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Abstract

Using the micro data underlying the U.S. CPI, we document several findings about firm price-setting behavior during and following the Covid-19 pandemic, a period with the highest levels of inflation seen in around forty years. 1) The frequency of price change increased substantially as inflation took off, and has declined markedly as inflation has receded. 2) The average size of price changes also increased as price increases became more common, while the absolute value changed little. 3) The dispersion of price changes did not fall, contrary to the prediction of state-dependent models 4) A menu cost model fitted on pre-pandemic pricing data has more difficulty matching the increase in the frequency of price changes post-pandemic, compared to the high inflation period of the 1980s. A re-calibrated menu cost model with smaller menu costs and larger idiosyncratic shocks can match the elevated frequency seen in the post-pandemic period, but not the movements in the dispersion of price changes. Such a model also implies a faster pass-through of shocks to inflation than the model fitted to pre-pandemic data.

Keywords: Inflation, Microdata, Sticky prices
JEL Codes: D40, E31, D22

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1 Introduction

The Covid-19 pandemic and its aftermath have had enormous effects on activity across the economy, particularly with regards to inflation. As economic activity declined during the early portion of the pandemic, the year-on-year change in the U.S. Consumer Price Index (CPI) dropped to 0.2% in May 2020. By 2021, the economic recovery was underway and inflation took off, reaching 9.0 percent in June 2022, a rate not seen in the United States since the 1980s. Since then, inflation has fallen substantially but has remained somewhat elevated relative to what was normal before the pandemic. Firms have thus had to react to an inflation environment that is without precedent in modern times. In this paper, we explore how firms responded to these developments at the individual price level. We report a set of facts that offer insights about the margins of adjustment and shocks that drove this inflationary episode and that provide lessons for the price setting models that are used to analyze inflation and monetary policy.

We document several facts related to firm price-setting since the start of the Covid-19 pandemic through August 2024 using the Bureau of Labor Statistics CPI microdata. Since the CPI micro data is available starting in 1977, the Covid era represents the second large inflationary episode that can be studied with these data. We use these data to determine how price setting changed, or did not change, in the midst of the changes and disruptions that characterized the Covid-19 period. We then compare our empirical findings to the predictions of standard price-setting models to infer the kinds of price setting constraints and shocks that firms faced, and how these affected inflation dynamics.

We uncover several important empirical patterns. First, the median frequency of price change increased somewhat at the start of the pandemic, but then more than doubled in 2022 relative to its pre-pandemic level. The frequency generally tracks inflation closely and has been trending down as inflation has been receding. The increase in the frequency was driven primarily by a rise in the frequency of price increases. While the frequency of decreases did not fall despite the high inflation, the disproportionate increase in the frequency of increases means that the average size of price changes (which can be though of as the *intensive margin* of price setting) increased substantially. As we show in an inflation decomposition, the increase in the intensive margin quantitatively accounted for almost all of the increase in inflation in our data.

Second, the average absolute value of price changes increased only modestly in recent years and shows little co-movement with inflation. The magnitude of price increases or decreases separately also did not change substantially.[1] The dispersion of price changes fluctuated throughout this period but also appears uncorrelated with inflation. The general patterns mentioned so far (increase in overall frequency mainly due to the frequency of price increases, higher size of price changes and little change in the absolute value) held for most categories of consumer spending. We also find that the categories that had a relatively high frequency of price changes pre-pandemic continued to be the ones with the highest frequency in recent years. Our finding that frequency and overall inflation tend to co-move also applied generally across categories.

Having documented these facts, we then simulate a very standard menu cost model based on Golosov and Lucas 2007 and Nakamura and Steinsson 2010 to test its predictions.[2] Our goal in this exercise is to test whether a commonly-used price setting model in the sticky price literature, calibrated to pre-pandemic data, can account for the price setting behavior that we document for 2020 onwards. The model can match many of the qualitative patterns: It also predicts that the frequency of price change increases with inflation and that the absolute value changes little. These are consistent with the findings of Nakamura, Steinsson, et al. 2018, who studied the high inflation of the 70s and 80s. In addition, menu cost models generally also predict that the share of price changes that are positive increases, and that most of the variation in inflation is driven by the intensive margin (Klenow and Kryvtsov

[1] There is a subtle but important distinction between the average size and absolute value of price changes. For the former, we average positive and negative price changes together. For the latter, we first take the absolute value of each price change and then average them together. The difference stems from the treatment of negative price changes, which account for a significant share of all price changes.

[2] Although our results focus on a model very similar to the one in Golosov and Lucas 2007, the same qualitative results would hold for a broad range of state-dependent models.

2008).

Surprisingly, we find that the model cannot match the *magnitude* of the increase in the frequency. Given the inflation seen in the U.S. in recent years, a menu cost model predicts that the frequency of price change increases by a few percentage points. In our data, we find that the frequency increased by more than 10 percentage points. This discrepancy between the data and the model also stands in stark contrast to the previous case of high U.S. inflation. Nakamura, Steinsson, et al. 2018 had found that the frequency of price changes more or less tracked the predictions of the menu cost model fitted to the U.S. inflation series starting in 1978. Decomposing the frequency of price changes into increases and decreases, we find that our model both underestimates the increase in the frequency of price increases and predicts that the frequency of decreases should fall when inflation rises. In summary, the model's failure to match the magnitude of the increase in frequency suggests either that this period saw changes in the extent of price rigidity faced by firms, or that shocks omitted from the model were important, or both.

To discern what may have caused the unexpected increase in the frequency, we re-calibrate the model so that it can match the frequency of price change averaged across the post-pandemic period, with overall minor changes to the key parameter values. However, the re-calibrated model cannot match the magnitude of changes in frequency within this period. These results suggest that price setting frictions were smaller, and thus the shocks faced by firms larger, than before the pandemic. Other types of shocks not present in this class of model may have been important. The re-calibrated model implies less monetary non-neutrality than the model calibrated to pre-pandemic data and predicts that aggregate shocks pass through to inflation more rapidly.

Our theoretical analysis focuses on a simple menu cost model, along the lines of Golosov and Lucas 2007, even thought there is now a large literature that extends this model in various ways but still within the framework of state-dependent pricing.[3] However, these

[3]Such models include, for example, Midrigan 2011,Nakamura and Steinsson 2010,Alvarez, Bihan, and Lippi 2016,Luo and Villar 2021.

extensions generally produce models that have less aggregate flexbility and therefore predict a smaller increase in the frequency of price change than the Golosov and Lucas 2007 model. As a result, these other models would also fail to match the data.

Related Literature. This paper contributes to the as-of-yet small but growing literature that uses price micro data to answer questions about the recent surge in inflation, both in the U.S. and in other countries. In this way, it is closely related to Cavallo, Lippi, and Miyahara 2024, who use web scraped price data from several countries and also find that the frequency rose substantially. They calibrate a very general price setting model on pre-pandemic data and show that it implies a very large and rapid pass-through of aggregate shocks to inflation. Their analysis relies heavily on the fact that the frequency increases with inflation both in the data and in their estimated model. We focus more on whether state-dependent models can match the magnitude of the increase in frequency seen in the data, given the amount of inflation seen in the U.S. CPI, and consider a greater set of price setting moments with which to evaluate the models.[4] The data we use also covers a much broader set of spending categories than the web-scraped data.

More generally, our study fits into the empirical sticky price literature that studies the dynamics of individual (micro) price setting and attempts to draw lessons for modelling sticky prices and for how monetary policy transmits to the economy. Some of the seminal papers in this literature are Bils and Klenow 2004, Klenow and Kryvtsov 2008, and Nakamura and Steinsson 2008, who were the first to use the CPI micro data. More recently, several studies have been able to look at such data covering high inflation periods, both in the U.S. (Nakamura, Steinsson, et al. 2018) and abroad (Alvarez, Neumeyer, et al. 2018, Gagnon 2009). While all these studies have also found that the frequency of price change rises with inflation, ours is the first to document similar patterns for the U.S. during the post-pandemic period, which was the first high inflation episode in almost four decades.

[4] In an earlier and shorter study (Montag and Villar 2023) we documented some of the facts described in this paper. Here, we describe additional facts and study the comparison with price-setting models more formally.

Beyond the empirical sticky price literature, the high inflation seen in most of the world has renewed interest in the slope of the Phillips Curve and whether changes in the slope can help explain this episode. One set of explanations argues that the Phillips Curve may be non-linear, meaning that the large shocks seen in recent years could have pushed the economy into a steep portion of the Phillips Curve, magnifying their inflationary impact. Benigno and Eggertsson 2023 and Harding, Linde, and Trabandt 2024 develop models that extend the canonical New Keynesian model and imply a non-linear Phillips curve. Blanco et al. 2024b present an extension of a time-dependent sticky price model that endogenizes the frequency of price change. Their model is relatively tractable and implies that the slope of the Phillips Curve varies over time, being higher in high inflation periods. Relatedly, Cerrato and Gitti 2022 provide empirical reduced-form evidence supporting the notion of a non-linear Phillips curve, based on the variation in unemployment and inflation across U.S. metropolitan areas. Karadi et al. 2025, for their part, solve for optimal monetary policy in a menu cost model, and emphasize the importance of changes in the slope of the Phillips Curve for how policy should respond to different shocks. Our paper, among others, provides a key set of motivating facts for many of these models and illustrates the mechanisms at play in them by documenting the positive relationship between inflation and frequency. In addition, our finding that a re-calibrated menu cost model can match some of the empirical patterns and predicts a more rapid pass-through of shocks to inflation supports the idea that the Phillips Curve may have been steeper in the post-pandemic period. [5]

This paper contributes to the non-linear Phillips Curve literature theoretically as well. We find that standard menu cost models fail to match the extent to which the frequency of price change increased, given the level of inflation seen. Our results question some of the assumptions of these models, as the results imply that there may be other shocks that are not being accounted for in the models.

[5] Many of the papers cited here also cite our earlier study (Montag and Villar 2023) and some of them use our estimates of price change statistics in model estimations and calibrations. As another example, Morales-Jimenez and Stevens 2024 use our estimates of several price change statistics to produce structural estimates of the degree of price rigidity.

Finally, many studies have now tried to account for the high post-pandemic inflation using structural multi-sector models. For example, Ferrante, Graves, and Iacoviello 2023 and Luo and Villar 2023 use sticky price models with production networks to isolate the shocks and mechanisms that pushed up inflation in the U.S. Giovanni et al. 2023 propose a similar model for multiple countries with trade linkages. In addition, Guerrieri et al. 2020 propose a multi-sector model in which inflation can also be driven by sectoral reallocation, and in which such inflation should not be leaned against by the central bank. Our paper weighs in on the role of sectoral dispersion and shocks.

The remainder of the paper is organized as follows. Section 2 describes the data that we use. Section 3 documents facts related to the frequency, size, magnitude, and dispersion of price changes following the start of the pandemic. Section 4 looks at differences in how pricing moments evolved across sectors and to to draw inference about the relevance of sectoral shocks. Section 5 presents a standard menu cost model, which we test against some of the empirical facts that we find. Section 6 concludes.

2 Data

This paper draws upon the Bureau of Labor Statistics Consumer Price Index (CPI) Research Database. These microdata, which have been extensively used by other researchers, is constructed from the Commodities and Services survey (C&S) that is collected by the Bureau of Labor Statistics to estimate the non-housing portion of the CPI. The C&S regularly samples price quotes of about 90,000 products from over 80 metropolitan areas throughout the U.S. 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 important advantage of covering spending categories that account for about 70% of the goods and services that consumers regularly purchase. In this way, the coverage is much greater than in “scanner” or web-scraped sources of price microdata. Additionally, the C&S micro data are available in some form going back to 1977, which enables comparisons between the Covid era and earlier periods of elevated inflation. We know of no other large price data set that goes back as far in time. An important 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. Most 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 it's Entry Level Item (ELI) as defined by the BLS and calculate most statistics through a two-step process.[6][7] First, we create a statistic for each ELI category each month (e.g. frequency of price changes for ELI AA011 in January 2024). 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 weight of different ELI's. This leaves us with a monthly time series for each statistic. We can similarly create weighted averages of each statistic by broader category (e.g. household furnishings, apparel, services).

Many ELI's are so narrowly defined that there are only a handful of price changes for a given month within the ELI. For higher moment statistics, such as variances, this paucity may make our estimates excessively sensitive. We calculate these statistics by "major group", which is a higher level of aggregation. We then find the weighted mean of the statistics across major groups, and use that as our aggregate estimate.

We highlight three challenges to constructing statistics based on price changes: 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 se-

[6]For example, the code "AA011" corresponds to men's suits. The "A" corresponds to all apparel, "AA" corresponds to men's apparel.

[7]The BLS organizes goods and services in the CPI by (in decreasing order of aggregation) Expenditure Class, Item Strata, and Entry Level Item. We use the ELI 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.

ries 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

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

We do not make such adjustments for statistics related to the value of the price change (size, absolute value, dispersion). For each ELI-month, we calculate the value of a statistic as the observation-weighted average between the versions calculated from monthly and bi-monthly observations (after the adjustment above, for the frequency).

Second, businesses often discontinue or change some feature of the 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 performing a substitution, that is, finding another version of the good that is similar enough and when necessary performing quality adjustments. We follow standard practice and drop product substitutions.

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.[8] We use the sales flag recorded by the C&S field agents to identify sales. Most of the literature that has worked with these data also excludes temporary sales and product substitutions. Following Eichenbaum et al. 2014, we drop any price changes less than 1% in magnitude in the ELIs that they identified as being likely to generate false small price changes due to the particular data collection methods of those categories. Additionally, we drop any price changes that are smaller than 0.01% or larger than 100% in magnitude as outliers.[9]

[8] For example, see Nakamura and Steinsson 2008.

[9] Several 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.

3 Empirical Results

In this section we present how statistics such as the frequency and the magnitude of price changes have evolved since the start of the pandemic.[10] 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 by constructing counterfactual inflation rates. We then document the dispersion of price change throughout this period, and finally lay out of the significance of the share of price changes that are increases.

3.1 Frequency, Size, and Magnitude

State dependent and time dependent pricing models provide very different predictions about how businesses would set prices during the Covid- and post-Covid-era. Given the large supply shocks throughout the pandemic, as well as shifting consumer demand as the economy closed and reopened, firms' optimal prices likely moved significantly. Under a state-dependent model, such as the 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.[11] 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, with the frequency being constant by assumption. Thus, simply looking at the behavior of the frequency, size and absolute value of price changes can help distinguish between these models.

Figure 1 displays the frequency, size, and magnitude of price changes after the start of the Covid pandemic. We show a further two years of data before the pandemic for comparison. We follow Nakamura and Steinsson 2008 in emphasizing the median frequency of price changes across ELI's, as the median is more indicative of how pricing behavior affects the transmission of monetary shocks. For the magnitude and size we show the mean across

[10] We use the terms "magnitude" of price change and "absolute value" of price change synonymously.

