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Assessing the Role of Global Demand and Supply Shocks in the Recent US Inflation Experience Using a Cross-Country Panel Dataset of Professional Forecasts

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Abstract: Although there have been a range of studies investigating the role and importance of global supply and demand shocks in US inflation developments during and since the pandemic, this study uses a heretofore unused dataset for this purpose: a quarterly panel of professional forecasts from *Consensus Economics*. We use real-time data with daily vintage snapshots since 2005 from the Federal Reserve Board of Governors FAME database to disentangle forecast errors from revisions and to exploit the monthly frequency and partial availability of CPI inflation and industrial production. Our measures of global demand and supply shocks account for nearly 60 percent, and 20 percent, respectively, of the total variability of the five global factors we identify. The global demand shock accounts for a greater share of unanticipated US economic activity growth and inflation than the global supply shock both prior to the pandemic and during and after 2020. Since 2020, however, global demand and global supply shocks have accounted for similar shares of the nowcast errors for US inflation.

JEL classification: C32, E31, E37, F47

Key words: global shocks, professional forecasts, inflation

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Section 1: Introduction

Not unlike the so-called Great Inflation marking the volatile but generally rising period of inflation from the mid-1960s to the early 1980s, there has been a host of explanations for the rise and subsequent fall of inflation during and since the COVID-19 pandemic. Some of the major culprits identified for the most recent surge include, rapidly changing preferences for goods relative to services, large measures of fiscal and monetary stimulus, changes in labor force attachment and labor market tightness, disruptions of supply chains domestically and globally, and global shocks more generally. Very good summaries and analysis of this recent literature are provided by Lipinska et al. (2025) and Hajdini et al. (2025).

As we review in more detail below, such explanations are often grounded with a historical decomposition and often based on a model or a few key equations. Inflation decompositions are often based on a Phillips curve or a vector autoregression (VAR) that may or may not be structural. Even within one of these empirical approaches, modeling choices can play an important role in the results. For the Phillips curve this includes, what is the measure of slack used (unemployment rate and/or a job vacancy based measure), how are inflation expectations and lagged inflation measured and handled, are there any important nonlinearities, etc. For the VAR based approach, even more technical details can matter. Bergholt et al. (2024) and Giannone and Primiceri (2024) discuss the importance of how the VAR's determenistic components are handled with the Bayesian priors which many of the VAR based studies use.

There is a somewhat smaller literature on using subjective, often professional, forecasts to construct these sorts of decompositions. A noteworthy recent example is Bekaert et al. (2024) who use forecast errors of real GDP growth and inflation from the Federal Reserve Bank of Philadelphia's *Survey of Professional Forecasters* to identify a time series of supply and demand shocks for the U.S.

Less common is using cross country subjective forecasts for shock identification and decompositions[1]. As we discuss below, cross country empirical frameworks are often implemented with factor models since those are perhaps more naturally suited to identifying common shocks across countries than VARs are for instance. The International Monetary Fund is probably the most widely referred to source for global macroeconomic forecasts across countries. But most of those forecasts are for outcomes on an annual – or less commonly a fourth-quarter over fourth-quarter – basis making them less amenable to

[1] One partial exception is IMF (2022) and Koch and Noureldin (2024), who use recent IMF forecast across countries to explain recent inflation developments. These might be better thought of as case studies, since they use a small number of years.

the econometric shock decomposition frameworks that are utilize monthly or quarterly data. An alternative source of international forecasts is *Consensus Economics* (CE) which, as we describe in more detail below, has been collecting quarterly forecasts across countries since 1989. Work has been done evaluating these forecasts including Ager et al. (2009) and Crowe (2010) who find evidence of forecast inefficiencies common to other professional forecasts, Batchelor (2001), Timmerman (2007), and An et al. (2018) who compare CE and IMF forecasts and find the former more than hold their own[2], and Devereux et al. (2012) and Kwas et al. (2024) who evaluate exchange rate forecasts from the survey.

One reason perhaps why others haven't used CE forecast data to identify global shocks is because apart for the U.S., the forecasts aren't presented as one quarter growth rates. To best get around this issue requires using real-time data – so as to avoid forecast errors being contaminated by data revisions – which is as readily accessible for some countries/indicators as it is for the U.S. either at the original reporting agency (e.g. previously published GDP at the Bureau of Economic Analysis) or in the real-time databases maintained by the Federal Reserve Banks of Philadelphia and St. Louis. The use of real-time data also allows us to disaggregate the CPI inflation and industrial production forecasts from a quarterly basis to a monthly basis[3]. This disaggregation allows for a more precise identification of the forecast errors for these variables. As we discuss in further detail below, the quarterly CE forecasts are collected once a month in the third month of each quarter. For a number of the European countries in the sample, the only missing CPI data point for the quarter is for the last month[4]. Sticking with the original quarterly reporting frequency for cases like these would imply only capturing a forecast error for the last month of the quarter and it could be further clouded by data revisions for the first month or two of the quarter.

Our disaggregation of quarterly to monthly forecasts will effectively involve VAR based interpolation using constrained conditional forecasts that might be useful for others. Although we aren't aware of others using this exact approach, the Federal Reserve Bank of Philadelphia[5] and Aruoba (2016) convert a discrete set of inflation point forecasts into a full term structure from 3 months to 10 years, and *Blue Chip Econometric Detail*, a quarterly addendum to the monthly *Blue Chip Economics Indicators* publication, disaggregates

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[2] As Loungani et al. (2023) note, *Consensus Economics* forecasts have been used to assess the quality of the IMF forecasts.

[3] Even if CPI inflation and industrial production growth were collected on a one-quarter basis, the forecast error would be contaminated

[4] In particular, Germany, Italy, the Netherlands, and Switzerland have at least a so-called flash CPI estimate for 2 of the 3 months in the survey quarter for over 80 percent of the quarters in our sample. Conversely Canada, Japan, and the United Kingdom never have more than one CPI release available (though they do always have 1), while the United States has 2 CPI releases for the quarter at the time of the survey on only 4 occasions.

[5] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/atslx

forecasts across both the time (annual to quarterly) and panel dimensions (disaggregating GDP and partial subset of subcomponent forecasts into more granular subcomponent detail).

Our approach will allow us to identify a global demand and a global supply shock. The demand shock explains a greater share of the variation of both global and U.S. GDP growth and inflation since 2005, but the global demand and supply shocks account for fairly similar shares of U.S. inflation since 2020. Using a local projections approach we find some evidence that global demand and supply shocks have a peristent impact on measures of underlying US CPI inflation, but not as consistently or immediately as a domestic US shock.

Section 2 of this piece discusses the related literature on global and domestic demand supply shocks, focusing particularly on their impacts so far this decade. Section 3 discusses the merged real-time and Consensus Economics forecast datasets used and constructed for this study (An appendix has further details). Section 4 presents results on the global supply and demand shocks, their impacts on US inflation, and impulse response functions from a local projections based estimation. Section 5 concludes.

Section 2: Literature on global, demand, and supply shocks.

There has been a sizable recent literature on the role both global and supply/demand factors have played in inflation developments since the onset of the pandemic, only some of which we refer to here. As mentioned in the introduction, Lipinska et al. (2025) and Hadjini et al. (2025) provide good overviews.

A factor model decomposition by Cascaldi et al. (2024) found that a global component has explained a larger share of cyclical headline and core inflation in the 2020s across countries than it did in the 60 years prior to that despite it explaining smaller shares of consumer food and energy price inflation. A recursively (Cholesky) identified VAR model estimated that global demand, and to a lesser extent commodity prices, accounted for much of the runup of global inflation in 2021 and early 2022, before giving way to idiosyncratic country specific shocks in the latter part of that year. The first of a pair of New York Fed Liberty Street blog posts by Akinci et al. (2025 a, b) found that both in the 30 years before and after the onset of the pandemic, global factors accounted for much of U.S. inflation. The second of the pair of blogs found that supply, rather than demand, shocks accounted both for much of the run-up in trend global core goods inflation in 2021 and its subsequent decline.

Bai et al. (2024) constructed a measure of global supply chain disruption using container ship data and found that it played the largest role in the 2021 U.S. goods inflation increase.

Related work on supply chain issues by Comin et al. (2024) found that capacity constraints accounted for roughly half of the 2021-22 increase in U.S. inflation. Consistent with these findings, Bernanke and Blanchard (2025) find that commodity shocks and shortages accounted for much of the initial 2021-2023Q1 runup in U.S. inflation though they do find a not insignificant role for labor market tightness at the end of that period.

Somewhat at odds with these findings are Giannone and Primiceri (2024) and Bergholt et al. (2025) which find, for their preferred structural VAR specifications, that demand shocks accounted for a larger share of the 2021-22 runup in inflation in the U.S. (and the E.U.) than supply shocks. Studies also putting relatively more weight on demand, rather than supply, factors in the 2021-22 runup in U.S. inflation include Di Giovanni et al. (2023) and Benigno and Eggertsson (2024). As in Bernanke and Blanchard (2024), the latter of these studies uses a wage Phillips curves as one of the building blocks of their decomposition but unlike that work allows for a nonlinearity that causes the Phillips curve to be a steeper and labor demand shocks to become more powerful once a labor shortage regime threshold has been breached.

With statistical models using granular monthly PCE price and quantity subcomponent data, Shapiro (2022) and Leiva-León et al. (2025) are able to decompose PCE inflation into demand, supply, and 1 or 2 other components such as inflation expectations in the latter study. Estimates from those models, which are regularly updated by the Federal Reserve Banks of San Francisco and Boston[6], respectively, show that the runup of inflation from its 2017-19 average to its peak in 2022 was fairly evenly concentrated in demand and supply factors[7]. However, Dupor and Hogan (2025) using an extension of Shapiro's (2022) approach with granular PCE data find that demand factors were responsible for more of the 2021-22 run-up in inflation (nearly ¾ of it) than supply factors (just over ¼ of it).

