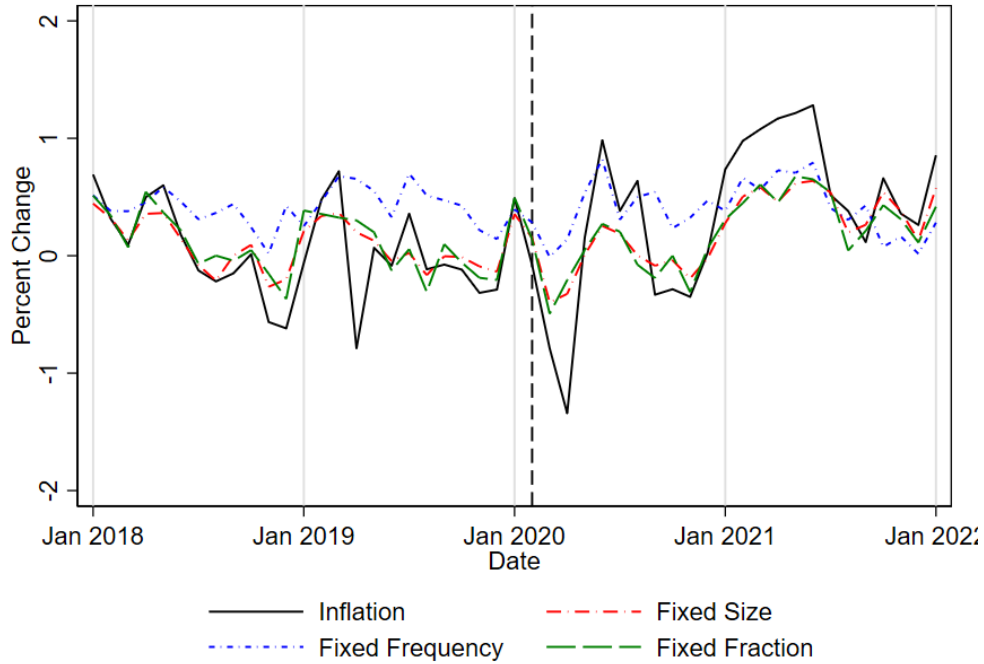
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series are the median values for each month across all ELI categories. The vertical dashed line corresponds to February 2020. Price changes due to sales are excluded. The year-on-year change in the BLS CPI-U is provided for comparison. Price change frequencies are smoothed with a 3-month moving average.

Figure 7: Size, Increases and Decreases



Notes: These graphs are constructed with the BLS CPI research database. The size time series are the median values for each month across all ELI categories. The vertical dashed line corresponds to February 2020. Price changes due to sales are excluded. The year-on-year change in the BLS CPI-U is provided for comparison. Price change frequencies are smoothed with a 3-month moving average.

Figure 8: Inflation Counterfactuals



Notes: All three time series in this graph are constructed with data from the BLS CPI research database. Inflation is defined as the fraction of prices that change multiplied by the average price change. The fixed size time series is the counterfactual inflation rate where the size of price changes is fixed at the January 2020 level, while allowing frequency to vary over time. The fixed frequency counterfactual inflation rate is the case where frequency is fixed at the January 2020 level, and size is allowed to vary. All time series are defined as month-on-month changes. The vertical dashed line corresponds to February 2020. All price changes due to sales are excluded.

The inflation time series may not match the CPI-U because of sectors not included in the Commodities and Services Survey and observations dropped during the authors calculations. Time series are smoothed with a 3-month moving average.