[11] Nakamura, 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, but more sensitive at moderate levels of inflation. Nakamura, Steinsson, et al. 2018 also showed that the absolute value of price changes was remarkably stable over time in the U.S., in both high and low inflation periods.

ELI's. The figure also shows the evolution of year-over-year CPI inflation for reference.

We present the statistics with and without sales for comparison, but focus on estimates without sales in our discussion. The frequency of price changes excluding sales rises from around 10% in the year preceding the start of the pandemic to 14% on average in subsequent four months.[12] It then continued to rise throughout 2021 and peaked slightly above 20% in early 2022, before trending down as overall inflation has come down. Overall, the frequency remains somewhat elevated compared to its pre-pandemic levels: the average between January and August 2024 (the last month in our series) is around 13%. We particularly emphasize the extent of the increase in the frequency in the high inflation period: it increased by more than 10 percentage points and more than doubled between the levels seen in 2018-2019, and the peak in early 2022. [13]

The average size and absolute value of price changes show different patterns. The absolute value of price changes rose from about 9.5% on average in the year before February 2020, to 11% in early 2020, before falling back to slightly above 9% for a majority of 2021. Both including and excluding sales, the absolute value of price changes is relatively flat throughout the sample period, which indicates that firms are changing their prices by roughly the same magnitude even as inflationary pressures rise. In contrast, the average price change (what we also refer to as the "size") surges from around 1% in early 2020 to above 4% in early 2022. The series then falls and fluctuates around levels slightly higher than they were before the pandemic. This discrepancy between the two statistics can be explained by an increase in the share of price changes that are positive, which we discuss later.[14]

While time dependent models can only explain the empirical patterns related to the intensive margin, all three of these patterns are qualitatively consistent with the predictions

[12]The frequency also increased somewhat in the few months prior to the outbreak of the pandemic in the U.S. However, this increase is smaller than the subsequent increases.

[13]The *mean* frequency, not shown in these figures, also increased by around 10 percentage points over the same period. However, because the mean frequency is generally substantially higher than the median this represents a smaller *proportional* increase.

[14]Holding the magnitude of price increases and of decreases each fixed, an increase in the share of price changes that are increases would raise the average size of price changes, but would leave the average magnitude unchanged.

of state-dependent models. This provides evidence supporting the use of state-dependent models to try to explain and understand this recent inflationary episode, as is done by several recent studies (Cavallo, Lippi, and Miyahara 2024, Blanco et al. 2024a, Harding, Linde, and Trabandt 2024).[15]

3.2 Intensive-Extensive Margin Decomposition

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 construct a version of inflation defined as the frequency of price changes multiplied by the size of price changes, or $\pi_t = fr_t * dp_t$. We calculate such 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, this inflation series is slightly different from the officially published CPI inflation series. [16]

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 its average over 2019, while the size of price changes varies. The second counterfactual inflation holds constant the size of price changes at its 2019 average 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

[15] In Section 5, we will investigate to what extent state-dependent models can quantitatively match the empirical patterns that we find.

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

$$\pi_t^{freq} = \bar{fr} \cdot dp_t$$

$$\pi_t^{size} = fr_t \cdot \bar{dp},$$

where fr denotes the frequency and dp denotes the size of price changes. Figure 2 plots our inflation rate and the two counterfactual inflation rates. 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. In the next sub-section, we will further explore the role of the fraction of price changes that are increases.

We further compare the significance of frequency and size of price changes by decomposing inflation variation into its extensive and intensive margins, as in Klenow and Kryvtsov 2008. We limit our analysis to the post-March 2020 period in order to focus on how firms responded during the pandemic. The decomposition is:

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

Table 1 displays the decomposition of inflation variance between the intensive and extensive margins. As in Klenow and Kryvtsov 2008, the intensive margin of adjustment explains the 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. If firms can adjust their prices through sales, then the overall frequency fluctuates more often.

It may seems puzzling that the frequency of price changes contributes little to inflation, even though the frequency increased significantly. However, the size of price changes moves substantially more. Intuitively, changes in the share of price increases that are positive lead to large changes in the size, which contribute a great deal to inflation under this decomposition. We also note that, as Klenow and Kryvtsov 2008 showed, both time and state-dependent models predict that the bulk of inflation movements are accounted for by the intensive margin under this decomposition.

3.3 Price Increases and Decreases

In this subsection, we decompose price changes between price increases and price decreases to investigate this mechanism in more detail.[17] Our results here suggest that the share of price changes that are increases plays an important quantitative role in how firms respond to inflation.

First, Figure 3, displays the median frequency of price changes, price increases, and price decreases. As before, we disregard any price changes due to sales. The frequency of price increases and price decreases both rose in 2020. As inflation begins to pick up in 2021, the frequency of price decreases fluctuates around 4%, while the frequency of price increases surges from 8% to 15% in early 2022. This suggests that a key margin of adjustment behind the rise in inflation, particularly in 2021, has been price increases constituting a greater share of the price changes that occur, and price decreseas a smaller share. At the same time, it is striking that the frequency of price decreases slightly *rises* once inflation increases, and remains elevated compared to its pre-pandemic level throughout the high inflation period.[18]

Next, Figure 4 shows the median magnitude of price increases and decreases across ELIs. As found by Nakamura and Steinsson 2008, we find that the magnitude of price decreases is substantially larger than price increases prior to the pandemic, but also that this gap has

[17] As earlier work such as Nakamura and Steinsson 2008 has noted, a substantial fraction of price changes are actually price decreases even though inflation tends to be positive. Studies 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.

[18] Because 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. The fraction of price changes that are price increases is calculated separately.

narrowed after 2020. [19] Starting in 2020, the magnitude of both increases and decreases rose slightly. As inflation rose in 2021 and 2022, the size of price increases remained elevated above the pre-Covid trend, possibly suggesting that the shocks affecting firms' optimal prices became larger or more volatile. Starting in late 2023, both magnitudes appear to be trending down towards the levels they stood at before 2020.

We further evaluate the significance of the share of price increases through a different series of inflation counterfactuals and decompositions. Extending the logic in the previous section, the inflation rate can be decomposed into a price increase component and price decrease component, as in Gautier et al. 2022, as follows:

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

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. This decomposition extends the one underlying Figure 2 by considering the different behavior of price increases and decreases.

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

[19] One possible explanation for price decreases being larger 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.

$$\pi_t^{\bar{dp}^+,\bar{dp}^-} = f_t^+\bar{dp}^+ - f_t^-\bar{dp}^- \tag{1}$$

$$\pi_t^{\bar{f}^+,\bar{f}^-} = \bar{f}^+dp_t^+ - \bar{f}^-dp_t^- \tag{2}$$

$$\pi_t^{\alpha} = \alpha_t\bar{f}^+\bar{dp}^+ - (1-\alpha_t)\bar{f}^-\bar{dp}^-. \tag{3}$$

We refer to the first case as the fixed size inflation, the second case as the fixed frequency, and the third case as the varying fraction. The difference with the previous counterfactual series (the ones shown in Figure 2) is that here the first two series are based on frequency and size of increases and decreases separately, as opposed to the overall frequency and size, and that the third series allows for the fraction of price changes that are increases to vary.

Figure 7 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.

Table 2 reports the correlations between the four time series after February 2020. The series that fixes the size of price increases and decreases but allows the frequency of price changes to vary is mostly uncorrelated with the overall inflation rate. Fixing the frequency of price increases and decreases and allowing the size to vary results in a much higher correlation. The fixed frequency series having a higher correlation with inflation is consistent with our finding in the previous sub-section that the intensive margin quantitatively accounted for more of the variation in inflation.[20] If we instead fix the frequency and magnitude of changes and only allow the fraction of price changes that are increases to vary, the correlation is quite high at 0.931. We interpret these results as indicating that the intensive margin is

[20] The fixed size series in Figure 7 seems to vary more than the fixed size series in Figure 2, as fixing the size of increases and decreases separately makes the series behave differently than when it is the overall size that is fixed. However, the low correlation of the fixed size series in Figure 7 with inflation confirms that the extensive margin was not a very significant driver of inflation quantiatively.

quite important for determining inflation dynamics and that a key component of this is the fraction of price increases.

Finally, Figures 5 and 6 display our estimates for frequency (overall, increases, and decreases) and size and absolute value over the whole period for which we have data, that is, 1978-2024. As we discuss in greater detail in Section 5, the overall frequency in 2021 and 2022 was higher than during the peak of the 1980s inflation period. The post-pandemic increase in frequency is partially explained by the rise in the frequency of price decreases, which was higher in 2021 and 2022 than in any other time period in our sample. The post-pandemic period also saw the frequency of increases reach levels nearly as high as in the earlier high inflation period. The absolute value of price changes increased somewhat after 2020, but has overall been quite stable throughout the sample period, including during the Great Inflation. The size of price changes, meanwhile increased in 2021 and 2022, but remained below the norm for the 1980s.

3.4 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. Separately, Luo and Villar 2021 focus on how the co-movement of the dispersion and skewness with inflation can be informative about the degree of state-dependence. According to state-dependent models, when an aggregate shock pushes up inflation, price changes will become more concentrated on one side of the inaction region and dispersion will fall. If the dispersion of price changes does not fall, then either price setting is not entirely state dependent or additional shocks push the dispersion of price changes up.

We consider both the standard deviation and the interquartile range as measures of price change dispersion. In both cases we construct the price change statistic at the ELI2 level and use the weighted means across ELI2's as the aggregate dispersion measure. These measures thus reflect the within-ELI2 dispersion in price changes. We plot the result in Figure 8. We find that the dispersion of price changes rose sharply in March 2020 and remained high for much of 2020. However, in late 2020 the dispersion of price changes began trending down and remained flat throughout 2021. Dispersion spikes in 2022 and 2023 as inflation rises, but falls shortly after the spikes. The dispersion averaged over the year appears higher in 2022 and 2023 than in 2021. However, there is no systematic relation between dispersion in inflation during this episode, which stands in contrast to what Luo and Villar 2021 found for the earlier period of high inflation and to what state dependent models predict. This finding suggests that shocks that are not included in these models (such as sectoral shocks) may have affected the behavior of price changes to a greater extent than in the earlier inflationary episode.[21] We explore model predictions in more detail in Section 5.

4 Sectors

This section looks at differences in price setting patterns across sectors. First, we document how price change statistics evolved differently for different sectors. Second, we examine how sectoral inflation drives the frequency of price changes the dispersion of price changes, to assess whether more flexible sectors react more quickly to the shocks that occurred during this period.

4.1 Sectoral Patterns

In the previous section we showed that both the frequency and size of price change increased substantially with inflation in 2021 and generally comove with inflation. The share of price increases, rather the magnitude of price changes, explained the behavior in the size of price

[21] By calculating dispersion within ELI2 categories first, we are effectively controlling for shocks that affect all prices within an ELI2 (or within any broader category). Shocks that affect narrower categories, or relatively small groups of firms within sectors, would still affect our measure of dispersion. Our results point to such kinds of shocks being significant during this period.

changes. In this section, we explore how these patterns vary across different sectors of consumer spending to determine if the aggregate patterns documented earlier were driven by one or a few sectors.

Nakamura and Steinsson 2008 demonstrate that there are significant level differences in the frequency, size, and magnitude of price changes across different sectors. Taking these long-standing differences as given, here we consider how the evolution of price change statistics differed across sectors during this episode.

We present the key price-setting statistics by major group in Figures 10 and 11 and highlight three notable patterns. First, most sectors saw a significant increase in frequency in 2021 and 2022, and have since generally seen the frequency decline (in line with the aggregate numbers shown earlier). Some sectors, such as food, apparel, and recreational goods, saw a smaller but still noticeable bump in the frequency in 2020.[22] Second, many sectors also saw increases in the size of price change. In transportation goods (mostly new and used motor vehicles) and travel services, the frequency changed little, but movements in the size seem to have driven movements in inflation. In most sectors, both the frequency and size generally increased during the high inflation period.[23] Third, we note that the magnitude of price changes was quite stable in all sectors.

Next, we consider the evolution of price change dispersion across sectors. The rise and fall of the dispersion of price changes in figure 8 likely reflects a mix of sectoral and idiosycnratic shocks. If the dispersion of price changes was primarily due to large sectoral shocks, such as a decline in demand for services in 2020 or supply chain issues in 2021 and 2022, 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

[22] Apparel saw a large jump in frequency in 2019, and this seems to never have reversed. It is likely that this jump is due to the BLS switching to a new data provider for many of the apparel price quotes.

[23] In some sectors, such as apparel, travel services, educational and recreational goods, personal care goods and tobbacco, either the frequency or size or both exhibit strong seasonal patterns.

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

where i corresponds to a specific quote, 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 t. ω_j is the weight on ELI2 category j, and $Var(\hat{dp}_{i,j,t})$ denotes the variance of prices within ELI2 sector j. 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 9.

The between-sector dispersion is about twice as large as within-sector, which indicates that sectoral shocks played a significant role.[24] To the extent that sectors faced different supply shocks during and after the pandemic, the magnitude of between-sector dispersion is unsurprising. The within-sector shocks, on the other hand, can be thought of as firm-level idiosyncratic shocks.[25] Because the ELI2 categories are so broadly defined and even firms within the same sector may face different conditions, the within-sector dispersion can also be similarly high. Additionally, both dispersion components regularly fluctuate even pre-pandemic, possibly as a result of seasonal forces.[26]

Both components of dispersion rise suddenly in two periods: the early portion of the pandemic in Spring 2020 and the second half of 2022 as inflation was high. 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

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

[25] Firm-level idiosyncratic shocks are an important consistent feature of state-dependent models.

[26] Nakamura 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.

demand. In the latter case, a rise in between-ELI2 variance could reflect the fact that some sectors of the economy were more constrained by supply shocks than others. These results further the support the work of 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, [27] which predict the dispersion of price changes to fall as inflation rises.

4.2 Sectoral Regressions

We now test the inflation-dispersion relation at the sectoral level. In these regressions, the left-hand side is the dispersion of price changes for a specific ELI2 sector and date, and the right hand-side is the inflation rate for that specific ELI2 sector. We calculate the ELI2-specific inflation rates from the CPI-research database using the frequency of price changes and the size of price changes. The regression specification is

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

where j refers to an ELI2 category, $\sigma_{j,t}$ is standard deviation of price changes within an ELI2-date, $\pi_{j,t}$ refers to the month-on-month inflation rate for ELI j, and δ_j refers to ELI fixed effects.

Table 3 displays the result. In columns (1) and (2) we find a small negative relationship between the ELI2-specific inflation rate and the dispersion of price changes during the Covid pandemic. However, it is important to note that state-dependent models predict a positive correlation between inflation and dispersion when inflation is negative. Given that it is common for ELI2 sectors to feature negative inflation in some periods, columns (3)-(5) use the absolute value of ELI2 inflation. State-dependent models predict that there should be a strong negative relation between dispersion and the absolute value of inflation. Instead, we find a significant positive relation. Adding ELI2 fixed effects or the official month-on-month

[27] As mentioned before and shown by Luo and Villar 2021

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. The results are similar.