More in common with our approach, Koch and Noureldin (2024) and IMF (2022) analyze inflation forecast errors – those from semiannual releases of and semiannual updates to the IMF *World Economic Outlook* – across countries to ascertain possible reasons why the 2021-22 runup of inflation was largely unanticipated across a wide range of countries via a difference in difference approach. Among them are underestimating, ex ante, the respective sizes and impacts of fiscal stimulus, supply chain disruptions, and labor market tightness. Using the IMF forecasts allows for a larger set of countries than we can use here with the CE

[6] See https://www.frbsf.org/research-and-insights/data-and-indicators/supply-and-demand-driven-pce-inflation/ and https://www.bostonfed.org/publications/current-policy-perspectives/2025/parsing-out-the-sources-of-inflation.aspx.

[7] The Leiva-León et al. (2025) increase in demand and supply contributions both round up to 2.1 percentage points. The Shapiro (2022) increase in the supply and demand contributions are both closer to 2.5 percentage points. Leiva-León et al. (2025) also includes contributions from inflation expectations and idiosyncratic factors while the remaining Shapiro (2025) contribution is labelled ambiguous.

forecasts but with a tradeoff of a lower frequency (annual vs. quarterly) and a shorter time span.

In summary, much of this literature finds a role for demand and supply shocks, either global or domestic, in the rise and fall of U.S. inflation this decade. But there is not a single consensus regarding the relative importance of these shocks.

Section 3: Real-time and Consensus Economic datasets used.

The historical dataset of professional forecasts used in this analysis is from *Consensus Economics*, which has been collecting macroeconomic forecasts for the G7 countries – Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States – since October 1989 and has expanded to more countries over the years in addition to the Euro Zone in 2002. The CE forecast survey and the variables collected for it are similar in some respects to the U.S. and international forecasts collected in *Blue Chip Economic Indicators* (BCEI) and the domestic only forecasts collected in the Federal Reserve Bank of Philadelphia's quarterly *Survey of Professional Forecasters*, but has some important differences with respect to those surveys. Like both the BCEI and the SPF surveys, the CE survey collects both annual and quarterly forecasts. But while the CE and BCEI surveys are administered monthly, only BCEI collects quarterly forecasts each month. The quarterly CE forecasts are always collected in the third month of a quarter, usually on the second Monday of that month, but sometimes on the first Monday (often in December). The SPF survey is administered around the 10th day of the middle month of each quarter, limiting the comparability of the shortest horizon quarterly U.S. "nowcasts" in the SPF and "late quarter" CE surveys. The BCEI forecasts are released on the 10th day of each month and administered around the 5th day, implying that the BCEI forecasts collected in the third month of each quarter are nearly contemporaneous with the late quarter CE surveys, allowing a mostly "fair" accuracy comparison which we will provide below.

For our purposes, the primary advantage of the "third-month of quarter" CE surveys over BCEI is that they include quarterly forecasts for the Euro Zone and a set of 12 countries: the G7 countries as well as the Netherlands, Norway, Spain, Sweden, and Switzerland. The BCEI international forecasts are for annual frequency outcomes only, limiting their applicability for business cycle analysis. Obviously, the quarterly CE forecasts are heavily concentrated in Europe and the euro area. The quarterly-frequency forecasts collected in the late quarter CE surveys are for growth rates of real GDP, real consumption, industrial production (IP), and the Consumer Price Index (CPI) as well as an end-of-quarter 3-month interest rate. Although the quarterly CE forecasts generally extend 6 or 7 quarters into the future, we restrict ourselves to using short-horizon nowcasts consistent with much of the data and literature on measuring economic surprises. For the U.S., both seasonally adjusted one-quarter annualized and four-quarter growth rates are collected. For the remaining countries however, only four-quarter growth forecasts are collected, presumably because some of the country/variable measures are primarily or only reported as 4-quarter (or 12-month) growth rates and for the consumer price index, only a non-seasonally adjusted index is available for some countries.

While sensible, use of four-quarter growth rates implies the forecast errors can and often will be a combination of a genuine forecast error for outcomes occurring after the last month or quarter that was available to forecasters at the time of the survey date and revisions to the data that are inside the four-quarter calculation window in consecutive surveys. To separate, as best possible, the genuine forecast errors from revisions we utilize real-time vintage data from the Federal Reserve Board of Governors' FAME database which includes end-of-day snapshots for U.S. and international macroeconomic variables since mid-May 2005. A somewhat related complication is that IP and CPI data are available at the monthly frequency for all of the countries. When the CE panelists make their forecasts of the quarter t over quarter t-4 IP and CPI growth rates, they often have the 12-month growth rate for both variables for the first month of quarter t, and sometimes, particularly for some of the Euro Zone countries, at least a "flash" estimate of the 12-month CPI inflation rate for the middle month of the quarter.

Between the third-month quarter t and quarter t+1 CE surveys, it will often be the case that h_t months of new 12-month growth rate data for quarter t are released and h_{t+1} months of reported 12-month growth rates in quarter t+1 are released, with $0 < h_t, h_{t+1} < 3$, and $h_t + h_{t+1} = 3$. This implies the forecast error variance for the third-month quarter t survey forecast of that same quarter's four-quarter growth rate of IP or CPI growth will depend on the value of h_t, which is usually between and including 0 and 2. This wouldn't be an issue for the beginning month of quarter BCEI forecasts of CPI inflation and IP growth in the U.S. To minimize this monthly/quarterly distortion for IP and CPI growth in the CE dataset, we use the FAME vintage data and a combination of seasonal adjustment (when needed), conditional forecasting, and temporal disaggregation to disaggregate the quarterly forecasts into monthly forecasts and evaluate the errors based on forecasts of, what will often be, 3-month growth or inflation rates. Further details are described in the data appendix.

Acharya et al. (2024) found that for the EA and the UK, Consensus Economics was somewhat less accurate than a few other alternative and professional forecasters for the 1- to 5- year horizon over the 2014-2023 period[8]. They didn't look at short term forecasts however. As evidence that these CE nowcasts are of high quality for the US, we compare the

[8] A more narrative discussion/presentation on the CE forecasts for the EA aggregate and countries for 2021-22 is available in .

CE mean absolute errors (MAE) for the US with the more well known BCEI forecast errors in Table 1 below. The two sets of forecast error metrics are generally very similar and often, the CE forecast MAEs are slightly smaller than the BCEI MAEs. In both the BCEI and the CE projections, the forecasts covering the pre-pandemic period are more accurate than the forecasts starting in 2020:Q4 with the notable exception of industrial production. Similar results are obtained with comparison of mean squared forecast errors or median absolute forecast errors. In most cases, both the CE and BCEI forecasts have exactly one of the three monthly CPI or IP reports for the survey quarter[9].

Table 1: Mean absolute forecast errors for U.S.

		Consensus Economics			**Blue Chip**		
		Current Q	Next Q	2-quarter	Current Q	Next Q	2-quarter
GDP	05q2-25q1	1.12	2.04	1.46	1.16	2.07	1.42
	05q2-19q3	0.77	1.11	0.84	0.78	1.11	0.83
	20q4-25q1	1.56	2.51	2.11	1.61	2.48	2.07
CPI	05q2-25q1	0.58	1.66	0.83	0.66	1.67	0.89
	05q2-19q3	0.53	1.48	0.79	0.61	1.49	0.82
	20q4-25q1	0.73	2.09	0.96	0.84	2.09	1.17
Consumption	05q2-25q1	1.15	2.08	1.29	1.17	2.12	1.29
	05q2-19q3	0.81	1.08	0.51	0.81	1.06	0.52
	20q4-25q1	1.18	2.32	2.17	1.24	2.36	2.20
IP	05q2-25q1	1.87	3.41	2.13	2.04	3.51	2.22
	05q2-19q3	1.69	2.67	1.61	1.81	2.78	1.74
	20q4-25q1	1.90	2.09	2.01	1.97	1.99	1.99

Sources:

Author calculations using data from Wolters Kluwer *Blue Chip Economic Indicators*, *Consensus Economics*, US Bureau of Economic Analysis, US Bureau of Labor Statistics, and Federal Reserve Board of Governors

Note: Forecast errors are constructed using final-month of quarter surveys from *Blue Chip Economic Indicators* and the "quarter-over-quarter" set of projections from *Consensus Economics*. The growth rate units are percentage points at annualized rates. "Current Q" refers to forecasts for the same quarter in which the survey is administered, "Next Q" refers to the forecasted growth rate for the subsequent quarter, and 2-quarter refers to the annualized 2-quarter growth rate for the subsequent quarter. Errors are evaluated using "first release" vintage estimates.

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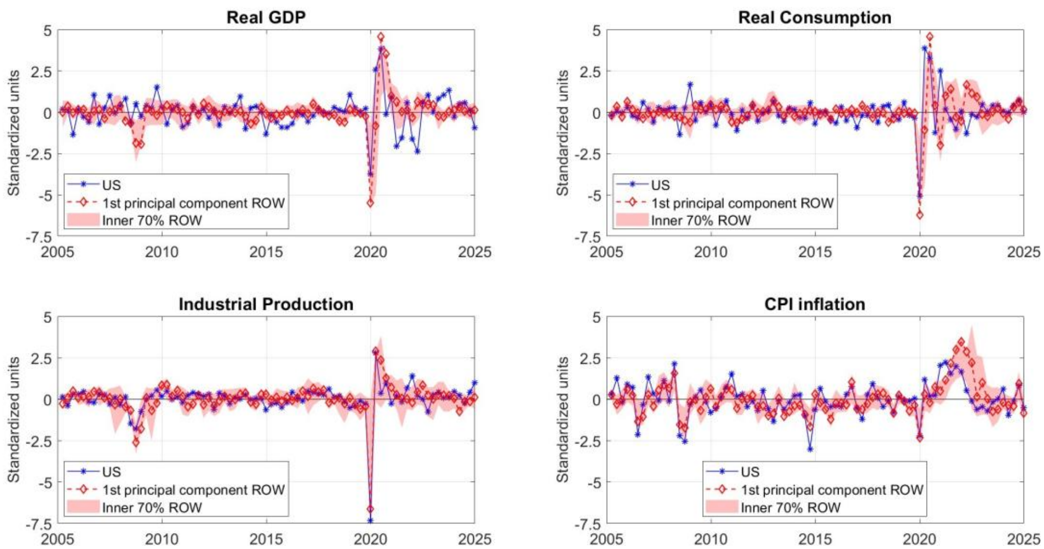
[9] The exceptions to this are the September 15, 2014 survey, which was the same day as the release of August 2014 industrial production, and the 9/14/2020, 6/14/2021, 3/14/2022, and 6/13/2022 CE surveys which were contemporaneous or preceded it.

