Inflation Dynamics During the COVID Era: A High-frequency Approach

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Draft: January 4, 2025

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Abstract

Exploiting a novel weekly panel dataset of prices and quantities across 14 sectors and the U.S. aggregate since January 2020, we study high frequency inflation dynamics with a particular focus on the Phillips curve and the pass-through of monetary policy. The novel dataset holds significant out-of-sample predictability for official inflation and retail sales measures, suggesting its usefulness for the inference of aggregate dynamics. Our model of Bayesian break detection suggests the Phillips curve steepened from mid-March 2020- July 2021 and then flattened afterward. These shifts are detected in real time with a lag of 6 weeks, providing timely signals about changes in the reduced-form Phillips curve. Last, monetary policy rapidly and significantly passed through to price and real sales during the regime of steeper Phillips curve and particularly among brick-and-mortar stores, likely preventing a deflationary spiral during the period of lockdown.

Keywords: Phillips curve, Inflation, Retail sales, High-frequency data, Impulse responses, Panel data, Structural breaks, Bayesian analysis, COVID-19

JEL classifications: C11, C22, E37, E52, E58

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Noah Chidester and Lucas Moyon provided excellent research assistance. Comments from Torben Andersen, Philippe Andrade, Jonas Arias, Regis Barnichon, Thorsten Drautzburg, Huberto Ennis, Jose Fillat, Simon Freyaldenhoven, Shigeru Fujita, Jim Hamilton, Paul Ho, Andreas Hornstein, Elmar Mertens, Alessandro Rebucci, Aysegul Sahin, Viacheslav Sheremirov, Allan Timmermann, Mark Watson, Jonathan Wright, Christian Wolf, and Alex Wolman as well as seminar and conference participants at the 2024 NBER Summer Institute, Federal Reserve Bank of Richmond, Federal Reserve Bank of Philadelphia, Federal Reserve Bank of Boston, and the 2024 North American Summer Meeting of the Econometric Society are appreciated. Any remaining errors are our own. The views expressed in this paper are those of the authors and do not necessarily reflect the views and policies of the Board of Governors or the Federal Reserve System. Information from The NPD Group, Inc. and its affiliates contained in this report is the proprietary and confidential property of NPD and was made available for publication under a limited license from NPD. Such information may not be re-published in any manner, in whole or in part, without the express written consent of NPD.

1. Introduction

"...in this age of shifts and breaks, where we do not yet know whether we are returning to the old world or entering a new one, how can we ensure policymaking remains robust?... In the ECB's case, we have made our future decisions contingent on three criteria: the inflation outlook, the dynamics of underlying inflation and the strength of monetary policy transmission." (Christine Lagarde, 2023.)[1]

"... A second issue for the FOMC is how long it takes for changes in monetary policy to affect economic activity and inflation. ... There is a wide range of views among researchers and policymakers as to how long it takes for the full effect of monetary policy to register in the economy. ... There are a lot of reasons to think that "big shocks travel fast," meaning they elicit a change in economic behavior that would not be associated with small shocks." (Christopher J. Waller, 2023)[2]

The Covid-19 pandemic unleashed a huge unforeseen shock to the economy which led to the macroeconomic environment evolving at a rapid pace, rendering traditional low-frequency (monthly or quarterly) data sources uninformative for real-time decision making. Policymakers, economists, and financial market participants have therefore turned increasingly toward more timely high-frequency datasets to understand the state of the economy.

Having been stable at a low level for several decades, inflation has surged in recent years. In the U.S., inflation reached levels not seen in almost half a century, and the causes of this surge are not well understood. Given the limited number of post-pandemic observations in traditional data sources, the rich granular information in high-frequency data are likely to be helpful here.

In this paper, we exploit a novel high-frequency panel data set of U.S. prices and retail sales during the COVID era to detect nonlinearities in inflation dynamics in real time—the key questions outlined in the opening quotes. This dataset has information about both prices and quantities by store type, and is updated with a lag of one week, which distinguished

[1]This quote is from ECB President Christine Lagarde's Jackson Hole speech "Policymaking in an age of shifts and breaks", August 25, 2023; https://www.ecb.europa.eu/press/key/date/2023/html/ecb.sp230825~77711105fe.en.html.

[2]This quote is from the FRB Governor Christopher J. Waller's speech at the Money Marketeers of New York University, New York, New York. See https://www.federalreserve.gov/newsevents/speech/waller20230713a.htm.

itself from the existing proprietary datasets such as the million price project that does not have the quantity information and the Nielsen data that are not available in real time. In this context, our dataset is suitable to study the Phillips correlation and propagation of monetary policy at high frequency and in real time. In fact, our dataset proves to be useful for the inference of aggregate dynamics and the prediction of aggregate CPI and retail sales. Second, we detect changes in the Phillips curve in real time based on the Bayesian panel breakpoint method developed by Smith and Timmermann (2021). This novel statistical method detects changes in the regimes of inflation dynamics—the trade off between prices and real quantities, in particular—in a timely manner. Finally, using the estimated regimes of reduced-form Phillips curve, we investigate the evolution in the the weekly pass-through of monetary policy shocks during the Covid era and further recovers changes in the weekly Phillips multiplier—the slope of structural Phillips curve.

Circana provides the weekly data of prices and retail sales in the U.S. for 14 sectors and the overall aggregate. This firm, formerly the NPD group, serves as an intermediary for some retailers to submit their responses to the Census Bureau's retail trade survey. The sample period starts at 2020. This gives us a rich panel dataset of about 3,000 observations with a time series of more than 200 observations. The disaggregate high-frequency data capture changes in consumption patterns in line with increased remote work and the related sectoral reallocation of demand during the pandemic.[3] Our data are also broken out by bricks-and-mortar sales only and bricks-and-mortar plus e-commerce sales, facilitating analyses of the impact of the Covid-induced lockdowns on the behavior of brick-and-mortar stores and providing implications for the rise in online sales.

The novel high-frequency dataset together with the recently-developed Bayesian panel breakpoint approach bring innovation to the literature on inflation dynamics and monetary policy in a few distinct ways. First, this paper is the first one that investigates the Phillips curve and the propagation of monetary policy to prices and quantities in weekly frequency with a particular focus on their nonlinearity during the Covid era. Second, none of the previous studies have investigated the real-time detection of changes in *weekly* inflation dynamics with the Bayesian panel breakpoint method.[4] This econometric method effectively

[3]For instance, increased working from home that has persisted after the lockdowns has likely reduced expenditure on office supplies. In this context, our dataset can effectively capture the pandemic-specific phenomenon, that is, inflationary supply-demand imbalances as supply could not reallocate at the same pace as demand due to constrained supply chains.

[4]Smith *et al.* (2023) apply the same method to estimate breaks in the Phillips curve using quarterly or annual data going back several decades. We deviate from them by focusing on high frequency data during

detects sudden changes in the reduced-form Phillips correlation in a timely manner, which is suitable to study the weekly inflation dynamics during the fast evolving Covid era. Third, our paper is the first one that uncovers differences in the Phillips curve (including the weekly Phillips multiplier) and monetary policy pass-through by store type.

Our empirical analysis provides new insights into inflation dynamics and monetary policy during the Covid era. First, we find that the Phillips curve steepened from mid-March 2020 to mid-2021 but was largely flat and statistically insignificant before and after this period. Notably, the steepening and subsequent flattening align with the lockdown and reopening phases, respectively. Without prior assumptions, our Bayesian method effectively captures the impact of social distancing measures on inflation dynamics. Importantly, this paper is the first to document the re-flattening of the Phillips curve after its steepening.[5] Second, the rich cross-sectional information from the panel dataset effectively detects the second regime that emerged at the 10th week in the sample and within 6 weeks. This effective real-time detection of changing inflation dynamics is useful for the implementation of preemptive monetary policy as mentioned by Lagarde (2023).

Third, monetary policy pass-through to prices and real sales is swift and statistically significant during the second regime (lockdown period), with stronger and faster effects in brick-and-mortar stores compared to the total category. Consistently, the weekly Phillips multiplier—the slope of structural Phillips curve measured with the ratio of cumulative impulse responses of prices and real sales to a monetary policy shock—is steeper during the lockdown and among brick-and-mortar stores than in other contexts. These novel results are robust to the choice of monetary policy shocks and the inclusion of various controls that capture the pandemic-related phenomena.

Our empirical findings suggests that the expansionary monetary policy was effective in supporting a swift recovery from the pandemic recession and preventing a deflationary spiral. The impact was particularly notable in the prices and real sales of brick-and-mortar stores. The steeper Phillips multiplier for brick-and-mortar stores also indicates that the economy was in a structural environment where monetary policy can be effective. During the pandemic recession, social distancing measures and COVID-19-related concerns intensified the retail downturn, placing retailers at risk of credit crunches and bankruptcy. Timely expansionary monetary policies helped alleviate these pressures. In this way, monetary policy contributed to stabilizing prices and sales. However, the pass-through effect weakens and loses statistical

the pandemic period.

[5]Previous studies like Cerrato and Gitti (2022) and Inoue *et al.* (2022) document the steepening only.

significance during the reopening phase, suggesting that monetary policy alone may not be the ultimate fix of stabilizing the surge and the elevated level in inflation seen from the mid 2021.

This paper makes a unique contribution to the literature on the Philips curve: Our paper is the first one that uncovers both the reduced-form and structural Phillips correlation in weekly frequency and further identifying the evolution of Phillips correlation during the Covid era. There is a long literature that estimates time-variation in the Phillips curve, typically using aggregate data (Roberts 2006; Ball and Mazumder 2011; Coibion *et al.* 2013; Matheson and Stavrev 2013; Coibion and Gorodnichenko 2015; Blanchard 2016; Leduc *et al.* 2017; Ball and Mazumder 2019; Galí and Gambetti 2019; Gilchrist and Zakrajšek 2019; Del Negro *et al.* 2020; Inoue *et al.* 2022). However, if the central bank is successful in targeting inflation, the use of aggregate data will bias the estimated Phillips curve slope coefficient towards zero (McLeay and Tenreyro 2020). Since the central bank does not target inflation in any one region or sector, one popular approach to circumvent this endogeneity problem is to use regional or sectoral level data to estimate the Phillips curve (Fitzgerald *et al.* 2020; Hooper *et al.* 2020; Cerrato and Gitti 2022; Hazell *et al.* 2022). The paper closest to ours uses the same Bayesian panel breakpoint model to estimate breaks using data at the quarterly or annual frequency than goes back several decades (Smith *et al.* 2023). Our contribution is to identify breaks in the Phillips curve using high frequency data during the pandemic. Given the rapidly changing nature of the economy during the pandemic, conventional low frequency data would not enable this identification.

Our paper also speaks to the emerging literature on high-frequency effects of monetary policy. For example, Jacobson *et al.* (2023) find that monetary policy lowers prices within a month after the shock's impact based on the daily price data spanning 2008-2015. Relatedly, Buda *et al.* (2023) find consumption declines significantly within five days after the impact of monetary policy based on the daily data spanning from April 2015 to December 2021. These studies suggest the existence of time aggregation bias in the estimated effects of monetary policy when using lower-frequency data. Our findings of lockdown pass-through are not inconsistent with those of previous findings, but the muted and statistically insignificant pass-through outside the lockdown period implies the importance of considering nonlinearity the analysis of time-aggregation bias in the measurement of monetary policy propagation.

The remainder of this paper is set out below. Section 2 introduces the high-frequency panel data set used in our analysis, while Section 3 explores whether these data hold predictive information for official measures of inflation and retail sales. Section 4 explores the

real-time detection of breaks in the reduced-form Phillips curve. Section 5 investigates the responsiveness of prices and real sales to monetary policy shocks. Section 6 concludes.

2. Data

We begin by describing our dataset. From Circana (formerly the NPD group), beginning at the start of 2020 we have weekly data for 14 industries and the overall aggregate for the US.[6] The data collectively cover U.S. retail spending for approximately 150 U.S. retailers across all non-grocery store retailers, including both brick and mortar (in stores) and e-commerce (online sales) transactions. These data are derived from point-of-sale systems at brick and mortar and e-commerce retailers. One appeal of these data is that Circana serves as an intermediary for some retailers to submit their responses to the Census Bureau's monthly retail trade survey, so they should in principle be useful for forecasting retail goods (27 percent of PCE). We focus on 52-week percent changes in sales and prices to control for seasonal effects as well as potential issues of nonstationarity for the baseline analyses. Later on, we take the week-over-week changes, seasonally adjust the data with a pre-existing algorithm by Ginker (2023), and show the robustness of the results.[7]

3. Predictive content for aggregate inflation and retail sales

In this section, we investigate whether the NPD data on retail sales and inflation hold any nowcasting predictive content for official measures of retail sales and inflation. The purpose of this analysis is to establish the usefulness of the novel dataset for forecasting the aggregates that policy makers pay attention to.

3.1. Delays in Data Releases

Since the CPI and retail sales data are released with a delay, it may be possible to exploit the NPD data to generate nowcasts of the official measures. Table 1 reports summary statistics – mean, standard deviation, minimum, and maximum – for the delay (measured in days) of

[6]The 14 product categories are accessories, auto, apparel, beauty, footwear, housewares, juvenile, office supplies, sports, tech, toys, small appliances, video games, and video entertainment.

[7]As seasonal adjustment of weekly data remains an ongoing research area, we directly use the 52-week change data provided by Circana to ensure transparency in our empirical analysis.

each CPI and retail sales release from the start of 2020 through the end of 2023. We see that both CPI and retail sales are released, on average, with about a two-week delay during our sample period, i.e. the April 2023 retail sales release pertaining to monthly inflation in March was released on April 14.

This lag in the release means that high-frequency NPD data covering the entire month of March is available prior to the official CPI and retail sales releases, implying that the NPD data may hold some predictive content for the CPI and retail sales data. This would be valuable information for numerous economic agents such as monetary policy makers and financial market participants.