Next, we look at differences in price flexiblity across sectors during the pandemic. As Nakamura and Steinsson 2010 showed, there is considerable variation in sectoral price setting flexibility, and thereby in the extent of pricing frictions. Given that the Covid pandemic and subsequent recovery has been characterized by large shocks, we study whether flexible firms have reacted more quickly along the extensive margin to changes in aggregate inflation. Our regression specification is

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

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

We find that sectors that were relatively flexible pre-pandemic remained more flexible during the pandemic. However, these flexible sectors did not see a larger sensitivity to aggregate inflation than less flexible sectors. These results suggest that the increase in frequency that happens once inflation increases may have been somewhat homogeneous across sectors. It is also possible that sectoral shocks were important drivers of changes in frequency in different sectors, which would make the sensitivity of sectoral frequency to aggregate inflation small.

5 Model Predictions

Prior to the Covid-19 pandemic, theoretical models were restricted to price-setting microdata started in the 1980s near the end of the Great Inflation. These models, such as Nakamura and Steinsson 2010, were estimated and calibrated on a period with low, stable inflation, excepting some brief periods of volatility during recessions.[28] The Covid-19 pandemic and post-pandemic period, with its transition from low to high and then to low inflation, offers a chance to further evaluate whether these models can match the pricing behavior of firms when inflation is elevated.

We compare a state-dependent price setting model's predictions to our empirical facts. We evaluate whether a standard menu cost model's fit on pre-Covid data can explain post-Covid price-setting developments. We estimate the model parameters using pricing micro-data that is restricted to the pre-pandemic period, specifically from 1988-2019. Significant discrepancies between the model and the data would suggest that the price setting frictions and/or shocks faced by firms were different than assumed in the model. We note that we will be focusing on state-dependent models because other time-dependent models have difficulty fitting the empirical patterns over the period.

5.1 Model Setup

In this subsection, we present a menu cost model as in Golosov and Lucas 2007, or a single sector version of the model in Nakamura and Steinsson 2010. Firms face aggregate and idiosyncratic shocks and must pay a fixed cost if they choose to change their nominal price. Ultimately, inflation is driven by an aggregate nominal demand shock.

This class of model features monopolistically competitive producers (firms), idiosyncratic productivity shocks, and labor as the only input into production. Firms face a fixed cost, denominated in units of labor, when they change their nominal price. The size of this cost is fixed over time and across firms, although the model can be extended to allow for random menu costs, which would allow the model to span a greater set of the models studied in the literature.[29] Aggregate nominal demand shocks shift marginal costs, and thus the desired

[28]Nakamura, Steinsson, et al. 2018 showed that a menu cost model could match many of the patterns of price adjustment during the high inflation period of the 1980s.

[29]We focus on the fixed menu cost model because it is the one that features the most state-dependence,

price of all firms. Below we provide a formal set-up of the model.

Households choose consumption (C_t) and labor supply (L_t) to maximize expected discounted utility of the following form:

$$E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} \left[\log C_{\tau+t} - \omega L_{\tau+t}\right].$$

There is a continuum of monopolistically competitive firms, indexed by z, each of which produces a differentiated product. Aggregate consumption is given by a constant elasticity of substitution aggregator. As a result, each firm faces the standard CES demand function for its good:

$$c_t(z) = \left(\frac{p_t(z)}{P_t}\right)^{-\theta} C_t,$$

where θ is the elasticity of demand, and P_t is the CES price aggregator. Firms produce output based on a linear production function:

$$y_t(z) = A_t(z) L_t(z).$$

Productivity is subject to idiosyncratic shocks, which follow a log AR(1) process as in Golosov and Lucas 2007 or Nakamura and Steinsson 2010, described below. [30]

$$\log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t,\ \epsilon_t \overset{iid}{\sim} N(0, \sigma_\epsilon^2).$$

In order to generate aggregate fluctuations, the model incorporates a stochastic process for nominal aggregate demand. As is standard in the literature, we model nominal output

and famously the most aggregate flexibility among this class of price setting models. Given that we are interested in whether the model can match the large *increase* in the frequency of price change, we believe this is a conservative assumption.

[30] The model can also be extended to feature leptokurdic, or "fat-tailed" shocks as in Midrigan 2011.

as a log random walk with drift,

$$\log S_t = \mu + \log S_{t-1} + \eta_t,\ \eta_t \overset{iid}{\sim} N(0, \sigma_\eta^2),$$

where $S_t \equiv P_t C_t$. In this model, nominal output is exogenous, μ determines the trend of inflation (trend real output growth is zero), and η_t represents any demand shocks that could move nominal output away from its trend. Inflation is determined by firms' endogenous pricing reactions to the aggregate demand process. Ultimately, inflation tends to follow its trend, and fluctuations around the trend are driven by the η_t shocks.

The price-setting constraint takes the form of a cost in terms of units of labor that must be paid for a firm to change its nominal price. Specifically, the period profit function takes the form:

$$\Pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - \chi W_t I\{p_t(z) \neq p_{t-1}(z)\}.$$

We solve the model with value function iteration and use an approximation as in Krusell and Smith 1998 for the law of motion of the price level with a finite set of moments. The model is calibrated as follows. The parameters for the aggregate demand process (μ and σ_η) are set to match the trend and volatility of U.S. nonshelter CPI inflation for the period 1988-2019. The consumer preference parameters are set as in Luo and Villar 2021 and Nakamura and Steinsson 2010. The remaining parameters govern firms' idiosyncratic shocks and the menu cost. These parameters are set to match the median frequency and median absolute value of price changes, averaged over the 1988-2019 period.

The first set of results draws upon a partial equilibrium version of this model, as described in Nakamura and Steinsson 2008. In that model, inflation follows an exogenous process that firms take as given and respond to. The setup has the advantage that it can take the empirical series for inflation and provide simulated series for various pricing moments to give an approximate sense of how those moments would respond to the inflation seen. We then confirm that the same patterns hold in the general equilibrium model, before considering the responsiveness of inflation to aggregate shocks.

5.2 Model Results: Pre-Pandemic Calibration

We first use the partial equilibrium version of the model to obtain model-implied pricing statistics. We feed the official monthly BLS CPI inflation to the model.[31] From this, we obtain the predicted frequency and size of price changes according to the model over 1978-2024. This is similar to some of the model comparisons in Nakamura and Steinsson 2008 and Nakamura, Steinsson, et al. 2018, but extended through 2024.

Figure 12 displays a series of graphs comparing the frequency and size of price changes between the data and the GS partial equilibrium model. Note that "frequency", "magnitude" and "size" of price changes corresponds to the definitions described in empirical portion. The underlying simulations and data are monthly, but the figure shows annual averages because the monthly series are quite volatile.

Although the GS model does an adequate job matching the frequency of price changes historically, it significantly underpredicts the increase in frequency that occurred during and after the pandemic. In particular, the model has the most difficulty matching the rise in the frequency of price decreases that occurs post-pandemic: the model predicts the opposite. At the same time, the model also cannot match the extent of the increase in the frequency of price increases.

We also emphasize the comparison between the two high inflation periods: the early 1980s and the post-pandemic period. In both cases, the frequency of price change was higher than the model predicts given the observed inflation rate.[32] However, the gap between the

[31] Specifically, we use the series for CPI excluding shelter, as our micro data does not contain data on shelter prices.

[32] The aggregate frequency series that we use throughout our analysis uses weights from the 2018 Consumer Expenditures survey to aggregate ELI-level frequency estimates. If, instead, we use weights from 1998 (which were used in Nakamura, Steinsson, et al. 2018), the empirical frequency series matches the model's predictions very closely in the 1980s. However, the empirical frequency series based on 1998 weights reaches even higher levels post-2020 than it does when using 2018 weights (as in Figure 12). Therefore, with weights from 1998, there is no discrepancy between the data and model for the 1980s, but there is still a large discrepancy for the post-pandemic period. The large discrepancy in the post-pandemic period is therefore robust to which

empirical series and the model predictions is much larger in the post-pandemic period.

The top-middle and top-right panels of Figure 12 show that much of the gap between the actual and model-predicted frequency after 2020 is coming from the failure of the model to match the rise in the frequency of price decreases. However, the extent to which the frequency of price increases rises is larger in the data than in the model prediction over the post-pandemic period. In contrast, the model matches the frequency of increases very closely in the 1980s and through most of the pre-pandemic period.

The behavior of inflation helps put these results in perspective. Inflation in the 1980s was very high for many years. As a result, the model predicts a frequency of price change that is considerably higher than subsequently, when inflation was low and stable. In the post-pandemic period, inflation reached high levels, but not as high as in the 1980s. In addition, these elevated levels were somewhat short-lived. That is why the model predicts an only modest increase in frequency, relative to the immediate pre-pandemic period. In the data, we see that the frequency is much higher in both of the high inflation episodes, compared to the intervening low inflation period. However, the frequency rises even higher in the post-pandemic period than it did in the 1980s. In addition, the frequency was elevated throughout the post-2020 years, even before and after inflation peaked. In this sense, the extent of the increase in the frequency after 2020 is surprising, even after observing that the frequency also increased in the 1980s (and by more than the model predicted). In this sense, the relationship between inflation and frequency was different in the post-pandemic period, compared to what it was in earlier periods.

The second row of Figure 12 depicts the mean absolute value of price changes, conditional on prices changing. On average, the model and data agree on the magnitude of price changes. However, as firms in the model pay a fixed cost for price changes, the magnitude is flat, almost fixed by the menu cost. In contrast, the size of price changes (not shown here) in the data fluctuates slightly.

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weights are used.

We turn to the general equilibrium model to confirm whether the same patterns hold in a model in which inflation is endogenous. The model is calibrated to match the average frequency (about 9.6 percent) and absolute value over 1978-2019. Inflation is determined by the firms' price setting decisions and is largely driven by an aggregate demand shock. There is a positive trend in nominal aggregate demand, which is equal to trend inflation because there is no aggregate productivity growth. Inflation can thus be driven by temporary shocks (what we will refer to as "short run" inflation), or by the trend in nominal aggregate demand ("long-run" inflation).

We simulate the model for 1000 periods and 50000 firms. From these simulations, we obtain the general equilibrium relationship between the inflation rate and frequency of price changes each period. The left subfigure in Figure 13 graphs the result for short-run inflation, in which one dot represents one monthly period in the simulation. This relationship between inflation and frequency is primarily driven by the aggregate demand shocks in the model. The primary result in the short-run panel of Figure 13 is that even when the annualized inflation rate rises from 0% to 10%, the frequency of price changes only increases from around 10% to 14%. The frequency of price changes is therefore somewhat inflexible even to large swings in inflation, and weaker than what we see in the data.

It is possible that the dampened frequency of price changes is due to the fact that the trend inflation rate is fixed at a constant rate in the left panel. Since the aggregate demand shocks are i.i.d., firms recognize that high inflation rates have low persistence, possibly affecting the inflation-frequency relation. To examine this hypothesis, we simulate a series of general equilibrium models with different trend inflation rates. The right panel in Figure 13 shows the relationship between trend inflation and the average frequency of price changes. We find that the frequency of price changes is no more responsive to the trend inflation rate. Even in an economy where the annualized average inflation rate is 10%, only about 13% of prices change each month. This relationship again severely under predicts the increase in price change frequency that we observe in the post-Covid period.

Figure 14 presents the evidence on the inflation-frequency relationship in a diferent way. Each circle represents a quarter between 1978 and June 2024. The horizontal axis is the 3-month annualized percent CPI ex. shelter inflation that occurred over the quarter, and the vertical axis is the median monthly frequency of price changes, averaged within the months of the quarter. Different colors represent different time periods (notably the red dots represent the late 70s and early 80s, while the blue dots represent the post-2020 period). The black squares show the relationship between trend inflation and frequency in the general equilibrium model (these are the same as the circles in the right panel of Figure 13). The data lines up with the model predictions quite well for the pre-2020 period. However, in the post-2020 period the frequency is generally higher than predicted by the model, in quarters of both moderate and high inflation.

Next, we look at how well the menu cost model can match the behavior of price increases and decreases. Figures 15 and 16 are similar to Figure 14 but show the frequency of increases and decreases, respectively, in the y-axis. As Figure 15 shows, the frequency of increases in the post-pandemic period has tended to be higher than in previous years, at comparable inflation rates. The frequency of increases has also been somewhat higher than the model predicts, especially for more moderate inflation periods. Figure 16 illustrates how even before the pandemic the relation between the frequency of price decreases and inflation has been quite flat and substantially flatter than the model implies. Even so, the post-pandemic frequency of decreases has been even higher than in previous periods, especially when inflation is relatively high. Taken together, these results explain why for any level of inflation the frequency of price change has tended to be higher than the menu cost model predicts. This is mostly because the frequency of decreases has been considerably higher, but also to a smaller extent because the frequency of increases has been a bit higher.

We also consider what the menu cost model predicts for the dispersion of price changes. As mentioned earlier, Luo and Villar 2021 showed that a broad class of state-dependent models predict a sharp negative relationship between the dispersion of price changes and inflation, when inflation is positive. They also found that this relation held empirically between 1978 and 2014. Figure 17, replicating the results of Luo and Villar 2023, illustrates this relationship in the general equilibrium model that we have presented in this section.

As Figure 8 had shown, however, there is no discernible relationship between inflation and dispersion of price changes after 2020. This is true in the sense that the dispersion does not generally fall in the period when inflation increases, or rise when inflation recedes. The lack of relationship can also be seen in that the dispersion is on average no lower in the post-pandemic period than in the pre-pandemic period. If anything, price changes appear to be somewhat more dispersed post-pandemic, averaging over time. We therefore conclude that menu cost models calibrated to pre-pandemic data cannot match the behavior of price change dispersion in the post-pandemic period.

In summary, state-dependent price-setting models imply that the inflation seen in the post-pandemic period should be accompanied by an increase in the frequency of price change, and little movement in the average magnitude of price changes. However, these models fail to match at least two features of the data: the extent to which the frequency of price change increased, and the lack of a relationship between inflation and price change dispersion. We do not take this to mean that price setting was not state-dependent during this period. Indeed, time-dependent models assume a constant frequency, which is even more at odds with the data. Our interpretation is that state-dependent models capture some of the key features of price setting, but also that price setting was in some ways different during this period compared to the pre-pandemic period. In the following sub-section, we explore to what extent changing the model parameters can allow the menu cost model to match the empirical patterns.

5.3 Model Results: Post-Pandemic Calibration

The two key parameters in the menu cost model are the size of the menu cost and the variance of idiosyncratic shocks. Intuitively, a smaller menu cost should result in a higher frequency of price change for both increases and decreases. It should also lead to a somewhat smaller magnitude of price changes as the smaller menu cost makes relatively smaller price changes profitable from the firm's perspective. At the same time, a larger variance of idiosyncratic shocks would, all else equal, raise the frequency of price change as more firms face shocks that push their desired price outside the inaction region. The larger shocks would also lead to price changes that are both greater in magnitude and more dispersed. Therefore, it seems plausible that a model callibrated to post-pandemic data, with a smaller menu cost and a larger idiosyncratic shock variance, would better match the post-pandemic facts.