Section 4: Results

Figure 1 below shows standardized nowcast errors both for the United States and the 11 countries outside of the United States for which the 4 non-financial variables shown are both collected and forecasted at the quarterly frequency. The errors are evaluated using first-release estimates since the current quarter nowcasts of GDP and consumption are likely based on first or early release values of monthly variables like retail sales, monthly consumer spending, etc. that, along with GDP and consumption, are later revised. The charts are very similar when the errors are based off "latest vintage" data.

Figure 1: Standardized Consensus Economist Nowcast Errors for United States and 11 Countries outside of it.



Note: X-axis is aligned with survey date (e.g. x=2020 corresponds to March 2020 survey). Real GDP and real consumption forecast errors for current-quarter logarithmic growth rate. For industrial production and CPI inflation, forecast error is for average monthly growth rate for the, on average, 3 months first reported in - between the third-month quarter t and quarter t+1 *Consensus Economics Surveys*. Forecast errors are evaluated using real-time "first-release" estimates. The 11 rest-of-world (ROW) countries included are Canada, France, Germany, Italy, Japan, The Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.

For each of the four indicators, after standardizing the errors, we compute the simple 11-country inner 70 percent range and the first principal component (PC) as shown in the chart[10]. We also show the standardized errors for the United States. For each variable, the

[10] Industrial production excludes Norway as we don't have real-time FAME data to evaluate the forecast errors. There are quarters, particularly for consumption and industrial production, where one or at most a

United States and "rest-of-world[11]" (ROW) first PC are all positively correlated, but with a lower correspondence with the quarterly GDP and consumption variables (r = 0.40 and 0.36, respectively) than with the 3-month average growth industrial production and CPI variables (r = 0.87 and 0.67, respectively).

Tables 2a and 2b below show the first principal component ROW factor loadings, with the first table using forecast errors based on first-release estimates and the second table using forecast errors based on latest vintage estimates. In the first table we can see all have positive values with one exception (Switzerland) and predominantly have weights between 0.05 and 0.15. The coefficients in the second table are qualitatively similar. In the analysis below we use errors based on latest vintage estimate so as to purge statistical agency measurement error from the global shocks as best as possible.

Table 2a: First principal component factor weights for non-US countries (Real-time)

	Real GDP	Real Consumption	Industrial Production	Consumer Price Index
Canada	0.094	0.111	0.077	0.094
France	0.129	0.105	0.130	0.104
Germany	0.102	0.117	0.124	0.104
Italy	0.111	0.110	0.138	0.100
Japan	0.068	0.016	0.075	0.069
The Netherlands	0.099	0.102	0.033	0.080
Norway	0.044	0.080		0.080
Spain	0.109	0.098	0.118	0.094
Sweden	0.076	0.080	0.215	0.094
Switzerland	0.100	0.132	-0.012	0.096
United Kingdom	0.067	0.051	0.103	0.085

Note: Estimated using Stock and Watson (2002); factor weights normalized to sum to 1.0.

Table 2b: First principal component factor weights for non-US countries (Revised)

	Real GDP	Real Consumption	Industrial Production	Consumer Price Index
Canada	0.085	0.126	0.080	0.086
France	0.116	0.098	0.118	0.106
Germany	0.102	0.128	0.118	0.100
Italy	0.127	0.113	0.128	0.102

few country-indicator observations are missing. Thus, as is often used in the literature, the Stock and Watson (2002) procedure to estimate the first principal component with missing data is used.

[11] To simplify/shorten language, we refer to 12 surveyed countries outside of the U.S. as ROW for rest-of-world, keeping in mind that this includes a number of other countries with large economies.

Japan	0.065	0.021	0.066	0.065
The Netherlands	0.106	0.111	0.041	0.085
Norway	0.047	0.071		0.077
Spain	0.100	0.125	0.114	0.097
Sweden	0.089	0.057	0.264	0.096
Switzerland	0.085	0.048	-0.017	0.095
United Kingdom	0.078	0.100	0.088	0.092

Note: Estimated using Stock and Watson (2002); factor weights normalized to sum to 1.0.

To assess how well the principal components used for Table 2b may be capturing global shocks for each of the four indicators, Table 3 below shows the correlation of the US nowcast errors with the same for each of the other countries. The final row has the correlations of the principal components with weights in Table 2b with the corresponding US forecast errors for the same indicator. The correlation matrix entries are shaded as a heatmap with the darker shades of green indicating larger positive correlations and darker shades of red indicating stronger negative correlations. We see that the correlations are generally positive and that the principal component correlations with the US are often, and in the case of IP and the CPI always, higher than corresponding individual country correlations with the US. Also, the fact that the IP and CPI error correlations are relatively high suggests some efficacy in our conditional forecasting approach to converting quarterly forecasts to monthly forecasts for those two indicators. Also of interest is that the correlations with the three largest EU economies – Germany, France, and Italy – are often higher than the other correlations.

Table 3: Contemporaneous correlation of nowcast errors for US with same for other countries for 1-quarter or 3-month growth rates with other countries, entire 2005:Q3 - 2025:Q1 sample

	Real GDP	Real Consumption	Industrial production	CPI
Canada	**0.29**	**-0.02**	**0.57**	**0.67**
France	**0.43**	**0.81**	**0.84**	**0.56**
Germany	**0.29**	**0.33**	**0.84**	**0.45**
Italy	**0.52**	**0.72**	**0.78**	**0.47**
Japan	**0.09**	**-0.22**	**0.42**	**0.29**
Netherlands	**0.25**	**0.36**	**0.24**	**0.34**
Norway	**0.46**	**-0.03**		**0.34**
Spain	**0.06**	**0.10**	**0.68**	**0.65**
Sweden	**0.22**	**-0.30**	**0.27**	**0.38**
Switzerland	**0.41**	**0.45**	**-0.18**	**0.62**
United Kingdom	**-0.18**	**-0.19**	**0.47**	**0.48**

1st Principal Comp.	**0.40**	**0.36**	**0.87**	**0.69**

Sources:

Author calculations using data from *Consensus Economics*, US Bureau of Economic Analysis, US Bureau of Labor Statistics, and Federal Reserve Board of Governors

Note: Forecast errors are constructed using final-month of quarter surveys from *Consensus Economics*. Errors are evaluated using revised latest vintage estimates. Errors for implied forecasts for one quarter log changes are used for GDP and consumption while errors for implied average *n*-month industrial production and CPI log changes are used, where n is generally is 3 but on occasion may be 2 or 4 depending on the number of IP and CPI releases between consecutive end-of-quarter surveys.

To confirm the correlations in Table 3 aren't entirely driven by the early quarters of the pandemic, Table A2 in the appendix shows the same correlations after removing the observations for the first three quarters of 2020. Removing these observations partially, but usually not entirely, dampens these correlations. Moreover, the CPI and IP correlations exceed the same for GDP and consumption by an even greater margin in Table A2 on average than in Table 3. For GDP and consumption, only the last 3 weeks of the quarter occur after, rather than before, the point in time the forecasters make their projections. For these variables, the forecasters are trying to assess economic activity and outcomes that have largely already taken place but have not been reported by statistical agencies[12]. For the CPI and IP, there is often 7-to-8 weeks of future activity that genuinely needs to be forecasted and sometimes more. So, the higher CPI/IP correlations may result from commonality among future shocks than commonality across estimation errors for the recent past.

Tables 2 and 3 only have the one price measure – the overall Consumer Price Index – that we can use for estimating global shocks. Although the CPI is the only aggregate price measure in the CE surveys for which forecasts of quarterly variables are collected – forecasts of producer price indices are also collected but only on an annual outcome basis – the surveys also collect forecasted dollar values of oil prices both 3-months and 12-months ahead of the survey. As described in the data appendix, we convert forecasts of those oil prices into average monthly oil price growth forecasts contemporaneous – in aggregate -- with the average monthly ROW CPI inflation forecasts and include those oil price growth forecasts, after standardization and a second-stage principal component calculation along

[12] Ignoring the fact that some countries report monthly data on GDP and consumption that the forecasters may partially have in hand, and even more countries report related data like retail sales that may partially be available. This availability varies across countries.

with the 4 first principal components plotted in Figure 1. The weights from the second-stage principal component calculations are in Table 4 below.

Table 4: Rest of world principal component weights of forecast error principal components and oil price errors

	1st PC	2nd PC	3rd PC	4th PC	5th PC
Real GDP Error 1st PC	0.230	-0.148	-0.037	-0.179	0.435
Real Consumption Error 1st PC	0.222	-0.124	0.150	0.387	-0.022
Industrial Production Error 1st PC	0.227	-0.141	-0.149	-0.167	-0.416
Consumer Price Index Error 1st PC	0.168	0.271	0.344	-0.148	-0.063
Oil price error	0.152	0.316	-0.320	0.120	0.064
Variance share	57.8%	20.0%	11.3%	6.4%	4.4%

Note: Weights of all 5 principal components of 1st principal component errors plotted in Figure 1 and standardized oil price growth forecast errors. Weights are normalized so that their absolute values sum to 1 in each column. Errors are based off "latest" vintage data.

We can see that the first principal component for these 5 ROW aggregates has weights which are all positive and explain more than half of the total variability in the data. We label this as the global demand shock. The second principal component, which accounts for 20 percent of the variability in the data, has negative signs on the three real activity measures and positive signs on CPI and oil price inflation. Hence, we label this the “global supply” shock. The remaining principal components – which account for just over 20 percent of the variance – cannot be so easily labelled since both the price and the quantity variables have at least one positively and one negatively signed variable[13].