3.2. Nowcasting Inflation and Retail Sales

We regress the 12-month change in the official core retail sales measure in each month from the start of 2020 on our constructed annualized monthly NPD retail sales measure. A slope coefficient on this regressor of 1 implies perfect predictability. Column (2) of the top panel of Table 2 shows that the slope is a highly significant 0.59 and the regression yields an R-squared of 0.62, even higher than the 0.53 R-squared from the regression that uses only the lagged official core retail sales (column 1). Indeed, column (3) shows that a regression that includes both the contemporaneous NPD data alongside the lagged official retail sales measure generates an R-squared of 0.64. In this specification, the contemporaneous NPD measure is highly significant while the lagged core retail sales is not. This clearly demonstrates the valuable information these high-frequency data can provide to policy makers and market participants when attempting to nowcast retail sales.

The top left panel of Figure 1 displays the fitted values from this predictive regression (red line) against the corresponding official retail sales measure (black line). We see that the two lines follow a very similar contour. The bottom left panel displays a scatterplot of the two series against each other alongside the fitted regression line for the contemporaneous NPD measure. The slope is steep with only a few observations falling far from the fitted line, implying considerable predictability.

Turning to inflation, the lower panel of Table 2 shows results for the 12-month change in core goods CPI inflation using our corresponding NPD inflation measure. Column (2) shows that the NPD data continue to hold significant predictability for inflation, although a bit weaker than in the retail sales data. Column (3) shows that the NPD data also hold significant predictive content about inflation over and above the information contained in

lagged inflation which is striking given the highly persistent nature of inflation. As with retail sales, these results suggest a clear benefit from exploiting information in the high-frequency NPD data when attempting to predict inflation.

The top right panel of Figure 1 displays the fitted values from this predictive (black line) core goods CPI inflation (red line). As with retail sales, the contours of the two lines are broadly similar. The bottom-right panel displays a scatterplot of the two series with the fitted regression line which, as for retail sales, reflects the predictive power of these high frequency indicators.

Taken together, these results imply that the high-frequency measures contain considerable predictive content for retail sales and inflation, above and beyond the information that is contained in their lagged values. Given how much interest and difficulty there is in predicting these series, the predictive content in these high frequency measures may be extremely valuable to numerous economic agents.

The analysis presented thus far uses the full sample of information to make the predictions. Of course, this information would not have been available to market participants at the time they were making their predictions, and so the findings may be overstating their predictability. It is important to determine whether these high-frequency measures could have been used by policy makers and market participants in real time to help predict the official measures.

3.3. Out-of-Sample Predictability

Next, we conduct an out-of-sample analysis to evaluate whether these high-frequency measures could have been used in real time to generate improved predictability of the official measures.

We compare the out-of-sample predictive performance of the model specified in column (3) of the Table, which incorporates information from the high frequency data, against the AR(1) model specified in column (1). Both models are estimated recursively in real time using only the (current vintage of) data available at the time the forecast was made.[8] The model parameters are used to generate a one-month-ahead forecast at time t. Next, the estimation period is rolled forward by a month and a forecast is generated at time $t + 1$.

[8] Schorfheide and Song (2015) develop a Bayesian forecasting approach that uses data at mixed frequencies. Our approach is similar in spirit in that we will take advantage of a high-frequency (weekly) variable to forecast a lower-frequency (monthly) variable.

This process is repeated until the final forecast is generated at time $T-1$. We use an initial estimation period of six months.

The relative predictive performance of our model relative to the benchmark is first measured using the out-of-sample R-squared measure, computed as

$$R^2 = 1 - SSE_{NPD}/SSE_{Bmk} \tag{1}$$

in which SSE_{NPD} and SSE_{Bmk}, respectively, denote the sum of squared forecast errors (MSE) obtained from the model that uses the NPD measure as a predictor and the benchmark AR(1) model. Positive (negative) R-squared values indicate that our model has generated smaller (larger) mean squared forecast errors than the benchmark.

Table 3 displays the out-of-sample R-squared values. We see that our model outperforms the benchmark, generating a R^2 value of 38 percent, reflecting that the mean squared forecast error from our model is almost half of that generated by the benchmark. This extends the earlier nowcasting results, suggesting that this high-frequency indicator could have been used in real time to generate more accurate forecasts of inflation.

The top panel of Figure 2 displays the 12-month change in CPI since the start of 2020 (black line) against the corresponding forecasts generated from the benchmark autoregressive model (red line) and our model that includes the high-frequency inflation measure (blue line). We see that the forecasts generated from our model tend to be closer to the 12-month change in CPI, reflecting the additional predictive content the high-frequency indicator holds for the CPI.

An important next step is to determine whether any superior predictive performance is statistically significant. First, we use Clark and West (2007)'s popular test statistic which corrects the Diebold and Mariano (1995) test statistic which can have a nonstandard distribution when comparing the predictive performance of nested models, as is the case in our setting. Table 3 displays that the improved predictive accuracy in point inflation forecasts is significant at the five percent level using the Clark-West test.

Next, we evaluate whether the superior predictive performance generated by our model is consistent across the out-of-sample period or is concentrated around just one or two periods. The former scenario would instill more confidence in the model's predictive ability, whereas the latter would suggest that the model's outperformance may have occurred simply due to luck. The metric we use to measure whether the predictive outperformance is consistent across the out-of-sample period is the cumulative sum of squared forecast error differences

(CSSED).

The top panel of Figure 3 graphs the CSSED measure computed over the out-of-sample period constructed from the forecast errors of our model relative to the benchmark. Positive and rising (negative and falling) values of this CSSED measure imply that our model is outperforming (underperforming) the benchmark. A gradual upward-sloping curve without too many episodes of underperformance would imply consistent outperformance over the out-of-sample period.

We see that our model outperforms the benchmark quite consistently through the sample with only one notable episode of underperformance during mid- to late-2021. This strong and consistent outperformance is striking given how difficult the simple AR(1) model has proven to beat out of sample (Atkeson *et al.* 2001; Stock and Watson 2007). This result is particularly salient in light of the large forecast errors made by most models and professional forecasters during the post-pandemic surge in inflation.

The bottom panel displays the corresponding forecast errors from our model (black line) and the benchmark (red line). Aside from the period in mid-to-late 2021, we see that the forecast errors generated from our model are generally closer to zero (the dashed horizontal line) than those from the benchmark.

Finally, we conducted the same out-of-sample exercise for retail sales: comparing the predictive accuracy of our model that incorporates high frequency data on retail sales against the AR(1) benchmark model (see the bottom panel of Figure 2). Relative to this benchmark, the mean squared forecast error reduces considerably, yielding a R^2 value of 0.20 that is significant at the ten percent level (Table 3), implying improved point predictive accuracy that could have been used in real time.

4. Breaks in the Reduced-form Phillips correlation

The evidence from the structural Phillips curve indicates the importance of considering nonlinearities in the pandemic inflation dynamics. This section applies the Bayesian panel breakpoint approach of Smith and Timmermann (2021) to a reduced form Phillips curve model with breakpoints as a promising tool for inflation forecasting. The purpose of this analysis is to reliably detect the changing features of inflation dynamics in real time. This section is composed of four sections: Section 4.1 introduces the Phillips curve model with breakpoint detection; Section 4.2 reports the full sample estimation results; and Section 4.3 demonstrates the real-time reliability of breakpoint detection and parameter updating.

4.1. Phillips Curve Model with Breakpoint Detection

Our panel model which allows for multiple breaks, exploits rich information in the cross-section to obtain increased break detection power relative to time series break models.[9] The model assumes that the Phillips correlation slope coefficient is pooled across all sectors and that any identified breaks hit all sectors at the same time.

Formally, the model estimates the number of breaks (K) and their locations $\tau = (\tau_1, \ldots, \tau_K)$. Letting $i = 1, \ldots N$ denote the 14 different sectors and T denote the time series dimension, the model for regimes $k = 1, \ldots, K+1$ is:

$$\pi_{it} = \alpha_i + \gamma_t + \rho_k \pi_{it-1} + \lambda_k RS_{it} + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \ldots, \tau_k \tag{2}$$

in which π_{it} denotes the NPD inflation rate for the ith sector at time t, α_i and γ_t are two-way fixed effects[10], RS_{it} denotes the NPD measure of retail sales for the ith sector at time t, and ϵ_{it} is the residual for sector i at time t.[11] The persistence parameter ρ_k and the Phillips correlation λ_k are also allowed to vary across regimes, but not across series.

A. Prior on regime durations

We specify a Poisson prior distribution over the length of regimes $l_k = \tau_k - \tau_{k-1}$

$$p(l_k \mid \zeta_k) = Po(\zeta_k), \qquad k = 1, \ldots, K+1, \tag{3}$$

and a conjugate Gamma prior distribution over the intensity parameter ζ_k

$$p(\zeta_k) = Ga(c, d), \qquad k = 1, \ldots, K+1. \tag{4}$$

[9] Cavallo and Zavaleta (2023) apply time series break detection methods to daily inflation data across 25 countries from January 2022 to April 2023 to identify breaks in the mean of inflation.

[10] Time fixed effects control for changes in monetary policy over time but their inclusion renders inflation expectations not separately identifiable and thus they cannot be included in the model (Hazell *et al.* 2022). Other studies that estimate Phillips curves using disaggregate data include Hooper *et al.* (2020) and Fitzgerald *et al.* (2020).

[11] Residuals are assumed to be Normally distributed $\epsilon_{it} \sim N(0, \sigma^2_{ik})$, and the error variance is allowed to vary across sectors and across regimes separated by a break. Allowing volatility to time-vary may help identify time-variation in the slope of the Phillips correlation if it steepens during highly volatile periods due to volatile price determinants that reduce price stickiness as a larger fraction of sellers reset their prices (Hall 2023).

The hyperparameters of ζ_k, c and d, determine the *average* prior expected regime length, since regime lengths are allowed to differ and ζ_k is regime-specific. We set $d = 2$ and $c = 104$ so that our prior expected regime duration is one year (52 weeks).

B. Priors on regression parameters

In each regime, we specify that the residual variances have a standard inverse gamma prior distribution

$$p(\sigma_{ik}^2) \sim IG(a, b), \qquad i = 1, \ldots, N, \tag{5}$$

and that the regression coefficients have a conventional Gaussian prior

$$\begin{aligned} p(\lambda_k) &\sim N(0, \sigma_\lambda^2), \\ p(\rho_k) &\sim N(0, \sigma_\rho^2) \end{aligned} \tag{6}$$

where the degree to which λ_k and ρ_k are shrunk towards their prior means of zero is controlled by the hyperparameters σ_λ^2 and σ_ρ^2. These hyperparameters are set to a fairly uninformative value of 0.1, enabling the posterior estimates of λ_k and ρ_k to be determined by the data.[12] Note also that priors have a relatively small impact on the Phillips curve correlation estimate when pooling cross-sectional data as opposed to aggregate time series data are used (Jones *et al.* 2021).

C. Estimation

The model is estimated using a reversible jump Markov chain Monte Carlo algorithm (Green 1995; Smith *et al.* 2020) that comprises three steps. First, the regression coefficients are estimated using a Gibbs sampler. Second, the break dates are estimated using a random-walk Metropolis-Hastings algorithm. Third, the number of breaks is estimated using a reversible jump step that "jumps" across models with different numbers of breaks thereby approximating the posterior model probabilities.[13]

4.2. Full sample estimation eesults

The top panel of Figure 4 displays the posterior estimates of the number of breaks from the model displayed in Equation (2) using our full sample of data. More than ninety percent of

[12] We also set $a = 2$ and $b = 1$.

[13] For a full description of the estimation, see Smith and Timmermann (2021).

the posterior probability is assigned to two breaks occurring during the sample period, with the remaining posterior probability assigned to just one break. The lower panel shows that the posterior modes of the break dates are estimated to have occurred in mid-March 2020 and July 2021, respectively. Moreover, the break dates are estimated with considerable precision. This is in stark contrast to posterior break estimates from time series approaches (Pástor and Stambaugh 2001), and is the consequence of increased power derived from exploiting information in the cross-section.

The first three columns of Table 4 display the corresponding estimates of the Phillips correlation (PC) across the three regimes separated by these two breaks.[14]

First, we find that the Phillips correlation is flat at the beginning of our sample in line with earlier studies that have documented a flat Phillips curve in recent decades.[15] After the break in mid-March (the 10th week) 2020, however, the Phillips correlation steepened considerably to a value of about 0.2 and became highly significant.[16] After July 2021, we find that the slope became flat once again. In terms of the overall magnitude, the structural estimates are larger than the reduced-form estimates. It is worth emphasizing that we are the first to document the subsequent flattening, while other studies have documented a steepening of the Phillips correlation during the pandemic (Cerrato and Gitti 2022; Inoue *et al.* 2022).

Furthermore, we see that volatility has increased considerably from 5.39 to 7.96 across the October 2020 break, and then reverted back to the pre-pandemic level after July 2021. The pick-up in volatility reflects the post-pandemic inflationary surge that we observed as the economy re-opened from the pandemic-induced lockdowns, ending the decades of low and stable inflation that preceded the pandemic. This finding also supports Hall (2023)'s assertion that periods with higher volatility will likely align with steeper Phillips curves. However, the period of high volatility did not seem to last long, as the estimated volatility pretty much returned to the pre-pandemic level after mid 2021.

Note that the same model that precludes breaks estimates a relatively flat Phillips correlation throughout the sample (see final column of the Table 4) as it averages across the data

[14] Hazell *et al.* (2022) note that regional or sectoral Phillips curve estimates can be divided by the non-tradeables share to scale them to national/aggregate Phillips curve estimates.

[15] Greater trade openness and import penetration have been proposed as a potential explanation for the flattening of the Phillips curve observed over the decades before the pandemic (Auer *et al.* 2017; Gilchrist and Zakrajšek 2019; Stock and Watson 2020). However, services may be more sheltered from this impact relative to goods.

[16] The positive slope coefficient has the theoretically anticipated sign since greater retail sales reflects increased economic activity which would be expected to put upward pressure on inflation.

in all regimes. By detecting the breakpoints and estimating the model in each regime, our approach is able to reveal the steepening and subsequent flattening, which is entirely new in the literature.