Table 6 shows the results of the post-2020 calibration: it is unsurprising that the calibration matches the post-2020 frequency and magnitude well, as these moments are targeted. The frequency of increases and decreases separately are not targeted, and the model does not match these (notably, the frequency of decreases is higher than in the data).[33] The table contrasts the model statistics with the version callibrated on pre-pandemic data. The differences between the parameters across the two calibrations is quite modest: the pre-pandemic version of the model uses a menu cost that is 1.9 percent of firms' steady-state revenue; in the post-pandemic version this value is 1.6 percent. The standard deviation of idiosyncratic shocks increases from 3.8 to 4.4 percent.

Our results suggest that during the pandemic and post-pandemic period, firms found it somewhat easier to change prices because the cost of doing so (or their salience) may have become smaller. The scale of disruptions in various markets and industries may have made it relatively easier for firms to determine that price changes were needed and possibly made consumers more understanding of price changes. In addition, it seems plausible that the shocks affecting firms have been larger since the pandemic started, which is what the larger variance of idiosyncratic shocks captures. We also highlight again that only a modest change in the parameter values is enough to allow the model to match the overall frequency of price

[33]As before, the frequency of increases and decreases reported here do not sum to the overall frequency in the data column. The reason is that these are each weighted medians across ELIs. Because the model does not have multiple sectors, the frequency of increases and decreases in the model always sums to the overall frequency.

change seen in the post-pandemic period.

A more stringent test of the model involves assessing whether it can match the fluctuations in the frequency of price change within the post-pandemic period. Although both inflation and frequency were overall significantly higher in this period than before, there has also been substantial variation in both variables within this period.

Starting with the partial equilibrium model, Figure 18 shows results analogous to those in Figure 12, but with the model calibrated to post-pandemic data. The model can again match the level and flatness of the magnitude of price changes seen in the data. The model has more trouble matching the movements in the overall frequency of price change in the 2021-2022 period: the increase in the model simulation is smaller than that seen in the data. However, the model matches the changes in the frequency of price increases reasonably well. The fit of the frequency of price decreases is also quite close: the divergence seen in Figure 12 (under the pre-pandemic calibration) is no longer present.

In the general equilibrium model the frequency of price change also rises quite modestly with inflation. Figure 19 illustrates this relationship. Under the post-Covid calibration, an inflation rate of around 10 percent (still above the peak of inflation seen in reality), the frequency increases to just below 18 percent, which is only about two and a half percentage points higher than when inflation (in the model) runs at around a 4 percent rate. The peak level and changes of the frequency in the model are smaller than what we see in the data. Some of this is again due to the model predicting a decline in the frequency of decreases when inflation rises, which did not happen. In addition, the frequency of price increases does not respond to inflation quite as much as in the data.[34] In summary, the model comes closer to matching the relationship between inflation and the frequency of price increases than the relationship with the overall frequency or the frequency of price declines.

Finally, we also highlight that the model continues to predict that the dispersion of price

[34] The model implies that the frequency of increases rises by about 4 percentage points between moderate and high inflation periods, somewhat less than the increase of over 5 percentage points seen in the data (in Figure 3, for example)

changes should move quite sharply and inversely with the rate of inflation. As Luo and Villar 2021 showed, this is a general feature of state-dependent models and remains true in this model because the post-pandemic calibration does not fundamentally change the model. Existing menu cost models still have difficulty explaining the fact the dispersion of price changes did not steadily decline in the post-pandemic period.

5.4 Implications for Aggregate Flexibility

We examine how the changes to the model parameters in the post-pandemic calibration affect the responsiveness of prices and economic activity to monetary shocks. Following much of the sticky price literature, we define monetary non-neutrality as the variance in real consumption induced by aggregate demand shocks, given a certain set of parameter values. Intuitively, if prices are flexible in the aggregate then the demand shocks (which are purely nominal) should not lead to any changes in real consumption.

Under the pre-pandemic calibration, the variance of real consumption is 0.06×10^{-4}, while it is 0.03×10^{-4} under the post-pandemic calibration. In other words, non-neutrality is halved under the post-pandemic calibration of the model. The smaller menu cost and greater dispersion of idiosyncratic shocks makes prices more flexible in the model under the post-pandemic calibration, and thus more responsive to shocks. Note that non-neutrality in both these calibrations is considerably lower than in other sticky price models, as emphasized by Midrigan 2011, Nakamura and Steinsson 2010, and Luo and Villar 2021, among others.[35]

Figure 20 illustrates the same result by displaying the impulse response of cumulative inflation (or of the price level) to a one percentage point aggregate shock in the model under both calibrations. As in any model with nominal rigidities, such a shock eventually passes

[35] We emphasize that these calculations are carried out for calibrations of the Golosov and Lucas 2007 model. We have focused on this model because it predicts a responsiveness of the frequency of price change to inflation that is at least as great as other models, which seems necessary to match the facts we observe. At the same time, the limitations of the model's ability to match empirical facts highlighted by the papers cited above remain present even in the post-pandemic period. Along these lines we have emphasized the lack of a negative relation between inflation and price change dispersion (which the model predicts). Future research can investigate how to reconcile the model with these patterns, along with the generally high frequency of price change seen in this period.

through completely to the price level. In other words, the long term impulse response is always one. However, under the post-pandemic calibration the adjustment of the price level is greater on impact, and more rapid.

In this model, monetary non-neutrality corresponds directly to the impulse response to aggregate shocks. In the context of the post-pandemic inflation surge, we find it more informative to emphasize the impulse response as it speaks more directly to the behavior of inflation, which is of greater interest during this period. These results suggest that during the pandemic and post-pandemic period, a decline in the price-setting frictions could have increased the rapidity of the pass-through of aggregate shocks to inflation. This speedy pass-through could have contributed to the inflation's quick rise in 2021 and fall in the second half of 2022.

5.5 Discussion

Nakamura, Steinsson, et al. 2018 and Luo and Villar 2021 showed that state-dependent models fit the movement of price change statistics quite well. We have found that these models' qualitative prediction that the frequency increases with inflation is validated, but also that the models fail quantitatively on this front and in matching the distribution of price changes (e.g. the absence of a decline in dispersion). Taken together, these results suggest that price setting is state dependent, but also that the assumptions about shocks underpinning the menu cost model may not have held post-pandemic.

Along those lines, we find that a larger variance of idiosyncratic shocks is necessary for the models to match some of the features of the data, such as the slight increase in the magnitude of price changes and slightly higher frequency of price decreases. But the variation in the dispersion of price changes within the post-pandemic period suggests that the distribution of idiosyncratic shocks may have been changing significantly over time. It is also possible that shocks that do not feature in the model we considered (most notably sectoral shocks) were large and played an important role in price setting.

As we have also shown, the model can match the frequency of price change averaged over the post-pandemic period with a smaller menu cost parameter (compared to the pre-pandemic calibration). It seems reasonable that the large disruptions and changes brought about by the pandemic and the reopening of economies would imply changes to the cost of changing prices and the variance of shocks faced by firms. In addition, consumers' awareness of large changes and disruptions could have made them more accpeting of price changes, making the effective adjustment cost to firms smaller. The lower menu cost, reflecting less significant frictions to price adjustment, implies that aggregate shocks passed through to inflation more rapidly than in the pre-pandemic period.

This finding is generally in line with Cavallo, Lippi, and Miyahara 2024, who find that large shocks pass through more rapidly than small shocks in state-dependent models. In contrast to Cavallo, Lippi, and Miyahara 2024, however, we show that the calibration of the menu cost model needs to adjust in order to match the post-pandemic price setting behavior observed in the data. Our results also generally support the recent research providing evidence or micro-foundations for a nonlinear Phillips Curve (as in Harding, Linde, and Trabandt 2024, Blanco et al. 2024a, or Cerrato and Gitti 2022).[36]

At the same time, even with a new calibration the model cannot match the changes in the frequency of price change within the post-pandemic period as well as it does for the high inflation period in the 70s and 80s. Along with the failure to match the behavior of price change dispersion, this represents a limitation of the class of models we have considered.

In this paper we do not attempt to further extend menu cost models to address the shortcomings that we have highlighted. However, we believe that the possibility that changes in the distribution of shocks and sectoral shocks played an important role in price setting is worthy of consideration for future research. Extending the model in a way that allows it

[36]Blanco et al. 2024b present a tractable price-setting model in which the frequency of price change rises with inflation, which boosts the responsiveness of inflation to aggregate shocks when inflation is high. Although that model qualitatively matches the inflation-frequency relationship, it also implies a considerably smaller increase in frequency than the one seen in the data. Although the model does not feature menu costs, it produces comparable quantitative predictions along this dimension.

to match the features of the data that we have highlighted could yield important specific insights about the drivers of inflation in recent years, and about mechanisms important for monetary policy, such as the slope of the Phillips curve or monetary non-neutrality. As it stands, the evidence in our paper suggests that aggregate nominal shocks passing through a standard state-dependent pricing process cannot fully explain the joint behavior of price setting and of aggregate inflation.

6 Conclusion

In this paper, we have documented how firms have adjusted prices during and in the wake of 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 a number of empirical findings. First, the frequency of price changes has risen substantially, although the intensive margin of adjustment has a played a predominant role in contributing to inflation. Second, there are large sectoral differences in price-setting behavior. Firms were likely affected by both large sectoral and idiosyncratic shocks. Additionally, we find that the dispersion of price changes is uncorrelated with inflation, in contrast to typical menu cost model predictions. Third, 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.

We estimate partial equilibrium and general equilibrum menu cost models to examine the relationship between inflation and pricing statistics. Our key finding is that the menu cost model cannot match the increase in the frequency of price changes found in the data, even when we transition to general equilibrium.

The year-on-year CPI-U inflation rate remains above the pre-pandemic average. 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, at least if they assume that inflation is driven only by aggregate shocks. Future work can investigate what other types of shocks could have contributed to the inflation seen and explain the price setting patterns that we document. Similarly, changes to the price setting process embedded in these models could also help them better fit the empirical facts.

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Tables

Table 1: Klenow-Kryvstov (2008) Decomposition

	Intensive Margin	Extensive Margin
With Sales	.9509815	.0490185
No Sales	.9110341	.0889659

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 2: Counterfactual Inflation Increase/Decrease Correlations

	Inflation	Fixed Size	Fixed Frequency	Varying Fraction
Inflation	1	.2994156	.9870166	.9311487
Fixed Size	.2994156	1	.2766077	.3192922
Fixed Frequency	.9870166	.2766077	1	.93494
Varying Fraction	.9311487	.3192922	.93494	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.

Table 3: Price Change Dispersion on Inflation

	(1)	(2)	(3)	(4)	(5)
ELI Inflation	-0.357***	-0.017			
	(0.069)	(0.039)			
Abs. Val. of ELI Inflation			0.703***	0.322***	0.334***
			(0.079)	(0.058)	(0.058)
CPI-U					-0.009***
					(0.002)
Constant	0.160***	0.217***	0.153***	0.214***	0.217***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.005)
ELI2 Dummies	No	Yes	No	Yes	Yes
R^2	0.008	0.693	0.022	0.696	0.698
Observations	3506	3506	3506	3506	3506

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	-0.300***	-0.348***			
	(0.028)	(0.019)			
Abs. Val. of ELI Inflation			0.268***	0.074**	0.148***
			(0.031)	(0.026)	(0.025)
CPI-U					-0.026***
					(0.001)
Constant	0.138***	0.157***	0.136***	0.156***	0.163***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
ELI2 Dummies	No	Yes	No	Yes	Yes
R^2	0.004	0.540	0.002	0.535	0.553
Observations	32728	32728	32728	32728	32670

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.	0.867***	0.850***	0.878***	0.878***
	(0.009)	(0.011)	(0.012)	(0.012)
Pre-Pandemic Freq. X CPI-U		0.048*	-0.030	-0.030
		(0.019)	(0.025)	(0.025)
CPI-U			0.024***	
			(0.005)	
Constant	0.093***	0.093***	0.085***	0.076***
	(0.002)	(0.002)	(0.003)	(0.010)
Time Dummies	No	No	No	Yes
R^2	0.421	0.421	0.422	0.433
Observations	13791	13791	13791	13791

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: General Equilibrium Model: Pre- and Post-Pandemic Calibration

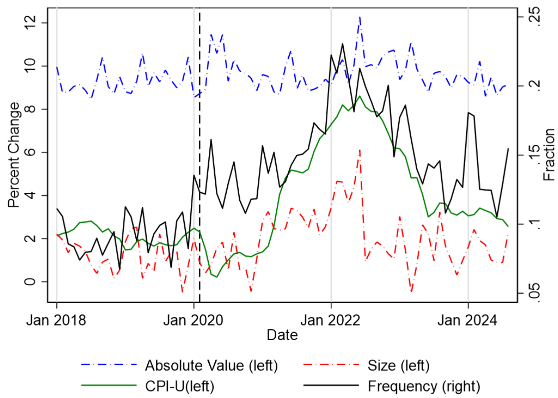
Statistic	Data, 2020-2024	Model, Pre-Pandemic	Model, Post-Pandemic
Overall Frequency	15.2	10.8	15.1
Frequency Increases	9.7	8.9	8.9
Frequency Decreases	4.5	2.0	6.2
Absolute Value	8.6	7.5	8.5

Notes: This table compares empirical estimates of various statistics to those implied by two different calibrations of the General Equilibrium menu cost model. All price changes due to sales are excluded in the empirical estimates. The values for the pre-pandemic version of the model are averages among simulated periods with annualized inflation above 5 percent, under the pre-pandemic calibration. The values for the post-pandemic version of the model are the model's steady-state values for each statistic, under the post-pandemic calibration.

