Inflation Since COVID: Demand or Supply

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Abstract

We estimate the slope of the Phillips curve before, during, and after COVID. To do so, we exploit panel variation in inflation and unemployment dynamics across US metropolitan statistical areas (MSAs), using a shift-share instrument to isolate demand-driven fluctuations in local unemployment rates. We specify a two-region New-Keynesian model to derive the slope of the aggregate Phillips curve from our MSA-level estimates. We find that the slope of the Phillips curve dropped to zero during the pandemic and more than tripled, relative to the pre-COVID era, from March 2021 onward, reaching its highest level since the mid-1970s. These estimates allow us to quantify the extent to which US post-pandemic inflation is propelled by demand factors. Demand-driven economic recovery explains around 1.4 out of the 5.6 percentage-point increase in all-items inflation observed from March 2021 to September 2022. Had the slope of the Phillips curve not steepened after COVID, the demand contribution to the rise in inflation would have been small and statistically insignificant.

Keywords: inflation, COVID, Phillips curve, demand, supply

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1 Introduction

In June 2022, the 12-month US inflation rate hit a 40-year high at 9% after averaging 2.2% between 2000 and 2020. At the same time, the US labor market reached exceptionally high levels of tightness (Crump et al. 2022; Michaillat and Saez 2022; Blanchard et al. 2022), while global markets suffered from remarkable spikes in commodity prices and supply chain disruptions. The Federal Open Market Committee statement of November 2, 2022, affirmed that "inflation remains elevated, reflecting supply and demand imbalances related to the pandemic, higher food and energy prices, and broader price pressures."

The debate among economists and policymakers has therefore focused on the distinct roles played by demand and supply factors in raising inflation (Di Giovanni 2022; Shapiro 2022a; Ball et al. 2022). Quantifying the extent to which demand-driven economic recovery is responsible for the increase in inflation is important for monetary policy. If demand factors drive inflation, a tighter monetary policy is required to cool down the economy, inducing firms to lower prices. If supply shocks force firms to raise prices, the monetary authority faces a trade-off between stabilizing inflation or output.

Macroeconomic models typically derive a structural relationship between inflation and the unemployment rate, commonly known as the Phillips curve (Phillips, 1958). This relationship formalizes the pattern in which workers ask for higher wages and firms increase prices during demand-driven booms. According to the New-Keynesian formulation of the Phillips curve, inflation is driven by shifts in expectations, supply-side shocks, and demand-side factors. The effect of demand-side factors on inflation is captured by the slope of the Phillips curve. Estimating the slope of the Phillips curve during and after the pandemic is challenging, as severe demand and supply shocks occurred contemporaneously and within an extremely narrow time frame, limiting statistical power.[1]

In this paper, we estimate the slope of the Phillips curve before, during, and after the COVID-19 pandemic. To do so, we combine the use of panel variation in inflation and unemployment at the US metropolitan area level with an instrumental variable approach. Panel data provide us with a larger sample size for parameter estimation than the time series (Mavroeidis et al., 2014). Our empirical strategy is based on a two-region New-Keynesian model of a monetary union that clarifies the threats to identification. Within the model, we derive the regional Phillips curve and relate it to its aggregate counterpart, showing that the slopes of the two coincide.

To our knowledge, this is the first paper providing quasi-experimental estimates of the causal effect of

[1] Ball et al. (2022) explicitly state that they "do not present results for the pandemic period alone, which would mean estimating seven parameters with ten quarters of data."

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demand factors on inflation during and after COVID. Our benchmark estimates imply a notable flattening of the Phillips curve during COVID and a more than threefold steepening relative to pre-COVID in the aftermath of the pandemic. Considering the estimates provided by the literature for periods prior to 1990,[2] we conclude that the US Phillips curve has recently been steeper than at any time since the late 1970s. Moreover, we find that the slope of the Phillips curve increased more distinctively in the early post-COVID phase and has recently experienced a reversion toward pre-pandemic levels. Finally, our results indicate that the flattening of the Phillips curve during COVID is driven by services, while the subsequent steepening is driven by goods.

We use our benchmark estimates to quantify the contribution of demand factors to the recent increase in inflation. We find that demand-driven economic recovery explains about one-fourth of the post-COVID increase in all-items inflation. Between March 2021 and September 2022, inflation increased by 5.6 percentage points, while the unemployment gap decreased by 1.7 percentage points.[3] Multiplying the change in the unemployment gap (i.e., 1.7%) by our estimate of the slope of the Phillips curve (i.e., 0.85), we obtain an estimate of the change in inflation imputable to demand factors (i.e., $1.7\% \times 0.85 = 1.4\%$). The remaining variation is attributable to shifts in long-run inflation expectations and supply-side shocks. Had the slope of the Phillips curve remained unchanged after COVID, the demand contribution to the rise in inflation would have been small and statistically insignificant.

To guide our empirical exercise, we rely on a New Keynesian general equilibrium model (Woodford 2003; Galí 2015) featuring two regions in a monetary union, along the lines of Beraja et al. (2019) and Hazell et al. (2022). Unlike them, we must account for the supply-side drivers of COVID and post-COVID inflation dynamics, such as the Great Resignation or semiconductor shortages. To do so, we allow for shifts in labor supply preferences and outline a vertically-linked production structure consisting of an international commodity market, a national perfectly competitive intermediate-input market, and local monopolistically competitive final-goods markets. Domestic firms operating in the intermediate-input sector use commodity and labor as factors of production, while final-goods firms employ intermediate input and labor to produce differentiated consumption goods. Conveniently, this structure matches the available MSA-level data on inflation, measured by the growth rate of all-items consumer price index (CPI).

In accordance with the resulting regional Phillips curve equation, local final-goods inflation is driven by

[2] See, for instance, Hazell et al. (2022).

[3] For our purposes, the unemployment gap is the difference between the unemployment rate and the efficient unemployment rate, as defined in Michaillat and Saez (2022).

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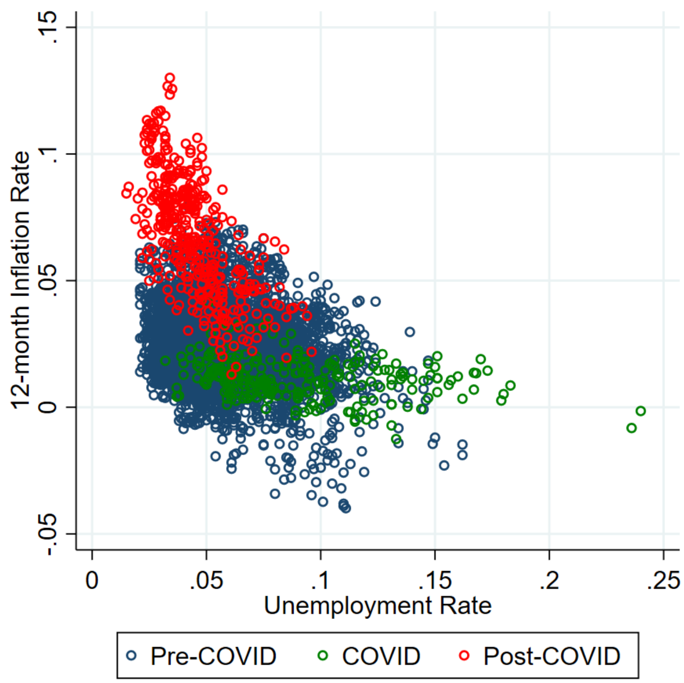
short-run inflation expectations, the local unemployment rate, and three distinct cost-push shock terms. The first denotes the incidence of commodity and intermediate-input price shocks on local inflation, capturing the impact of supply chain disruptions. The second represents local shocks to households' disutility of labor, which likely increased during the pandemic causing labor shortages. The third captures local productivity shocks in the final-goods sector, the supply shock typically featured in standard New-Keynesian models. Distinguishing among these three terms of the cost-push shock allows us to address identification concerns stemming from supply-side factors in our empirical estimation.

Figure 1: The Phillips Correlation Across US Cities



Notes. The scatter plot shows the relationship between the 12-month, all-items inflation rate and the unemployment rate for all observations in our sample. The blue dots denote observations belonging to the pre-COVID period (i.e., Jan 1990-Feb 2020), the green dots denote observations belonging to the COVID period (i.e., Mar 2020-Feb 2021), and the red dots denote observations belonging to the post-COVID period (i.e., Mar 2021-Sep 2022).

Figure 1 plots the relationship between 12-month inflation and unemployment rates for 21 MSAs before, during, and after COVID. Raw data clearly point to a flattening of the correlation during the pandemic and a steepening thereafter. However, the simple correlation shown in Figure 1 could be driven by aggregate and local confounders. At the national level, the Federal Reserve Bank acted promptly to support the economy as it was being hit by COVID and to fight inflation in subsequent periods. Endogenous policy responses bias the estimation of the slope of the Phillips curve when using time-series data, as Fitzgerald and Nicolini (2014) have stressed. In our setting, time fixed effects control for federal

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policy responses and long-run inflation expectations driven by the monetary policy regime in place, as in Hazell et al. (2022). At the local level, the pandemic may have triggered relevant structural changes, plausibly reflected in heterogeneous natural unemployment rate dynamics across metropolitan areas. The inclusion of MSA fixed effects – allowed to shift across the pre-COVID, COVID, and post-COVID periods – enables us to absorb them, as in McLeay and Tenreyro (2020).

Identification further requires us to distinguish changes in local final-goods inflation and labor market tightness driven by demand from those driven by cost-push shocks. To isolate demand-driven fluctuations in unemployment rates from local labor supply shocks, we construct a shift-share instrument proxying for MSA-level productivity shocks in the tradable intermediate-input sectors (Bartik, 1991). The intuition behind our instrument is that positive productivity shocks in the intermediate-input sector boost labor demand, raising employment and wages. Demand for final goods consequently increases, thereby driving up prices. This mechanism has a differential impact across cities based on the employment shares of their intermediate-input sectors. For instance, a national productivity shock in the manufacturing sector affects demand for consumption goods relatively more in manufacturing-intensive cities like Detroit.

However, positive productivity shocks in the intermediate-input sector also act as cost-saving shocks, decreasing the price at which intermediate inputs are traded nationally and causing final-goods firms to lower prices. Since local relative intermediate-input prices are observable, we address this concern by directly controlling for them in our empirical exercise. This variable also absorbs the impact of commodity price shocks on local inflation channeled through changes in relative intermediate-input prices. This term controls, for instance, for the impact of an increase in prices of internationally traded semiconductors on local inflation transmitted through a higher price of domestically produced cars.

Because of the pandemic, both intermediate-input and final-goods sectors experienced large labor demand fluctuations (Guerrieri et al., 2022). One may therefore worry that the shocks proxied by our instrument are correlated with local productivity shocks in the final-goods sector. To address this concern, we include in our main specification a shift-share control that has the same structure as our instrument and proxies for local productivity shocks in the final-goods sector. As a result, the conditional exogeneity of our instrument stems from national industry-level employment changes in the intermediate-input sectors (Borusyak et al., 2022), plausibly uncorrelated with industry-level aggregates of local labor supply shocks.

We address potential concerns about the validity of our results through several robustness checks. Most importantly, we show that the flattening of the Phillips curve during COVID and its subsequent

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steepening are not mainly driven by the food, energy, and shelter components of the CPI. In addition, we estimate the slope of the Phillips curve proxying labor market tightness by the vacancy-to-unemployment ratio, in light of recent literature recommending it as a more appropriate measure of economic slack than the unemployment rate.[4] Since MSA-level data on vacancies are not publicly available before 2020, we perform this analysis for the COVID and post-COVID periods only. We find a substantial increase in the slope of the Phillips curve after the pandemic irrespective of the proxy used for labor market tightness.

Our paper fills a relevant gap in the literature on post-COVID inflation dynamics. No other study has yet identified and estimated the slope of the Phillips curve during and after COVID. Using a real-time decomposition of personal consumption expenditure (PCE) inflation,[5] Shapiro (2022a) estimates that demand explains around one-third of the surge in inflation that occurred until April 2022, relative to the pre-pandemic average. Next, Di Giovanni (2022) uses a model-based approach[6] to quantify that around 60% of the increase in inflation from December 2019 to December 2021 is driven by aggregate demand shocks. Finally, Ball et al. (2022) decompose PCE headline inflation into core inflation and deviations of headline from core. After estimating the Phillips curve with pooled time-series data from 1985 to 2022, they conclude that labor market tightness explains about 2 out of the 6.9 percentage-point rise in inflation that occurred between December 2020 and September 2022.

The remainder of the article is structured as follows. Section 2 describes the model and the derivation of the regional and aggregate Phillips curves. Section 3 discusses data sources and presents summary statistics. Section 4 introduces the empirical strategy and Section 5 shows our main results. Section 6 presents the robustness checks. Section 7 concludes.

2 Vertical Supply Chains and the Phillips Curve

We propose a two-region New-Keynesian model of a monetary union with a common commodity market, an intermediate-input sector, and a final-goods sector in each region. The purpose of the model is to derive the regional Phillips curve in an economic environment featuring labor supply shocks as well as commodity and intermediate-input price shocks within vertical supply chains that are relevant to COVID and post-COVID inflation dynamics. We show that the slopes of the regional and aggregate Phillips curves

[4] See, for instance, Furman and Powell (2021) and Barnichon and Shapiro (2022).

[5] (Shapiro, 2022b) classifies PCE inflation rates by spending category as either demand- or supply-driven, based on the monthly correlation between unexpected movements in prices and quantities. Such surprises are computed as residuals from a reduced-form, one-month ahead forecasting model relying on strong identifying assumptions.

[6] Di Giovanni et al. (2022) and Baqaee and Farhi (2022) develop this approach formally.

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coincide. Our model also demonstrates that time fixed effects control for long-run inflation expectations.