To separate the ROW and domestic impacts, we regress the US nowcast errors on a constant and the five ROW PCs with weights in Table 4 and interpret the residual as a combined “domestic”. The regression specifications for GDP and consumption differ a bit from the regression specifications used for CPI inflation and industrial production due to their different primitive frequencies (quarterly vs. monthly). For the former two variables, which we illustrate with GDP, we use the following specification:

[13] The results are only modestly different if we throw out the first three quarters of 2020, with the same sign pattern for the first two PCs that explain 49 percent and 22 percent, respectively, of the variability in the factors excluding those three quarters.

$$(1)\ e_t^{GDP,US} = \theta^{GDP} + \theta_{Gdem}^{GDP} Gdem_t + \theta_{Gdem}^{GDP} Gsup_t + \sum_{i=1}^{3} \theta_{Goth,i}^{GDP} Goth_{t,i} + u_t^{GDP,US},$$

where $e_t^{GDP,US}$ denotes the forecast error[14] for US real GDP growth (quarterly, log percentage points) in quarter t, the same quarter in which the survey is administered in its concluding month, $Gdem_t$, $Gsup_t$, and $Goth_{t,i}$,denote the global demand, global supply, and other global shocks, respectively, (also for quarter t), and $u_t^{GDP,US}$ denotes a domestic US GDP shock which may be a combination of idiosyncratic non-global supply and demand shocks. The specification for consumption is exactly symmetric.

For US CPI inflation and industrial production growth, which we illustrate with the former, we use the following specification:

$$(2)\ e_t^{j,\pi,US} = \theta^{\pi} + \theta_{Gdem}^{\pi} Gdem_{h(t,j)} + \theta_{Gdem}^{\pi} Gsup_{h(t,j)} + \sum_{i=1}^{3} \theta_{Goth,i}^{\pi} Goth_{h(t,j),i} + u_{h(t,j)}^{\pi,US}.$$

The primary notational difference between the GDP specification and the CPI inflation specification regards time. In the latter specification, $e_t^{j,\pi,US}$ is the “forecast” error for US CPI inflation in the *j*th month of quarter t. This forecast error is derived from the constructed monthly inflation forecast that is derived from the quarterly US CPI forecasts, oil price and implied dollar exchange rate forecasts also in the survey, and a conditional monthly Bayesian vector autoregression forecast as described in the appendix. The $h(t,j)$ term is a function that assumes the value t if the CPI report for the *j*th month of quarter t has not been released yet when the survey in the third month of quarter t is administered. Otherwise, $h(t,j)$ equals t-1. The $u_{h(t,j)}^{\pi,US}$ term is an aggregate domestic shock, for US CPI inflation in month *j* of quarter t.

Table 5: US forecast error regression on constant and 5 global factors (2005Q3-2025Q1)

	Real GDP	Real Consumption	Industrial Production	CPI
Global demand factor	1.06***	1.22***	7.55***	1.20***
	(0.22)	(0.19)	(0.81)	(0.17)
Global demand factor	-0.42*	-0.48**	-0.87	0.90***
	(0.22)	(0.19)	(0.81)	(0.17)

[14] For this exercise, we base the forecast errors on fully revised (current vintage) data. Qualitatively similar results hold using real-time errors.

R-squared	0.38	0.50	0.34	0.27

Source: Author calculations using data from Consensus Economics and Federal Reserve Board.

Note: Dependent variable is forecast error for 400 times natural log quarterly difference for real GDP and real consumption and forecast error for 1200 times natural log monthly difference for industrial prouduction and the CPI. Forecast errors determined using latest vintage data for dependent variables. Standard errors in parantheses. Coefficients for constant and other global shocks not shown.

*Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

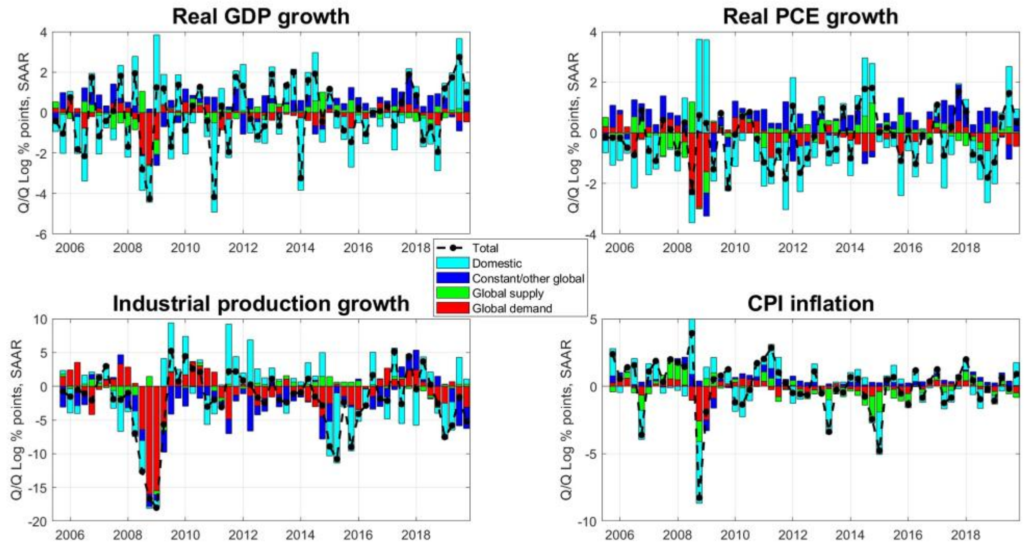
Table 5 above shows the key results from running the regression specifications (1) and (2). The coefficients are modestly above 1 for the global demand shocks in all but the IP specification and imply that a one standard global demand shock is associated with just over a 1 percentage point forecast error for the other three respective annualized growth rates.

The monthly CPI and IP shocks decompositions are translated into a quarterly shock using the distributed weighted lagged average of monthly shocks

$$(3)\ G_t = \frac{1}{9}(g_t^3 + 2g_t^2 + 3g_t^1 + 2g_{t-1}^3 + g_{t-1}^2),$$

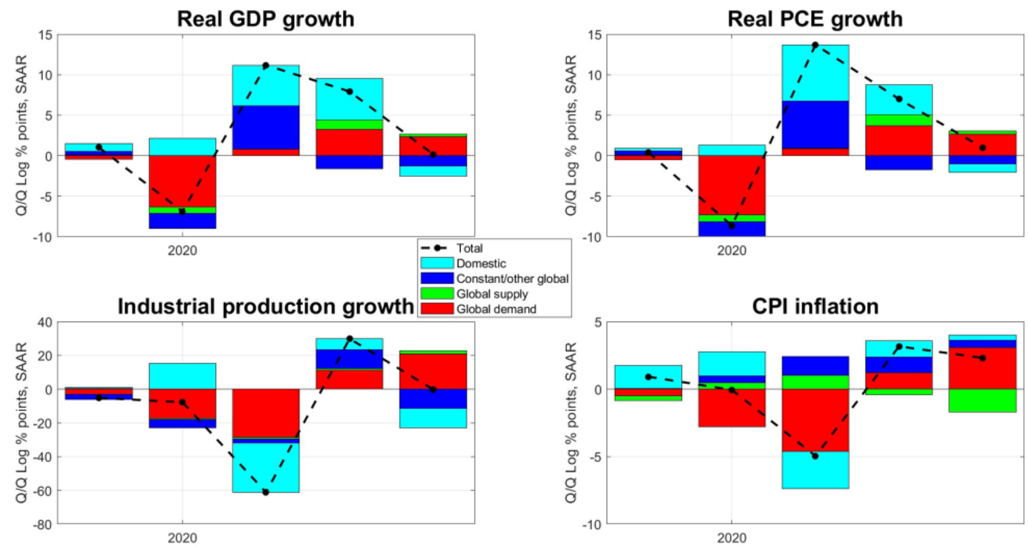
Where g_t^j is one of $\theta_{Gdem}^{\pi} Gdem_{h(t,j)}$, $\theta_{Gdem}^{\pi} Gsup_{h(t,j)}$, $\sum_{i=1}^{3} \theta_{Goth,i}^{\pi} Goth_{h(t,j),i}$, or $u_{h(t,j)}^{\pi,US}$ in equation (2) above. The use of (3) relies upon the fact that a 1-quarter annualized inflation rate for quarter t can be closely approximated by the weighted average of five annualized monthly inflation rates for the five consecutive months beginning with the second month of quarter t-1 and concluding with the third month of quarter t. Figures 2a-2d below show the forecast error decomposition for the annualized quarterly growth rates based on equations (1) – (3).

Figure 2a: Decomposition of 2005Q3-2019Q4 "Era 1" U.S. forecast errors.



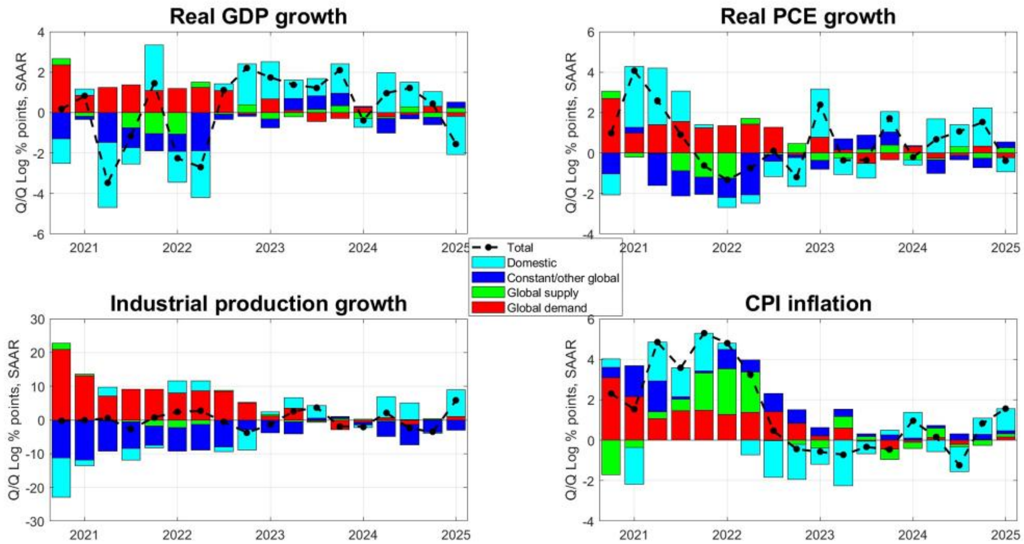
Note: X-axis is aligned with outcome date – i.e. 2016 denotes forecast errors for 2016:Q1 annualized quarterly real GDP/PCE growth rates. Real GDP and PCE growth 2016:Q1 errors are taken from the March 7, 2016 survey while labelled 2016:Q1 IP and CPI errors are based on the weighted 1-month annualized forecast errors between November 2015 and March 2016 as indicated in equation (3).