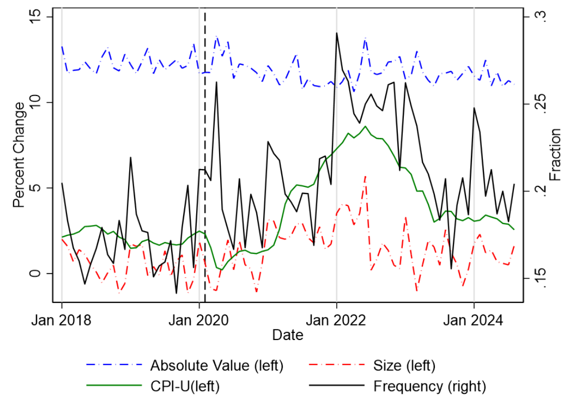
Graphs

Figure 1: Median Frequency and Magnitude of Price Changes

(a) Without Sales

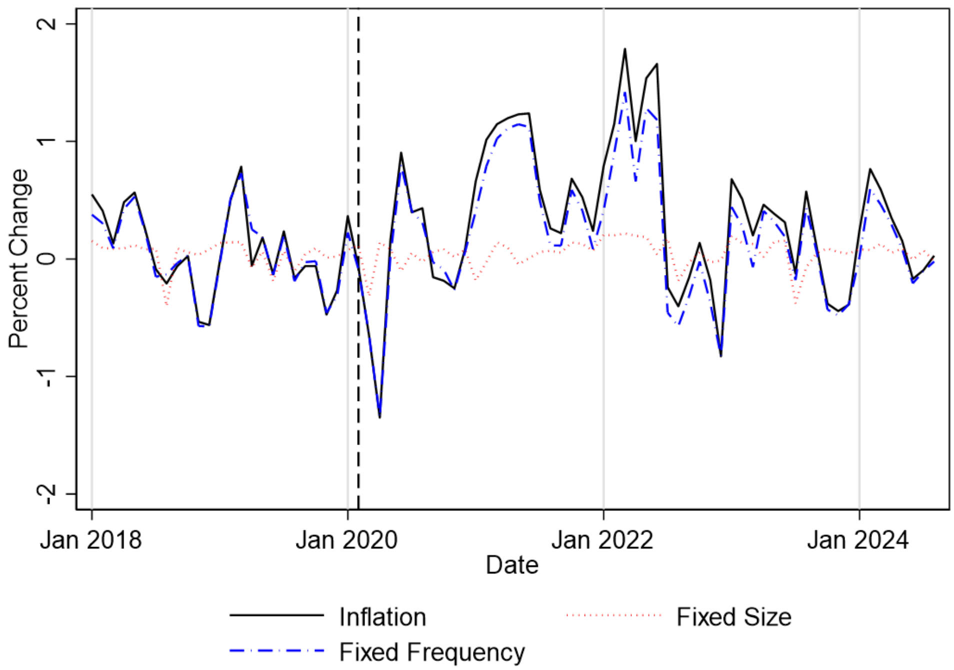


(b) With Sales



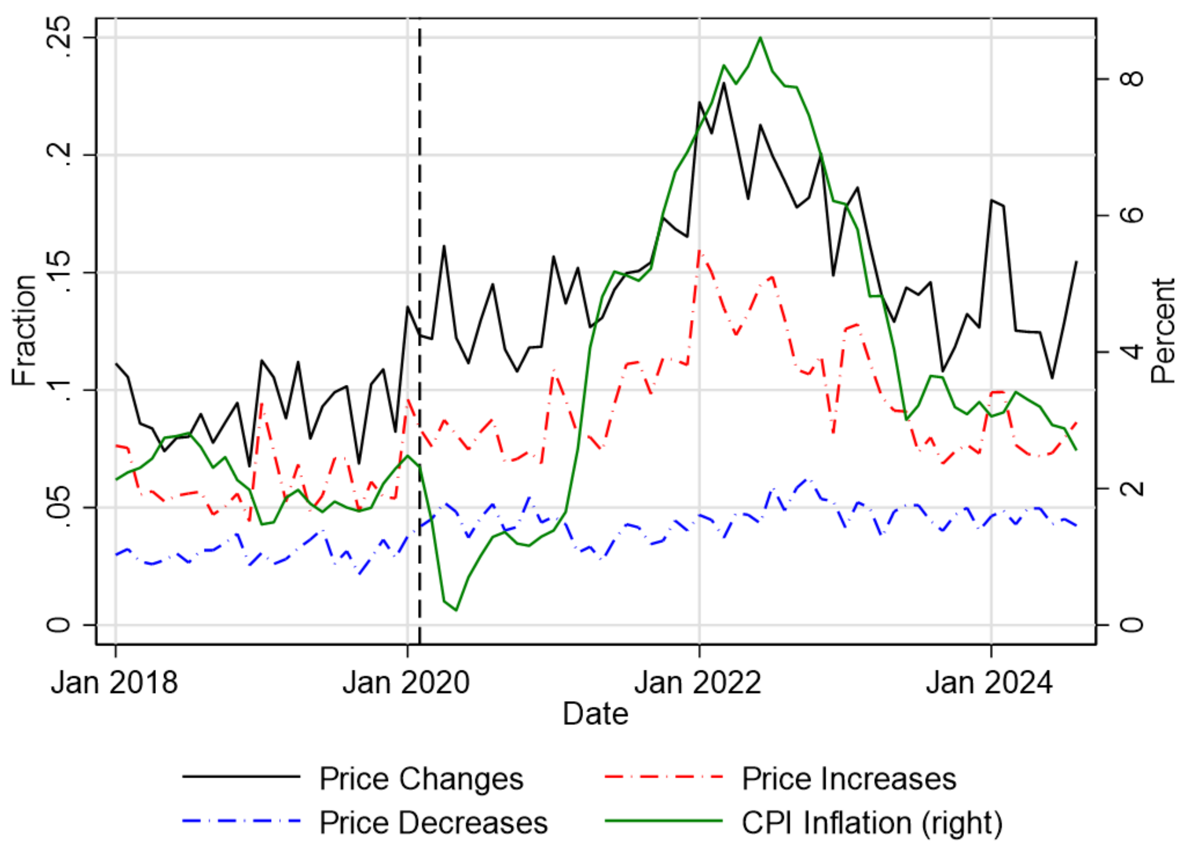
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series is the weighted median of the frequency of price changes for each month across all ELI categories. The size and absolute value series are the weighted mean of the respective statistics across ELI categories. 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.

Figure 2: Inflation Counterfactuals



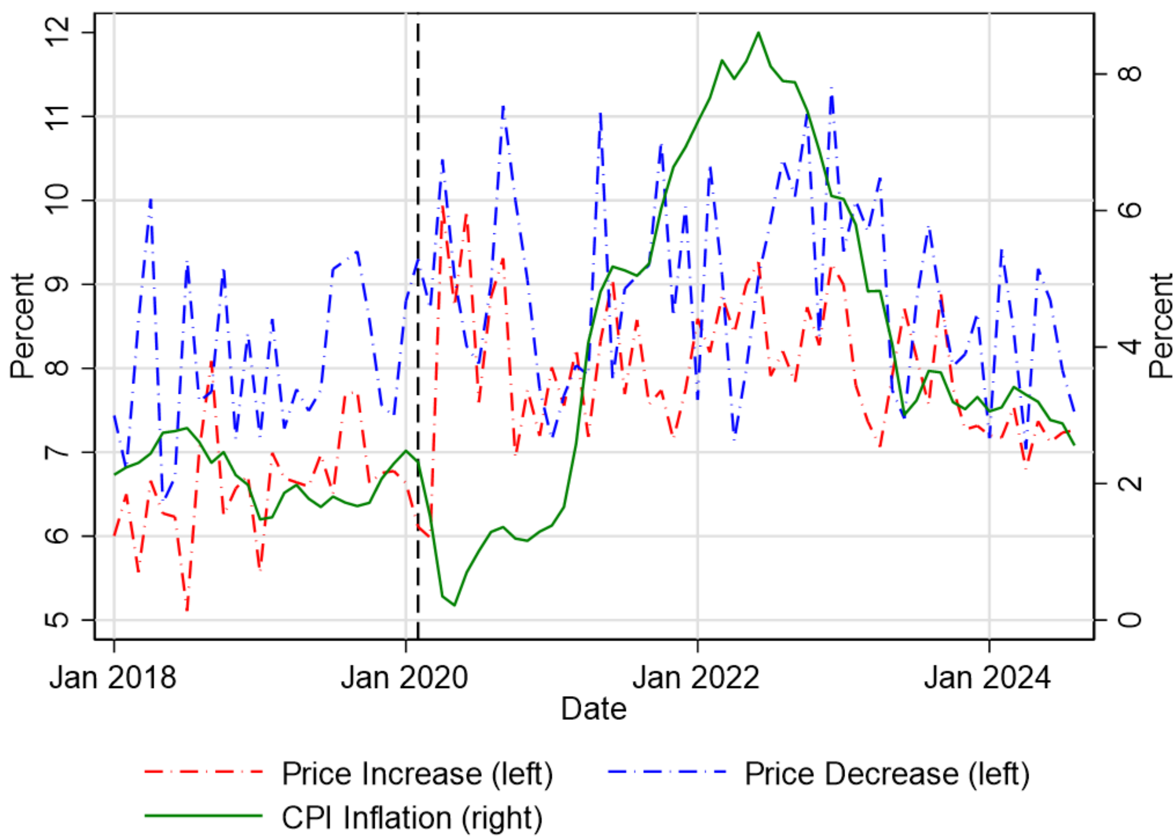
Notes: All three time series in this graph are constructed with data from the BLS CPI research database and are at monthly rates. Inflation is defined as the fraction of prices that change multiplied by the average price change summed over all ELI categories. The fixed size time series is the counterfactual inflation rate where the size of price changes is fixed at the average over 2019, while allowing frequency to vary over time. The fixed frequency counterfactual inflation rate is the case where frequency is fixed at the average over 2019, 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.

Figure 3: Frequency, Increases and Decreases



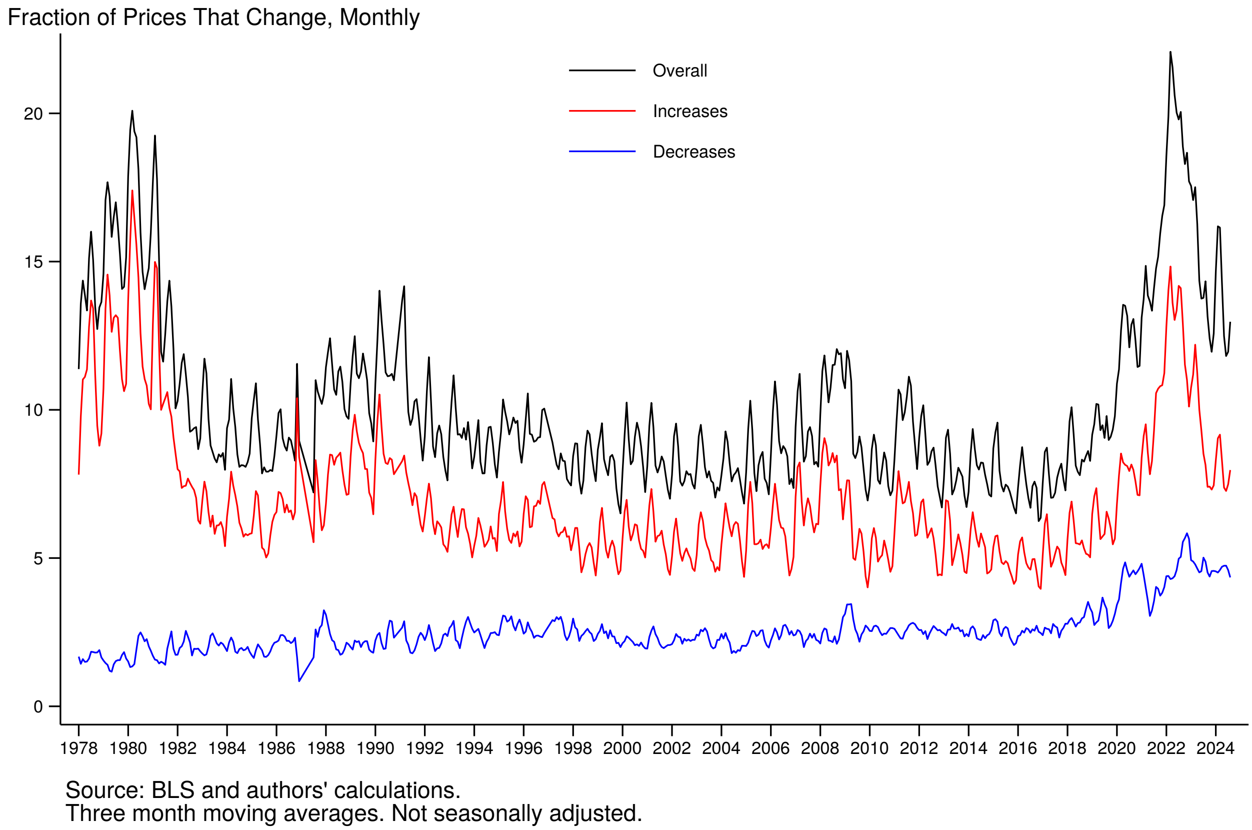
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series are the median values for each month across all ELI categories. The vertical dashed line corresponds to February 2020. Price changes due to sales are excluded. The year-on-year change in the BLS CPI-U is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

Figure 4: Size, Increases and Decreases



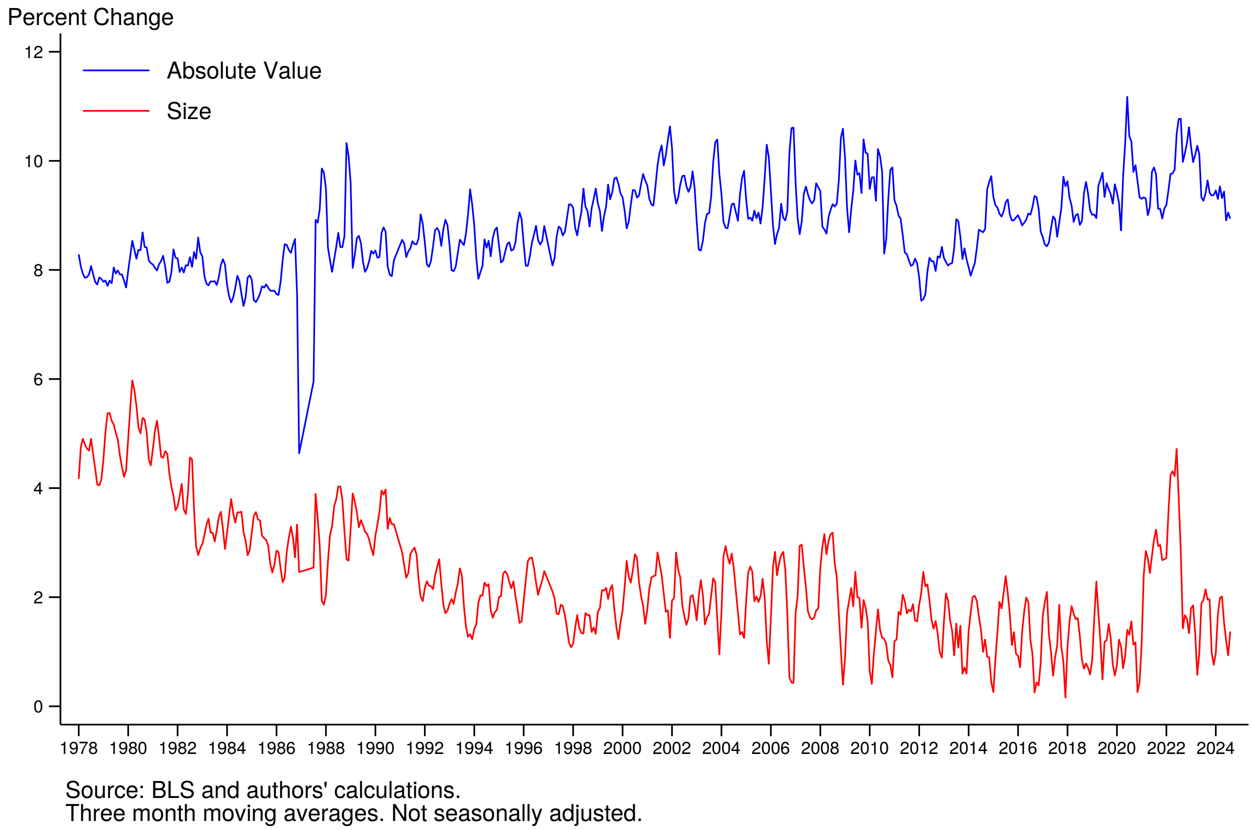
Notes: These graphs are constructed with the BLS CPI research database. The size time series are the median values for each month across all ELI categories. The vertical dashed line corresponds to February 2020. Price changes due to sales are excluded. The year-on-year change in the BLS CPI-U is provided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