Finally, we explore a potential determinant of the identified regimes.[17] Figure A1 presents the time series of the Covid Stringency Index, Supply Chain Pressure Index, and PPP loans to households and businesses. The first break aligns closely with the spike in the Covid Stringency Index, while the second break corresponds to its continued decline and the reduction in PPP loans. Notably, the level of stringency observed after the second break differs significantly from that before it, despite similar levels of fiscal stimulus.[18] This contrast highlights that the breaks align more closely with changes in Covid stringency, supporting the interpretation that the second regime represents the lockdown period.

4.3. Reliability of Real-time Assessment

It is crucial to note that the breakpoint detection is significantly reliable in real time, which proves its usefulness for practice. This section provides further in-depth discussions about this aspect, with particular attention to the real-time detection of breaks and real-time updating of parameters.

4.3.1. Real-time Detection of Breaks

The full sample results presented thus far illustrate how important it is to account for breaks when attempting to estimate the slope of the Phillips correlation. The steepening and subsequent flattening in the Phillips correlation is striking, demonstrating the need for economic agents such as monetary policy makers to be able to detect breaks in the Phillips correlation in real time with little delay. The unprecedented events spurred by the pandemic and the rapidly evolving macroeconomic environment highlighted this need. If breaks can only be detected with long delays, the ability for policy makers to act upon that information in real time is mitigated. The opposite problem is that of detecting "spurious breaks", that

[17] A statistically rigorous analysis is beyond the scope of this paper, as it would require more observations and additional regimes to provide sufficient inference power.

[18] Fiscal stimulus likely understates the effects of expansionary policy, suggesting that monetary policy effects could be stronger after the second break. However, the empirical results show the opposite, implying that fiscal stimulus is less likely to be the key determinant of the regimes.

is, detecting a break that is shown not to have occurred once more data become available. Such "spurious breaks" could be costly, depending on the loss function of the policy maker.

To this end, Figure 5 plots the sequence of break dates recursively estimated from our baseline panel break model. The vertical red line denotes the initial estimation period (26 weeks) and the 45 degree line (to the right of the vertical line) denotes the date at which a break could first be identified. The black circles mark the estimated break dates. The horizontal distance between the 45 degree line and the first black circle captures the delay with which that break is identified. The two breaks are detected within just a few weeks. In addition, there are no "spurious breaks" which would be represented by black circles occurring at random times. In fact, the break dates remain constant throughout the sample – as indicated by the sequence of horizontal black bands – and only change when a new break is detected.

Our model first detected a break with a delay ranging between four and five weeks across the two breaks. This is in stark contrast to traditional Phillips correlation break detection results that often struggle to detect breaks even when using the full historical sample period. This rapid break detection suggests that our approach can be used for real time decision making.

The ability of our model to rapidly detect breaks is driven by its use of (i) cross-sectional information which yields more power than using a single time series and (ii) high-frequency data.[19]

4.3.2. Real-time Updating of Parameters

The top panel of Figure 6 displays the real-time evolution in the posterior model probability assigned to our baseline model with either no breaks (dashed black line) and one break (solid black line). The plot therefore reflects how a monetary policy maker could have used Bayes' rule in real time to update her belief that the pandemic had caused a break in the Phillips correlation. The vertical red line denotes the week in which the posterior mode switches from no breaks to one break. We see that, during the month of April, the model rapidly learns about the occurrence of a break and so by the beginning of May shifts the posterior

[19] Cavallo and Zavaleta (2023) use daily inflation data combined with the single time series breakpoint approach of Bai and Perron (1998) to detect breaks within a few weeks. Our comparable speed in detecting breaks even though we use weekly data is obtained from exploiting information in the cross-section (Bai 2010).

mode to the one break model. By mid-May, almost all the posterior model probability is assigned to the one break model with the model being almost certain that a break has occurred. The bottom panel graphs the corresponding evolution of the slope coefficient. As the policy-maker learns of the occurrence of the break, they also learn the slope in the post-break regime (bottom panel). Again, the rapid real-time learning of the steepening of the slope is striking.

The rapid learning of the occurrence of a break and the corresponding steepening of the slope coefficient takes just a matter of weeks which is a key feature of the approach, delivering valuable information in real time that economic agents can use for decision making. Such rapid learning is difficult to achieve without the combination of our breakpoint methodology and high-frequency panel data.

5. The Pass-through of Monetary Policy Shocks During the Pandemic

This section examines the pass-through of monetary policy shocks into price and real sales in the weekly frequency. Our focus is changes in the pass-through across regimes identified from the panel break-point approach. The Phillips correlation is directly related to the effectiveness of monetary policy. In this way, the evolution of Phillips correlation is informative of nonlinearity in monetary policy effectiveness during the Covid era. Section 5.1 discusses the local projection model, and Section 5.2 the estimation result. Section 5.3 discusses the disaggregate results. Finally, Section 5.4 discusses the weekly Phillips multiplier.

5.1. Model

We employ a state-dependent local projection with the states pre-determined based on the reduced-form panel break-point detection approach. Consider the following local projection model:

$$y^j_{t+h} = \beta^j_{1,h}(1 - s_{t-1})z_t + \beta^j_{2,h}s_{t-1}z_t + \Gamma_j \mathbf{x}_{t-1} + e^j_{t+h} \quad \text{for} \quad h = 0, 1, ...H.$$

The dependent variable y^j_{t+h} is the cumulative weekly changes of variable j for $j = [\pi, RS]$ from t through $t+h$. We use 52-week percent changes in variable j divided by 52 for a proxy

of seasonally adjusted weekly changes in the variable j.[20] The externally identified shock is denoted by z_t, and we use the estimates based on the high-frequency identification from Bu *et al.* (2021).

Notation s_t is the regime indicator. We consider two regimes based on the identified break points: the lockdown regime and the non-lockdown regime. The lock-down regime is between mid March (the 11th week) and mid 2021 (the 78th week), and the non-lockdown regime is the period of time outside the lockdown regime. The indicator s_t takes a value 1 when the economy is in the lockdown regime, or 0 otherwise. As is standard in the literature (e.g., Auerbach and Gorodnichenko 2012), we interact z_t with s_{t-1} to prevent potential feedback effects from regime switches.[21] The coefficient $\beta^j_{1,h}$ captures the responses of variable j to a monetary policy shock in the lockdown regime (regime 1), and $\beta^j_{1,h}$ in the non-lockdown regime (regime 2).

The vector $\mathbf{x}_{t-1}$ includes the lags of macroeconomic variables and the monetary policy shock. We include the macroeconomic controls in a comprehensive manner. Specifically, we consider weekly indicators of price changes, real-sales changes, global supply chain pressure, two-year treasury yield, the term premium of a 10-year zero coupon bond, and the 10-year breakeven inflation rate.[22] The global supply chain pressure index, produced monthly by the Federal Reserve Bank of New York, is transformed into a weekly measure by assigning the same value for all weeks within a given month and computing lagged 4-week moving averages. We include the term premium as a proxy for the excess bond premium, following the rationale that Herbst and Johannsen (2020) argue its importance in analyses of monetary policy shocks. Due to the lack of weekly data for the excess bond premium, we use the term premium as a proxy. We further include a weekly indicator of inflation expectation to comprehensively control the inflationary environment not directly related to actual changes in prices and real sales in our experiment.[23] We consider total 12 lags for the macro controls

[20] In the appendix, we also consider employing seasonally adjusted week-over-week changes in prices and real sales for robustness checks, since weekly seasonal adjustment is still an ongoing research area. We use the method by Ginker (2023).

[21] The potential feedback effect is likely negligible given the high frequency; however, we follow the well-established prior approach to mitigate any potential feedback within a short horizon. Furthermore, the identified regimes are highly discrete, making endogenous gradual feedback of policy shocks on regime changes unlikely.

[22] The term premium is retrieved from `https://fred.stlouisfed.org/series/THREEFYTP10`, and the breakeven rate is retrieved from `https://fred.stlouisfed.org/series/T10YIE`. As an alternative weekly indicator of inflation expectation, one may consider the indirect consumer inflation expectation, but the indicator is only available from mid-2021.

[23] Diegel and Nautz (2021) claim that monetary policy can re-anchor inflation expectations based on a Bayesian structural VAR.

and one lag for the monetary policy shock estimate in $\mathbf{x}_{t-1}$.

For robustness checks, we further consider the weekly economic indicator from Federal Reserve Bank of New York, the Covid stringency index of US, and the fiscal stimulus effects from the Paycheck Protection Program (PPP, henceforth) loans.[24] We consider the weekly index of economic indicator to consider the aggregate economic activity, the stringency index to explicitly control the severity of Covid virus spread and social distancing, and the PPP loans provided to households and businesses to distinguish the effect from fiscal stimulus.

As a pre-identified monetary policy shock, we use the estimates from Bu *et al.* (2021) (BRW shock, henceforth). The BRW shock has an important advantage over other shock estimates for the analysis on monetary policy effectiveness particularly during the Covid pandemic. The policy rates and short-term yields reach the zero lower bound during the pandemic, which makes the estimation of monetary policy shocks from high-frequency changes of short-term asset prices less reliable. The BRW shock is relatively free from this issue, because high-frequency changes in the entire yield curve are used to infer monetary policy shocks, not just those of short-term assets (Brennan *et al.* 2024). We estimate effects of a one-standard deviation innovation of the BRW's monetary policy shock.[25] For robustness checks, we consider other popularly cited monetary policy shocks such as Jarocinski and Karadi (2020) and Kuttner (2001).

Last, we report heteroskedasticity and autocorrelation consistent (HAC) standard errors.

5.2. Estimation Results

We first examine the average effects of monetary policy shocks during the pandemic without considering the nonlinearity characterized by the two regimes.[26] Figure 8 presents the cumulative responses of prices and real sales to a one-standard-deviation monetary policy

[24]The stringency index data can be accessed at https://ourworldindata.org/metrics-explained-covid19-stringency-index, while the amount of PPP loans provided to households and firms are available at https://www.bea.gov/federal-recovery-programs-and-bea-statistics/covid-19-recovery. The PPP effect on personal income is reported monthly; we convert this series into a weekly format by interpolation and assigning the same values to all weeks within a given month. The estimation result remains robust to the inclusion of these variables (Figure A2).

[25]During our sample period, the standard deviation of BRW shock is 0.024. Alternatively, one can rescale the impulse responses with the impact effect of the BRW shock on two-year Treasury yield, so that the impulse responses have an interpretation like "effects of a 25bp increase in policy rate." Since the association between the externally identified shock and two-year Treasury yield is not always stable, which is likely so during the pandemic, we do not pursue this approach.

[26]We compute the average effects by setting $s_{t-1} = 0$ in Equation (5.1).

shock for total (Panel A) and brick-and-mortar stores (Panel B). For both categories, a contractionary monetary policy shock has statistically significant but small effects on real sales and statistically insignificant effects on prices. A one-standard-deviation shock reduces real sales of both total and brick-and-mortar stores by about 0.1 percentage point. The responses of brick-and-mortar stores become statistically insignificant approximately eight weeks after the impact, while those of total sales remain statistically significant for up to 20 weeks. In summary, during the pandemic, monetary policy has negligible effects on weekly price changes, while its effect is statistically significant for changes in total quantity sold, though somewhat limited for changes in real sales of brick-and-mortar stores.

Next, we examine nonlinearity in impulse responses. Figure 9 reports the cumulative changes in prices and real sales during the lockdown regime and the non-lockdown regime. We see stark differences in the effects of monetary policy between the two regimes. During the lockdown regime, a contractionary monetary policy shock lowers prices and real sales for both total (Panel A) and brick-and-mortar stores (Panel C). A one-standard deviation shock lowers prices by a quarter percentage point and real sales about three-quarter percentage point through 20th week after the impact and the effects are overall statistically significant. While the price effects become statistically significant 7-8 weeks after the impact for total, they are statistically significant from the impact for brick-and-mortar stores. For both total and brick-and-mortar stores, the responses of real sales are statistically significant from the impact, with the magnitudes a bit larger in brick-and-mortar stores than in total. Outside the lockdown regime, the effects of monetary policy are not statistically significant for both categories.[27]

The apparent nonlinearity in the pass-through suggests that the small but negative average effects of monetary policy (Figure 8) are largely driven by the lockdown period (Figure 9). We analyze the aggregate implications of a 25 basis-point monetary policy shock using the estimated impulse responses for the total category during the lockdown regime. Given that the data cover 1/5 of real GDP and 1/4 of personal consumption expenditure, and a

[27]One might argue that the total category should exhibit a faster and larger pass-through of monetary policy, given that price adjustments are typically more flexible in online stores compared to brick-and-mortar stores. However, this hypothesis cannot be fully explored as prices and real sales data for e-commerce are not separately available for our analyses. Moreover, prices and real sales in e-commerce are likely more volatile, contributing to the overall volatility of the total category. Therefore, the pass-through of monetary policy may not necessarily be stronger in total sales than in brick-and-mortar stores. Additionally, the rapid growth of e-commerce likely influences changes in prices and real sales more after the reopening period than during the lockdown. Nevertheless, our analysis indicates that the total category does not show a notably larger or more statistically significant pass-through of monetary policy compared to the brick-and-mortar category.

one-standard deviation BRW shock is 6 basis points (approximately 1/4 of the 25 basis-point shock), the aggregate real GDP or consumption responses are likely comparable to those in Figure 9. This implies that the 1.5 percentage-point drop in the federal funds rate at the pandemic's onset likely raised price inflation by one percentage point and real sales by three percentage points.[28] Considering that year-over-year CPI inflation fell by two percentage points between February and April 2020 and real GDP declined by seven percentage points in 2020:Q2, the expansionary policy effectively supported the recovery of prices and real economic activity during the pandemic recession.

This observation has important policy implications. The Fed's expansionary monetary policy implemented in March 2020 likely prevented further declines in prices and real sales, aiding the economy in swiftly recovering from the abrupt halt caused by the Covid shock. Importantly, the larger and faster pass-through of monetary policy to brick-and-mortar stores indicates that the policy was particularly effective in preventing further deceleration of the sectors that were harder hit by the pandemic-induced lockdown and social distancing.