Figure 2b: Decomposition of 2019Q4 and "Era 2" (2020Q1-2020Q4) U.S. forecast errors.



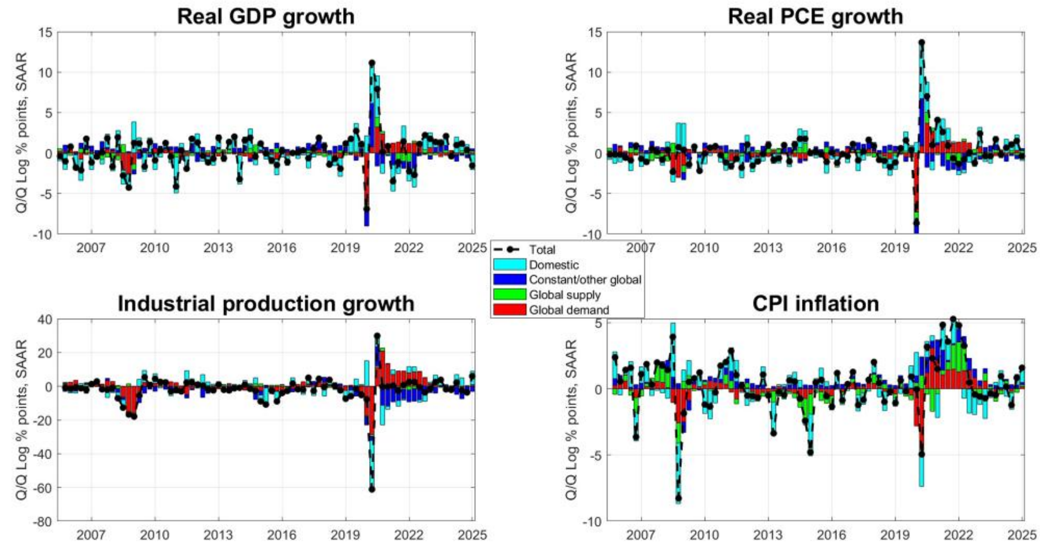
Note: X-axis is aligned with outcome date – i.e. 2020 denotes forecast errors for 2020:Q1 annualized quarterly real GDP/PCE growth rates. Real GDP and PCE growth 2020:Q1 outcomes are taken from the March 9, 2020 survey while 2020:Q1 IP and CPI errors are based on the weighted 1-month annualized forecast errors between November 2019 and March 2020 as indicated in equation (3).

Figure 2c: Decomposition of 2020Q4 and "Era 3" 2021Q1-2025Q1 U.S. forecast errors.



Note: X-axis is aligned with outcome date – i.e. 2025 denotes forecast errors for 2025:Q1 annualized quarterly real GDP/PCE growth rates. Real GDP and PCE growth 2025:Q1 errors are taken from the March 10, 2025 survey while labelled 2025:Q1 IP and CPI errors are based on the weighted 1-month annualized forecast errors between November 2024 and March 2025 as indicated in equation (3).

Figure 2d: Decomposition of 2005Q1-2025Q1 U.S. forecast errors.



Note: X-axis is aligned with outcome date – i.e. 2025 denotes forecast errors for 2025:Q1 annualized quarterly real GDP/PCE growth rates. Real GDP and PCE growth 2025:Q1 errors are taken from the March 10, 2025 survey while labelled 2025:Q1 IP and CPI errors are based on the weighted 1-month annualized forecast errors between November 2024 and March 2025 as indicated in equation (3).

These contributions are separated into three eras: pre-2020, 2020, and post-2020, and then combined in the final chart. This timing convention for the CPI and IP variables is different than the ones used in Figure 1 in which, e.g., the 2020:Q1 forecast errors are computed with the forecasts made only in the administered March 9, 2020 survey. This accounts for industrial production having a negative error in 2020:Q2 and GDP and consumption having positive errors in that quarter. The April 2020 IP forecast error that is averaged into the 2020:Q2 error with a weight of 1/3rd is based on a March 9, 2020 forecast that didn't foresee the extent of the pandemic's impact while the 2020:Q2 GDP and consumption errors are entirely based off the June 8, 2020 survey, when partial re-openings were often either in view or occurring.

Figures 2a-b shows our measure of global demand shocks played a significant role in the 2008:H2, 2009:Q1 and 2020 forecast errors of the economic activity growth and inflation measures that was generally larger than the impact of our global supply shock measure. Figure 2c shows that global demand shocks continued to play a larger role in U.S. economic activity forecast errors than global supply shocks in 2021-2022, but global supply shocks were significant upward factor in the U.S. inflation errors in the second half of 2021 and early 2022. This is consistent with Table 6 below showing the average absolute global supply shock inflation contribution neing only modestly smaller than its analog for global demand in the post-2020 period but not for the other three variables where global demand continues to dominate global supply.

Table 6: Average absolute contributions to US forecast errors (Log % points, SAAR)

		Global demand	Global supply	Other	Domestic	Total
Real GDP	Pre-pandemic	0.40	0.28	0.46	1.40	1.29
	2020	3.17	0.57	2.54	3.38	6.54
	Post-2020	0.63	0.35	0.62	1.41	1.54
Real PCE	Pre-pandemic	0.46	0.33	0.49	1.07	0.85
	2020	3.64	0.67	2.59	3.25	7.58
	Post-2020	0.73	0.40	0.67	1.24	1.19
IP	Pre-pandemic	2.58	0.49	1.54	2.87	3.58
	2020	19.51	1.06	7.58	15.54	24.74
	Post-2020	4.73	0.57	5.07	3.00	2.30
CPI	Pre-pandemic	0.42	0.51	0.30	1.00	1.36
	2020	2.93	0.90	0.91	1.53	2.62
	Post-2020	0.76	0.62	0.50	1.20	1.82

Source: Author calculations using data from Consensus Economics and Federal Reserve Board.

Note: Real GDP and real PCE statistics are mean absolute errors of 400 times natural log of gross 1-quarter. IP and CPI rows are calculated using equation (1) as described in the text. Pre-pandemic period is 2005:Q3 - 2019Q:4, and post-2020 period is 2021:Q1-2025:Q4

Figure 2c also shows there was some persistence in the errors and error contributions post 2020, particularly for inflation. Koch and Noureldin (2024) also observed this phenomenon in the IMF WEO forecasts for a number of countries and found statisically signifciant evidence of oversmoothing in the forecasts – i.e. putting too much weight on the previous forecast to the most recent information/forecast error – for 21 of the 54 countries considered in their analysis.

The decompositions we've provided in Figures 2a-2d assume no forecast error persistence. Even if this assumption is correct, which clearly it may not be, it does not imply that shocks can't have long lasting or even permanent effects. To assess the dynamic effects of the global shocks on U.S. inflation, we embed a set of control variables from an otherwise standard Phillips curve into the local projections framework pioneered by Jorda (2005). The specification we use is

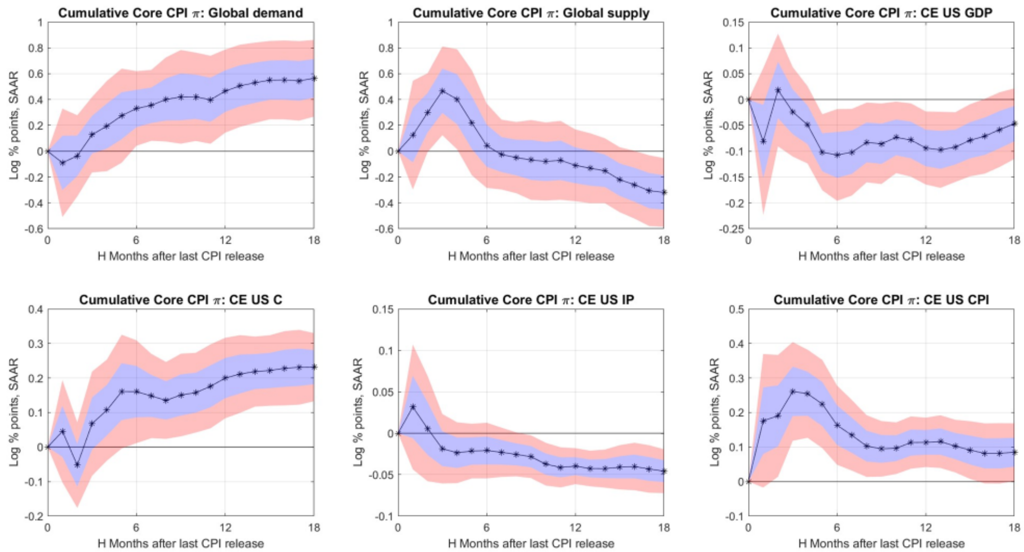
$$(4)\ y_{t+h}^{\pi} = \alpha + \rho_1\pi_t^3 + \rho_2\pi_{t-3}^3 - \beta UR_t + \gamma GSCPI_t + \delta CFNAI_t^3 + \theta_{Gdem}Gdem_t + \theta_{Gsup}Gsup_t + \theta_{USgdp}USgdp_t + \theta_{USpce}USpce_t + \theta_{USip}USip_t + \theta_{UScpi}UScpi_t + \varepsilon_{t+h}^{\pi}$$

where t is the month of the last month of CPI inflation data that a panelist would have had in a particular survey, and π_t^3 and π_{t-3}^3 are the three-month annualized (log) inflation rates in months t and t-3 respectively for a particular CPI price measure P_t. In our baseline specification y_{t+h}^{π} is the cumulative h-month (log) inflation rate $\frac{1200}{h}\ln\left(\frac{P_{t+h}}{P_t}\right)$ in month t+h , but we also use $y_{t+h}^{\pi} = 1200\ln\left(\frac{P_{t+h}}{P_{t+h-1}}\right)$ for Figures A4-A6 in the appendix. The Phillips curve control variables are the month t values of the unemployment rate UR_t, the New York Fed's Global Supply Chain Pressure Index (GSCPI), and the 3-month moving average of the Chicago Fed's National Activity Index (CFNAI). The first two of these three Phillips curve controls have been commonly used in recent studies while the last of these is a possible predictor of future unemployment that may be related to more distant inflation outcomes. The $Gdem_t$ and $Gsup_t$ terms are the global demand and global supply shocks defined above. The last 4 variables preceding the error term in equation (4) are the US domestic standardized consensus forecast errors for real GDP, real PCE, IP, and CPI growth after controling (i.e. residualizing for) for the 5 global shocks via equation 2.