2.1 Model Setup

The economy is made of two regions, Home (H) and Foreign (F), which share the same preferences, market structure, and firm behavior. Both regions are characterized by a continuum of population of size ζ and $(1-\zeta)$, respectively. Labor is immobile across regions and perfectly mobile across sectors within a region. A common monetary authority sets interest rates following a Taylor rule, featuring a long-run inflation target and a consistent unemployment rate target. In its simplest form, the model abstracts from fiscal policy. The representative household in each region consumes final goods, supplies labor, and invests in bonds. Financial markets are assumed to be complete and common across the two regions. Households have CES preferences over final-goods varieties and GHH preferences (Greenwood et al., 1988) over the final consumption good aggregator and labor. We capture labor supply shocks allowing households' disutility of labor to shift exogenously and denote the Frisch elasticity of labor supply by the parameter ϕ. Importantly, GHH preferences imply no income effects on labor supply.

The production side of the economy represents the novelty of our model. We feature three sectors vertically linked to capture the incidence of supply chain disruptions on inflation. We assume that commodities are traded on international markets and their inverse supply curve takes the form $P_t^o = c_t^o O_t$, where P_t^o denotes the commodity price, c_t^o denotes the marginal cost of production and is assumed to be exogenous, and O_t denotes the quantity of commodity produced. Firms operating in the intermediate-input sector use labor and commodities to produce a tradable homogeneous intermediate good, according to a constant return to scale (CRS) Cobb-Douglas production function characterized by region-specific technology. The intermediate input produced by local representative firms is traded on a perfectly competitive national market. Hence, its price is common across regions.

The final-goods sector in each region is characterized by a continuum of firms that use intermediate input and labor to produce non-tradable differentiated consumption goods. Production is carried out according to a CRS Cobb-Douglas technology with region-specific productivity shocks and satisfies local demand. Final-goods firms compete monopolistically, facing Calvo-style frictions in price setting (Calvo, 1983). They set their price equal to a constant markup over a weighted average of current and expected future marginal costs, as with some positive probability they will not be able to change their price in future periods. The price level in each region is an index over final-goods firms' prices. Appendix B presents a formal setup of the model, as well as all derivations.

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2.2 Regional and Aggregate Phillips Curves

An equilibrium in this economy is an allocation consistent with households' and firms' optimization, the interest rate rule, and market clearing conditions. Log-linearizing the model around a zero-inflation steady state and combining optimal final-goods pricing and households' labor supply conditions, we obtain the following expression for the regional Phillips curve in H:

$$\pi_{Ht} = \beta E_t \pi_{Ht+1} - \kappa \hat{u}_{Ht} + \underbrace{\lambda(1-\alpha)\hat{p}^x_{Ht} + \lambda\alpha\hat{\chi}_{Ht} - \lambda\hat{a}^y_{Ht}}_{\nu_{Ht}}, \tag{1}$$

where π_{Ht} is regional inflation, $E_t\pi_{Ht+1}$ captures regional short-run inflation expectations, $\kappa = \lambda\phi^{-1}\alpha$ denotes the slope of the regional Phillips curve, and the parameter $\lambda = \frac{(1-a\beta)(1-a)}{a}$ captures frictions in price setting. We define unemployment in H as $u_{Ht} = 1 - N_{Ht}$. Then, to a first order approximation, $\hat{u}_{Ht} = -\hat{n}_{Ht}$, and the same applies in F. The regional cost-push shock ν_{Ht} is decomposed into three terms. First, $\hat{p}^x_{Ht} = \left(\frac{\hat{P^x_t}}{P_{Ht}}\right)$ denotes the percentage deviation of the regional relative price of intermediate input (i.e., the ratio between the national intermediate-input price, P^x_t, and the regional price level, P_{Ht}) from its steady-state value. Next, $\hat{\chi}_{Ht}$ represents local shocks to households' disutility of labor, while $\hat{a}^y_{Ht}$ captures local shocks to final-goods sector productivity. Appendix B presents the formal derivation of the regional Phillips curve.

Combining the regional Phillips curves in H and F, we obtain the aggregate Phillips curve

$$\pi_t = \beta E_t \pi_{t+1} - \kappa \hat{u}_t + \underbrace{\lambda(1-\alpha)\hat{p}^x_t + \lambda\alpha\hat{\chi}_t - \lambda\hat{a}^y_t}_{\nu_t}. \tag{2}$$

The intuition behind the presence of $\hat{p}^x_{Ht}$ and $\hat{p}^x_t$ in the regional and aggregate Phillips curves is that inflation is increasing in the relative price of intermediate input. Given that the price of intermediate input, P^x_t, is common across regions, an identical absolute intermediate-input price change has a higher (lower) pass-through on regional inflation rates the lower (higher) the regional CPI level. A similar logic applies to the impact of intermediate-input price variations on aggregate inflation in the time series. This term shows how to properly control for the direct effect of supply-side shocks affecting intermediate-input prices (i.e., intermediate-input sector productivity shocks and shocks to marginal costs of commodity production) on final-goods inflation rate.

An important implication of this derivation is that the slopes of the regional and aggregate all-items Phillips curves coincide and are equal to κ. This result is different from the one obtained by Hazell et al.

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(2022) insofar as they show that the slope of the non-tradable regional and the all-items aggregate Phillips curves coincide. In addition, the coefficients on $\hat{u}_{Ht}$ and $\hat{p}^x_{Ht}$ in our Phillips curve equations are scaled by α and $(1-\alpha)$, respectively, where α denotes the final-goods CRS production function parameter. Both discrepancies reflect differences in the structure of the economy and sector-specific production functions between the two models. These derivations imply that regional Phillips curve estimates using all-items inflation rates as dependent variable, as done in Fitzgerald and Nicolini (2014) and McLeay and Tenreyro (2020), can still be informative about the slope of the aggregate Phillips curve, provided that the relative intermediate-input price dynamics do not diverge substantially across regions.

2.3 From κ to ψ

To estimate the slope of the regional Phillips curve, we follow Hazell et al. (2022) and solve it forward, obtaining

$$\pi_{Ht} = E_t\pi_{t+\infty} - E_t\sum_{j=0}^{\infty}\beta^j\kappa\tilde{u}_{Ht+j} + \underbrace{E_t\sum_{j=0}^{\infty}\beta^j(\lambda(1-\alpha)\hat{p}^x_{Ht+j} + \lambda\alpha\hat{\chi}_{Ht+j} - \lambda\hat{a}^y_{Ht+j})}_{E_t\sum_{j=0}^{\infty}\beta^j\nu_{Ht+j}}, \tag{3}$$

where $\tilde{u}_{Ht} = u_{Ht} - E_t u_{Ht+\infty}$ denotes the deviation of the current regional unemployment rate from the expected long-run regional unemployment rate and $E_t\sum_{j=0}^{\infty}\beta^j\nu_{Ht+j}$ denotes the expected present discounted value of all current and future regional cost-push shocks. This expression for the regional Phillips curve is particularly convenient, as it shows how time fixed effects in a panel data setting control for long-run inflation expectations. Indeed, $E_t\pi_{t+\infty}$ is assumed to be common across regions and to depend solely on the monetary policy regime in place.

Assuming that $\tilde{u}_{Ht}$, $\hat{p}^x_{Ht}$, and $\hat{a}^y_{Ht}$ follow an AR(1) process with autocorrelation coefficients ρ_u, ρ_{p^x}, and ρ_{a^y}, the regional Phillips curve takes the form

$$\pi_{Ht} = E_t\pi_{t+\infty} - \psi\tilde{u}_{Ht} + \delta\hat{p}^x_{Ht} - \eta\hat{a}^y_{Ht} + \omega_{Ht}, \tag{4}$$

where $\psi = \frac{\kappa}{(1-\beta\rho_u)}$, $\delta = \frac{\lambda(1-\alpha)}{(1-\beta\rho_{p^x})}$, $\eta = \frac{\lambda}{(1-\beta\rho_{a^y})}$, and $\omega_{Ht} = E_t\sum_{j=0}^{\infty}\beta^j\lambda\alpha\hat{\chi}_{Ht+j}$. Equations (3) and (4) are useful to acknowledge the difference between κ and ψ. κ denotes the effect of current unemployment on current inflation, while ψ denotes the effect of current and expected future deviations of unemployment from its long-run steady state on current inflation. Since unemployment is fairly persistent, ψ is typically larger than κ.

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As we lack sufficient forward periods in the post-COVID sample to provide insightful estimates of κ, we estimate ψ only. Our estimates provide an upper bound for the effect of contemporaneous demand-driven labor market tightness on inflation. Indeed, they capture the impact of current and future expected unemployment, and high unemployment today typically implies high expected unemployment in future periods. Since the persistence of unemployment declined after COVID, the estimate of ψ in the post-COVID period is closer to κ than it is in the pre-COVID period. As a result, the Phillips curve steepening that we document based on the estimates of ψ is likely to provide a lower bound than the steepening based on estimates of κ.

The result that the slope of the regional Phillips curve coincides with the slope of the aggregate Phillips curve relies on several assumptions. The estimates we provide therefore might not deliver the exact slope of the aggregate Phillips curve. They do, however, constitute useful empirical moments characterizing post-COVID inflation dynamics.

3 Data and Descriptive Evidence

We collect data covering 21 US metropolitan areas from January 1990 to September 2022. The Bureau of Labor Statistics (BLS) provides monthly or bi-monthly MSA-level CPI data. All prices are collected monthly in the New York, Chicago, and Los Angeles metropolitan areas. In other locations, food and energy prices are collected monthly, and the prices of other items are collected bi-monthly. The starting date of CPI data collection differs among the metropolitan areas included in the sample. For a more detailed description of CPI data, we refer to Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008). We focus on broad item categories, such as all items, all items excluding energy, all items excluding food and energy (i.e., core CPI), all items excluding shelter, goods, and services.

We use these data to construct our dependent variables (i.e., inflation) as 12-month percent differences in the CPI. We linearly interpolate MSA-specific CPI series that are collected bi-monthly to fully exploit the variation of MSA-level unemployment rates and instrumental variables in the COVID and post-COVID samples. Since interpolation introduces measurement error in our dependent variable (i.e., inflation) only, our estimates do not suffer from attenuation bias. Appendix C discusses the properties of the inflation interpolation errors in more detail, showing that they are centered at zero and do not correlate with the instrumental variable used in our empirical strategy. We acknowledge that all inflation measures are potentially subject to various types of error, particularly so during a pandemic that

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dramatically shifted consumers' habits. In this regard, Reinsdorf (2020) and Cavallo (2020) argue that CPI weights reflecting pre-COVID consumption bundles are likely to bias the measure of inflation during COVID.

Monthly MSA-level labor market data are available through the BLS's Local Area Unemployment Statistics (LAUS). The LAUS program uses non-survey methodologies to estimate the number of employed and unemployed individuals for sub-national areas, using the national not-seasonally-adjusted estimates from the Current Population Survey as controls. LAUS provide MSA-level estimates of the labor force, employment, unemployment, and unemployment rate. We use the unemployment rate as our main independent variable to proxy for labor market tightness.

To construct our shift-share instrument and control variables, we need additional data. For the shift components, we draw monthly data on national employment by industry, starting from January 1990, from the Current Population Survey. For the share components, we construct MSA-level industry employment shares from the 1990 Census, our baseline period. Finally, we collect national producer price index (PPI) data for the manufacturing sector from the BLS from January 1990 to September 2022 to construct the relative intermediate-input price index.

Recent studies have argued that a more suitable measure of labor market tightness is the vacancy-to-unemployment ratio, as it provides superior inflation forecasts for prices and wages than the unemployment rate (Barnichon et al. 2021; Furman and Powell 2021; Barnichon and Shapiro 2022). In the post-COVID period, the US vacancy-to-unemployment ratio has dramatically increased, reaching its highest level since World War II in March 2022 (Michaillat and Saez, 2022). Unfortunately, publicly available MSA-level data on vacancies are not available before 2020. We collect data on city-level online vacancies from the Burning Glass Help Wanted OnLine Index available from January 2020 onward. We use these data to check the robustness of our COVID and post-COVID estimates to measuring labor market tightness through the vacancy-to-unemployment ratio.