This result is consistent with the spike in real M2 at the onset of the pandemic (Figure 7). Fed's expansionary monetary policy as well as the fiscal stimulus contributed to an unprecedented rise in M2. It is important to note that the estimation result is robust to the inclusion of the measure of fiscal stimulus through the PPP loans provided to households and businesses.[29] This result, combined with the larger pass-through to the brick-and-mortar stores, suggests that the expansionary monetary policy is likely to have helped mitigating the credit crunch faced by retail businesses. One might argue that the policy effects may have propagated more through households not businesses. However, if this was the case, we would have seen the larger pass-through in the total category that includes the e-commerce sector than in the brick-and-store stores.[30]

The swift pass-through of monetary policy shocks to weekly prices and real sales indicates that *even a large monetary policy shock traveled fast* during the pandemic, providing timely help to the sectors in need. Despite these policy actions, the closure of retail stores in 2020 still reached a record high, attributed to sustained social distancing and increased

[28] These estimates are subject to considerable uncertainty.

[29] See Figure A3 in the appendix for more details. The results are robust even with seasonally adjusted week-over-week changes in prices and real sales.

[30] Considering that households become more likely to rely on e-commerce than brick-and-mortar stores, the pass-through of monetary policy to e-commerce through households may be captured with detailed high-frequency household data.

online shopping.[31] After the lockdown period, however, the pass-through of monetary policy weakens, suggesting that monetary policy has become less effective in stabilizing inflation during the subsequent period of recovery and reopening.[32] This result implies that monetary policy is not an ultimate fix to high inflation seen during the Covid era.[33]

Our finding is robust to the choice of monetary policy shocks. As discussed by Brennan *et al.* (2024), there has been no single best estimate of monetary policy shocks, and economists have endeavored to refine the shock estimates (e.g., Jarocinski and Karadi 2020; Bauer and Swanson 2022). To check the robustness of our empirical results, we estimate our model with alternative estimates of monetary policy shock. We consider the estimates from Kuttner (2001) and Jarocinski and Karadi (2020).[34] Our key finding—nonlinearity in the pass-through and larger and faster price and quantity responses during the lockdown regime—is robust to the choice of monetary policy shock (Figures A5 and A7).[35]

5.3. Disaggregate responses

We further examine the pass-through of monetary policy to disaggregate prices and real sales. The statistically significant pass-through during the lockdown regime is broad-based, with particularly strong and rapid effects observed in the apparel, beauty, and footwear sectors. These three sectors constitute about one third of total real sales in our dataset. Figure 10

[31] See, https://fortune.com/2021/01/07/record-store-closings-bankruptcy-2020/.

[32] Our unique finding for the pandemic contrasts the previous findings on asymmetric effects of monetary policy where a contractionary policy has larger effects than an expansionary policy (e.g.,Barnichon *et al.* 2017).

[33] Consistent with this implication, the real M2 stock stepped down with the implementation of contractionary monetary policy, but still remained significantly elevated relative to the level seen prior to the pandemic.

[34] Each shock estimate is reported in Figures A4 and A6. Note that we do not take stance on which shock estimate is more reliable than another.

[35] Some of well-cited previous studies based on monthly data also find statistically significant impact effects of monetary policy and speedy pass-through to prices and real activities. For example, Bauer and Swanson (2022) show that a 25 basis-point orthogonalized monetary policy shock significantly reduces industrial production and CPI from the impact during the sample period 1973:M2-2020:M2. Specifically, the shock lowers industrial production by over 1 percentage point and CPI by more than 0.5 percentage points throughout one year after the impact. These estimates are based on SVAR-IV, which should produce estimates similar to those of local projection. The responses become a bit muted if Chair's speeches are included in the orthogonalized shock, but the statistical significance in the impact effects and the subsequent responses are still robust. Bu *et al.* (2021) show that their monetary policy shock reduces CPI one month after the impact, and their shock estimate, excluding the information effect, also decreases industrial production one month after the impact for the sample period 2008:M1-2017:M12. The effects are statistically significant. In this context, our estimates of the weekly pass-through of monetary policy are not inconsistent with the previous findings in terms of magnitudes and speed in spite of differences in the data.

displays the selected impulse responses of these sectors for both the pandemic period (left column) and the lockdown regime (right column).

Our empirical results are consistent with anecdotes of a retail apocalypse during the Covid-19 pandemic. Owing to social distancing, bankruptcies among retail corporates and store closings spiked in 2020. Retail companies that filed for bankruptcy during the pandemic included large firms and department stores selling clothing, footwear, beauty products, and more.[36] These anecdotes suggest that brick-and-mortar stores and certain retail sectors were severely affected by the Covid-19 shock and faced significant credit crunch. Our results indicate that the expansionary policy implemented during the lockdown regime effectively prevented further deceleration in prices and real sales in sectors that were hardest hit during the pandemic.

5.4. Implications for the structural Phillips curve

Conceptually, the Phillips correlation is the slope of aggregate supply curve. The slope can be recovered with an aggregate demand shock that shifts the aggregate demand curve along the aggregate supply curve. Distinguishing the slope of aggregate supply curve from the reduced-form Phillips correlation, we call the former the structural Phillips correlation. Since monetary policy shock is unarguably an aggregate demand shock, we can estimate the structural Phillips correlation with the estimated impulse responses. For this, we take the ratio of the cumulative responses of prices and those of real sales at each horizon after the shock's impact. We call the ratio at each weekly horizon the *weekly Phillips multiplier*. This multiplier is conceptually similar to the Phillips multiplier from Barnichon and Mesters (2021).

Table 5 presents the estimates of the dynamic structural Phillips multiplier for the lockdown period and the entire sample period, disaggregated by store type. Notably, during the lockdown period, the weekly Phillips multiplier is steeper for brick-and-mortar stores compared to the total category (Columns (c) and (e)). Both the total and brick-and-mortar categories exhibit statistically significant Phillips multipliers from the initial impact up to 20 weeks ahead. This steepening of the structural Phillips curve for brick-and-mortar stores emerges as the key driver of the overall steepening of the structural Phillips curve. Similarly,

[36]These firms include J. Crew, Century 21, Neiman Marcus, Lord & Taylor, Stage Stores, Stein Mart, JCPenney, Tuesday Morning, and Pier 1 Imports (see, for example, https://www.businessinsider.com/stores-closing-in-2021-list-2021-3).

the average Phillips multiplier for the total category is smaller than that for brick-and-mortar stores (Columns (b) and (d)). While the multiplier for the total category remains statistically significant across all horizons of shock propagation, the multiplier for brick-and-mortar stores loses statistical significance about a month after the shock's impact. These average results are primarily driven by the real sales responses to the monetary policy shock, which are statistically significant overall for the total category but become insignificant for brick-and-mortar stores after a month.[37]

Overall, these estimates highlight the apparent steepening of the structural Phillips curve among brick-and-mortar stores during the lockdown period as a critical feature of the nonlinearity in the Phillips multiplier. This result suggests the trade-off between price and quantity becomes larger, and hence the economy was in an environment where the transmission of expansionary monetary policy can effectively raise both prices and real sales.

6. Conclusion and Implications for Policy

In the COVID era, policy makers have faced uncertainty about whether the dynamics of inflation— including its persistence and the Phillips curve—has changed and how effective monetary policy has been in stabilizing inflation. Relatedly, in the past few years, there were divergent views regarding whether the surge in inflation is largely transitory or reflects a step-up in inflation trend. Even more uncertain and challenging was to evaluate the speed and magnitude of monetary policy pass-through. Almost five years into the COVID era, we still do not have a good understanding of whether the expansionary monetary policy in the early phase of the pandemic and the subsequent monetary tightening have been effective in stabilizing the dramatic swing in inflation.

Given the fast-evolving nature of the COVID economy, a large part of the uncertainty arises from difficulties in understanding the high-frequency dynamics of inflation and the transmission of monetary policy in real time. In this context, our work brings innovations to the realm of inflation forecasting and monetary policy in two aspects. First, our analysis is based on the weekly data of prices and retail sales that are available in real time during the Covid-19 pandemic. The weekly data have information about disaggregate sectors and store types, comprehensively capturing heterogeneous effects of Covid shocks on inflation dynamics

[37]This finding may indicate that e-commerce real sales exhibited statistically significant responses to monetary policy shocks, particularly during the COVID-19 era.

and improving the precision of real-time estimates. Second, our econometric methodologies—the Bayesian breakpoint model of the Phillips curve and the structural VAR model—provide reliable real-time signals about the changing inflation trend and uncertainty, as well as the pass-through of monetary policy by suitably distilling information from the weekly data. In this way, our approach is likely to prove useful for the monetary authority and inflation forecasters in times of frequent shifts of aggregate dynamics.

We find that the Phillips curve steepened from mid-March 2020 to July 2021, followed by a flattening thereafter. As variation in inflation trends and uncertainty are key drivers of nonlinear inflation dynamics, real-time detection of shifts in the Phillips curve offers timely insights into changing inflation dynamics. The steepening coincides with the lockdown period, while the flattening aligns with reopening, though the model imposes no a priori restrictions linking these changes to social distancing. Notably, our paper is the first to document the subsequent flattening of the Phillips curve following its steepening.

Interpreting the periods of changing Phillips curves as different regimes of inflation dynamics, we examine nonlinearity in the weekly pass-through of monetary policy. We find that the pass-through of monetary policy to prices and real sales was fast and statistically significant during the period of lockdown, effectively preventing a deflationary spiral. This swift and significant pass-through was mainly driven by brick-and-mortar stores, suggesting that monetary policy likely helped to mitigate credit crunches that retailers were experiencing because of social distancing. From the second half of 2021, however, the pass-through likely became weaker, suggesting monetary tightening may have been less effective in subsequently stabilizing elevated inflation. This result implies that monetary policy is not the ultimate fix of high inflation seen during the Covid era. Nevertheless, these implications are, of course, subject to the caveat that another break in our model could occur. In such a case, our method would likely detect the change quickly given its reliable real-time properties.

Using the estimated weekly impulse response, we recover the weekly Phillips multiplier, which represents the slope of the structural Phillips curve at a weekly frequency. The multiplier is steeper for brick-and-mortar stores and during the lockdown period than for the total category or outside the lockdown. This indicates a significant trade-off between prices and quantities, suggesting that expansionary monetary policy was effective in alleviating economic distress. During the lockdown, the Fed's actions likely prevented a deflationary spiral. However, the subsequent flattening of the structural slope implies that monetary tightening was less effective in addressing the inflationary surge from mid-2021 onward, highlighting the need for coordination with fiscal policy to achieve sustainably stable inflation.

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Table 1: Release delays

Statistic	Release delays (days)	
	CPI	Retail sales
Mean	11.66	15.55
St. dev.	1.44	1.02
Min	10	14
Max	14	18

Note: This table reports summary statistics – mean, standard deviation, minimum, and maximum – for the delay (measured in days) of each CPI and retail sales release from the beginning of 2020.

Table 2: Nowcasting Retail sales and Inflation

	(1)	(2)	(3)
Retail sales			
ΔRS_{T-1}	0.73^{***}		0.31
ΔNPD_T		0.59^{***}	0.46^{***}
R^2	0.53	0.62	0.64
$Adj.R^2$	0.52	0.61	0.61
CPI			
ΔCPI_{T-1}	0.97^{***}		0.92^{***}
ΔNPD_T		0.46^{***}	0.12^{***}
R^2	0.94	0.36	0.96
$Adj.R^2$	0.94	0.34	0.96

Note: The top panel of this table reports results from nowcasting OLS regressions of the 12-month change in core retail sales each month from the start of 2020 using either the lagged change in core retail sales (column 1) or the contemporaneous NPD data (column 2). Specifically, we use the monthly average of the 52-week change in the NPD retail sales data across all weeks in the corresponding month (column 2). We also combine this variable with the lagged dependent variable in another specification (column 3). The lower panel presents corresponding results for core goods CPI inflation in which the NPD predictor here is the 52-week change in the NPD price data across all weeks in the corresponding month. *, **, and ** denote statistical significance at the 10, 5, and 1 percent levels using Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors.

Table 3: Statistical significance from pairwise forecasts comparisons

	CPI	RS
R^2	0.38^{*}	0.20^{*}

Note: This table evaluates the statistical significance of the improved out-of-sample predictive power of our model that incorporates the high frequency measure of either inflation or retail sales from NPD relative to the benchmark AR(1) model. We report the (i) out-of-sample R^2 measured using the point forecasts generated from our model relative to those from the benchmark. Significance is evaluated using the Clark-West (CW) test for point forecasts. Significance at the 5 and 10 percent levels are denoted by $**$ and $*$. All results assume a six month initial estimation period.

Table 4: Breaks in the Phillips Curve

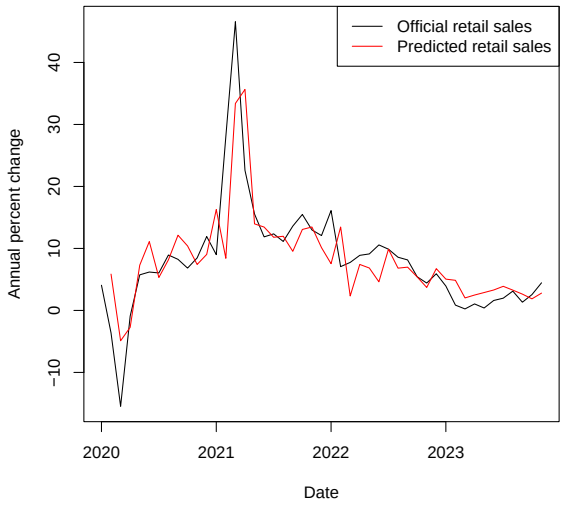
	Jan 2020 - Oct 2020	Oct 2020 - Jul 2021	Jul 2021 - Dec 2023	Jan 2020 - Dec 2023
PC	0.04	0.17***	0.01	0.07**
vol.	5.39	7.96	5.54	6.22
skew.	0.35	1.65	0.19	0.82

Note: The first three columns of this table display estimates from our baseline panel break model displayed in Equation (2) using the full sample of data from NPD. The table reports, in each regime, the estimated Phillips curve slope (PC) and the consumption expenditure-weighted volatility (vol.). Skewness is also reported in each regime. The final column reports results for the full sample by estimating the same model but precluding breaks. *, **, and ** denote statistical significance at the 10, 5, and 1 percent levels using Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors.