Figure 5: Longer Frequency Time Series



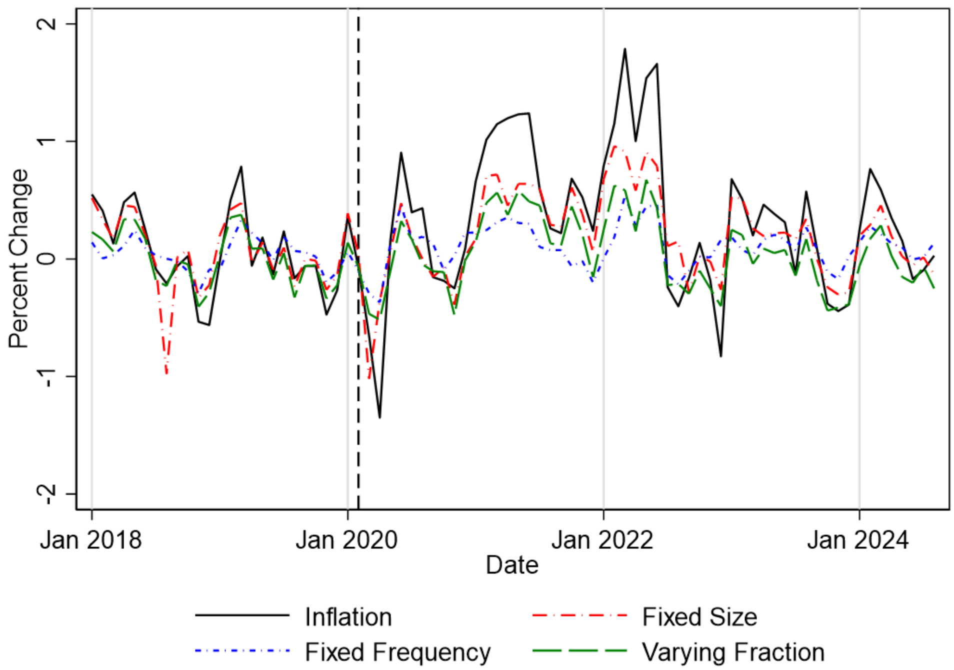
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series are the median values for each month across all ELI categories. Price changes due to sales are excluded.

Figure 6: Longer Size and Absolute Value Time Series



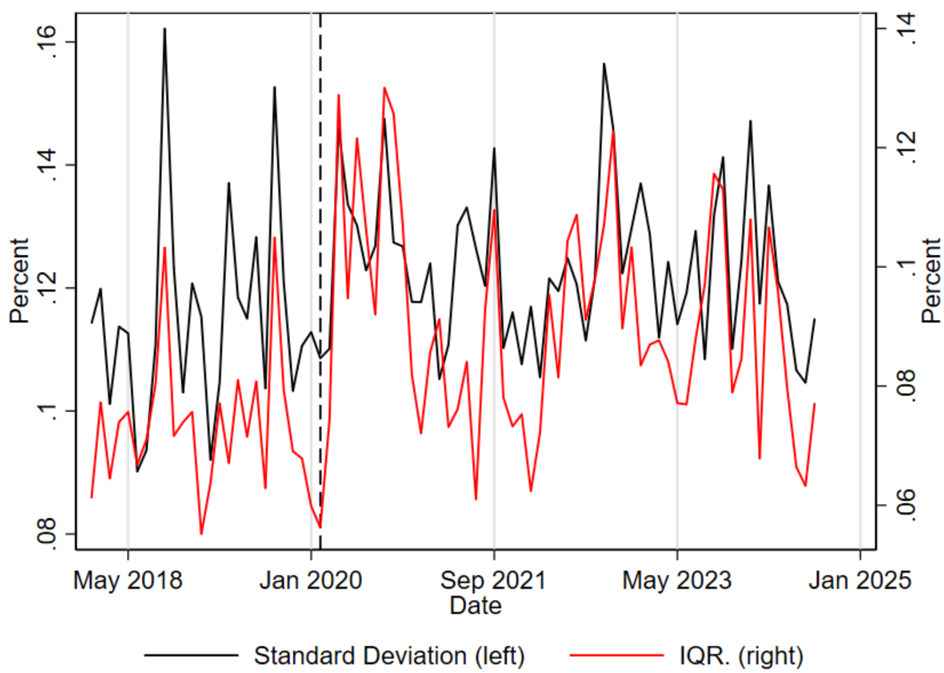
Notes: These graphs are constructed with the BLS CPI research database. The frequency time series are the median values for each month across all ELI categories. Price changes due to sales are excluded.

Figure 7: Inflation Counterfactuals, Increases and Decreases



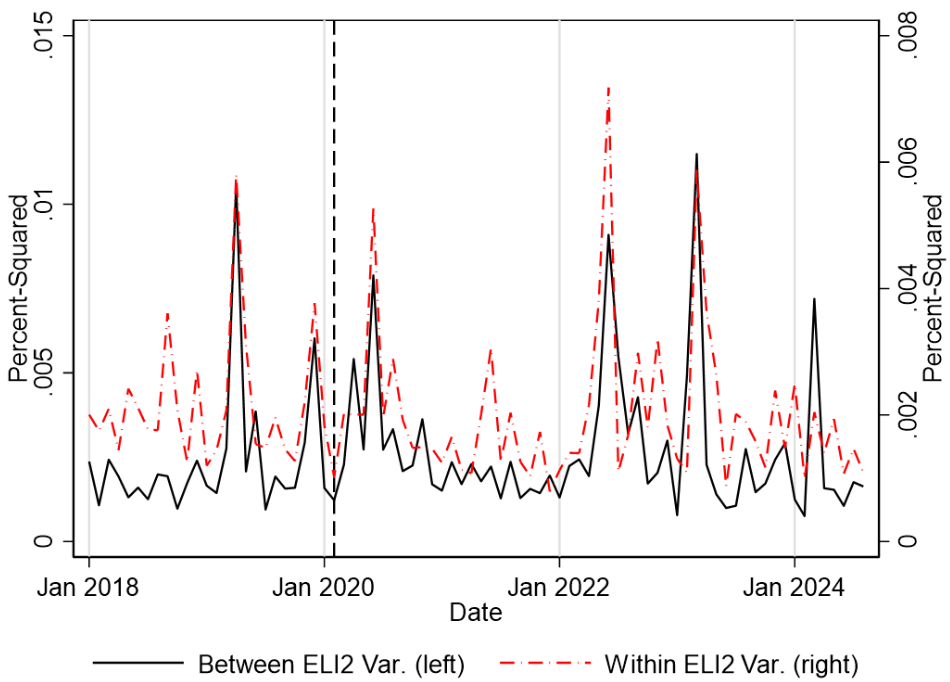
Notes: All four time series in this graph are constructed with data from the BLS CPI research database and are at monthly rates. Inflation is defined as the fraction of prices that change multiplied by the average price change summed over all ELI's. The fixed size time series is the counterfactual inflation rate where the size of price increases and size of price decreases are held fixed at the averages over 2019, while allowing the frequency of increases and frequency of decreases to vary over time. The fixed frequency counterfactual inflation rate is defined likewise, with size and frequency switched. 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.

Figure 8: Price Change Dispersion



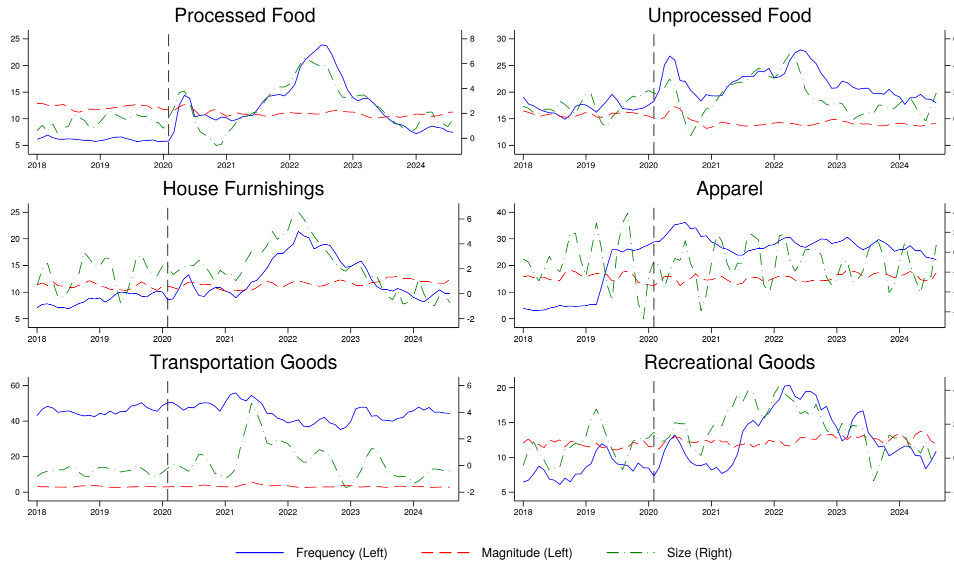
Notes: Both time series are constructed from the BLS CPI research database. They refer to the weighted median standard deviation or iqr across ELI2.

Figure 9: Price Change Dispersion Decomposition



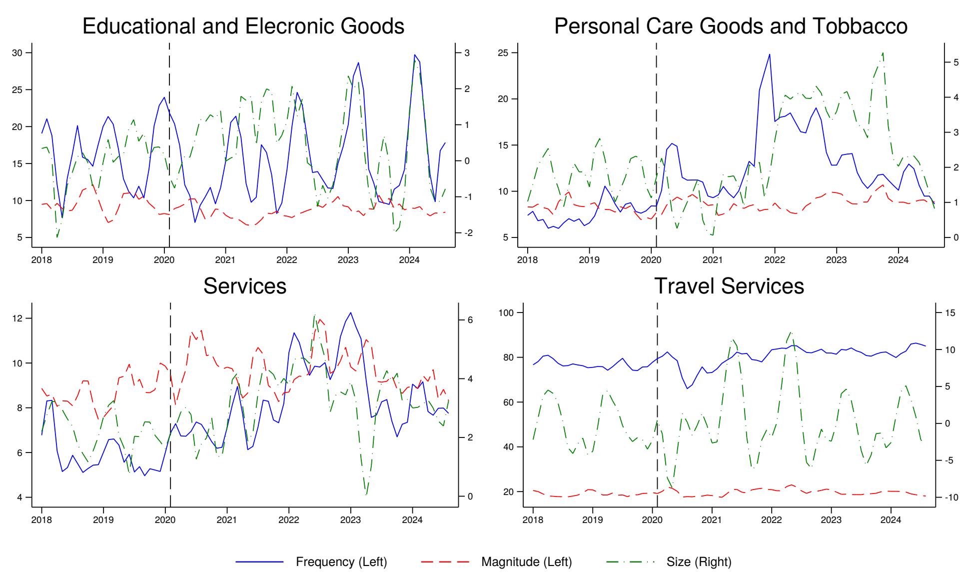
Notes: These graphs are constructed with the BLS CPI research database. The variance of price changes for each date are decomposed into between-ELI2 and within-ELI2 components. Price changes due to sales are excluded from this sample. The vertical dashed line corresponds to February 2020.

Figure 10: Frequency, Size, and Magnitude of Price Change by Major Group



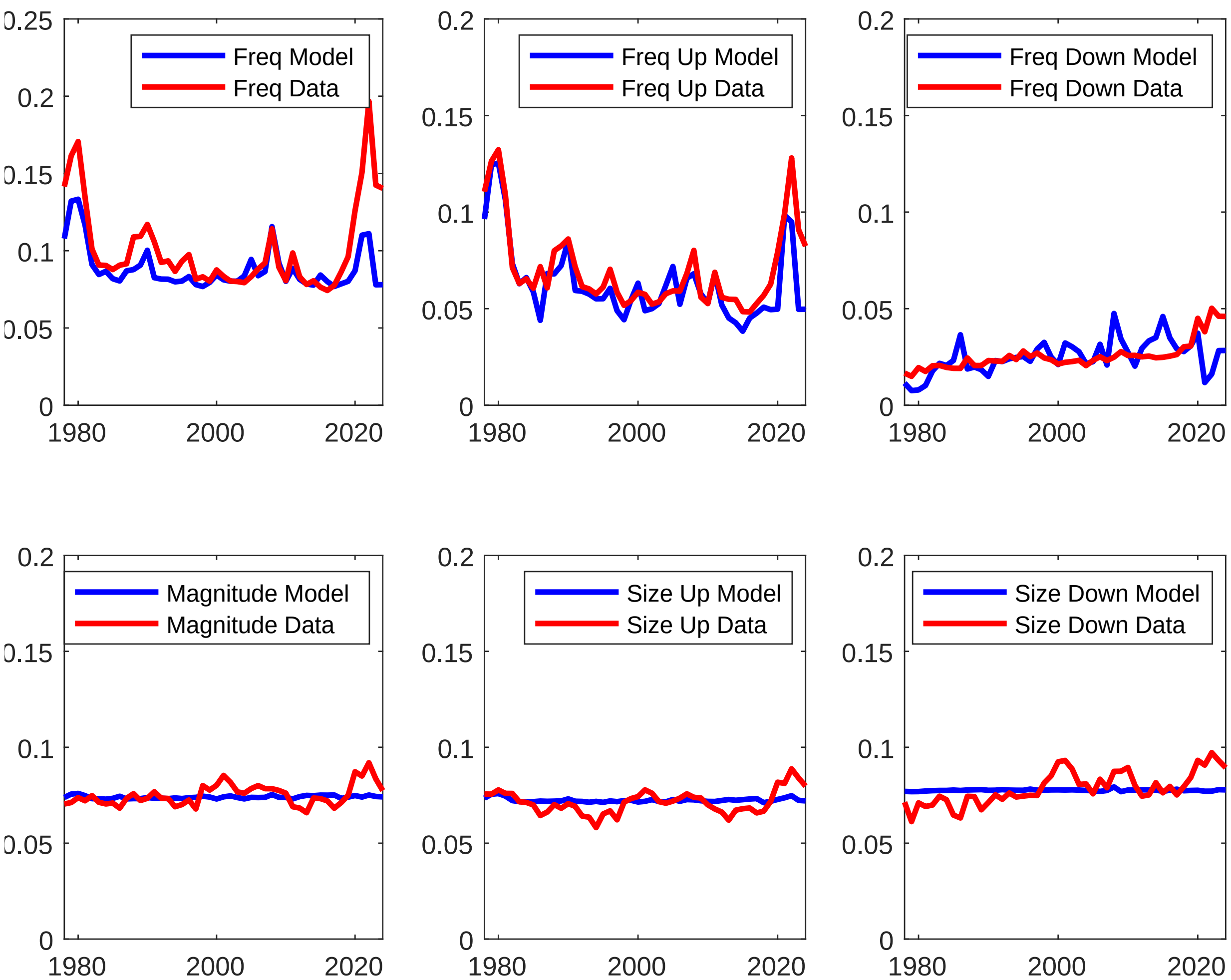
Notes: These graphs are constructed with the BLS CPI research database. Within each major group, the frequency is a weighted median across ELIs, the size and magnitude are weighted means. All series are three month moving averages. The vertical dashed line corresponds to Feburary 2020. Series are not seasonally adjusted.