The three price measures we consider in equation (2) are the standard core (ex food and energy) CPI and the Cleveland Fed 16% trimmed-mean and median CPI measures. We don't use the headline CPI because the standardized global and domestic CE forecast error measures include information on oil price forecast errors which, via gasoline prices, can account for a significant amount of short-term variation in headline CPI inflation. We also don't use PCE price measures because there are some instances when the panelists will have one extra month of CPI data beyond the last PCE price report.

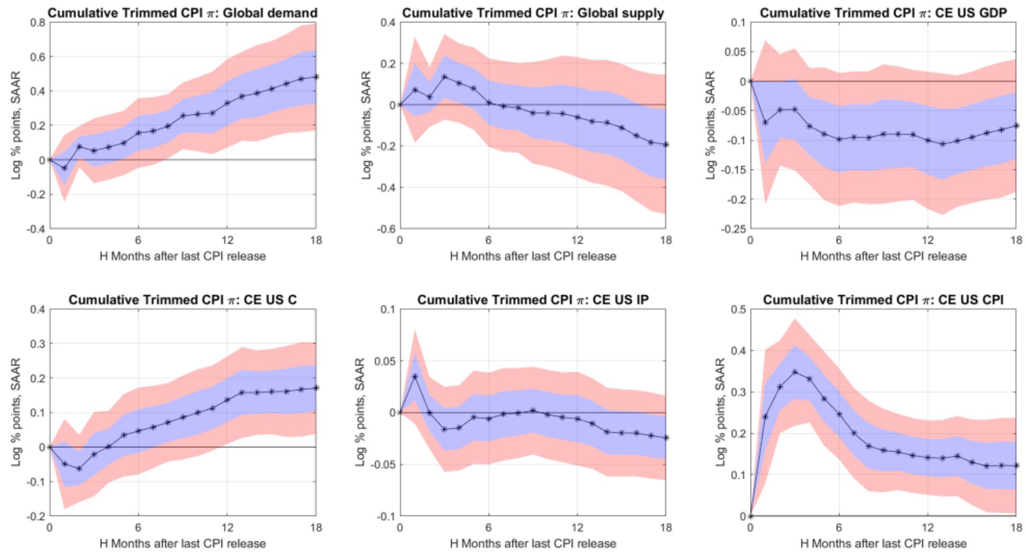
Figures 3 – 5 below, which show the local projections based responses to the forecast shock measures, indicate that initially a positive global demand shock has little or even a negatively signed impact on cumulative inflation. But the impact turns positive and significantly positive 6 to 15 months after the shock. A positive global supply shock generally has a positive effect on cumulative inflation within the first 6 months of the shock, but only significantly so in one case. Thereafter the sign is generally significantly negative.

Figure 3: Local projections impulse responses of cumulative US core CPI inflation to global and domestic CE forecast shocks.



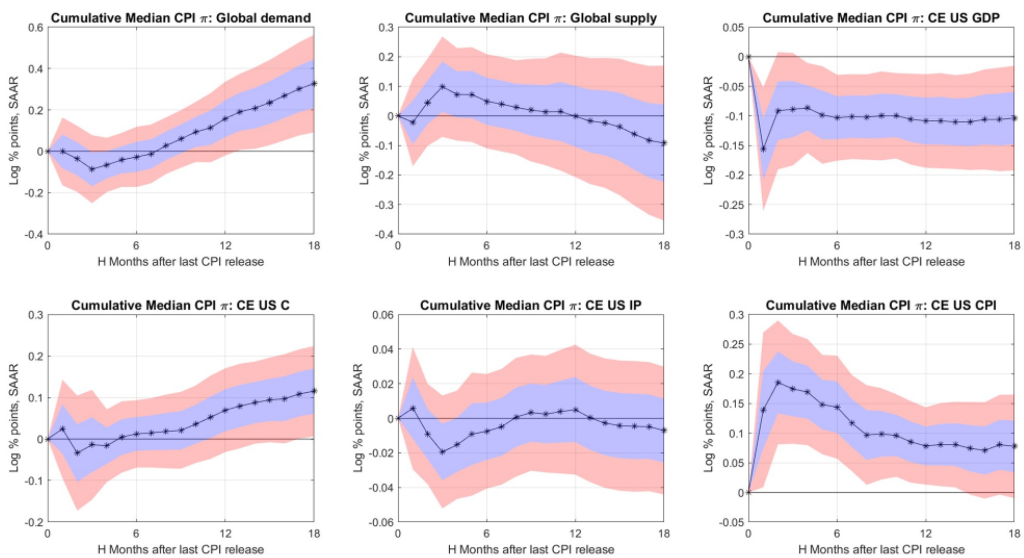
Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is cumulative annualized log change in the core CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

Figure 4: Local projections impulse responses of cumulative US trimmed mean CPI inflation to global and domestic CE forecast shocks.



Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is cumulative annualized log change in the Cleveland Fed trimmed mean CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

Figure 5: Local projections impulse responses of cumulative US median CPI inflation to global and domestic CE forecast shocks.



Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is cumulative annualized log change in the Cleveland Fed median CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

With respect to the (residualized on global) domestic shocks, the CPI forecast error shock perhaps not surprisingly has a significant impact on inflation. The IP and GDP shocks often have a negative impact on inflation, but not usually significantly so, faintly suggesting these terms are picking up positive supply shocks. The consumption shock impact is often negative, and sometimes significantly so, suggesting it may be capturing a consumption preference demand shock. Figures A1-A3 in the appendix show the cumulative inflation responses to the control variables, which generally have the expected signs in that lagged inflation and GSCPI responses are usually positively, and often significantly, related to those values while the inflation response is inversely related to the unemployment rate, at least in the initial responses. Figures A4-A6 show the h-step ahead monthly inflation responses to the forecast error shocks, which are admittely often noisy. At each response horizon, these regressions are estimated with no more than 79 (quarterly) observations. Hence the power from these local projections regressions is admittedly somewhat limited.

Section 5: Conclusion

This study has found that global demand and supply shocks have accounted for meaningful shares of US inflation this decade. Although these global shocks are derived from forecast error data for non-US countries, given the size and importance of the US economy, it certainly could be the case that a portion of these shocks originated in the US and were transmitted to the rest of the world. Our identification of forecast errors and shocks is also not without its own issues. Indeed, our finding of periods of persistent forecast errors in the same dirrection is consistent with the literature finding the same phenomenon suggesting possible forecast inefficiencies. While this criticsm is valid, persistent errors could also imply forecasters using models that are misspecified and/or have incorrect parameters (such as nonlinearities in or the slope of the Phillips curve). The same shortcoming of models can also be true, but professional forecasters are perhaps better able to incorporate specific shocks – such as the early stages of the COVID pandemic and the beginning and ending of pandemic-era stimulus and benefits packages – that are harder to incorporate into a relatively parsimonius model.

Given the diversity of findings in statistical modeling the literature with respect to the shock contributions to U.S. inflation this decade, it is perhaps both comforting and not surprisingly that we find both global demand and global supply shocks identified by nowcast errors of professional forecasters have played an important role in its recent rise and fall. Table 6 indicates that apart from 2020, the aggregate domestic shock had a larger average impact on the inflation forecast errors than either the global demand or global supply shock did in isolation. A natural question is what is the source of these domestic shocks. Given it's limited set of variables, and in particular the absence of any quarterly labor market variables in the survey, it would be difficult to refine these domestic shocks into demand, supply or other factors using just the information in the quarterly CE survey. One could possibly augment these forecasts by using the current and 1-quarter ahead unemployment rate forecasts in the nearly contemporaneous third month of quarter *Blue Chip Economic Indicators* survey or by incorporating and interpolating the CE forecasts of the annual unemployment rate and annual Employment Cost Index growth by further adapting the conditional forecasting approach used here. We leave this to future research.

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Appendix: Forecast data construction and additional tables and charts

This study uses the *Consensus Economics* (CE) last month of quarter forecast surveys of quarterly outcomes of real GDP, real consumer spending, industrial production, and the Consumer Price Index or related inflation variable. For all but the United States, the only outcomes collected for GDP and consumption are for 4-quarter growth rates. So that the forecast errors do not incorporate revisions to the prior 3-quarter GDP and consumption growth rates, we use real-time seasonally adjusted (SA) quarterly real GDP and consumption data collected from the Federal Reserve Board's FAME database – which has vintage data snapshots extending back to May 2005 – to derive the implied 1-quarter real GDP growth rate for the same quarter survey is administered in.

As mentioned in the main text, for industrial production and the Consumer Price Index we temporally disaggregate the quarterly forecasts into a monthly frequency. If the FAME data is only available on a non-seasonally adjusted (NSA) basis, we seasonally adjust each NSA vintage used and assume that the most recently estimated seasonal factors repeat themselves every 12 months beyond the last available month. Additionally, for the CPI, the forecasts represent 4-quarter growth rates of the non-seasonally adjusted data. We force the 4-quarter NSA inflation rate to equal the CE projection, but the 4-quarter SA inflation rate may differ slightly from it as seasonal factors can change slowly over time. For the current quarter, we assume the quarterly seasonal factor is the average of the three monthly seasonal factors. The approximation error induced by this simplifying assumption is very small.