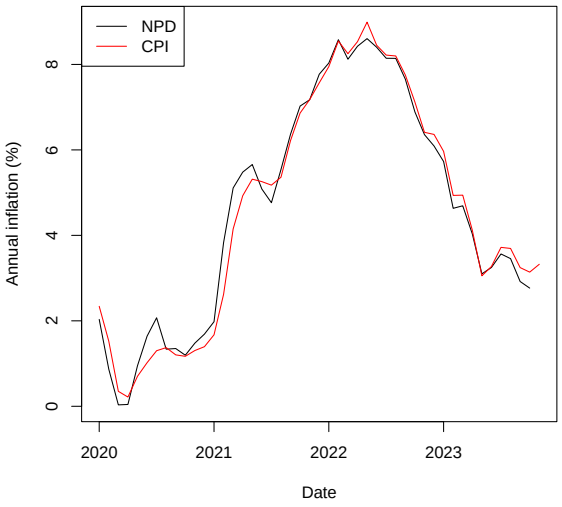
Table 5: Weekly Phillips Multiplier by Store Type

	Total		**Brick-and-Mortar**	
Horizon	**Average**	**Lockdown**	**Average**	**Lockdown**
h=0	0.17**	0.30**	0.37**	0.53**
	[0.06,0.29]	[0.19,0.40]	[0.31,0.43]	[0.52,0.54]
h=4	0.09	0.19**	0.32**	0.50**
	[-0.04,0.23]	[0.19,0.20]	[0.19,0.45]	[0.48,0.49]
h=8	0.15**	0.53**	0.30	0.53**
	[0.02,0.29]	[0.42,0.64]	[0.00,0.61]	[0.42,0.64]
h=16	0.23**	0.26**	0.11	0.69**
	[0.08,0.39]	[0.17,0.35]	[-1.01,0.61]	[0.56,0.83]
h=20	0.21**	0.25**	-0.4	0.69**
	[0.04,0.25]	[0.15,0.38]	[-1.42,0.34]	[0.57,0.80]

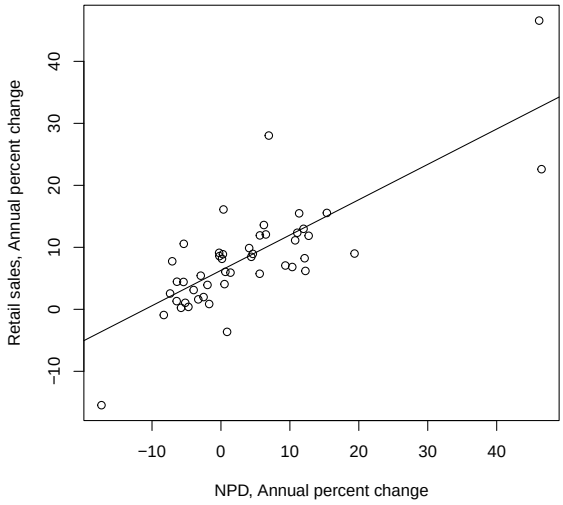
Note: The first column indicates the number of weeks following a monetary policy shock. The second and third columns present the Phillips multiplier for the total category during the sample average and the lockdown period, respectively. Similarly, the fourth and fifth columns report the Phillips multiplier for Brick-and-Mortar stores under the same conditions. ** denotes statistical significance at the 5 percent level, calculated using heteroskedasticity and autocorrelation robust standard errors following Newey and West (1987).



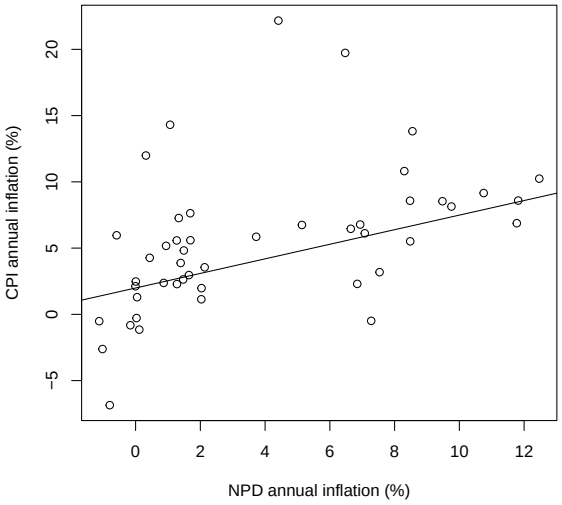
(a) Fitted vs. actual (Retail sales)



(b) Fitted vs. actual (CPI)

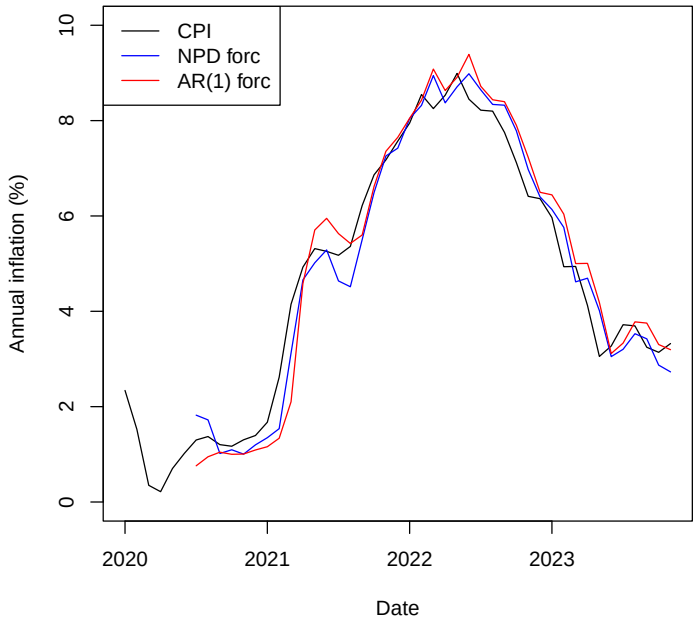


(c) Regression fit (Retail sales)

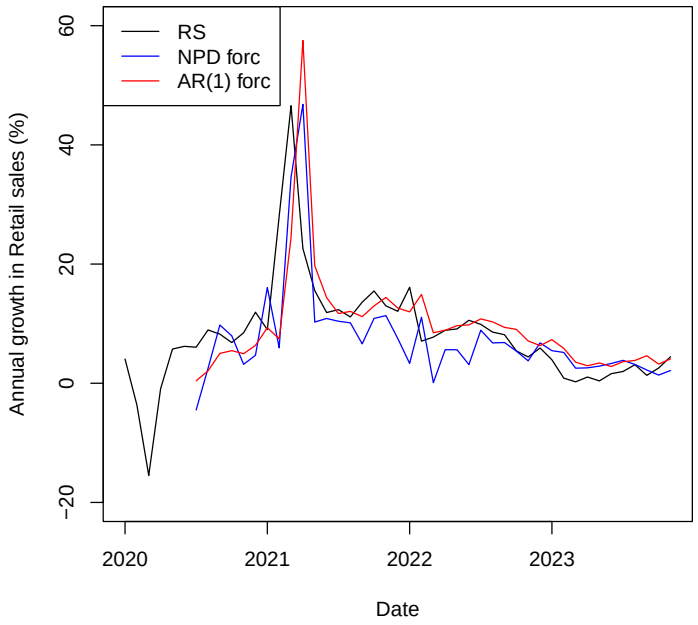


(d) Regression fit (CPI)

Figure 1: The top-left panel of this figure displays the fitted values (red line) from a linear regression of the 12-month change in retail sales for each month from the start of 2020 on the corresponding annualized percent change change in each month of the aggregate NPD bricks and mortar plus e-commerce dollar sales data and a lagged dependent variable against the realized 12-month change in monthly retail sales data (black line). The lower-left panel displays a scatter plot of the two series with the regression fitted line. The top-right panel of this figure displays the fitted values (black line) from a linear regression of the 12-month change in core goods CPI inflation for each month from the start of 2020 on the corresponding annualized percent change change in each month of the aggregate NPD bricks and mortar plus e-commerce price data and a lagged dependent variable against the realized 12-month change in monthly core goods CPI inflation data (red line). The lower-right panel displays a scatter plot of the two series with the regression fitted line.

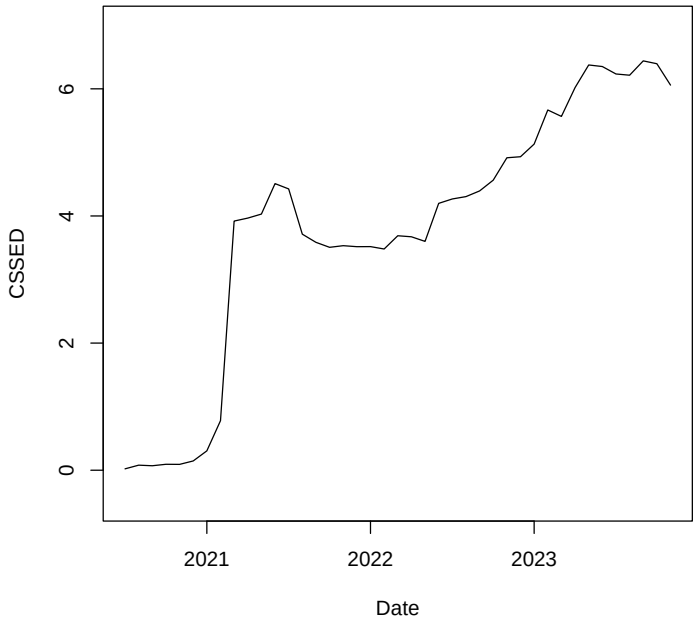


(a) CPI inflation

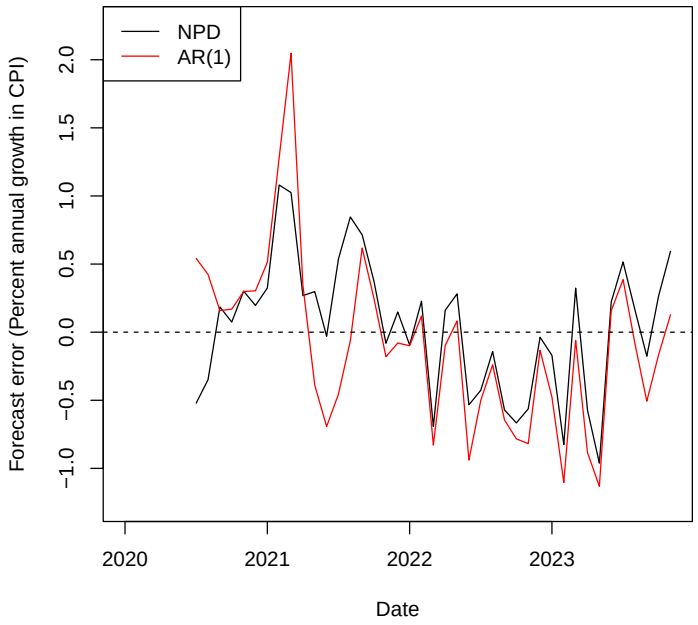


(b) Retail Sales

Figure 2: The top panel of this figure displays the 12-month change in CPI from January 2020 (black line) against the corresponding out-of-sample predictions generated from the AR(1) model (red line) estimated using OLS, and the same model that includes the NPD inflation measure as a predictor (blue line). The lower panel shows the same information for the annual growth rate in retail sales, in which the blue line uses the high frequency measure of retail sales rather than inflation.

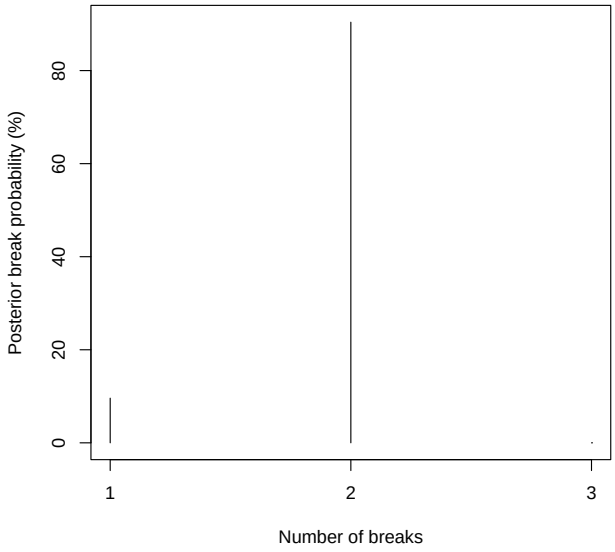


(a) CSSED (CPI)

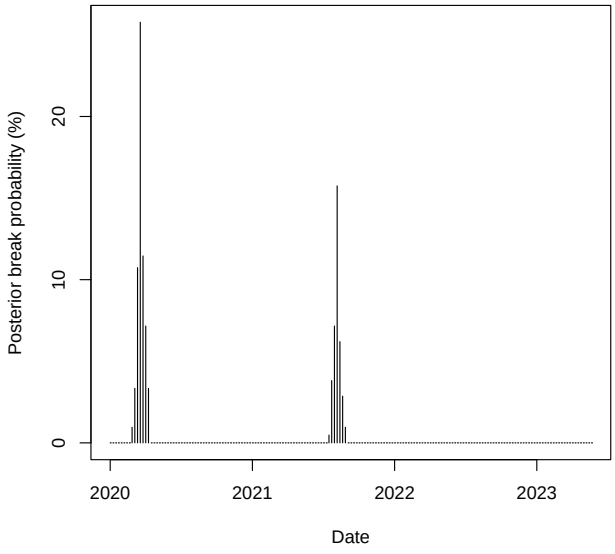


(b) Forecast errors (CPI)

Figure 3: The top panel of this figure graphs the CSSED measure computed over the out-of-sample period constructed from the forecast errors of the AR(1) model relative to the same model that includes the high frequency inflation data from NPD when forecasting the 12-month change in CPI inflation at the monthly frequency. The bottom panel displays the corresponding forecast errors from the AR(1) model (red line) and the same model that includes the NPD inflation measure as a predictor (black line).