The resulting dataset is a panel of MSA-year-month observations. Table A.1 in Appendix A shows pre-COVID, COVID, and post-COVID descriptive statistics of inflation and unemployment rates, as well as the CPI data collection starting date for all MSAs included in the sample. Figure 2 reveals a remarkable degree of geographical heterogeneity in inflation across MSAs. As of September 2022, Phoenix-Mesa-Scottsdale (Arizona) was the MSA with the highest 12-month, all-items inflation rate in the US (12.6%), while San Francisco-Oakland-Hayward (California) was the MSA experiencing the lowest inflation rate (5.8%). Unemployment rates instead vary to a lesser extent across MSAs. As of September

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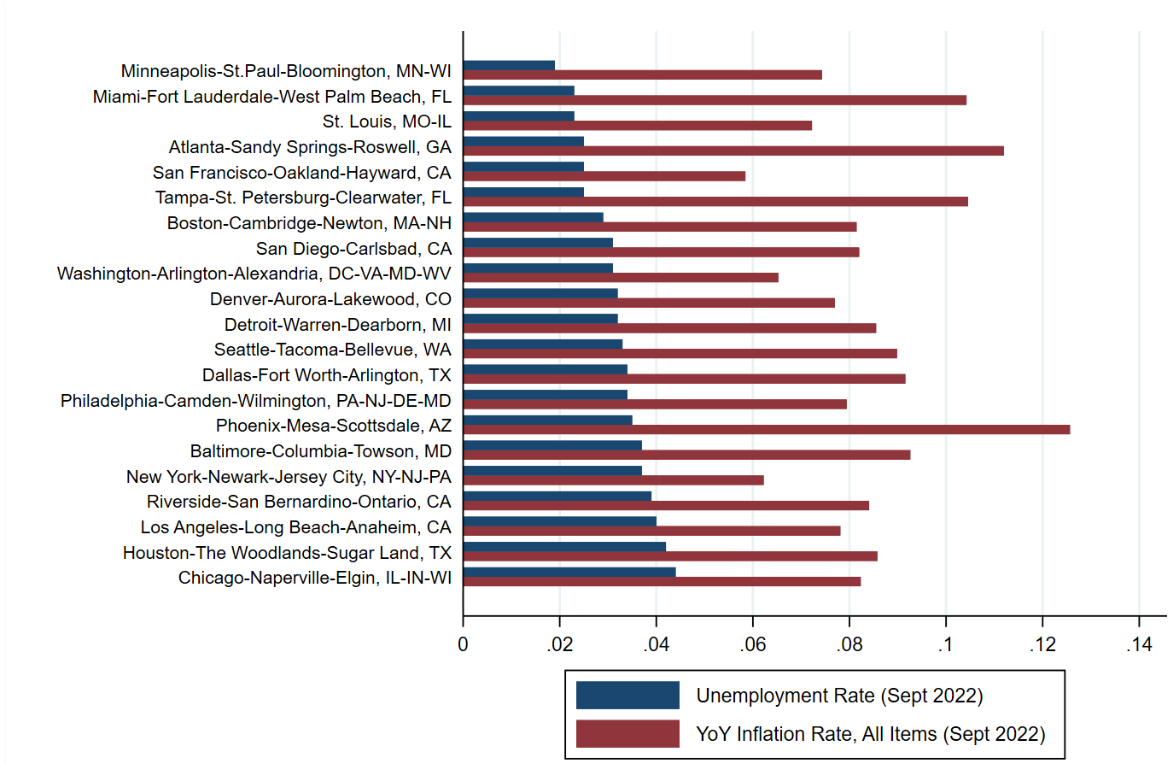
2022, Chicago-Naperville-Elgin (Illinois-Indiana-Wisconsin) experienced the highest unemployment rate (4.4%), while Minneapolis-St.Paul-Bloomington (Minnesota-Wisconsin) displayed the lowest figure in the sample (1.9%).

Figure 2: Unemployment and Inflation Across US Cities



Notes. The bar graph shows the September 2022 unemployment rate (blue bar) and the September 2022 12-month, all-items inflation rate (red bar) by US metropolitan area. Monthly unemployment rates at the MSA level come from the LAUS. Monthly CPI data at the MSA level come from the BLS. Inflation rates are computed as 12-month percent differences of MSA-level CPIs.

The simple correlation between inflation and unemployment across US metropolitan areas presents clear non-linearities. Figure 1 in Section 1 shows that MSA-level inflation rates decrease non-linearly in the unemployment rate. That is, the response of the inflation rate to the unemployment rate is higher at low rather than at high unemployment rate levels. This descriptive non-linearity is particularly visible in the COVID and post-COVID periods and motivates our empirical estimation.

4 Empirical Strategy

Our empirical exercise aims to estimate the parameter ψ in Equation (4) before, during, and after COVID. We define the COVID period as starting in March 2020, when the first COVID cases were reported in the

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US, and the post-COVID period as starting in March 2021, when real consumption expenditures reverted to their pre-pandemic trend. Figure A.1 in Appendix A shows the time series of US real consumption expenditures from January 2018 to September 2022, as measured by the Bureau of Economic Analysis.

To perform our analysis, we specify the following empirical model:

$$\pi_{it} = \alpha_i + \gamma_t - \psi u_{it} + \delta \hat{p}^x_{it} - \eta z^y_{it} + \omega_{it} \tag{5}$$

In our benchmark specification, π_{it} denotes the 12-month, all-items inflation rate in MSA i and year-month t. Using the 12-month inflation rate as dependent variable allows us to eliminate seasonality. α_i denotes MSA fixed effects, absorbing time-invariant characteristics of metropolitan areas, such as differences in long-run economic fundamentals across cities. MSA-specific constant terms are allowed to shift between the three periods to control for structural changes at the MSA level brought about by the pandemic. γ_t denotes year-quarter fixed effects, absorbing aggregate shocks, such as endogenous fiscal and monetary policies. As we show in Section 2, the inclusion of time fixed effects is essential to difference out common beliefs about the long-run monetary policy regime in place, a major determinant of sudden fluctuations in inflation (Sargent, 1982). u_{it} denotes the unemployment rate in city i and year-month t.

Identifying the parameter ψ in Equation (5) further requires u_{it} to be uncorrelated with regional cost-push shocks that might bias OLS estimates of Equation (5). As we derive formally in the model, cost-push shocks are driven by local relative intermediate-input price, unobserved local labor supply, and local final-goods sector productivity shocks – $\hat{p}^x_{it}$, $\hat{\chi}_{it}$, and $\hat{a}^y_{it}$ in Equation (1), respectively. To isolate demand-driven fluctuations in local unemployment rates from unobserved local labor supply shocks, $\hat{\chi}_{it}$, included in the error term ω_{it}, we construct a shift-share instrument capturing productivity shocks in the tradable intermediate-input sectors. Positive shocks have two distinct effects on inflation. They act as local labor demand shifters, thus decreasing unemployment, raising wages, and causing final-goods firms to increase prices. This is the channel we intend to capture through our instrument.

However, productivity shocks in the intermediate-input sector lower marginal costs of production, decreasing the price of intermediate inputs common across regions. As a consequence, local final-goods firms decrease prices. Since intermediate-input prices are observable, we control for their direct incidence on local inflation including $\hat{p}^x_{it}$ in our main specification. This variable is measured as the ratio between the US manufacturing PPI and the CPI in MSA i and year-month t. $\hat{p}^x_{it}$ also absorbs the impact of commodity price shocks on local inflation channeled through changes in relative intermediate-input prices. For instance, this term differences out changes in car prices set by local dealers due to a sudden

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increase in prices of internationally traded semiconductors that raises marginal costs for domestic car producers. In Appendix D, we show model-based impulse response functions of endogenous variables to a positive productivity shock in the intermediate-input sector, summarizing the mechanisms at the basis of our identification strategy.

Our instrument takes the following form:

$$z_{it}^{x} = \sum_{j=1}^{N^x} \frac{E_{ij1990}}{E_{i1990}} \times \Delta_{3Y} \log E_{USjt},$$

where $j = 1, ..., N^x$ denotes 1990 2-digit tradable intermediate-input Census industries. These industries include agriculture, mining, manufacturing of durable and non-durable goods, wholesale trade, and financial services. $\frac{E_{ij1990}}{E_{i1990}}$ denotes MSA-level industry employment shares measured in 1990, the baseline period in our sample. Finally, $\Delta_{3Y} \log E_{USjt}$ denotes the three-year percentage change in national employment by industry as in Hazell et al. (2022), capturing labor demand shocks in the intermediate-input sectors at business cycle frequencies. Differences in national employment by industry capture short-run shifts in labor demand, while baseline MSA-level industry employment shares measure local exposure to such national shocks.

We address the remaining concern that local unemployment rates are correlated to the productivity shocks of the local final-goods sectors, $\hat{a}_{it}^{y}$. This has likely been the case especially during and after COVID (Guerrieri et al. 2022), when local economies experienced robust labor demand recoveries across all sectors. If local productivity shocks in the final-goods sector correlate with the variation in unemployment rates captured by our instrument, then our estimate of ψ would be biased. As our model illustrates, a positive productivity shock in the final-goods sector increases labor market tightness but also negatively affects final-goods prices. We therefore follow Borusyak et al. (2022) and include in our main specification the shift-share control variable z_{it}^{y}, proxying for productivity shocks in the final-goods sectors in MSA i and year-month t. This variable has the same structure as our shift-share instrument and is constructed using 2-digit Census non-tradable final-goods industries (i.e., construction, retail, business, personal, recreation, and professional services).

The conditional exogeneity of our instrument stems from the shocks (Borusyak et al., 2022) rather than from the shares (Goldsmith-Pinkham et al., 2020). Our identifying assumption is therefore that, conditioning on MSA fixed effects, time fixed effects, $\hat{p}_{it}^{x}$, and z_{it}^{y}, industry-level employment growth rates in the intermediate-input sectors capture labor demand shocks plausibly uncorrelated with industry-level

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aggregates of regional labor supply shocks. Finally, we instrument the term $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it} = \left(\frac{\hat{P}^x_t}{P_{it-24}}\right)$ to offset the negative mechanical correlation between $\hat{p}^x_{it}$ and the dependent variable π_{it}, induced by the presence of P_{it} in the numerator of π_{it} and in the denominator of $\hat{p}^x_{it}$.

Table 1: First Stage Coefficients

	u_{it}			$\hat{p}^x_{it}$		
	(1) Pre-COVID	(2) COVID	(3) Post-COVID	(4) Pre-COVID	(5) COVID	(6) Post-COVID
z^x_{it}	-0.49***	-2.01***	-0.71***	-0.19	-0.05	-0.31
	(0.09)	(0.53)	(0.16)	(0.12)	(0.14)	(0.18)
$\hat{p}^{x*}_{it}$	0.02	0.23**	0.02*	0.86***	0.55***	0.58***
	(0.02)	(0.07)	(0.01)	(0.04)	(0.06)	(0.02)
z^y_{it}	-0.10	0.05	-0.48***	-0.20	0.09**	-0.16
	(0.16)	(0.13)	(0.10)	(0.18)	(0.03)	(0.15)
Observations	5211	252	399	5211	252	399
F-Statistic	25.11	11.80	9.40	273.69	78.27	544.94
MSA-Period FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Notes. This table presents the first stage regression coefficients for IV estimation of Equation 5. In columns (1) to (3), the dependent variable is the unemployment rate, u_{it}. In columns (4) to (6), the dependent variable is local relative price of intermediate input, $\hat{p}^x_{it}$. The first and fourth columns present the first-stage coefficients for the pre-COVID period (i.e., from January 1990 to February 2020), the second and fifth columns present the first-stage coefficients for the COVID period (i.e., from March 2020 to February 2021), while the third and sixth columns present the first-stage coefficients for the post-COVID period (i.e., from March 2021). The shift-share instrument constructed with tradable intermediate-input industries, z^x_{it}, and intermediate-input price relative to 24-month lagged local CPI, $\hat{p}^{x*}_{it}$, denote the main independent variables. The shift-share variable constructed with non-tradable final-goods industries, z^x_{it}, denotes the main control variable. The specification includes MSA-specific constant terms and year-quarter fixed effects. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 shows the first-stage coefficients and F-statistics for the pre-COVID, COVID, and post-COVID periods. In columns (1) to (3), the dependent variable is the unemployment rate, u_{it}. The instrument z^x_{it} significantly predicts labor market tightness, exhibiting negative coefficients across all specifications. The F-statistics indicate that our instruments are relatively strong in all periods. Column (2) shows that $\hat{p}^{x*}_{it}$ is positively correlated with u_{it} during COVID, suggesting that the supply shocks that occurred during the pandemic harmed local labor markets. Moreover, z^y_{it} positively and significantly correlates with labor market tightness in the post-COVID sample, pointing to the importance of this control in the aftermath of the pandemic. In columns (4) to (6), we show that the instrument $\hat{p}^{x*}_{it}$ strongly predicts the local relative intermediate-input price, $\hat{p}^x_{it}$.

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5 Results and Aggregate Implications

5.1 Demand-Driven Inflation After COVID

Table 2 summarizes our main results, documenting that the Phillips curve flattened during COVID and steepened in the aftermath of the pandemic. A naive OLS estimation of the slope of the Phillips curve delivers an almost eightfold steepening from pre- to post-COVID, compared to the more than threefold steepening estimated following our empirical strategy. The results from the OLS specification controlling only for MSA fixed effects are reported in column (1). We allow the MSA-specific constant terms to shift between the three periods to absorb COVID-induced structural changes that occurred at the local level. The estimate of ψ increases from 0.18 before COVID to 1.36 after COVID, dropping to 0.09 in the COVID period.

Adding a control for the relative price of intermediate inputs in column (2) halves the coefficient in the post-COVID period, reflecting the importance of commodity and intermediate-input supply shocks in driving inflation dynamics after the pandemic. In column (3), we further control for year-quarter fixed effects. The inclusion of such a control shrinks the coefficients on u_{it} toward zero in the COVID and post-COVID periods. This result points to the relevance of aggregate shocks (e.g., changes in inflation expectations, endogenous policy responses, etc.) in explaining the recent spike in inflation. The coefficients on $\hat{p}^x_{it}$ turn negative in all periods. The reason is the presence of P_{it} (i.e., the CPI in MSA i in period t) in the numerator of π_{it} and in the denominator of $\hat{p}^x_{it}$, inducing a negative mechanical correlation between the two variables in the cross-section.

We address the simultaneity between local demand and supply shocks in column (4). To do so, we proceed as follows. First, we isolate demand-driven variations in local unemployment rates from contemporaneous local labor supply shocks instrumenting u_{it} with z^x_{it}, our proxy for productivity shocks in the intermediate-input sector. Second, we condition on the shift-share control variable z^y_{it} to absorb the productivity shocks of the final-goods sectors. Finally, we instrument $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$ to deal with the aforementioned negative mechanical correlation between π_{it} and $\hat{p}^x_{it}$. Column (4) reports our preferred estimates of ψ, i.e., 0.25 before COVID, -0.02 during COVID, and 0.85 after COVID. These results indicate that the Phillips curve flattened during the pandemic and steepened by a factor of more than three afterward, relative to the pre-COVID period.