Assume for the monthly IP or CPI variable y_t^j, which denotes the logged value of the variable in the jth month of quarter t, that we have exactly h_t months of data for that quarter, with $0 \leq h_t < 3$. With the monthly FAME real-time data, we estimate a Bayesian vector autoregression (BVAR). The CPI BVAR variables include that monthly variable as well as oil prices and an exchange rate. We use the *Consensus Economics* projections of the price of oil[15] and the exchange rate[16] both 3-months from the survey date and 12-months from the survey to generate monthly average forecasts of these variables using log-linear interpolation. For oil, a seasonal adjustment step is done as well; i.e. the oil prices are seasonally adjusted and the seasonally adjusted prices are log-linearly interpolated so that the NSA prices – assuming the seasonal factors remain at their one year-ago levels – are

[15] Prior to 2013, West Texas Intermediate oil prices were forecasted by the panelists. After this Brent oil prices were used. We make this switch as well

[16] For countries besides the U.S., the exchange rate is the currency vs. the dollar. For the U.S. we construct a synthetic trade weighted exchange rate index of the non-dollar currencies that are forecast and forecast this synthetic currency assuming that the trade weights remain at their most recent value.

exactly equal to the CE projections 3- and 12-months hence. The seasonal adjustments are done on a weekly basis with the Bureau of Labor Statistics' movereg procedure in EViews (see Evans et al. (2021)) and the weekly seasonal factors are (linearly) interpolated to the daily frequency. Exchange rates are assumed to have no seasonal patterns. The combined actual and forecast monthly exchange rate and oil price data are converted to monthly average frequencies. For the quarter t growth rate nowcast, we impose the constraint

$$\text{(A1)}\ 400\log\left(1+\tfrac{CE_t}{100}\right)=\tfrac{400}{3}\left(\left(\textstyle\sum_{j=1}^{h_t}y_t^j+\sum_{j=1+h_t}^{3}\hat{y}_t^j\right)-\left(y_{t-1}^1+y_{t-1}^2+y_{t-1}^3\right)\right),$$

where CE_t is either the published (in the U.S. case) or derived (for other countries) annualized seasonally adjusted quarterly growth forecast and $\hat{y}_t^j$ is a forecasted monthly log level[17]. For the quarter t+1 growth rate forecast we have the second constraint

$$\text{(A2)}\ 400\log\left(1+\frac{CE_{t+1}}{100}\right)=\frac{400}{3}\left(\left(\hat{y}_{t+1}^1+\hat{y}_{t+1}^2+\hat{y}_{t+1}^3\right)-\left(\sum_{j=1}^{h_t}y_t^j+\sum_{j=1+h_t}^{3}\hat{y}_t^j\right)\right)$$

If h_t < 2, we treat (A1) and (A2) as separate constraints. If, however, h_t = 2, we combine (A1) and (A2) together so that monthly forecasts through the third month of quarter t+1 are consistent with the CE implied 2-quarter growth rate forecast. We don't impose (A1) in this case because issues such as rounding/decimal precision[18] and uncertainty around seasonal factors can lead to implausible forecasts for $\hat{y}_t^3$. For k > 1 out to the longest horizon forecasts (often 7 or 8 quarters ahead), we have the constraints

$$\text{(A3)}\ 400\log\left(1+\frac{CE_{t+k}}{100}\right)=\frac{400}{3}\left(\left(\hat{y}_{t+k}^1+\hat{y}_{t+k}^2+\hat{y}_{t+k}^3\right)-\left(\hat{y}_{t+k-1}^1+\hat{y}_{t+k-1}^2+\hat{y}_{t+k-1}^3\right)\right)$$

Conditions (A1-A3) are imposed via a slight generalization of an approach described Waggoner and Zha (1999). In particular, we form the matrix **C** where each row imposes a constraint either on the oil price or the exchange rate (in which case the corresponding row of **C** contains all 0s apart from a single 1). If we order these constraints first, the next one or two rows of **C** will impose (A1) and (A2) separately for h_t < 2 or the combined (A1 – A2)

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[17] Whenever the upper limit of a summand is smaller than the lower limit, we set the sum to 0.

[18] The CPI index levels are often rounded to one decimal place for countries outside of the U.S. When the index levels are close to 100, as they often are, this implies the range of uncertainty for a single annualized monthly inflation rate due to decimal precision is in the vicinity of 1 percentage point.

constraint for h_t = 2. For each of the remaining (A3) constraints, the corresponding rows of **C** will have 3 entries of $\frac{400}{3}$, 3 entries of entries $\frac{-400}{3}$, and remaining entries of 0. **C** imposes the constraints when it multiplies the monthly observations $[\hat{y}^j_{t+k},$ $\log(OIL^j_{t+k}), \log(FX^j_{t+k})]'$ stacked into a column vector so that the first three entries are the first forecasted month, the fourth through sixth entries are for the second forecasted month, etc. Call this stacked forecast vector **c**. We have omitted accounting for the "non-hat" y^j_{t-1} and y^j_t in constraints (A1) and (A2). Since these are known values, we can rearrange (A1) and (A2) [or the combined (A1-A2) constraint when applicable] so that only the "non-hat" terms appear on the right hand side of the constraint(s) and add these terms to **z** in equation (A4) below. Using the notation in Waggoner and Zha (1999), the stacked forecast error terms consistent with the constraints is determined by the following pair of equations

$$\text{(A4) } \boldsymbol{D} = \boldsymbol{c} - \boldsymbol{C}Z$$

$$\text{(A5) } \boldsymbol{\epsilon}^{MLE} = (R(a)\boldsymbol{C}')(\boldsymbol{C}R(a))^{-1}(R(a)\boldsymbol{C}')\boldsymbol{D}$$

where the r(a), $R(a)$, and Z terms are all defined in Waggoner and Zha (1999). The constrained forecast is then the stacked forecast error $\boldsymbol{\epsilon}^{MLE}$ added to the stacked unconditional forecasts. For CPI inflation, the specification of the BVAR follows Banbura et al. (2010) with the cointegration and sum of coefficient dummies and hyperparameters λ=0.5, δ=1 [for each of the three variables], τ=1, a decay rate of 1 on lags (of which there are 13 so that BVAR nests the 12-month inflation rate as one of the feasible models). The conditional forecasts will only (closely) approximately be consistent with the published percentage point growth rates because of log approximations. So we include a final clean-up proportional Denton (1971) interpolation using the conditional monthly CPI forecast.

The forecasting approach for monthly industrial production consistent with the quarterly forecasts uses a very similar BVAR-based approach. All of the BVARs include the log of an end-of-month broad equity price index for the country. The additional conditioning variables included in the BVAR are country specific and are listed in Table A1. They are also obtained from the Federal Reserve Board's real-time FAME database. The variables, apart from the sentiment, diffusion index, and unemployment rate measures are entered in logs.

Table A1: Monthly variables included in industrial production BVARs

Canada	Total Employment	New Factory Orders		
France	Bus. Confid. Index	Economic Sent. Index	Reuters Manuf. PMI*	
Germany	Total Civ. Empl.	Bus. Confid. Index	Econ. Sent. Ind.	Reuters Man. PMI*
Italy	Unemp. rate**	Bus. Confid. Index	Econ. Sent. Ind.	Reuters Man. PMI*
Japan	Unemp. rate	Avg. overtime hours		
Netherlands	Unemp. rate**			

Spain	Unemp. rate		
Sweden	Total Employment	Unemployment rate	
Switzerland	Unemp. rate		
UK	Business Sentiment Ind. Production Tendency		
US	ISM Manufact. PMI	Avg W Hrs: Prod Manuf	Manufacturing Employment

Notes: Norway excluded due to lack of real time IP measure.

*France/German/Italy Reuters PMI included beginning in January 2020.

**Italian unemployment included beginning with December 2009 forecast.

#Italian Business Confidence Index included beginning with January 2007 forecast.

Because the onset of the pandemic, in a statistical outlier sense, had a more profound impact on industrial production than it did for CPI inflation, for the IP BVARs we utilize the Cascaldi-Garcia (2025) pandemic prior BVAR for the constrained IP forecasts using the default prior parameter settings in Cascaldi Garcia's Matlab code[19] (setting the number of COVID time dummies to 0 before March 2020 and the minimum of 6 and the number of months in the complete data estimation sample after February 2020). This has the effect of increasing the residual variance during the height of the pandemic thereby reducing these months influence on the regression parameter estimates.

[19] See https://sites.google.com/site/cascaldigarcia/research .

Table A2: Contemporaneous correlation of nowcast errors for US with same for other countries for 1-quarter or 3-month growth rates with other countries, 2005:Q3 - 2025:Q1 sample excluding 2020:Q1 - 2020Q3

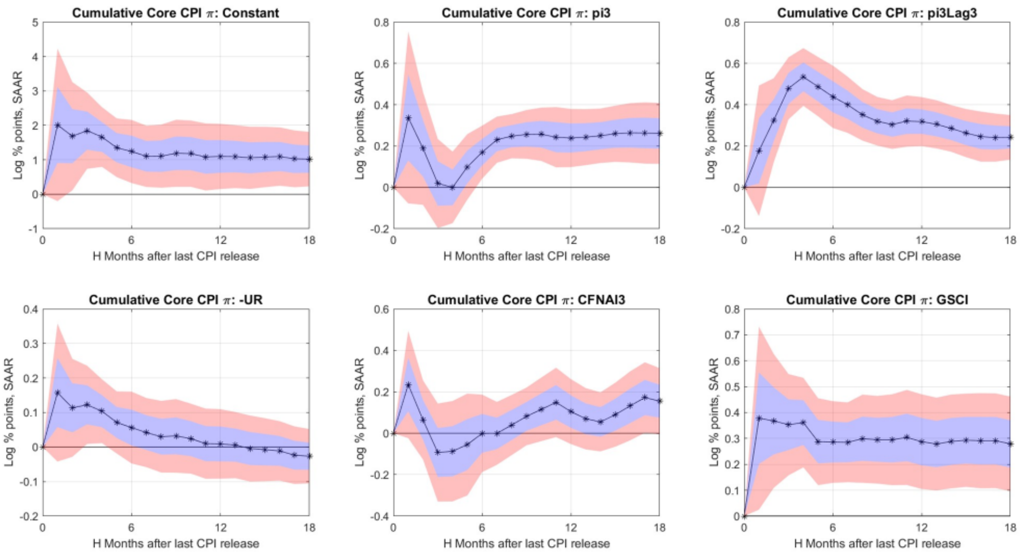
	Real GDP	Real Consumption	Industrial production	CPI
Canada	**0.19**	**0.09**	**0.35**	**0.66**
France	**-0.01**	**0.21**	**0.52**	**0.55**
Germany	**-0.05**	**-0.17**	**0.48**	**0.49**
Italy	**-0.03**	**0.17**	**0.34**	**0.49**
Japan	**0.25**	**0.04**	**0.48**	**0.27**
Netherlands	**-0.12**	**0.18**	**0.33**	**0.35**
Norway	**0.13**	**-0.32**		**0.32**
Spain	**0.10**	**0.44**	**0.14**	**0.64**
Sweden	**0.19**	**0.30**	**0.27**	**0.33**
Switzerland	**0.11**	**-0.14**	**0.06**	**0.61**
United Kingdom	**0.07**	**0.21**	**0.17**	**0.45**
1st Principal Comp.	**0.09**	**0.19**	**0.52**	**0.67**