(a) Posterior number of breaks



(b) Posterior timing of breaks

Figure 4: The top (bottom) panel of this figure displays the posterior estimates of the number (timing) of breaks from our baseline model displayed in Equation (2) when using the full sample of data from NPD.

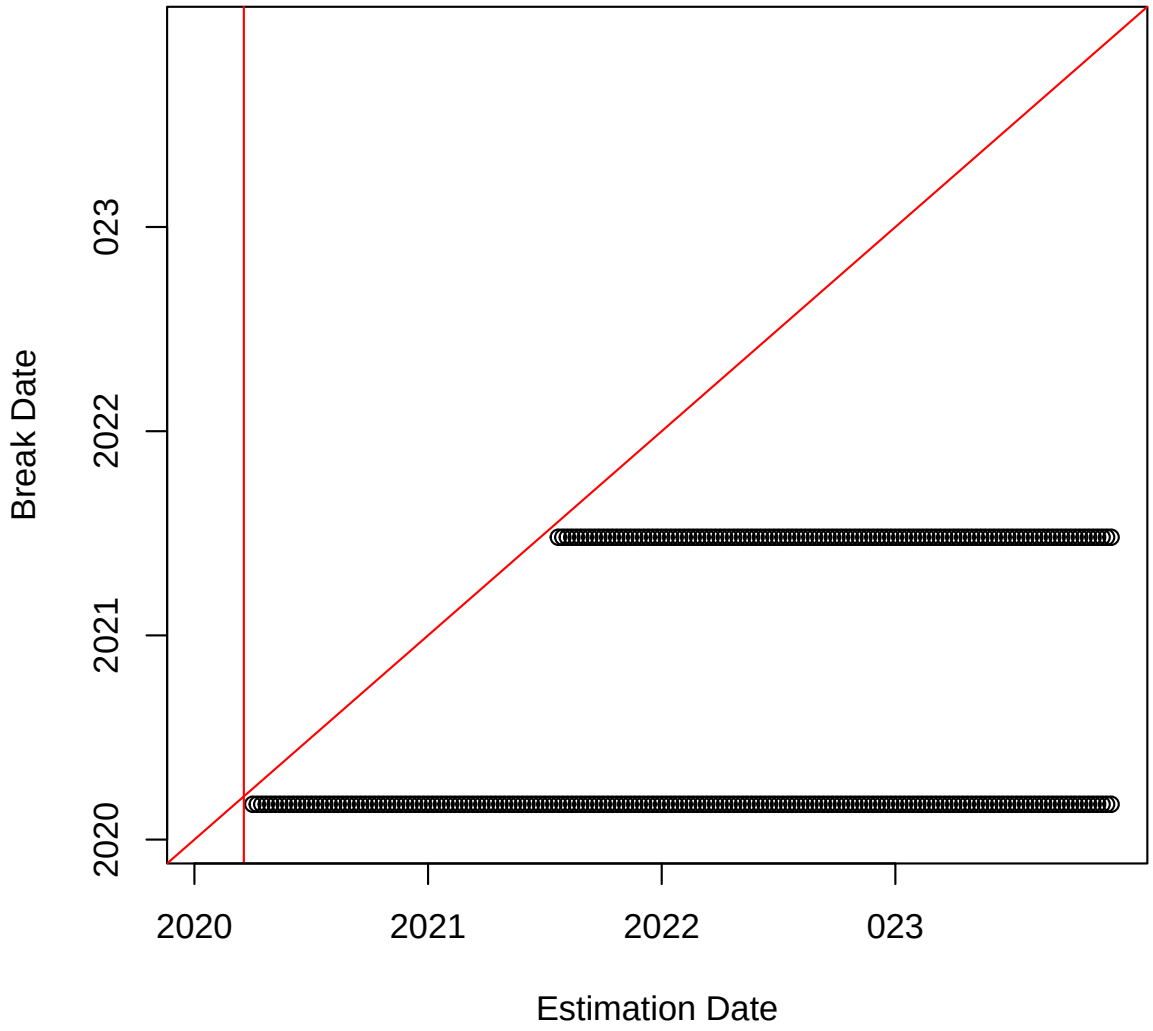
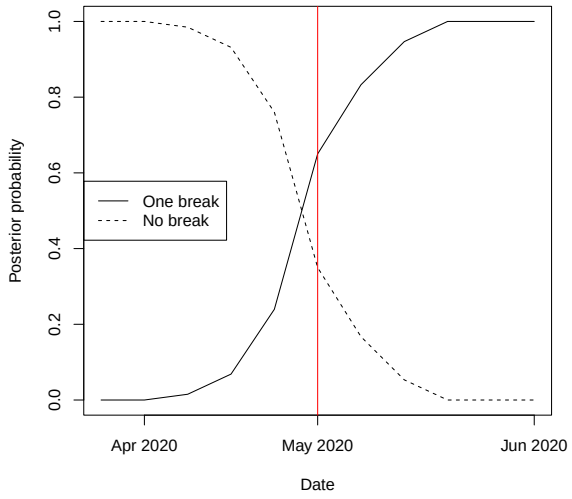
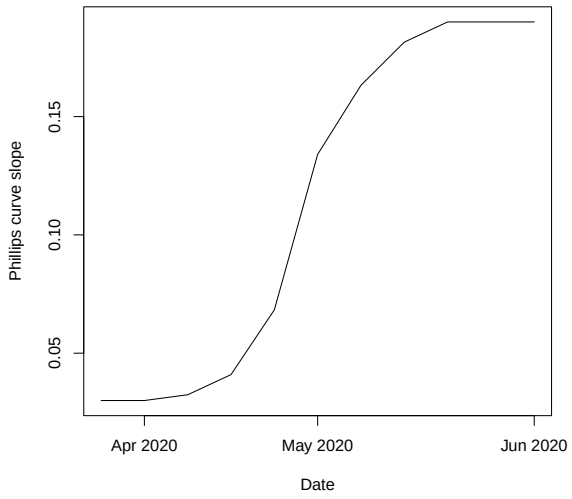


Figure 5: This figure displays the real-time break detection from estimating our panel break model displayed in Equation (2) recursively using only the NPD high frequency data that were available at the time. The vertical red line denotes the initial estimation period (26 weeks) and the 45 degree line (to the right of the vertical line) denotes the date at which a break could first be identified. The black circles mark the estimated break dates. The years on the x and y axes mark the first week of each year.



(a) Real time evolution of pandemic break probability



(b) Real time evolution of Phillips correlation

Figure 6: The top panel of this figure displays the real-time evolution in the posterior probability of our baseline model with $K = 0$ (dashed black line) and $K = 1$ breaks (solid black line), respectively, estimated recursively from our baseline model displayed in Equation (2) using only the information that was available at the time of the estimation. The plot therefore reflects how a monetary policy maker could have used Bayes' rule in real time to update her belief that the pandemic had caused a break in the Phillips curve. The vertical red line denotes the week in which the posterior mode switches from no breaks to one break. The bottom panel graphs the corresponding real-time evolution of the Phillips correlation slope coefficient. The x-axis month labels in both figures correspond to the first week of that month.

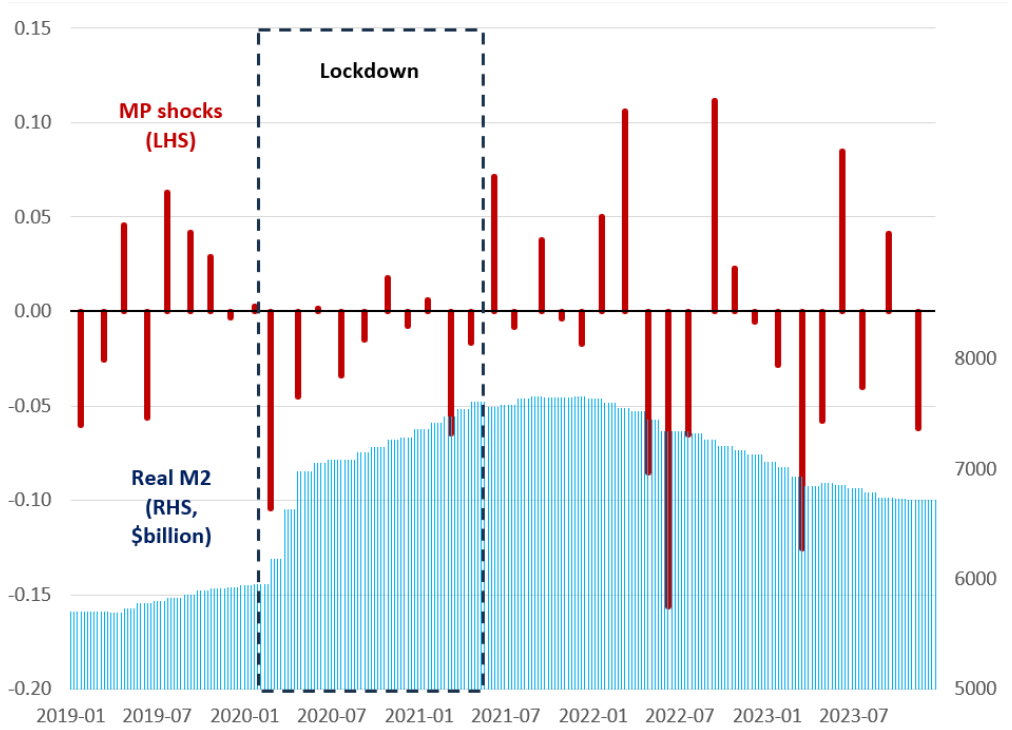


Figure 7: **Monetary policy shocks of Bu *et al.* (2021) and Real M2** This figure reports the estimates of monetary policy shocks from Bu *et al.* (2021) and the stock of real M2. Refer to the left axis for the monetary policy shock and the right axis for the real M2 (units in billion dollars). The X-axis is calendar date in weeks.

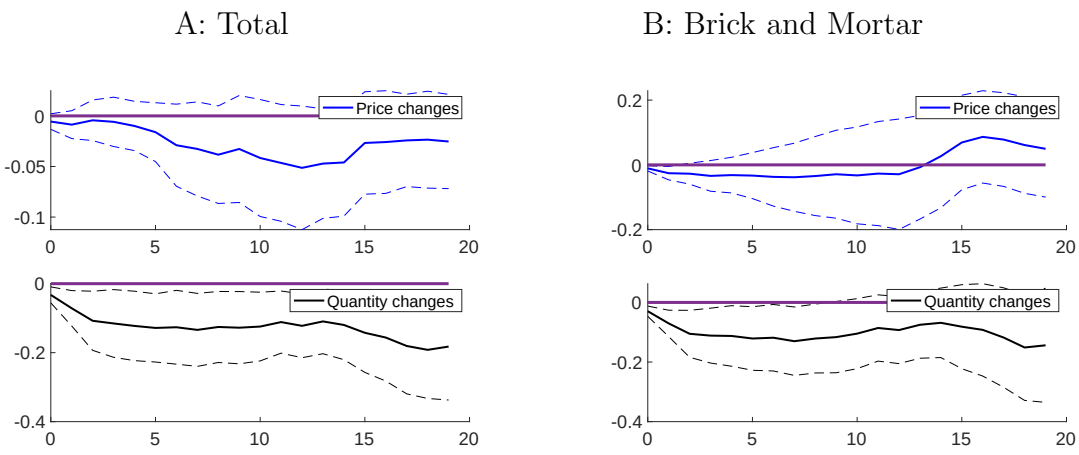


Figure 8: **Cumulative changes in prices and quantities to monetary policy shocks** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Bu *et al.* (2021) for the entire sample period. Panel A displays the responses of total category. Panel B displays the responses of Brick-and-Mortar category. The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.