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Table 2: Estimates of ψ from Equation (5)

	(1) OLS	(2) OLS	(3) OLS	(4) IV
Pre-COVID				
u_{it}	-0.18***	-0.29***	-0.20***	-0.25
	(0.03)	(0.04)	(0.04)	(0.15)
$\hat{p}^x_{it}$		0.09***	-0.06***	0.06**
		(0.02)	(0.02)	(0.03)
z^y_{it}				0.13
				(0.09)
COVID				
u_{it}	-0.09***	-0.08***	-0.04	0.02
	(0.02)	(0.02)	(0.02)	(0.07)
$\hat{p}^x_{it}$		0.02	-0.23**	0.33***
		(0.05)	(0.08)	(0.08)
z^y_{it}				0.01
				(0.04)
Post-COVID				
u_{it}	-1.36***	-0.71***	0.10	-0.85**
	(0.15)	(0.12)	(0.13)	(0.34)
$\hat{p}^x_{it}$		0.24***	-0.08	0.20***
		(0.03)	(0.05)	(0.04)
z^y_{it}				-0.14
				(0.16)
Observations	5862	5862	5862	5862
MSA-Period FE	✓	✓	✓	✓
Year-Quarter FE			✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID (i.e., from January 1990 to February 2020), COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods. All specifications feature the 12-month, all-item inflation rate as dependent variable and u_{it} as the main independent variable. Columns (1) to (3) display OLS coefficients, column (4) displays IV coefficients. Column (1) controls for MSA fixed effects, allowed to shift across the pre-COVID, COVID, and post-COVID periods. Column (2) adds a control for the local relative price of intermediate input, $\hat{p}^x_{it}$. Column (3) additionally controls for year-quarter fixed effects. Column (4) displays IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it}, controlling for the productivity shocks of the non-tradable final-goods sectors, z^y_{it}, and instrumenting $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. The first-stage coefficients for the specification in column (5) are displayed in Table 1. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The difference between the post-COVID estimates of ψ in columns (3) and (4) suggests that the instrument effectively addresses potential measurement error of the independent variable and simultaneity concerns. Such biases drive the OLS estimates toward zero and might even deliver positive coefficients

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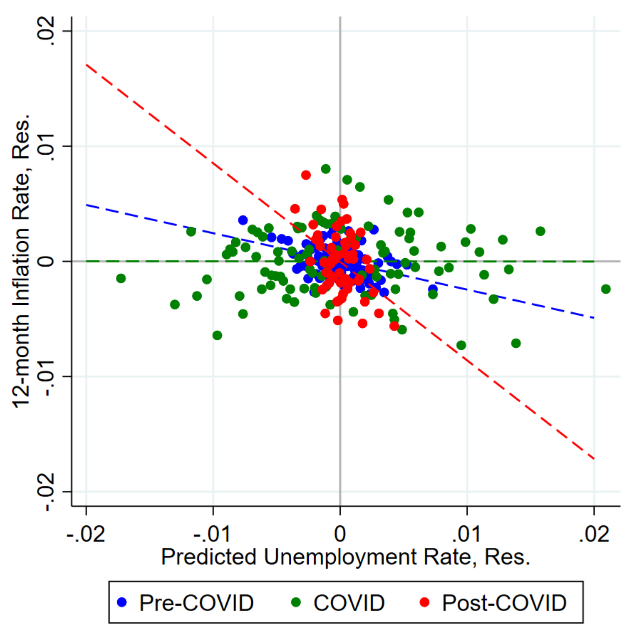
in the presence of relevant local supply shocks. Figure 3 plots the 12-month inflation rate against the predicted unemployment rate binned residuals, providing a graphical representation of the estimates in column (4). These results also show that the inflation rate during COVID was mostly driven by supply shocks from the commodity and intermediate-input sectors. Indeed, the coefficient on $\hat{p}^x_{it}$ in column (4) increased from 0.06 in the pre-COVID period to 0.33 in the COVID period. In the aftermath of the pandemic, the estimated coefficient is 0.2, indicating that supply shocks might still be playing a relevant role. Considering the most recent historical estimates of ψ from the regional Phillips curve literature, we infer that, since the mid-1970s, the slope of the US Phillips curve has never been as high as in recent times.[7]

Figure 3: Estimates of ψ from column (4) of Table 2



Notes. This figure provides a graphical representation of our benchmark estimates of ψ before, during, and after COVID (Table 2, column (4)). The figure plots binned residuals from a regression of the 12-month, all-items inflation rate on MSA fixed effects, year-quarter fixed effects, the relative intermediate-input price, and the final-goods shift-share control variable z^y_{it} against binned residuals of the same specification with predicted unemployment rate as dependent variable. Predicted unemployment rate (i.e., $\hat{u}_{it}$) comes from the first-stage regression using z^x_{it} to instrument u_{it}. Blue, green, and red dots denote observations belonging to the pre-COVID, COVID, and post-COVID samples, respectively. The dashed lines represent the best linear fits in the three periods, showing the flattening of the Phillips curve during COVID and its steepening after COVID, relative to the pre-COVID period.

Our benchmark estimates imply that demand-driven economic recovery explains about one-fourth of

[7]The IV estimates of ψ obtained by Hazell et al. (2022) using state-level variation for the pre-1990 and post-1990 periods are 0.42 and 0.33, respectively.

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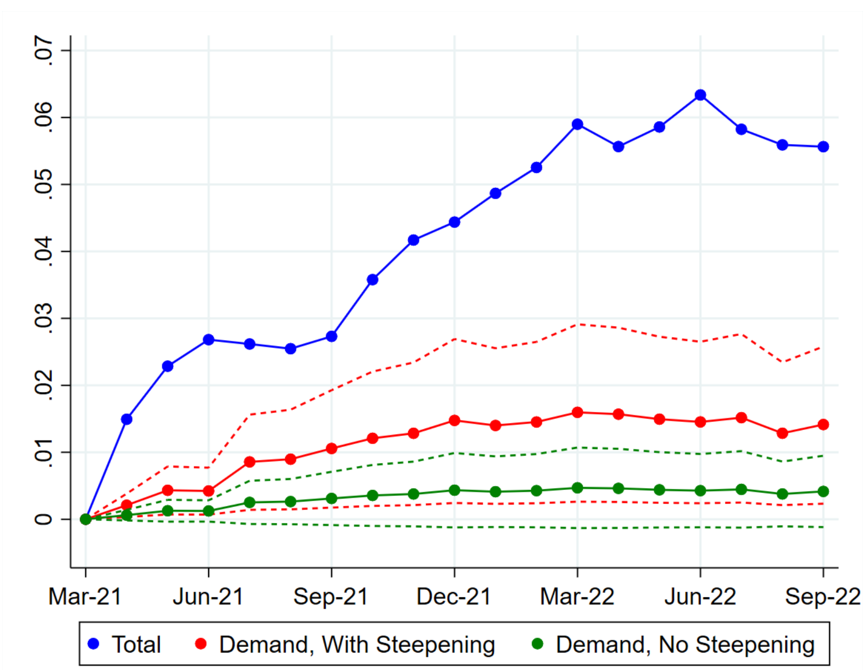
the post-COVID spike in inflation. Between March 2021 and September 2022, all-items inflation increased by 5.6 percentage points, while the unemployment gap decreased by 1.7 percentage points. We define the unemployment gap as the difference between the unemployment rate and the efficient unemployment rate, following Michaillat and Saez (2022). According to their Beveridgean framework, the efficient unemployment rate is affected only by supply shocks. The right panel of Figure A.2 in Appendix A shows the evolution of the unemployment and the efficient unemployment rates from January 2018 to September 2022. The unemployment gap was close to zero before the pandemic, increased dramatically during COVID, and fell below zero from May 2021. Multiplying the change in the unemployment gap (i.e., 1.7%) by our benchmark estimate of the slope of the Phillips curve (i.e., 0.85), we obtain an estimate of the change in inflation imputable to demand factors (i.e., $1.7\% \times 0.85 = 1.4\%$). The remaining variation is attributable to shifts in long-run inflation expectations and supply-side shocks.

Figure 4: 12-month Inflation Rate, Change relative to March 2021



Notes. The figure shows the evolution of the 12-month, all-items inflation rate (blue line), the demand-driven component of this increase with no steepening (green line) and with steepening (red line) of the post-COVID Phillips curve, as reported by the coefficients in Table 2, column (4). Between March 2021 and September 2022, all-items inflation increased by 5.6 percentage points, while the unemployment gap – computed following the Beveridgean framework outlined by Michaillat and Saez (2022) – decreased by 1.7 percentage points. The estimates of ψ before and after COVID are 0.25 and 0.85, respectively. The red line indicates that the decrease in unemployment explains 1.4 ($= 1.7 \times 0.85$) out of the 5.6 percentage-point increase in inflation. The green line indicates that the same decrease in unemployment would have explained only about 0.4 ($= 1.7 \times 0.25$) of the 5.6 percentage-point increase in inflation, had the slope of the Phillips curve remained unchanged.

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Figure 4 shows that the demand contribution to the rise in inflation would have been small and statistically insignificant had the slope of the Phillips curve not steepened after COVID. The blue line shows the evolution of the 12-month, all-items inflation rate relative to March 2021, while the red line represents the demand-driven component of this increase, assuming a steepening of the post-COVID Phillips curve. The green line indicates that the same decrease in unemployment would have explained only about 0.4 of the 5.6 percentage-point inflation increase, had the Phillips curve's slope remained unchanged. These observations imply that Phillips curve steepening is quantitatively important in explaining the post-COVID increase in inflation.

5.2 Heterogeneity of Phillips Curve Steepening Over Time

Labor market tightness reached its highest level since World War II in March 2022 (Michaillat and Saez, 2022), one year into our post-COVID period. Figure A.2 in Appendix A shows that the unemployment rate had dropped to 3.6% by the same time, in line with its pre-pandemic level, and has remained relatively constant after that. Motivated by this fact, we perform a heterogeneity analysis to test the sensitivity of our estimates of ψ to different horizons of the post-COVID period. We estimate the slope

Table 3: IV Estimates of ψ from Equation (5) for different post-COVID periods

	(1) Pre-COVID	(2) COVID	(3) March 2022	(4) June 2022	(5) September 2022
u_{it}	-0.25	0.02	-1.18***	-1.04**	-0.85**
	(0.15)	(0.07)	(0.37)	(0.33)	(0.34)
$\hat{p}^x_{it}$	0.06**	0.33***	0.10	0.21***	0.20***
	(0.03)	(0.08)	(0.06)	(0.04)	(0.04)
z^y_{it}	0.13	0.01	-0.54**	-0.39**	-0.14
	(0.09)	(0.04)	(0.17)	(0.18)	(0.16)
Observations	5211	252	273	336	399
MSA-Period FE	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID period in column (1) (i.e., from January 1990 to February 2020), for the COVID period in column (2) (i.e., from March 2020 to February 2021), and for different post-COVID periods, i.e., from March 2021 to March 2022 in column (3), from March 2021 to June 2022 in column (4), and from March 2021 to September 2022 in column (5) – our baseline post-COVID period. All specifications feature the 12-month, all-items inflation rate as outcome variable and control for MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods), year-quarter fixed effects, relative intermediate-input prices, and the shift-share control variable z^y_{it}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it} and $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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of the Phillips curve from March 2021 to March 2022 (when most of the recovery occurred), to June 2022, and to September 2022.

Table 3 shows that the slope of the Phillips curve reached its highest level by March 2022, as displayed in column (3). Including subsequent months – columns (4) and (5) – significantly decreases our point estimate of ψ, suggesting that the slope of the Phillips curve might be experiencing a reversion toward pre-pandemic levels in more recent months. Interestingly, inflation dynamics in the early post-COVID period were not significantly affected by supply shocks but by labor market tightness and productivity shocks of final-goods sectors. From March 2022 onward, however, supply shocks have become progressively more relevant, as they were during COVID.

5.3 Heterogeneity of Phillips Curve Steepening Across Items

Distinct CPI item categories have not equally contributed to the increase in inflation experienced by the US since March 2021. The right panel of Figure A.3 in Appendix A shows the 12-month inflation rates for goods and services in recent months. The post-pandemic increase in inflation seems driven more by goods than by services. As noted by many, real consumption expenditures for goods have been steadily stationed above their pre-COVID trend in the past two years, while those for services have reached their pre-pandemic levels only in March 2022 (Figure A.3, left panel). Such a dynamic indicates that demand has shifted from services to goods during and after COVID, reflecting a sluggish return to pre-pandemic consumption habits in the aftermath of the recession. A natural extension of the analysis in Table 2 would therefore be to investigate the extent to which the post-COVID increase in the slope of the Phillips curve is driven by goods and services, respectively.

The heterogeneity analysis in Table 4 shows that the post-COVID Phillips curve steepening is mainly driven by goods rather than services. At the same time, the flattening that occurred during COVID is driven by services rather than goods. Columns (1) to (3) document an exponential increase in the slope of the goods Phillips curve, which grows from 0.12 before COVID to 0.21 during COVID, reaching 2.24 after COVID. Columns (4) to (6) show that there is no significant steepening in the services Phillips curve. Unexpectedly, supply shocks occurring in the commodity and intermediate-input markets affect goods more than services across all periods, especially during and after COVID. These results are consistent with the presence of congestion in the goods market since the onset of the pandemic, with demand stationing above trend and supply struggling to expand.