Figure 11: Frequency, Size, and Magnitude of Price Change by Major Group (cont'd)



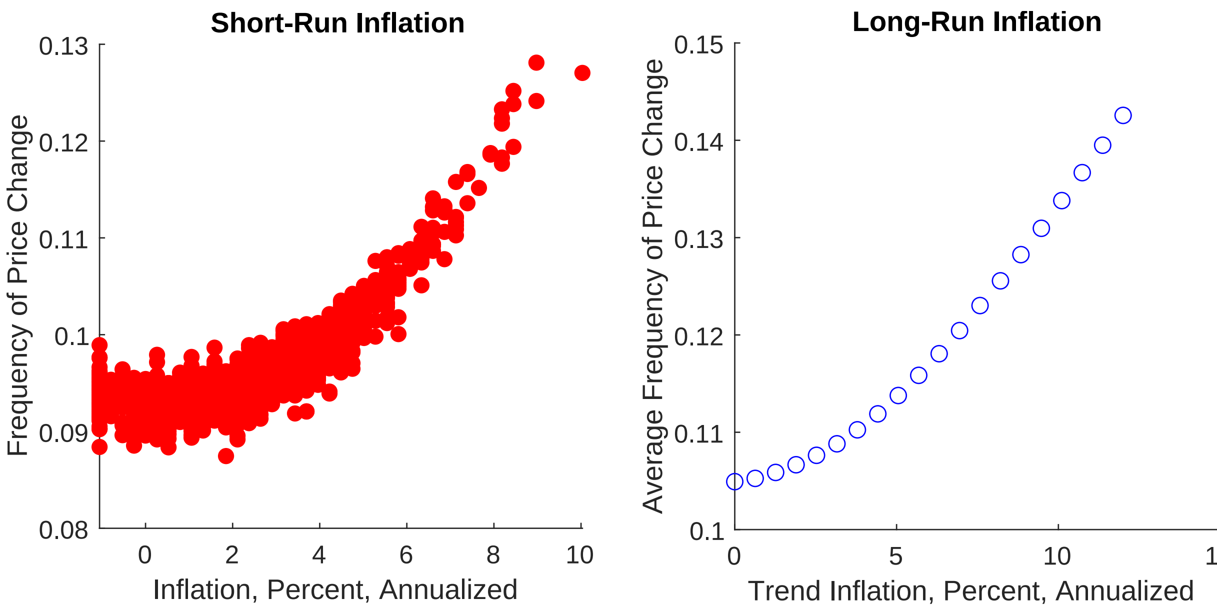
Notes: These graphs are constructed with the BLS CPI research database. Within each major group, the frequency is a weighted median across ELIs, the size and magnitude are weighted means. All series are three month moving averages. The vertical dashed line corresponds to Feburary 2020. Series are not seasonally adjusted.

Figure 12: Partial Equilibrium Model



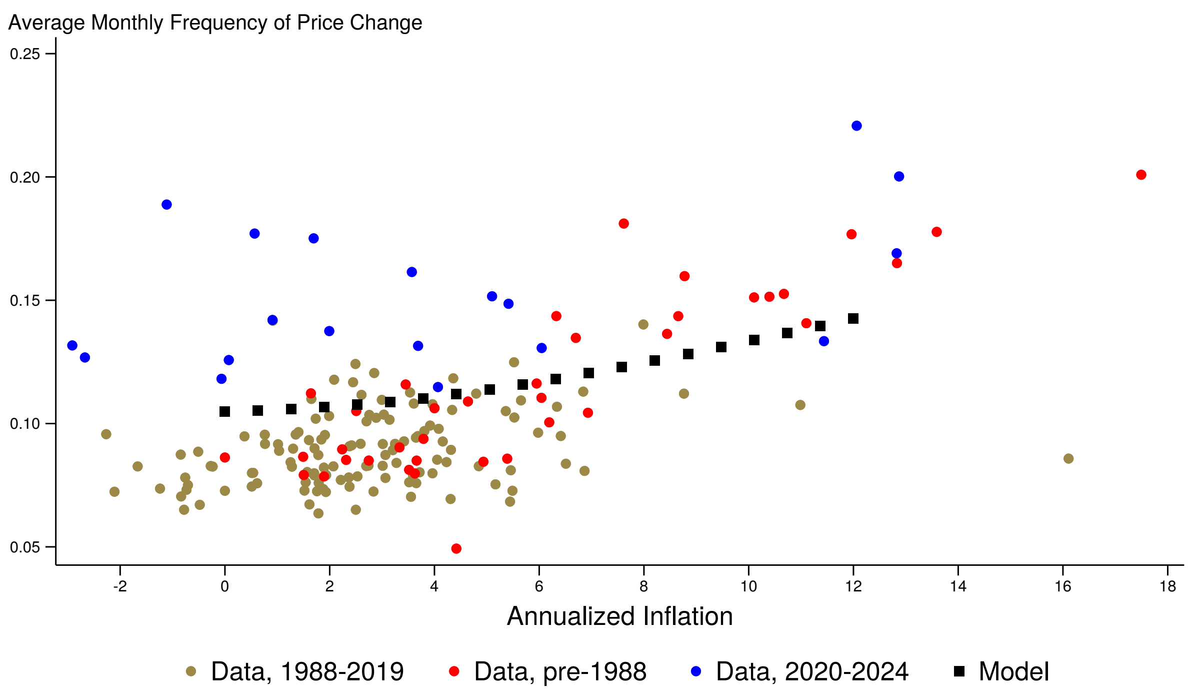
Notes: Time series in black represent pricing statistics derived from the BLS CPI research database. Time series in red represent pricing statistics derived from a menu cost partial equilibrium model with the actual BLS CPI monthly inflation data. All time series are annual averages of monthly results.

Figure 13: General Equilibrium Model



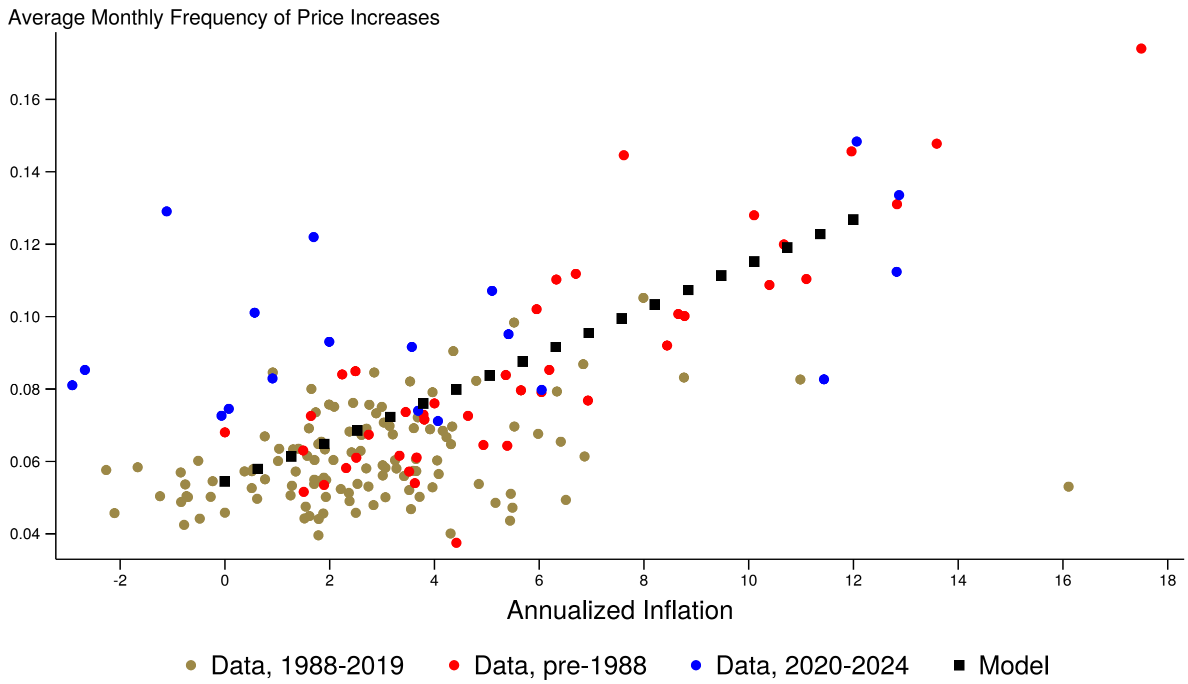
Notes: Both subfigures display results derived from a general equilibrium Golosov-Lucas-style menu cost model. The menu cost model is estimated using pricing microdata from 1978-2014. Inflation in both figures is endogenous and driven by iid aggregate demand. See text for futrher details of the model simulation. The subfigure Short-Run Inflation displays a scatterplot of the annualized inflation rate and frequency of price changes in the model simulation. The subfigure Long-Run Inflation estimates a series of simulations with different long-run trend inflation rates. The subfigure shows the relationship between average long-run inflation and the average frequency of price changes.

Figure 14: General Equilibrium Model and Data: Frequency



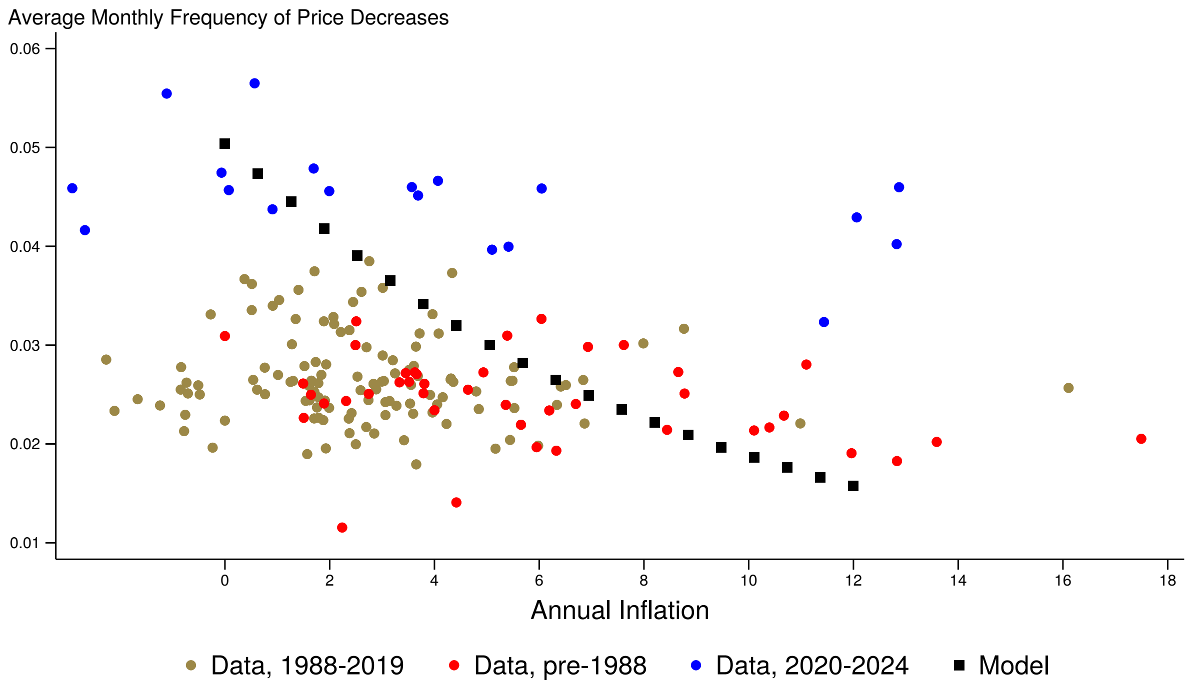
Notes: This figure displays the relationship between inflation and frequency, both in the General Equilibrium menu cost model and in the data. The black squares denote the model-implied average frequency of price change for different values of annualized trend inflation. The colored circles denote the median monthly frequency of price change, averaged by quarter, estimated from the CPI micro data 1978-2024. Quarters with an annualized inflation rate of less than -3 percent are not shown. Different colors denote different time periods. See text for further details of the model simulation and empirical estimates.