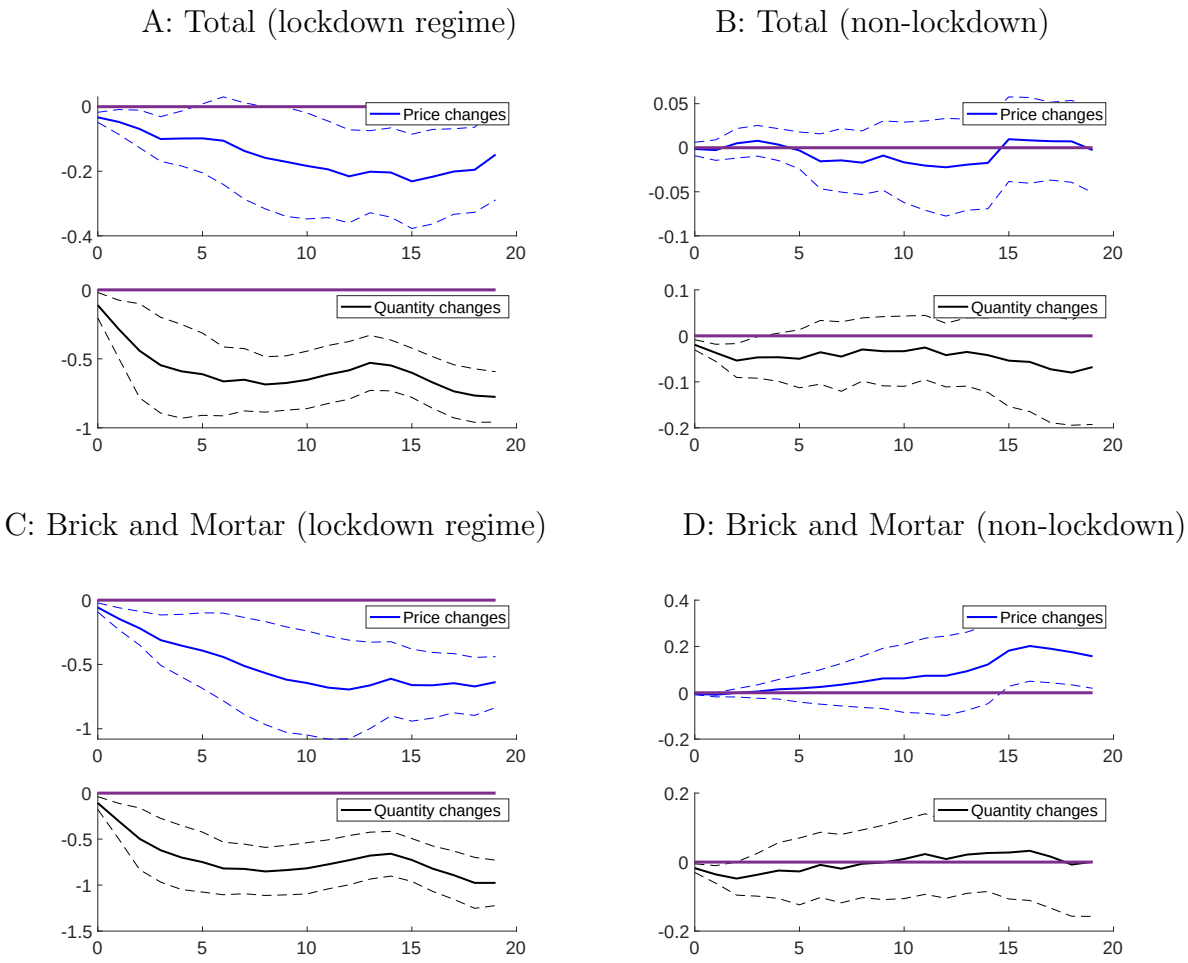


Figure 9: **Cumulative changes in prices and quantities to monetary policy shocks with an alternative lockdown regime** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Bu *et al.* (2021) for the two regimes. The lockdown regime spans 11th week – 78th week in the sample. The non-lockdown regime is the sample period outside the lockdown regime. Panel A displays the responses of total category in the lockdown regime. Panel B displays the responses of total category in the non-lockdown regime. Panel C displays the responses of Brick-and-Mortar category in the lockdown regime. Panel D displays the responses of Brick-and-Mortar category in the non-lockdown regime. The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.

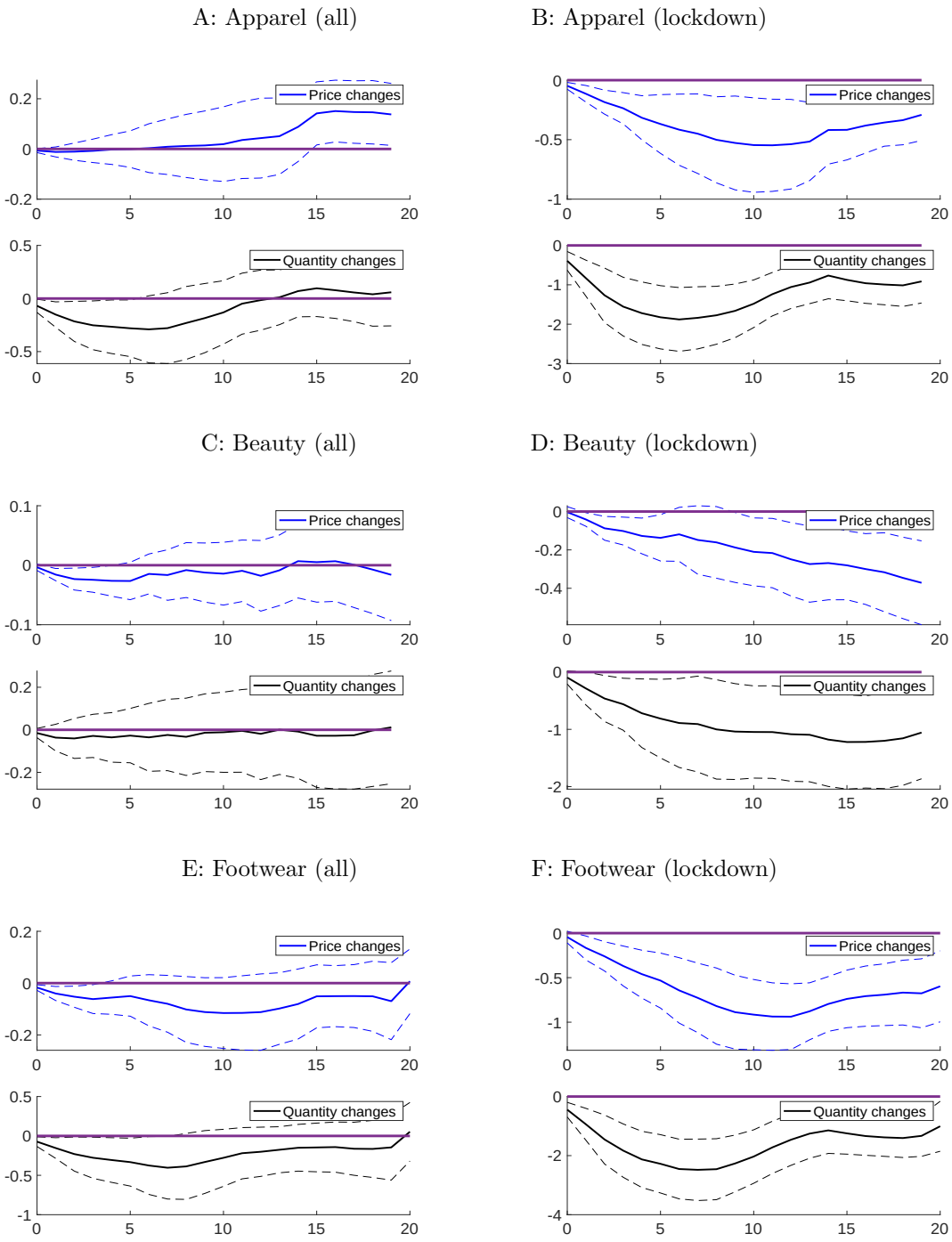


Figure 10: **Cumulative changes in disaggregate prices and quantities to monetary policy shocks: Apparel, beauty, and footwear**

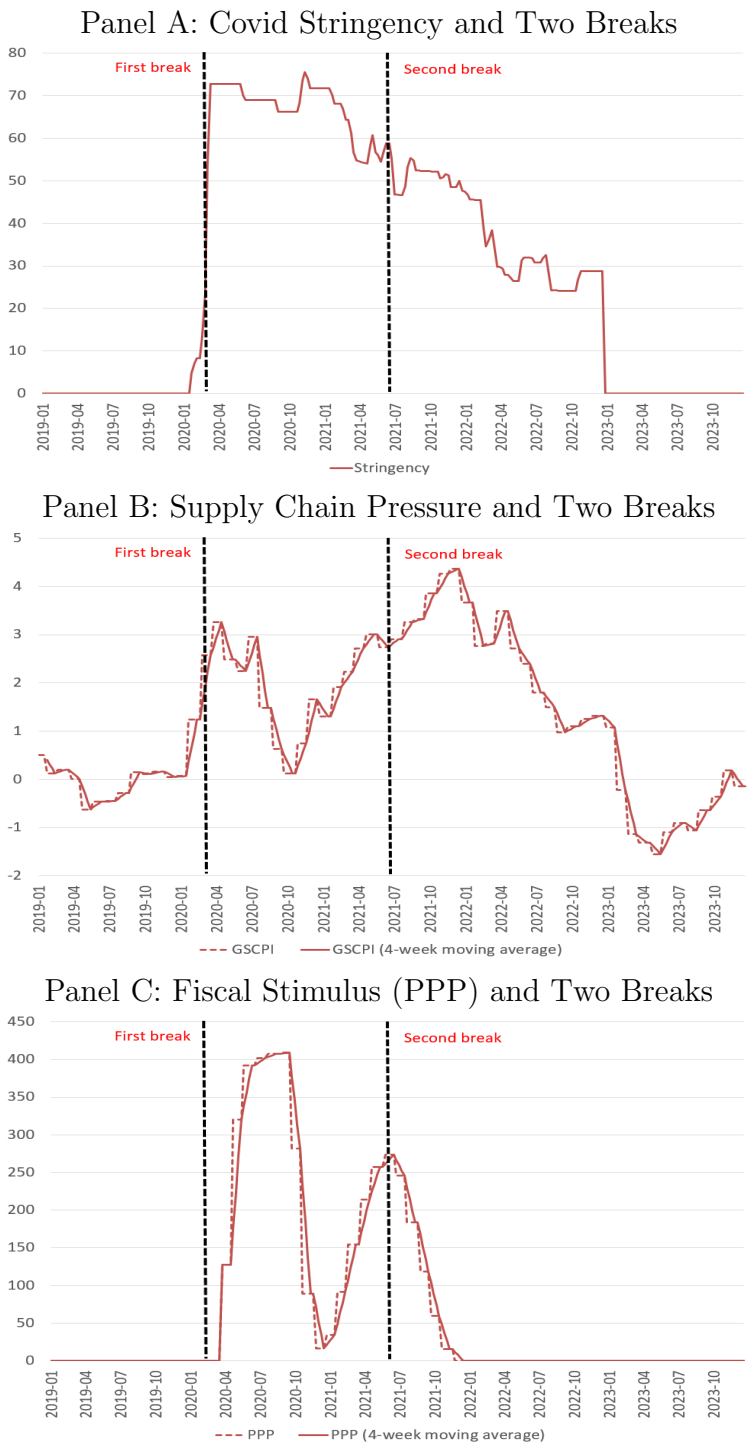


Figure A1: **Determinants of Two Break Points (2019:w1-2023:w52)** Panel A displays the U.S. Covid Stringency index and the two breaks (bold vertical dashed lines). The stringency index is from https://ourworldindata.org/metrics-explained-covid19-stringency-index. Panel B displays the Global Supply Chain Pressure Index (GSCPI) and the two breaks. The solid line is the lagged 4-week moving average and the dotted line is the raw monthly estimate available on https://www.newyorkfed.org/research/policy/gscpi#/overview. Panel C displays the amount of PPP loans provided to households and firms and the two breaks. The solid line is the lagged 4-week moving average and the dotted line is the raw monthly estimate available on https://www.bea.gov/federal-recovery-programs-and-bea-statistics/covid-19-recovery.

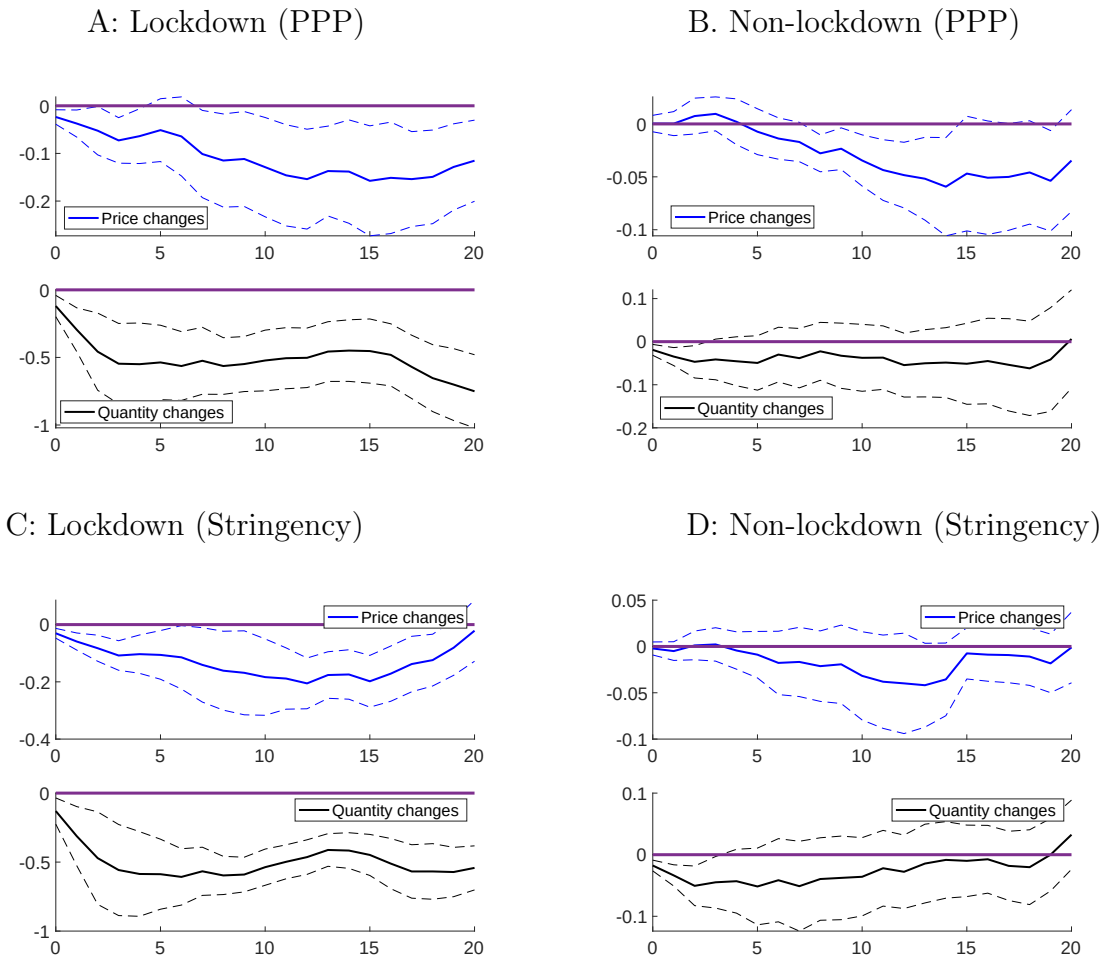


Figure A2: **Cumulative changes in prices and quantities to monetary policy shocks with the PPP loans and the stringency considered (2019-2023)** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Bu *et al.* (2021) for 2019-2023, estimated additionally with the fiscal stimulus through the PPP loans provided to households and businesses (Panels A and B) and the Covid stringency index (Panels C and D). For the result displayed in Panels A and B, the monthly estimate that is not interpolated into a weekly series is used. Using the interpolated series does not change the result materially. The lockdown period is from mid-March to mid 2021. The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.