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Table 4: IV Estimates of ψ from Equation (5) for broad CPI categories

	Goods			Services		
	(1) Pre-COVID	(2) COVID	(3) Post-COVID	(4) Pre-COVID	(5) COVID	(6) Post-COVID
u_{it}	-0.12	-0.21**	-2.24***	-0.32	0.10	-0.35
	(0.15)	(0.08)	(0.65)	(0.23)	(0.06)	(0.36)
$\hat{p}^x_{it}$	0.24***	0.65**	0.64***	0.05**	0.08	0.09**
	(0.07)	(0.27)	(0.09)	(0.02)	(0.07)	(0.04)
z^y_{it}	0.08	-0.07	-0.57*	0.12	0.04	0.01
	(0.07)	(0.10)	(0.31)	(0.15)	(0.04)	(0.19)
Observations	5211	252	399	5211	252	399
MSA-Period FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID (i.e., from January 1990 to February 2020), COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods. Columns (1) to (3) use the 12-month goods inflation rate as dependent variable. Columns (4) to (6) use the 12-month services inflation rate as dependent variable. All specifications control for MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods) year-quarter fixed effects, intermediate-input prices relative to the corresponding CPI categories, and the shift-share control variable z^y_{it}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it} and $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Robustness Checks

In this section, we address potential concerns about the validity of our results. First, using all-items inflation as dependent variable may mislead the interpretation of our results, as labor market tightness is often considered a driver of core inflation only. Indeed, the food and energy components of the CPI are disproportionally more responsive to supply-side shocks (e.g., oil price shocks) and more volatile as a result. Moreover, a large share of expenditures in core inflation is represented by the shelter component of housing services, measured by rents. As the pandemic significantly affected real estate market dynamics within large US cities (Ramani and Bloom 2021; Mondragon and Wieland 2022), we assess the extent to which rents drive our results. We therefore check whether the post-COVID Phillips curve steepening documented with all-items inflation is robust to different inflation measures (i.e., all items excluding energy, core, or excluding shelter).

Reassuringly, Table A.2 in Appendix A shows that the slope of the Phillips curve decreased during COVID and substantially increased afterward, independently of the outcome variable used. The estimates

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of ψ for all-items inflation excluding energy in column (2) are almost identical to the estimates of ψ for all-items inflation in column (1). Conversely, the estimated coefficients on $\hat{p}^x_{it}$ diverge during and after COVID, being higher and statistically significant only in the specification with all-items inflation as dependent variable. This result highlights the ability of $\hat{p}^x_{it}$ to control for relevant supply shocks.

The post-COVID estimated slope of the Phillips curve with core inflation in column (3) is slightly smaller than those with all-items and all-items excluding energy. This result suggests that the food component contributed more than other CPI items to the steepening of the Phillips curve. Replicating our back-of-the-envelope calculation to quantify the contribution of demand factors to core inflation in the post-COVID period, we find that they explain 1.2 ($= 1.7 \times 0.71$) of the 5 percentage-point increase in core inflation experienced by the US between March 2021 and September 2022 (i.e., around one-fourth of the variation). Finally, column (4) shows that the estimate of ψ for inflation excluding shelter is close to zero before and during COVID and slightly higher than other estimates after COVID. These results imply that the shelter component contributed to the impact of tightness on inflation before COVID but does not drive the post-COVID Phillips curve steepening.

Second, Furman and Powell (2021) and Barnichon and Shapiro (2022) argue that the unemployment rate underestimates labor market tightness, pointing to the vacancy-to-unemployment ratio as a more suitable measure. We therefore assess whether our main result about post-COVID Phillips curve steepening is sensitive to measuring labor market tightness by the vacancy-to-unemployment ratio. Since city-level vacancy data are publicly available only from January 2020 onward, we are able to estimate ψ for the COVID and post-COVID periods only. Table A.3 in Appendix A shows the results of this robustness check with different measures of inflation as dependent variables, instrumenting the vacancy-to-unemployment ratio v_{it} with z^x_{it}. The vacancy-to-unemployment ratio has a positive and statistically significant effect on inflation only from March 2021 onward, implying that the Phillips curve steepened after COVID independently of the adopted measure of labor market tightness. Moreover, the coefficient on $\hat{p}^x_{it}$ drops in the post-COVID period relative to our benchmark specification, pointing to a less significant impact of supply shocks on inflation once labor market tightness is measured through the vacancy-to-unemployment ratio.

Third, one may worry that the long span of the pre-COVID period covers substantial changes in the slope of the Phillips curve between January 1990 and February 2020. To address this concern, we evaluate the sensitivity of our estimates to different definitions of the pre-COVID period. We consider two alternative starting dates (i.e., January 2000 or 2010), instead of January 1990. Columns (1) to

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(3) in table A.4 of Appendix A show that the estimates of ψ are fairly stable across pre-COVID period samples. The slope of the Phillips curve estimated from 1990 until the onset of the pandemic represents an upper-bound (i.e., 0.25 relative to 0.10 from 2000 and 0.18 from 2010).

Since our estimates of ψ capture the effect of current and expected future unemployment on current inflation, they could mainly be driven by expectations about local future economic conditions. If we observed short-run inflation expectations at the local level, we could estimate Equation 1. In that case, the estimated slope of the Phillips curve would only capture the effect of current unemployment on current inflation, the parameter κ. Coibion and Gorodnichenko (2015) argue that households may form their short-run inflation expectations by observing the changes in prices of salient goods, such as gasoline. We therefore proxy for local short-run inflation expectations by the 12-month MSA-level gasoline inflation rate and include this control in our main specification.

Our estimates are robust to the inclusion of this proxy for local inflation expectations. Table A.5 shows that the only coefficients significantly affected by the inclusion of this control are the ones on $\hat{p}^x_{it}$ in the pre-COVID and COVID periods. This likely reflects a mechanical correlation between local gasoline prices and relative intermediate-input prices, driven by oil price dynamics. To the extent that local inflation expectations are influenced by gasoline inflation, they do not seem to drive the steepening of the Phillips curve after COVID.

Finally, in Section 4 we explain how we control for the rapid structural changes in local economies brought about by the pandemic. By adding MSA-period fixed effects to our benchmark specification, we allow time-invariant structural economic conditions of cities, such as the natural unemployment rate, to vary across the three periods considered in our analysis (i.e., before, during, and after COVID). If such conditions changed more frequently within periods, however, this would bias our estimates of ψ. We therefore estimate Equation (5) interacting MSA fixed effects with tighter time fixed effects (i.e., year, year-semester, and year-quarter fixed effects), to absorb higher-frequency local shocks.

Table A.6 in Appendix A shows that our results are qualitatively robust to the inclusion of higher-frequency MSA-time fixed effects. Columns (2) to (4) control for MSA-year, MSA-year-semester, and MSA-year-quarter fixed effects, respectively. The pre-COVID and post-COVID coefficients progressively diverge from column (2) to column (4), while the coefficient during COVID is fairly similar across specification. If anything, these results reveal a more pronounced steepening of the Phillips curve after COVID when controlling for higher-frequency local shocks. We are cautious, however, in interpreting these results, as the identifying variation comes from higher frequency changes in the unemployment rate and

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inflation, which might be driven by measurement error.

7 Conclusion

In this paper, we estimate the slope of the Phillips curve before, during, and after COVID to quantify the share of the post-COVID increase in inflation in the US that is attributable to demand-driven economic recovery. To do so, we exploit MSA-level variation in inflation and unemployment combined with an instrumental variable approach. We relate our cross-sectional estimates to the aggregate parameter through a two-region New-Keynesian model of a monetary union. The model features labor supply shocks and a production side with a vertical supply chain (i.e., an international commodity market, a national intermediate-input market, and local final-goods sectors) to capture supply-side shocks relevant to post-COVID inflation dynamics. We derive the regional and aggregate Phillips curves, showing that their slopes coincide.

To our knowledge, this is the first paper to provide quasi-experimental estimates of the slope of the Phillips curve during and after COVID. In our benchmark specification, we estimate the Phillips curve to have flattened during COVID and substantially steepened subsequently. Our estimates show that 1.4 out of the 5.6 percentage-point increase in inflation between March 2021 and September 2022 are due to the contemporaneous decrease in the unemployment gap. Not allowing the slope of the Phillips curve to change across the three periods makes the demand contribution to the recent rise in inflation small and statistically insignificant. Furthermore, we perform a heterogeneity analysis showing that the increase in the slope of the Phillips curve was more pronounced in the early phase of the post-COVID period and was driven mainly by goods rather than services.

Our results point to the presence of non-linearities in the Phillips curve during and in the aftermath of the pandemic. The literature, however, has not yet established the precise mechanisms behind this result. In our model, the slope of the Phillips curve depends on the frequency of price change and the elasticity of labor supply. Structural changes of these parameters potentially explain the non-linearities, although different models can point to alternative channels. For instance, Harding et al. (2022) provide a possible explanation based on a quasi-kinked demand curve. One may also think about a model featuring structural non-linearities in the aggregate supply, as in Eggertsson et al. 2019. Other potential causes are listed in Del Negro et al. (2020). This is an exciting path for future research.

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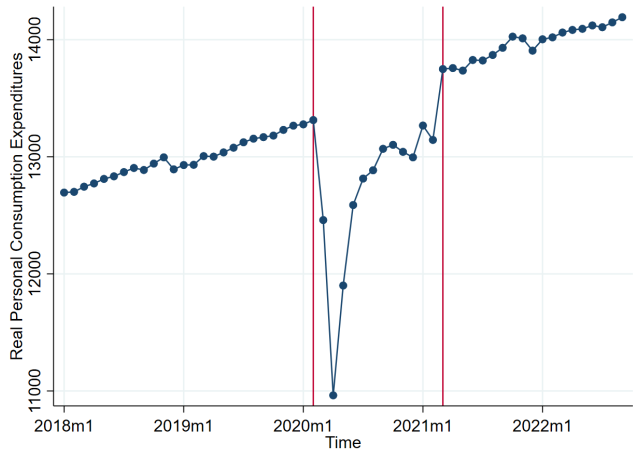
Appendix

A Figures and Tables

Figure A.1: Real Personal Consumption Expenditures (Jan 2018-Sep 2022)

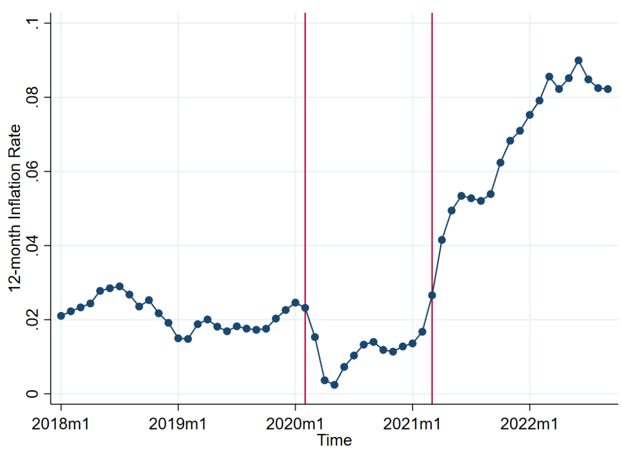


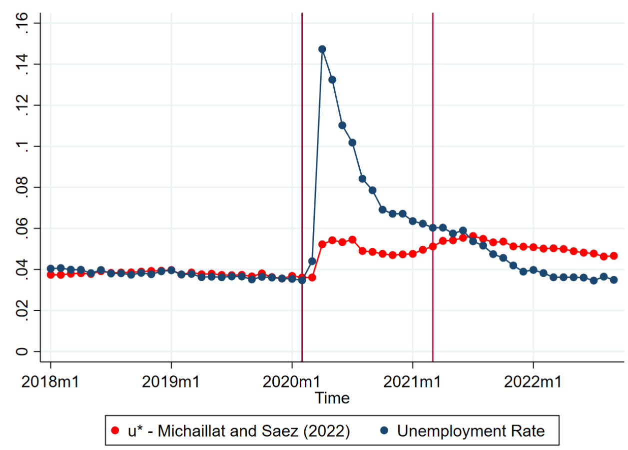
Notes. The figure shows the time series of US real personal consumption expenditures as made available by the BEA from January 2018 to September 2022. We set the start of the post-COVID period in March 2021, when the time series reverts to its pre-pandemic trend after the pandemic shock. The vertical red lines separate the pre-COVID, COVID, and post-COVID periods according to our definition.

Figure A.2: Inflation Rate, Unemployment Rate, and Efficient Unemployment Rate (Jan 2018-Sep 2022)

(a) Inflation Rate

(b) Unemployment Rates





Notes. The figure shows the time series of US 12-month inflation rate (A.2a) from the BLS, the US unemployment rate (A.2b, blue line) from the BLS, and the efficient unemployment rate (A.2b, red line) computed following Michaillat and Saez (2022) from January 2018 to September 2022. The vertical red lines separate the pre-COVID, COVID, and post-COVID periods according to our definition.

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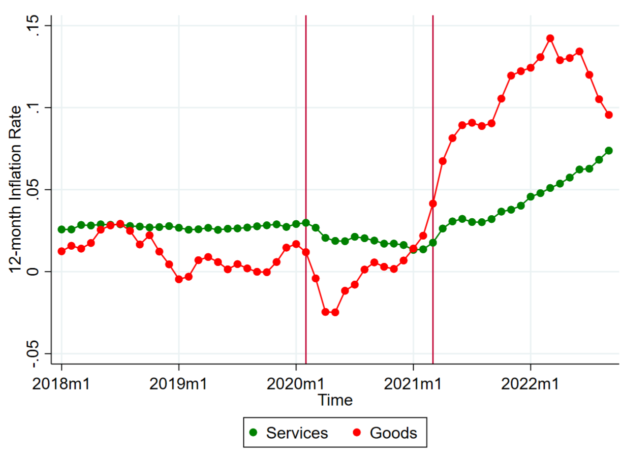
Figure A.3: Real Consumption Expenditures and Inflation, Goods vs. Services (Jan 2018-Sep 2022)

(a) Real Consumption Expenditures

(b) Inflation Rates



Notes. The figure shows the time series of US real consumption expenditures for goods vs. services (A.3a) from the BEA and the 12-month inflation rate for goods vs. services (A.3b) made available by the BLS from January 2018 to September 2022. We set the start of the post-COVID period in March 2021, when the time series of real personal consumption expenditures reverts to its pre-pandemic trend after the pandemic shock. The vertical red lines separate the pre-COVID, COVID, and post-COVID periods according to our definition.