Figure 15: General Equilibrium Model and Data: Frequency of Increases



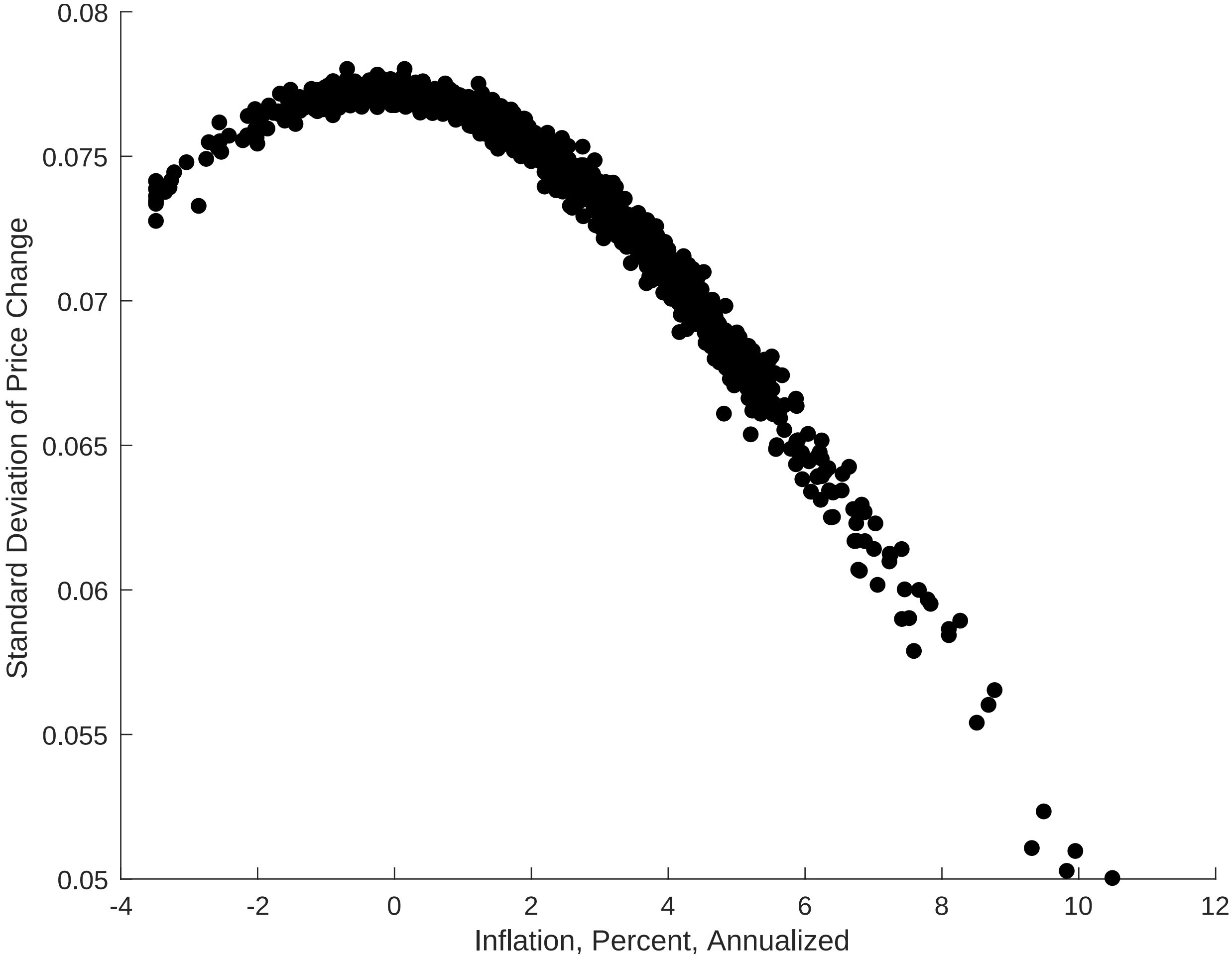
Notes: This figure displays the relationship between inflation and the frequency of price increases, both in the General Equilibrium menu cost model and in the data. The black squares denote the model-implied average frequency of price increases for different values of annualized trend inflation. The colored circles denote the median monthly frequency of price increases, averaged by quarter, estimated from the CPI micro data 1978-2024. Quarters with an annualized inflation rate of less than -3 percent are not shown. Different colors denote different time periods. See text for further details of the model simulation and empirical estimates.

Figure 16: General Equilibrium Model and Data: Frequency of Decreases



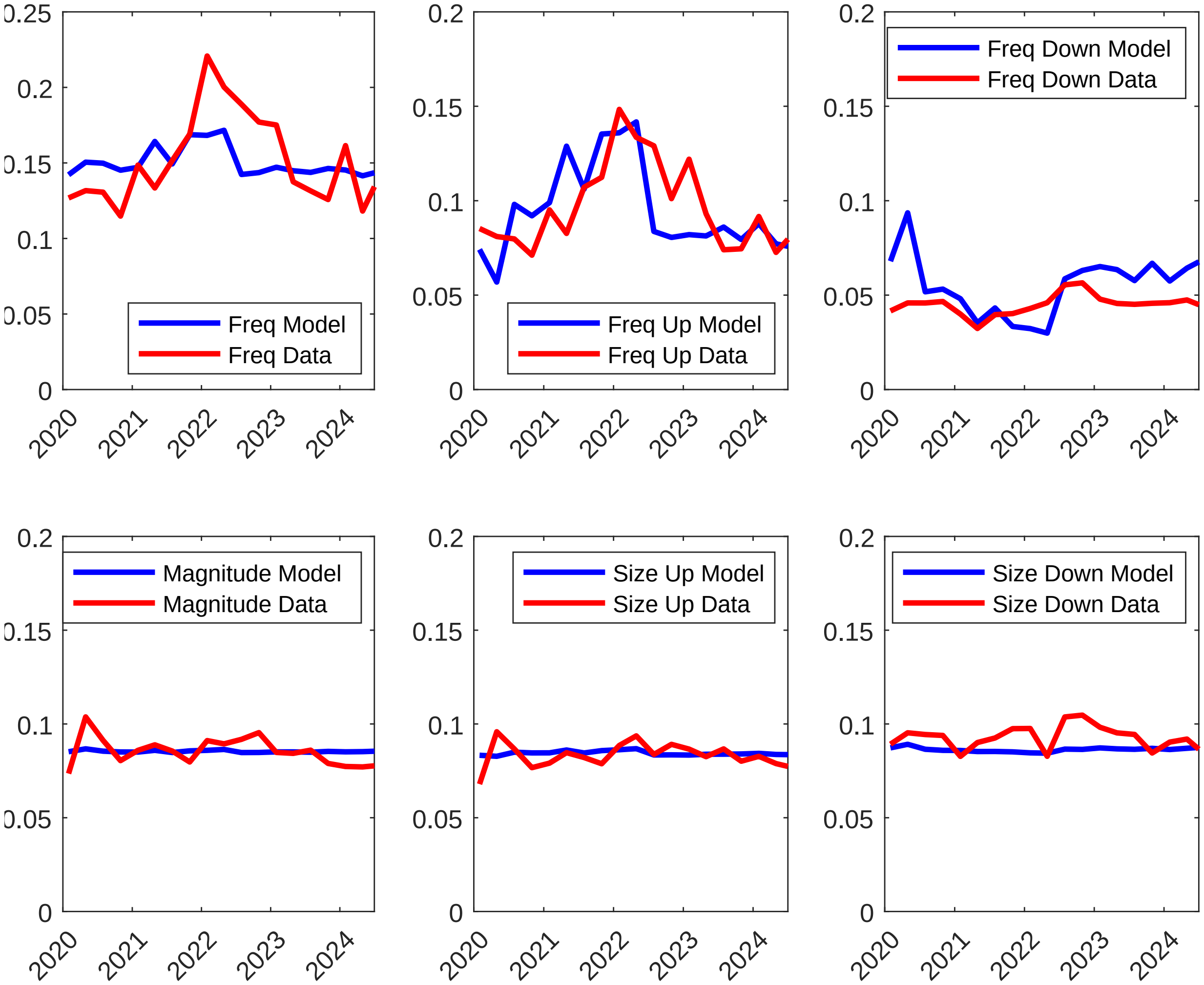
Notes: This figure displays the relationship between inflation and the frequency of price decreases, both in the General Equilibrium menu cost model and in the data. The black squares denote the model-implied average frequency of price decreases for different values of annualized trend inflation. The colored circles denote the median monthly frequency of price decreases, averaged by quarter, estimated from the CPI micro data 1978-2024. Quarters with an annualized inflation rate of less than -3 percent are not shown. Different colors denote different time periods. See text for further details of the model simulation and empirical estimates.

Figure 17: General Equilibrium Model: Dispersion



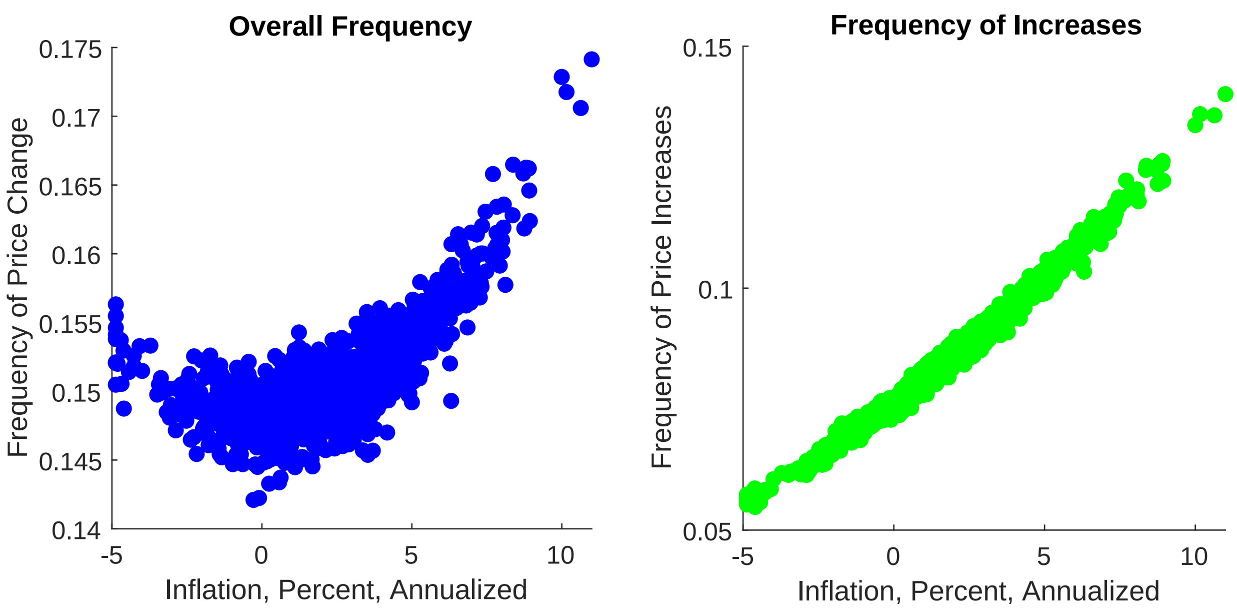
Notes: This figure displays results derived from a general equilibrium Golosov-Lucas-style menu cost model. The menu cost model is estimated using pricing microdata from 1978-2014. Inflation is endogenous and driven by iid aggregate demand. See text for futrher details of the model simulation. The figure shows the relationship between inflation and the standard deviation of price changes.

Figure 18: Partial Equilibrium Model: Post-Covid Calibration



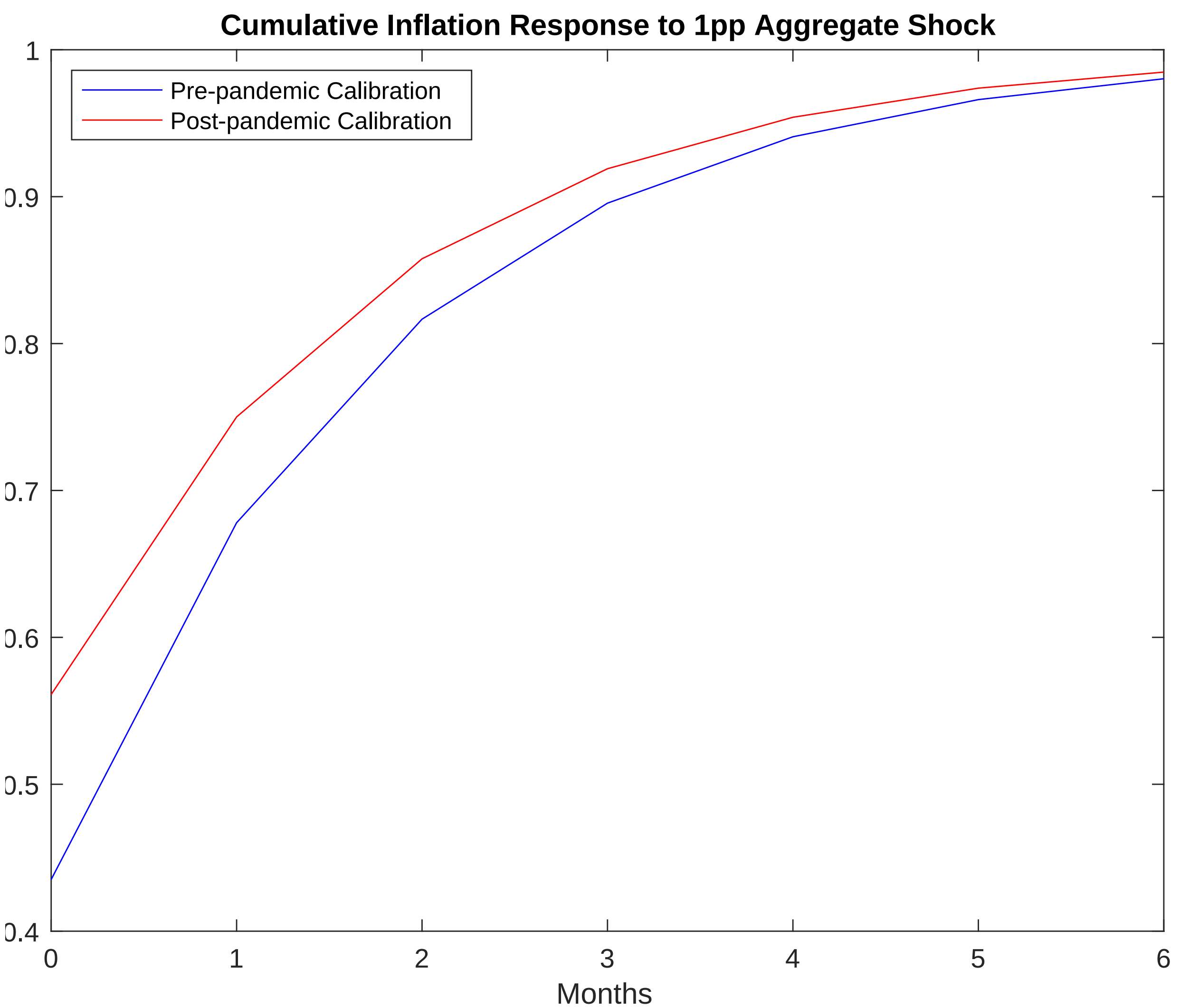
Notes: Time series in blue represent quarterly pricing statistics derived from the BLS CPI research database. Time series in red represent pricing statistics derived from a Menu cost partial equilibrium model, calibrated to the 2020-2024 data, with the actual BLS CPI monthly inflation data.

Figure 19: General Equilibrium Model: Post-Pandemic Calibration Frequency of Price Change



Notes: This figure displays results derived from a general equilibrium Golosov-Lucas-style menu cost model. The menu cost model is estimated using pricing microdata from 2020 onwards. Inflation is endogenous and driven by iid aggregate demand. See text for futrher details of the model simulation. The figure shows the relationship between inflation and both the overall frequency of price changes and the frequency of price increases.

Figure 20: General Equilibrium Model: Response to Aggregate Shocks Under Different Calibrations



Notes: This figure displays results derived from a general equilibrium Golosov-Lucas-style menu cost model, under two different calibrations, described in the text. The two lines show impulse responses of cumulative inflation to a one-time one percentage point nominal aggregate demand shock.