Figure A3: **Cumulative changes in prices and quantities to monetary policy shocks with seasonally adjusted data (2019-2023)** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Bu *et al.* (2021) for 2019-2023, estimated with seasonally adjusted data. The responses are smoothed with 4-weak moving averages. The lockdown period is from mid-March to mid 2021. In addition to the baseline controls, the stringency index, the interpolated income effect of PPP loans, and a dummy for November and December (capturing the holiday seasons). The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.

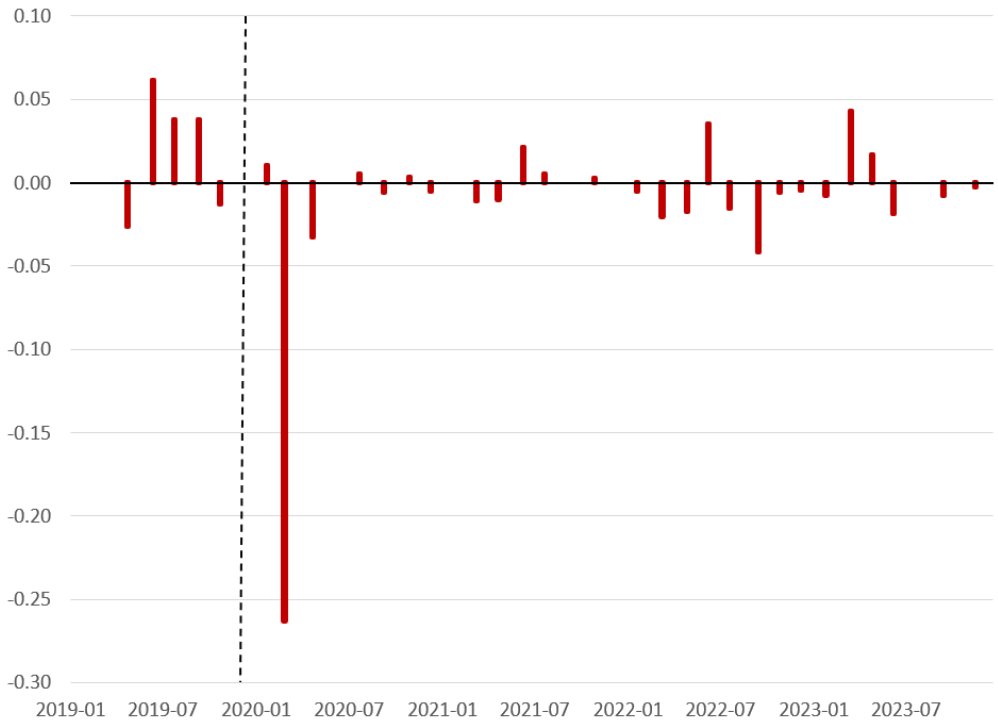


Figure A4: **Monetary policy shocks of Kuttner (2001)** This figure reports the estimates of monetary policy shocks from Kuttner (2001). The X-axis is calendar date in weeks.

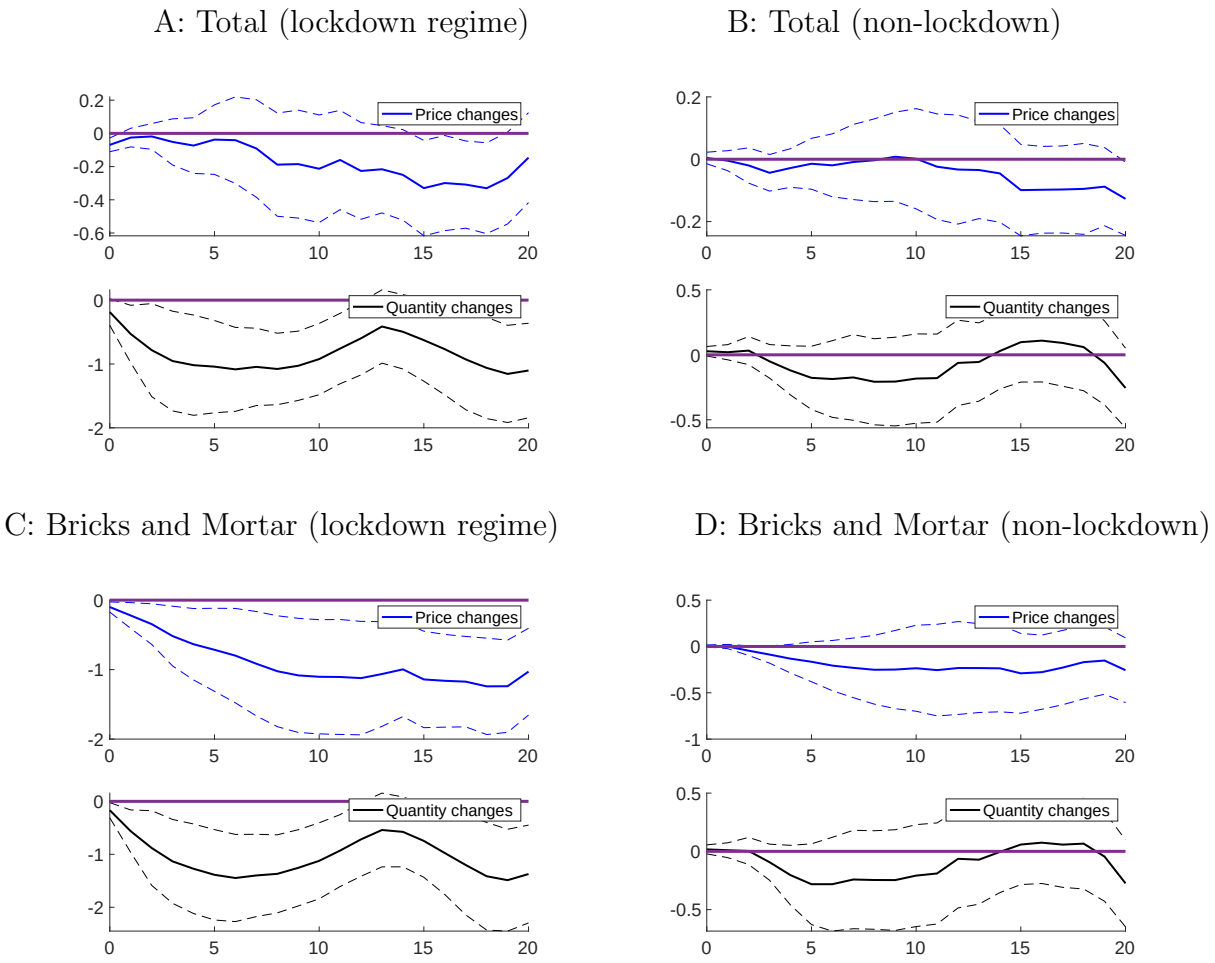


Figure A5: **Cumulative changes in prices and quantities to monetary policy shocks from Kuttner (2001)** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Kuttner (2001) for the two regimes. The lockdown regime spans 11th week – 78th week in the sample. The non-lockdown regime is the sample period outside the lockdown regime. Panel A displays the responses of total category in the lockdown regime. Panel B displays the responses of total category in the non-lockdown regime. Panel C displays the responses of Brick-and-Mortar category in the lockdown regime. Panel D displays the responses of Brick-and-Mortar category in the non-lockdown regime. The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.

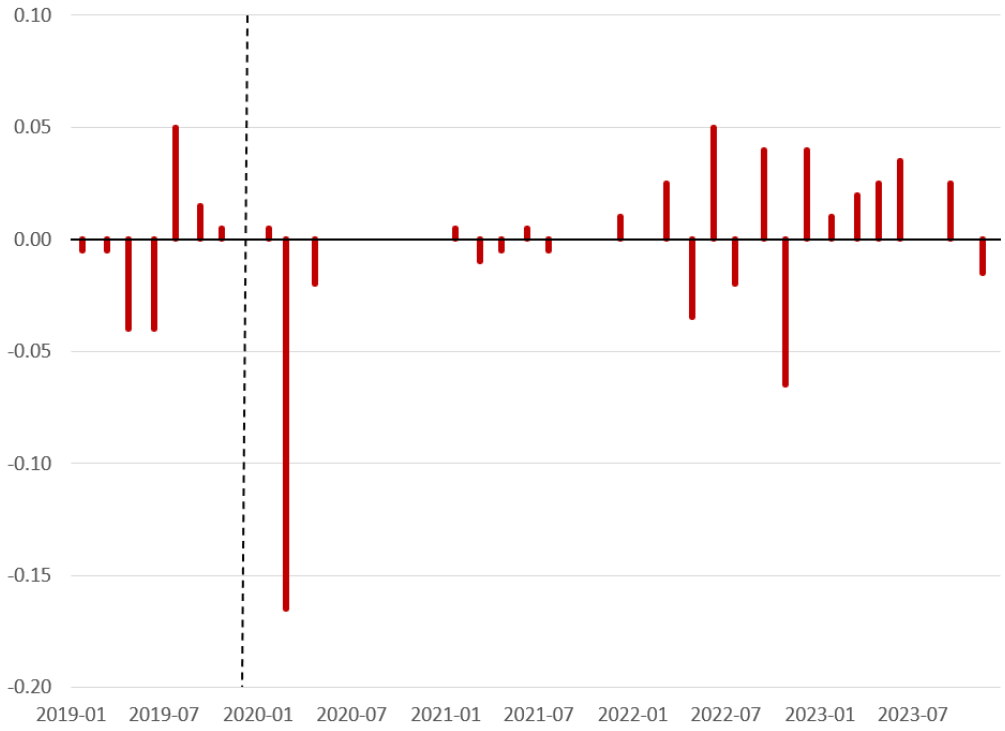


Figure A6: **Monetary policy shocks of Jarocinski and Karadi (2020)** This figure reports the estimates of monetary policy shocks from Jarocinski and Karadi (2020). The X-axis is calendar date in weeks.

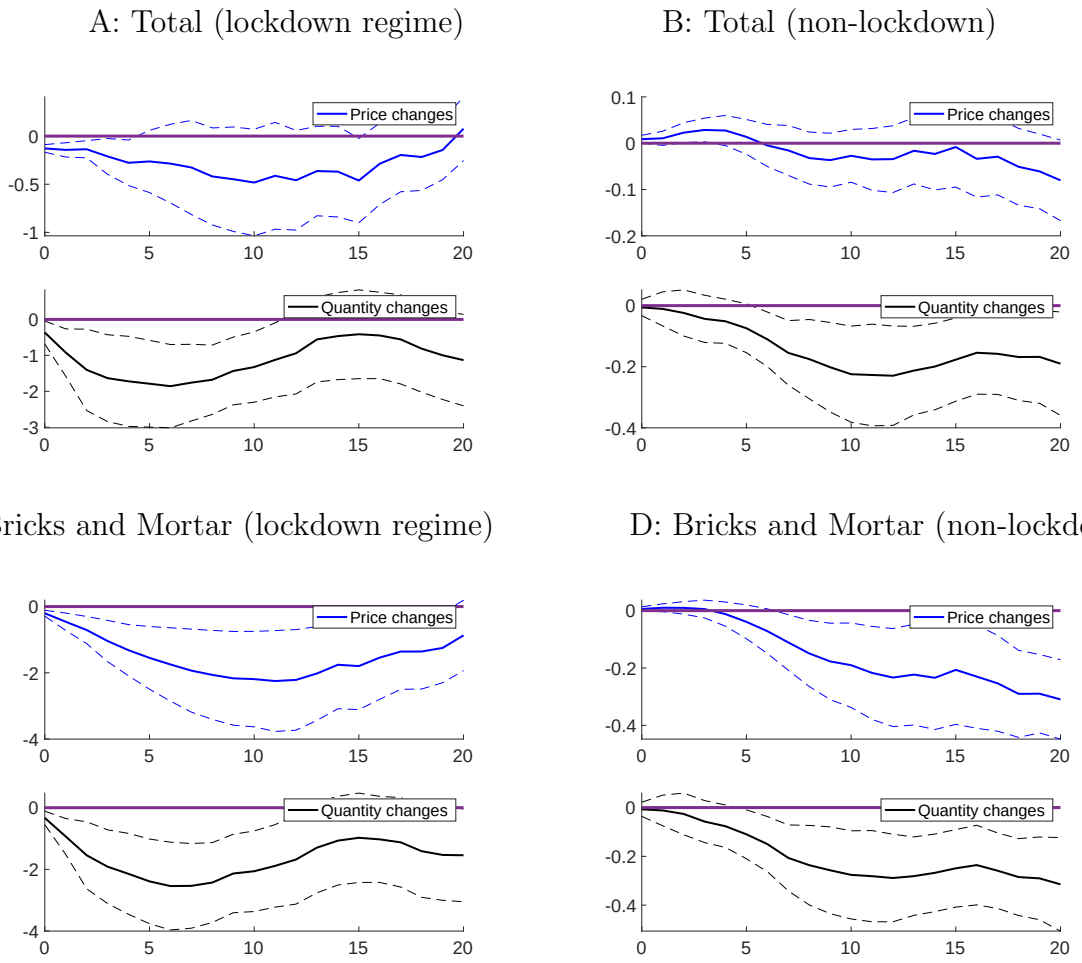


Figure A7: **Cumulative changes in prices and quantities to monetary policy shocks from Jarocinski and Karadi (2020)** The figures report the responses of prices and real sales to a one-standard deviation monetary policy shock from Jarocinski and Karadi (2020) for the two regimes. The lockdown regime spans 11th week – 78th week in the sample. The non-lockdown regime is the sample period outside the lockdown regime. Panel A displays the responses of total category in the lockdown regime. Panel B displays the responses of total category in the non-lockdown regime. Panel C displays the responses of Brick-and-Mortar category in the lockdown regime. Panel D displays the responses of Brick-and-Mortar category in the non-lockdown regime. The dashed lines denote 90% confidence intervals based upon HAR standard errors. The unit for the Y-axis is the percentage point, and that for the X-axis is weeks after the shock impact.