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Table A.1: Descriptive Statistics

City	All-Items Inflation			Unemployment Rate			Start of
	Pre	COVID	Post	Pre	COVID	Post	CPI data
Atlanta	2.00	1.10	8.93	5.50	7.07	3.33	12/1997
	(0.016)	(0.007)	(0.024)	(0.021)	(0.026)	(0.006)	
Baltimore	2.45	0.87	7.14	5.40	6.82	4.75	01/1988
	(0.015)	(0.004)	(0.028)	(0.014)	(0.018)	(0.008)	
Boston	2.58	0.77	5.47	4.97	9.66	4.19	01/1988
	(0.014)	(0.004)	(0.020)	(0.016)	(0.040)	(0.011)	
Chicago	2.23	0.90	6.29	6.42	10.11	5.31	01/1988
	(0.015)	(0.003)	(0.018)	(0.019)	(0.036)	(0.011)	
Dallas	2.32	0.62	7.38	5.18	7.65	4.26	01/1988
	(0.015)	(0.008)	(0.018)	(0.015)	(0.024)	(0.008)	
Denver	3.25	1.47	6.14	4.70	7.77	4.41	11/2017
	(0.004)	(0.010)	(0.025)	(0.019)	(0.025)	(0.012)	
Detroit	2.21	0.64	6.70	7.03	12.09	5.23	02/1988
	(0.014)	(0.007)	(0.019)	(0.028)	(0.066)	(0.013)	
Houston	2.35	0.02	6.86	5.69	9.34	5.44	02/1988
	(0.015)	(0.006)	(0.022)	(0.013)	(0.024)	(0.010)	
Los Angeles	2.58	1.25	6.06	6.87	12.65	6.28	01/1988
	(0.015)	(0.005)	(0.020)	(0.023)	(0.039)	(0.021)	
Miami	2.70	0.85	7.36	5.95	9.12	3.70	01/1988
	(0.015)	(0.006)	(0.028)	(0.023)	(0.032)	(0.012)	
Minneapolis	2.66	1.09	6.69	4.07	6.68	2.67	11/2017
	(0.004)	(0.009)	(0.016)	(0.014)	(0.026)	(0.008)	
New York	2.56	1.52	4.85	6.17	11.28	5.79	01/1988
	(0.013)	(0.003)	(0.014)	(0.017)	(0.037)	(0.015)	
Philadelphia	2.35	0.61	6.32	5.70	9.62	5.25	01/1988
	(0.015)	(0.005)	(0.019)	(0.015)	(0.031)	(0.012)	
Phoenix	3.90	1.39	8.72	5.04	7.49	3.68	12/2017
	(0.005)	(0.007)	(0.033)	(0.018)	(0.023)	(0.010)	
Riverside	2.88	1.85	7.73	7.70	10.82	5.76	12/2017
	(0.002)	(0.005)	(0.018)	(0.029)	(0.030)	(0.018)	
San Diego	2.35	1.54	6.86	5.78	10.36	4.84	11/2017
	(0.002)	(0.006)	(0.013)	(0.022)	(0.035)	(0.017)	
San Francisco	2.87	1.55	4.55	5.27	9.12	4.12	01/1988
	(0.012)	(0.003)	(0.012)	(0.020)	(0.030)	(0.015)	
Seattle	2.41	1.55	7.08	5.10	8.88	3.95	12/1997
	(0.012)	(0.004)	(0.022)	(0.015)	(0.037)	(0.009)	
St. Louis	2.16	0.74	7.20	5.57	7.17	3.87	01/1988
	(0.008)	(0.006)	(0.013)	(0.017)	(0.026)	(0.009)	
Tampa	2.91	2.55	8.49	5.33	8.22	3.38	11/2017
	(0.007)	(0.010)	(0.023)	(0.022)	(0.031)	(0.009)	
Washington	2.46	0.97	5.65	4.15	6.78	4.17	01/1988
	(0.013)	(0.006)	(0.016)	(0.011)	(0.019)	(0.009)	

Notes. This table presents pre-COVID, COVID and post-COVID averages with standard error in parentheses of 12-month, all-items inflation rate and unemployment rate for the 21 Metropolitan Statistical Areas in our sample. In the last column, we report the starting collection date of CPI data.

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Table A.2: IV Estimates of ψ from Equation (5) with different inflation measures

	(1) All Items	(2) No Energy	(3) Core	(4) No Shelter
Pre-COVID				
u_{it}	-0.25	-0.27	-0.25	0.06
	(0.15)	(0.17)	(0.19)	(0.11)
$\hat{p}^x_{it}$	0.06**	0.05*	0.05**	0.13**
	(0.03)	(0.02)	(0.02)	(0.05)
z^y_{it}	0.13	0.14	0.13	0.04
	(0.09)	(0.11)	(0.15)	(0.05)
COVID				
u_{it}	0.02	0.02	0.03	-0.05
	(0.07)	(0.06)	(0.06)	(0.08)
$\hat{p}^x_{it}$	0.33***	0.09	0.13*	0.32**
	(0.08)	(0.06)	(0.07)	(0.14)
z^y_{it}	0.01	0.03	0.01	0.04
	(0.04)	(0.03)	(0.03)	(0.06)
Post-COVID				
u_{it}	-0.85**	-0.81***	-0.71**	-1.11**
	(0.34)	(0.25)	(0.25)	(0.40)
$\hat{p}^x_{it}$	0.20***	0.05	0.02	0.33***
	(0.04)	(0.03)	(0.03)	(0.04)
z^y_{it}	-0.14	-0.29**	-0.23	-0.47**
	(0.16)	(0.12)	(0.15)	(0.19)
Observations	5862	5862	5862	5862
MSA-Period FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID (i.e., from January 1990 to February 2020), COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods. Column (1) uses 12-month, all-items inflation rate as dependent variable - our benchmark outcome variable. Column (2) uses 12-month all-items excluding energy inflation rate as dependent variable. Column (3) uses 12-month, core inflation rate (i.e., all items excluding food and energy) as dependent variable. Column (4) uses 12-month, all-items excluding shelter inflation rate as dependent variable. All specifications control for MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods), year-quarter fixed effects, intermediate-input prices relative to the corresponding CPI category, and the shift-share control variable z^y_{it}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it} and $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table A.3: IV Estimates of ψ from Equation (5) with v_{it} (V/U) measuring labor market tightness

	(1) All Items	(2) No Energy	(3) Core	(4) No Shelter
COVID				
v_{it}	-0.014	-0.017	-0.021	0.044
	(0.057)	(0.037)	(0.040)	(0.064)
$\hat{p}^{x}_{it}$	0.355	0.093	0.135	0.103
	(0.237)	(0.097)	(0.107)	(0.352)
z^{y}_{it}	-0.034	0.017	-0.012	0.009
	(0.063)	(0.040)	(0.051)	(0.068)
Post-COVID				
v_{it}	0.041***	0.041***	0.038***	0.052***
	(0.013)	(0.011)	(0.013)	(0.014)
$\hat{p}^{x}_{it}$	0.004	-0.113	-0.129	-0.004
	(0.104)	(0.075)	(0.082)	(0.128)
z^{y}_{it}	-0.147	-0.286**	-0.252**	-0.410**
	(0.123)	(0.103)	(0.114)	(0.158)
Observations	630	630	630	630
MSA-Period FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) using v_{it} (i.e., the vacancy-to-unemployment ratio) as a measure of labor market tightness for the COVID (i.e., from March 2020 to February 2021) and post-COVID (i.e., from March 2021) periods. Columns (1) to (4) use the 12-month, all-items inflation rate, all-items excluding energy inflation rate, core inflation rate (i.e., all items excluding food and energy), and all-items excluding shelter inflation rate as dependent variables, respectively. All specifications control for MSA fixed effects (allowed to shift across the COVID and post-COVID periods), year-quarter fixed effects, relative intermediate-input prices, and the shift-share control variable z^{y}_{it}. All columns display IV estimates of ψ obtained by instrumenting v_{it} with the shift-share instrument z^{x}_{it} and $\hat{p}^{x}_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table A.4: IV Estimates of ψ from Equation (5) for different pre-COVID periods

	(1) From 1990	(2) From 2000	(3) From 2010	(4) COVID	(5) Post-COVID
u_{it}	-0.25	-0.10	-0.18	0.02	-0.85**
	(0.15)	(0.26)	(0.14)	(0.07)	(0.34)
$\hat{p}_{it}^{x}$	0.06**	0.12***	0.01	0.33***	0.20***
	(0.03)	(0.03)	(0.04)	(0.08)	(0.04)
z_{it}^{y}	0.13	0.24*	0.22*	0.01	-0.14
	(0.09)	(0.12)	(0.10)	(0.04)	(0.16)
Observations	5211	3652	1852	252	399
MSA-Period FE	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID, COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods and assesses the sensitivity of the estimates to differences in the definition of the pre-COVID period. Column (1) defines the pre-COVID sample period from January 1990 to February 2020. Column (2) defines the pre-COVID sample period from January 2000 to February 2020. Column (3) defines the pre-COVID sample period from January 2010 to February 2020. Columns (4) and (5) report our preferred estimates from Table 2, column (5), for COVID and post-COVID periods. All specifications use 12-month, all-items inflation as the outcome variable and control for MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods), year-quarter fixed effects, relative intermediate-input prices, and the shift-share control variable z_{it}^{y}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z_{it}^{x} and $\hat{p}_{it}^{x}$ with $\hat{p}_{it}^{x*}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table A.5: IV Estimates of ψ from Equation (5) with proxy of local inflation expectations

	(1) All Items	(2) No Energy	(3) Core	(4) No Shelter
Pre-COVID				
u_{it}	-0.20	-0.23	-0.21	0.07
	(0.14)	(0.15)	(0.18)	(0.09)
$\hat{p}^x_{it}$	0.04*	0.05*	0.05**	0.06*
	(0.02)	(0.02)	(0.02)	(0.03)
π^{gas}_{it}	0.04***	-0.00	-0.00	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
z^y_{it}	0.13	0.14	0.13	0.05
	(0.09)	(0.12)	(0.16)	(0.05)
COVID				
u_{it}	0.05	0.04	0.05	-0.00
	(0.06)	(0.06)	(0.06)	(0.07)
$\hat{p}^x_{it}$	0.03	-0.02	0.00	0.04
	(0.07)	(0.06)	(0.07)	(0.11)
π^{gas}_{it}	0.05***	0.02**	0.03**	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
z^y_{it}	0.00	0.02	0.00	0.03
	(0.04)	(0.03)	(0.03)	(0.06)
Post-COVID				
u_{it}	-0.84**	-0.76**	-0.66**	-1.11**
	(0.35)	(0.27)	(0.28)	(0.39)
$\hat{p}^x_{it}$	0.21**	0.10	0.06	0.30***
	(0.09)	(0.07)	(0.07)	(0.06)
π^{gas}_{it}	-0.00	-0.02	-0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.01)
z^y_{it}	-0.12	-0.16	-0.13	-0.51**
	(0.20)	(0.17)	(0.19)	(0.21)
Observations	5646	5646	5646	5646
MSA-Period FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID (i.e., from January 1990 to February 2020), COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods, controlling for a proxy of local inflation expectations. Column (1) uses 12-month, all items inflation rate as dependent variable - our benchmark outcome variable. Column (2) uses 12-month all-items excluding energy inflation rate as dependent variable. Column (3) uses 12-month, core inflation rate (i.e., all-items excluding food and energy) as dependent variable. Column (4) uses 12-month, all-items excluding shelter inflation rate as dependent variable. All specifications control for MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods), year-quarter fixed effects, intermediate-input prices relative to the corresponding CPI category, gasoline inflation in MSA i in period t that proxies for local inflation expectations, and the shift-share control variable z^y_{it}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it} and $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table A.6: IV Estimates of ψ from Equation (5) with more stringent MSA-time FE

	(1)	(2)	(3)	(4)
Pre-COVID				
u_{it}	-0.25	-0.02	-0.12	-0.16
	(0.15)	(0.20)	(0.13)	(0.10)
$\hat{p}^x_{it}$	0.06**	0.31***	0.29***	0.33***
	(0.03)	(0.03)	(0.03)	(0.03)
z^y_{it}	0.13	0.05	0.02	0.02
	(0.09)	(0.03)	(0.02)	(0.02)
COVID				
u_{it}	0.02	-0.00	-0.04	-0.04
	(0.07)	(0.06)	(0.05)	(0.06)
$\hat{p}^x_{it}$	0.33***	0.30***	0.22***	0.15***
	(0.08)	(0.06)	(0.05)	(0.04)
z^y_{it}	0.01	0.00	-0.00	0.01
	(0.04)	(0.04)	(0.03)	(0.03)
Post-COVID				
u_{it}	-0.85**	-1.01***	-1.33***	-1.33***
	(0.34)	(0.29)	(0.29)	(0.25)
$\hat{p}^x_{it}$	0.20***	0.19***	0.17***	0.16***
	(0.04)	(0.04)	(0.03)	(0.03)
z^y_{it}	-0.14	-0.36***	-0.40***	-0.41***
	(0.16)	(0.08)	(0.10)	(0.11)
Observations	5862	5858	5858	5816
MSA-Period FE	✓			
MSA-Year FE		✓		
MSA-Year-Semester FE			✓	
MSA-Year-Quarter FE				✓
Year-Quarter FE	✓	✓	✓	

Notes. This table presents estimates of ψ from Equation (5) for the pre-COVID (i.e., from January 1990 to February 2020), COVID (i.e., from March 2020 to February 2021), and post-COVID (i.e., from March 2021) periods to assess the sensitivity of the estimates to the inclusion of more stringent MSA-time fixed effects. Column (1) reports our preferred estimates from Table 2, column (4), with MSA fixed effects (allowed to shift across the pre-COVID, COVID, and post-COVID periods). Column (2) controls for MSA-year fixed effects. Column (3) controls for MSA-year-semester fixed effects. Column (4) controls for MSA-year-quarter fixed effects. All specifications use 12-month, all-items inflation as the outcome variable and control for relative intermediate-input prices and the shift-share control variable z^y_{it}. All columns display IV estimates of ψ obtained by instrumenting u_{it} with the shift-share instrument z^x_{it} and $\hat{p}^x_{it}$ with $\hat{p}^{x*}_{it}$. Standard errors in parentheses are clustered at the MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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B Model

B.1 Households Problem

The representative household in H seeks to maximize

$$E_0 \sum_{t=0}^{\infty} \beta^t u(C_{Ht}, N_{Ht}).$$

Households have CES preferences over varieties and GHH preferences over the final consumption good aggregator and labor, such that

$$u(C_{Ht}, N_{Ht}) = \frac{\left(C_{Ht} - \chi_{Ht} \frac{N_{Ht}^{1+\phi^{-1}}}{1+\phi^{-1}}\right)^{1-\sigma^{-1}}}{1-\sigma^{-1}},$$

where χ_{Ht} is an exogenous variable governing the intensity of disutility of labor, ϕ denotes the Frisch elasticity of labor supply, and

$$C_{Ht} = \Big[\int_0^1 C_{Ht}(z)^{\frac{\theta-1}{\theta}} \, dz \Big]^{\frac{\theta}{\theta-1}},$$

where $C_{Ht}(z)$ denotes consumption of variety z in H. The parameter $\theta > 1$ denotes the elasticity of substitution between different varieties. The representative household is subject to the following budget constraint

$$\int_0^1 C_{Ht}(z) P_{Ht}(z) \, dz + E_t[M_{Ht,t+1} B_{H,t+1}] \leq B_{Ht} + W_{Ht} N_{Ht} + \int_0^1 \Pi_{Ht}(z) \, dz,$$

where $P_{Ht}(z)$ denotes the price of variety z, B_{Ht} is a random variable denoting payoffs of the state contingent portfolio held in period t, $M_{Ht,t+1}$ is the one-period-ahead stochastic discount factor, W_{Ht} denotes the nominal wage rate, $\Pi_{Ht}(z)$ are the profits of the firm producing variety z. There is a complete set of financial markets across the two regions. To rule out Ponzi schemes, we assume that household debt cannot exceed the present value of future income in any state.

Households in H trade off current consumption, C_{Ht} and current labor supply, N_{Ht}. Given that the utility function is assumed to have a GHH form, the optimal labor supply takes the following form:

$$\chi_{Ht} N_{Ht}^{\phi^{-1}} = \frac{W_{Ht}}{P_{Ht}}, \tag{B.1}$$

where P_{Ht} denotes the lowest cost of purchasing a unit of the composite consumption good C_{Ht}.

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Households optimally trade off consumption in the current and in the next periods, as captured by the following Euler equation:

$$\left(C_{Ht} - \chi_{Ht}\frac{N_{Ht}^{1+\phi^{-1}}}{1+\phi^{-1}}\right)^{-\frac{1}{\sigma}} = \beta R_t E_t\left[\left(C_{Ht+1} - \chi_{Ht}\frac{N_{Ht+1}^{1+\phi^{-1}}}{1+\phi^{-1}}\right)^{-\frac{1}{\sigma}}\frac{P_{Ht}}{P_{Ht+1}}\right], \tag{B.2}$$

where R_t is the gross nominal interest rate, common to both H and F. Furthermore, household optimization implies that a standard transversality condition must hold, and that the stochastic discount factor takes a standard form.

Households choose how much to purchase of each variety, $C_{Ht}(z)$, in order obtain the desired level of consumption C_{Ht} at a minimal expense. The minimization problem implies the following demand curve for variety z:

$$C_{Ht}(z) = C_{Ht}\left(\frac{P_{Ht}(z)}{P_{Ht}}\right)^{-\theta} \tag{B.3}$$

and the following price index:

$$P_{Ht} = \left[\int_0^1 P_{Ht}(z)^{1-\theta}dz\right]^{\frac{1}{1-\theta}}. \tag{B.4}$$

The problem is analogous for the representative household in F.

B.2 Commodity Sector

Commodities are supplied by an international market, according to the following production process:

$$P_t^o = c_t^o O_t,$$

where P_t^o is the international price of commodities, c_t^o is an exogenous marginal cost shock, and O_t is the quantity of commodity produced.

B.3 Intermediate-Input Sector

The intermediate-input sector is tradable and is characterized by perfect competition. Hence, the price of intermediate input, P_t^x, is common across the two regions. The representative firm in H uses commodity O_{Ht} and labor N_{Ht}^x to produce a homogeneous good, according to the following production function

$$X_{Ht} = A_{Ht}^x N_{Ht}^{x\gamma} O_{Ht}^{1-\gamma},$$

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where A^X_{Ht} denotes local exogenous technology of the intermediate-input sector. In every period, the representative firm solves the static maximization problem

$$\max_{O_{Ht}, N^x_{Ht}} \; P^x_t A^x_{Ht} O_{Ht} - W_{Ht} N^x_{Ht} - P^o_t O_{Ht},$$

implying the following demands for commodity and labor:

$$P^o_t O_{Ht} = (1-\gamma) MC^x_{Ht} X_{Ht}, \tag{B.5}$$

$$W_{Ht} N^x_{Ht} = \gamma MC^x_{Ht} X_{Ht}, \tag{B.6}$$

where $MC^x_{Ht} = \frac{1}{A_{Ht^x}} \left(\frac{W_{Ht}}{\gamma}\right)^{\gamma} \left(\frac{P^o_t}{1-\gamma}\right)^{1-\gamma}$. The problem for intermediate-input firms in F is analogous.

B.4 Final-Goods Sector

The final-goods sector in H is composed by a continuum of monopolistically competitive firms indexed by z. Each firm specializes in the production of a differentiated good consumed locally. The production function is characterized by constant returns to scale

$$Y_{Ht}(z) = A^y_{Ht} X_{Ht}(z)^{1-\alpha} N^y_{Ht}(z)^{\alpha},$$

where A^y_{Ht} denotes local productivity of the final-goods sector, and $X_{Ht}(z)$ and $N^y_{Ht}(z)$ denote, respectively, the quantity of intermediate good and labor used by firm z. Final-goods firm z maximizes

$$E_t \sum_{k=0}^{\infty} M_{Ht,t+k} [P_{Ht+k}(z) Y_{Ht+k}(z) - W_{Ht+k} N_{Ht+k}(z) - P^x_{t+k} X_{t+k}]$$

subject to the production technology and

$$Y_{Ht}(z) = Y_{Ht} \left(\frac{P_{Ht}(z)}{P_{Ht}}\right)^{-\theta},$$

which denotes the demand for its product. The maximization problem takes this dynamic form as, in each period, final-goods producers are able to reset their price only with probability $a < 1$. The optimal choices of labor and intermediate input imply the following demand curves:

$$W_{Ht} N_{Ht}(z) = \alpha MC^y_{Ht} Y_{Ht}, \tag{B.7}$$

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$$P_t^x X_{Ht}(z) = (1-\alpha) MC_{Ht}^y Y_{Ht}, \tag{B.8}$$

where $MC_{Ht}^y = \frac{1}{A_{Ht}^y}\left(\frac{P_{Ht}^x}{1-\alpha}\right)^{1-\alpha}\left(\frac{W_{Ht}}{\alpha}\right)^{\alpha}$. If firm z is able to reoptimize its price in t, it will set $P_{Ht}(z)$ to satisfy

$$\sum_{k=0}^{\infty} a^k E_t \left[M_{Ht,t+k} Y_{Ht+k}(z) \left(\frac{P_{Ht}(z)}{P_{Ht-1}} - \frac{\theta}{\theta-1} RMC_{Ht+k}^y \frac{P_{Ht+k}}{P_{Ht-1}} \right) \right] = 0, \tag{B.9}$$

where $M_{Ht,t+k}$ is the stochastic discount factor between period t and $t+k$ and $RMC_{Ht}^y = \frac{MC_{Ht}^y}{P_{Ht}}$ denotes real marginal costs. Intuitively, the firm will set its price to be equal to a constant markup, $\frac{\theta}{\theta-1}$, over a weighted average of current and expected future marginal costs, as with probability a^k the firm will not be able to change price in future period $t+k$. The problem for final-goods firms in F is analogous.

B.5 Monetary Authority

The monetary authority implements a common monetary policy across the two regions following the Taylor rule

$$r^n = \phi_\pi(\pi_t - \bar{\pi}_t) - \phi_u(\hat{u}_t - \bar{u}_t) + \varepsilon_{rt},$$

where hatted variables represent deviations from a zero-inflation steady state and lower-case variables are logs of upper-case variables. $\pi_t = \zeta\pi_{Ht} + (1-\zeta)\pi_{Ft}$ denotes economy-wide inflation, where $\pi_{Ht} = p_{Ht} - p_{Ht-1}$ is consumer price inflation in H and π_{Ft} is the counterpart in F. Within this framework, we define unemployment in H as $u_{Ht} = 1 - N_{Ht}$. Then, to a first order approximation, $\hat{u}_{Ht} = -\hat{n}_{Ht}$, and the same applies in F. Hence, $\hat{u}_t = -\hat{n}_t = -(\zeta\hat{n}_{Ht} + (1-\zeta)\hat{n}_{Ft})$ denotes the deviation of aggregate unemployment rate from its steady-state value. Finally, $\bar{\pi}_t$ represents a time-varying inflation target. We assume that the monetary authority targets an unemployment rate consistent with its long-run inflation target, i.e. $\bar{u}_t = \frac{(1-\beta)\bar{\pi}_t}{\kappa}$. Finally, ϕ_π and ϕ_u ensure a unique locally bounded equilibrium, and ε_{rt} denotes a transitory monetary shock, assumed to follow an AR(1) process. The model in its simplest form abstracts from fiscal policy, as the government does not tax, spend, nor issues debt, and monetary policy has no fiscal implications.

B.6 Derivation of Regional and Aggregate Phillips Curve

Log-linearazing Equation (B.9) around the zero inflation steady state yields

$$p_{Ht}(z) - p_{Ht-1} = (1-a\beta)\sum_{k=0}^{\infty}(a\beta)^{\kappa} E_t \left[\hat{mc}_{Ht+k} - (p_{Ht+k} - p_{Ht-1}) \right],$$

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where

$$\hat{mc}_{Ht} = -\hat{a}^y_{Ht} + (1-\alpha)(p^x_{Ht} - p_{Ht}) + \alpha(\hat{w}_{Ht} - p_{Ht}). \tag{B.10}$$

Rearranging the equation, we obtain

$$p_{Ht}(z) - p_{Ht-1} = a\beta E_t \left[p_{Ht+1}(z) - p_{Ht}\right] + (1-a\beta)\hat{mc}_{Ht} + \pi_{Ht}, \tag{B.11}$$

where π_{Ht} is derived from the definition of the price index in Equation (B.4). Indeed, only $(1-a)$ firms are able to reset their price, and since they are faced by the same probability of changing price in the future and the same current and expected same marginal costs, they will choose the same price P^*_{Ht}. Hence, the price index becomes

$$P_{Ht}^{1-\theta} = aP_{Ht-1}^{1-\theta} + (1-a)P_{Ht}^{*1-\theta}.$$

Taking a log-linear approximation of this last expression yields

$$p_{Ht} = ap_{Ht-1} + (1-a)p^*_{Ht},$$

which implies

$$\pi_{Ht} = (1-a)(p^*_{Ht} - p_{Ht}). \tag{B.12}$$

Substituting Equation (B.12) in Equation (B.11), after some manipulations we obtain

$$\pi_{Ht} = \beta E_t \pi_{Ht+1} + \lambda \hat{mc}_{Ht}, \tag{B.13}$$

where

$$\lambda = \frac{(1-a\beta)(1-a)}{a}.$$

The log-linearized equation of the labor supply is

$$\hat{w}_{Ht} - p_{Ht} = \hat{\chi}_{Ht} + \phi^{-1}\hat{n}_{Ht}. \tag{B.14}$$

Combining Equations (B.10) and (B.14), we get

$$\hat{mc}_{Ht} = -\hat{a}^y_{Ht} + (1-\alpha)(p^x_{Ht} - p_{Ht}) + \alpha(\hat{\chi}_{Ht} + \phi^{-1}\hat{n}_{Ht}). \tag{B.15}$$

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Substituting Equation (B.15) into Equation (B.13), we obtain the regional Phillips curve

$$\pi_{Ht} = \beta E_t \pi_{Ht+1} + \kappa \hat{n}_{Ht} + \underbrace{\lambda(1-\alpha)\hat{p}^x_{Ht} + \lambda\alpha\hat{\chi}_{Ht} - \lambda\hat{a}^y_{Ht}}_{\nu_{Ht}}, \tag{B.16}$$

where $\kappa = \lambda\alpha\phi^{-1}$ and $\hat{p}^x_{Ht} = p^x_{Ht} - p_{Ht}$. The regional cost-push shock, ν_{Ht}, is decomposed into three terms: $\hat{p}^x_{Ht}$, $\hat{\chi}_{Ht}$, and $\hat{a}^y_{Ht}$.

In order to derive the aggregate Phillips curve, we start by the definition of aggregate inflation, which is

$$\pi_t = \zeta\pi_{Ht} + (1-\zeta)\pi_{Ft}. \tag{B.17}$$

Substituting Equation (B.16) and its foreign counterpart into Equation (B.17), after some manipulation we obtain the aggregate Phillips curve

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \hat{n}_t + \underbrace{\lambda(1-\alpha)\hat{p}^x_t + \lambda\alpha\hat{\chi}_t - \lambda\hat{a}^y_t}_{\nu_t}, \tag{B.18}$$

as

- $\hat{n}_t = \zeta\hat{n}_{Ht} + (1-\zeta)\hat{n}_{Ft}$,
- $p^x_t = \zeta p^x_{Ht} + (1-\zeta)p^x_{Ft}$,
- $p_t = \zeta p_{Ht} + (1-\zeta)p_{Ft}$,
- $\hat{\chi}_t = \zeta\hat{\chi}_{Ht} + (1-\zeta)\hat{\chi}_{Ft}$,
- $\hat{a}^y_t = \zeta\hat{a}^y_{Ht} + (1-\zeta)\hat{a}^y_{Ft}$.

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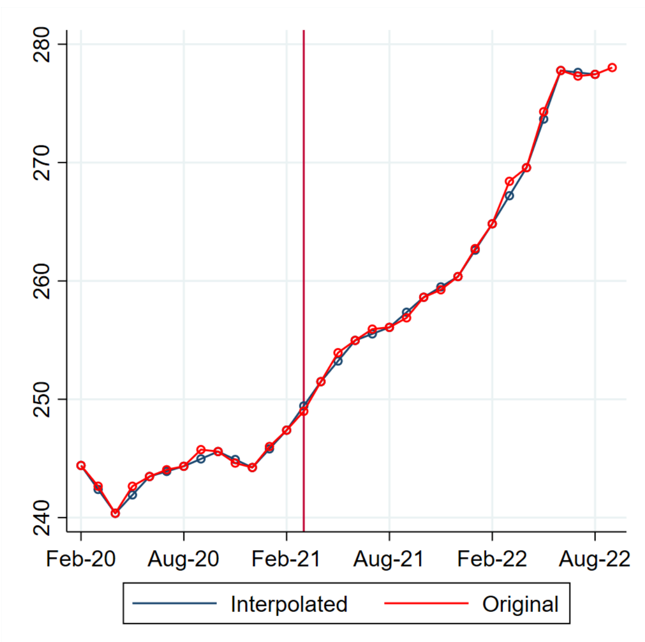
C Interpolation

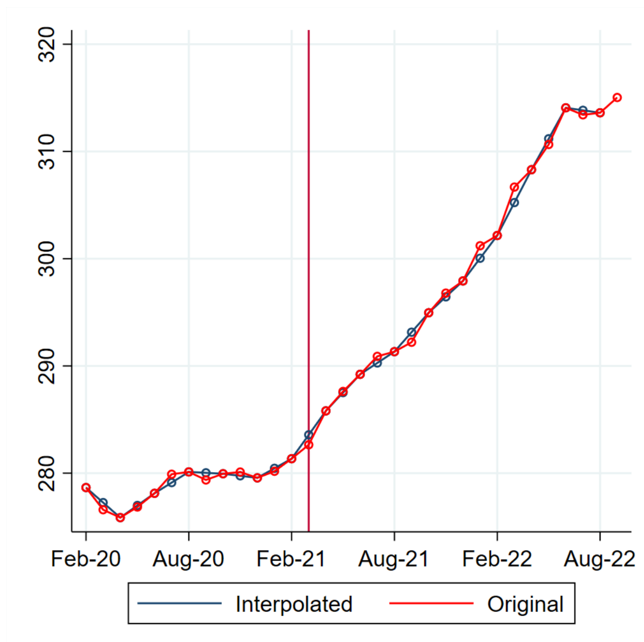
As discussed in Section 3, the CPI data we use from the BLS are made available at a monthly frequency for three metropolitan areas (i.e., Chicago-Naperville-Elgin, Los Angeles-Long Beach-Anaheim, and New York-Newark-Jersey City) and at a bi-monthly frequency for all other MSAs. We linearly interpolate the data for all MSAs for which the CPI is made available at a bi-monthly frequency. On the one hand, by doing so, we obtain a larger sample size, which greatly benefits statistical power for parameter estimation in the post-COVID period, characterized by a narrow time window. On the other hand, our imputed measures of the CPI are affected by measurement error. In this Appendix section, we discuss how large the measurement error we introduce is likely to be and address potential concerns about the correlation between imputed inflation values and our instrument.

Figure C.1: Original vs. Interpolated CPI series, Chicago and Los Angeles (Feb 2020-Sep 2022)

(a) Chicago-Naperville-Elgin (IL-IN-WI)



(b) Los Angeles-Long Beach-Anaheim (CA)



Notes. The figure compares original and linearly interpolated time series of the all-items CPI for Chicago-Naperville-Elgin (C.1a) and Los Angeles-Long Beach-Anaheim (C.1b) from February 2020 to September 2022. The blue line denotes the interpolated time series, while the red line denotes the original time series. The interpolated series are produced by imputing odd months observations. The vertical line indicates the beginning of the post-COVID period, starting in March 2021.

To evaluate how large the interpolation measurement error might be, we conduct the following exercise. For the three metropolitan areas for which CPI data are reported at a monthly frequency, we produce interpolated CPI time series, by declaring CPI observations missing in odd (or even) months

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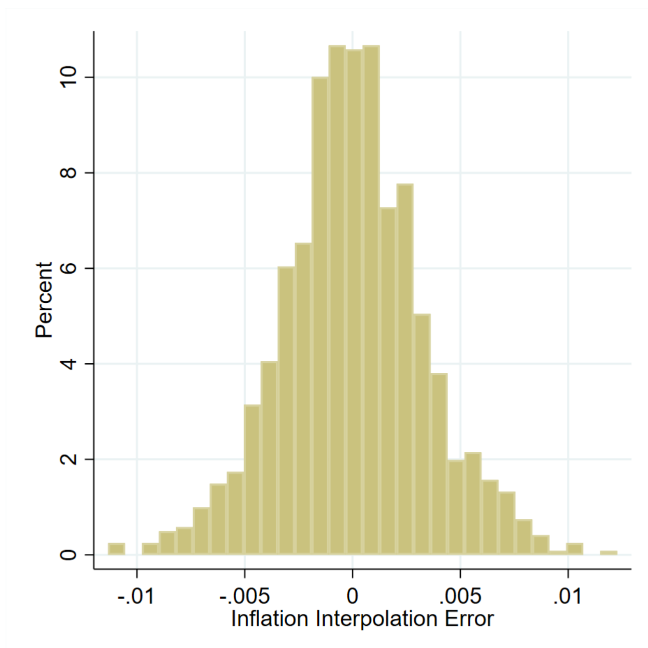
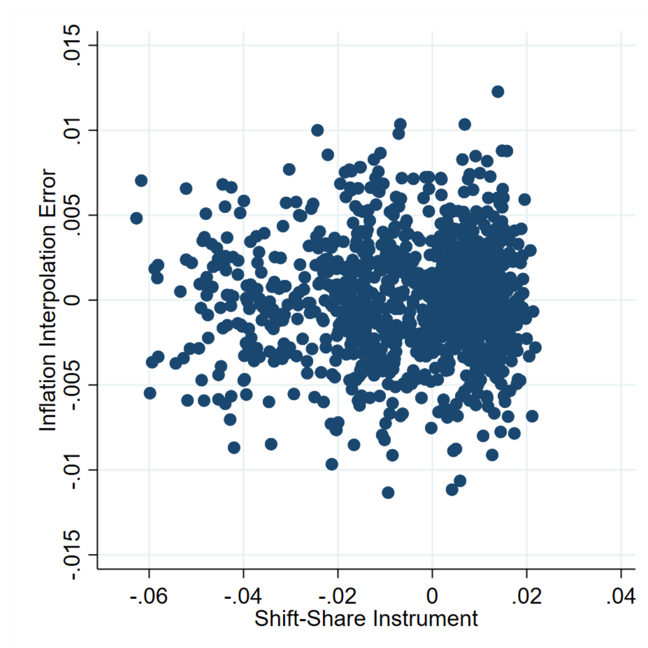
and imputing them through linear interpolation. Next, we compare the original CPI time series with the interpolated one, and compute measurement errors for imputed observations. Figure C.1 compares original and linearly interpolated time series of the CPI obtained by imputing observations in odd months for Chicago-Naperville-Elgin and Los Angeles-Long Beach-Anaheim from February 2020 to September 2022. The interpolated series match closely the original ones for both MSAs. Provided that measurement error is not systematically different for imputed observations in Chicago-Naperville-Elgin, Los Angeles-Long Beach-Anaheim, and New York-Newark-Jersey City, imputed observations for all other MSAs should closely approximate true values.

Figure C.2: Inflation Interpolation Error Distribution and Correlation with z_{it}^x

(a) Inflation Interpolation Error Distribution



(b) Scatter Plot: Inflation Intepolation Errors vs. z_{it}^x



Notes. The figure shows the distribution of inflation interpolation errors in for Chicago-Naperville-Elgin, Los Angeles-Long Beach-Anaheim, and New York-Newark-Jersey City (C.2a) and plots them against the shift-share variable z_{it}^x that we use to instrument u_{it} in Equation 5 (C.2b). The distribution of inflation interpolation errors pools errors obtained by imputing odd- and even-month observations in the three aforementioned MSAs. The coefficient of a linear regression with inflation interpolation errors as an outcome variable and the shift-share instrument as regressor is 0.002 (0.005).

We can construct interpolated inflation series by computing the 12-month percent difference in the interpolated CPI series. The interpolated inflation series for all MSAs are also characterized by measurement error with respect to the original ones. However, to the extent that such error terms are not systematically correlated with the exogenous instrument z_{it}^x, our estimates of ψ should not be biased. Figure C.2 shows the pooled distribution of inflation interpolation errors computed in odd and even

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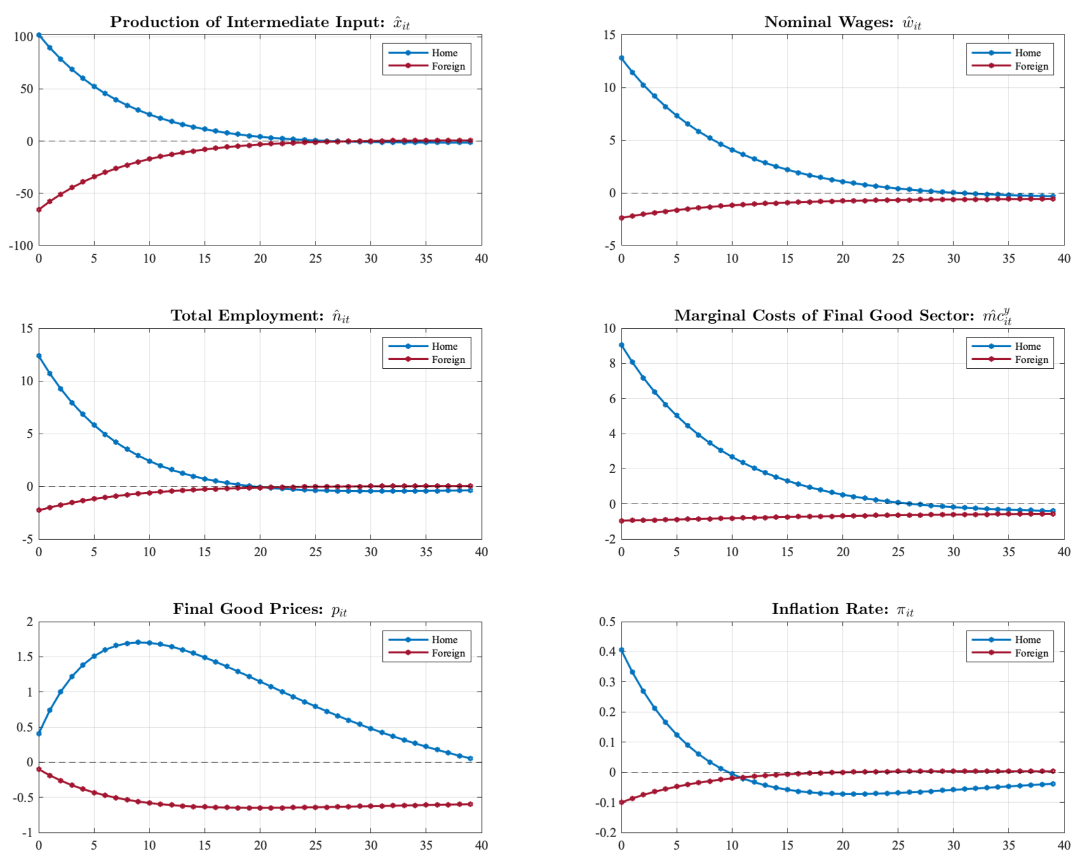
months for Chicago-Naperville-Elgin, Los Angeles-Long Beach-Anaheim, and New York-Newark-Jersey City (left panel) and plots them against the shift-share instrument z_{it}^{x} (right panel). As the right panel shows, there is no correlation between inflation interpolation errors and our instrument. Therefore, linearly interpolating our outcome variable allows us to exploit to the full extent the exogenous variation stemming from our instrumental variable.

D Empirical Strategy: Model-Based Impulse Response Functions

In this Appendix section, we illustrate through the model the mechanisms at the basis of our identification strategy. Figure D.1 shows the impulse response functions of the main endogenous variables in our model to an intermediate-input sector productivity shock in region H.

Figure D.1: Impulse Response Functions to Intermediate Sector Productivity Shock



Notes. The figure shows the impulse response functions over 40 periods of the main endogenous variables in our model to an intermediate-input sector productivity shock in region H. The blue lines refer to IRFs in region H, while the red lines refer to IRFs in region F. From the upper-left panel to the lower-right panel, the figure displays the IRFs of (i) production of intermediate input, (ii) nominal wages, (iii) total employment, (iv) final-goods sector's marginal costs, (v) final-goods prices, (vi) inflation rate.

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As a result of this shock, the production of intermediate input significantly increases in H and decreases to a lesser extent in F. Higher productivity in the intermediate-input sector in H increases labor demand, thus raising equilibrium employment and nominal wages in H. Higher nominal wages cause final-goods sectors' marginal costs to increase, inducing final-goods firms in H to raise prices and boost inflation. The opposite mechanism takes place with less intensity in F, thus generating the identifying cross-sectional variation we capture with our instrument z^x_{it}.

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