Sources:

Author calculations using data from *Consensus Economics*, US Bureau of Economic Analysis, US Bureau of Labor Statistics, and Federal Reserve Board of Governors

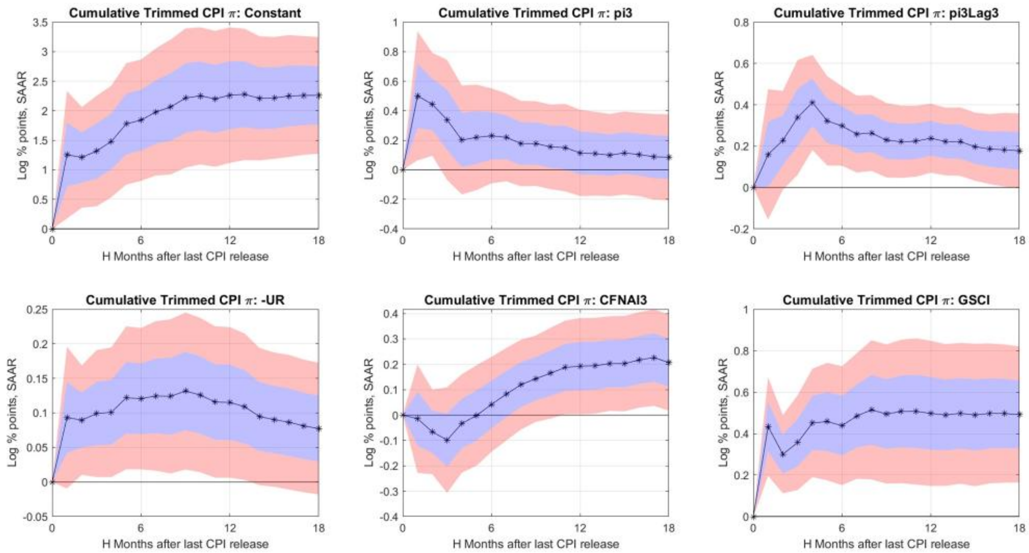
Note: Forecast errors are constructed using final-month of quarter surveys from *Consensus Economics*. Errors are evaluated using revised latest vintage estimates. Errors for implied forecasts for one quarter log changes are used for GDP and consumption while errors for implied average *n*-month industrial production and CPI log changes are used, where n is generally is 3 but on occasion may be 2 or 4 depending on the number of IP and CPI releases between consecutive end-of-quarter surveys.

Figure A1: Local projections impulse responses of cumulative US core CPI inflation to control variables.



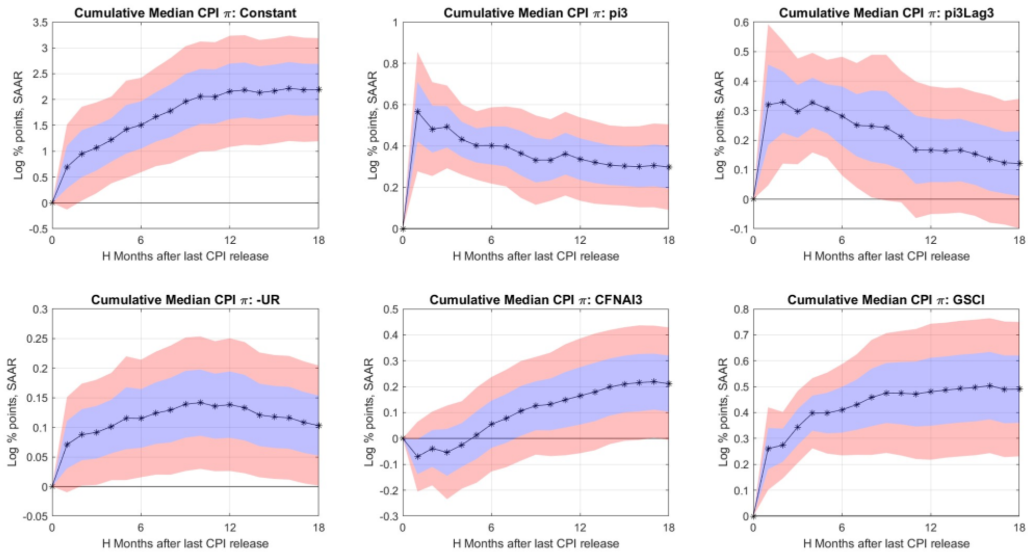
Note: The charts show regression coefficients on control variables in local projections regressions. Dependent variable is cumulative annualized log change in the core CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

Figure A2: Local projections impulse responses of cumulative US trimmed mean CPI inflation to control variables.



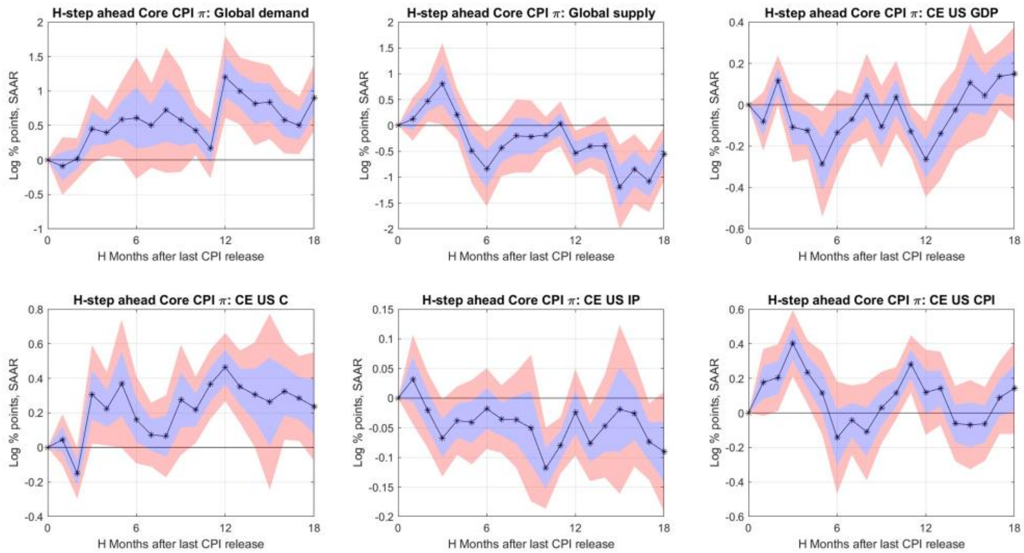
Note: The charts show regression coefficients on control variables in local projections regressions. Dependent variable is cumulative annualized log change in the Cleveland Fed trimmed-mean CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

Figure A3: Local projections impulse responses of cumulative US median CPI inflation to control variables.



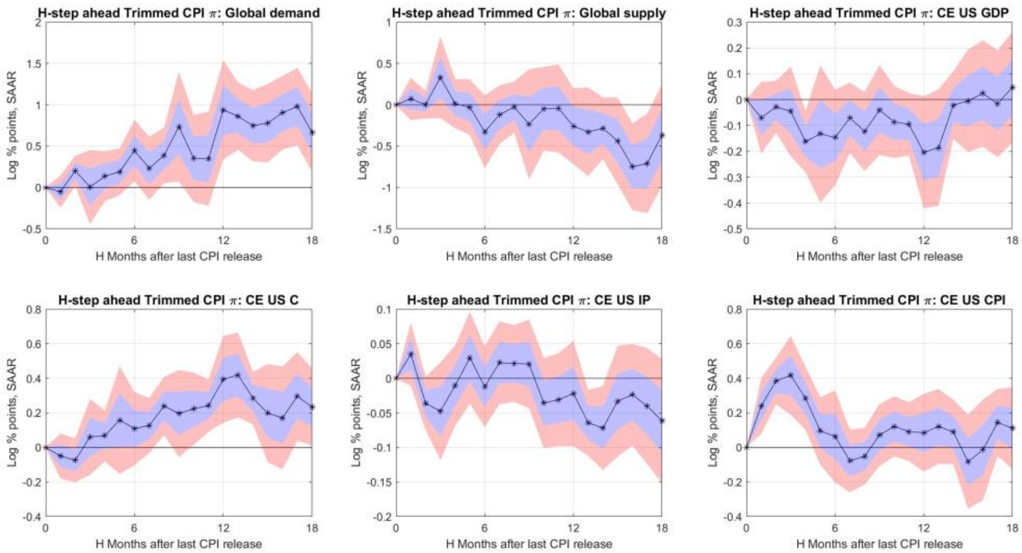
Note: The charts show regression coefficients on control variables in local projections regressions. Dependent variable is cumulative annualized log change in the Cleveland Fed median CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using “HAC” command in Matlab.

Figure A4: Local projections impulse responses of h-step ahead 1-month US core CPI inflation to global and domestic CE forecast shocks.



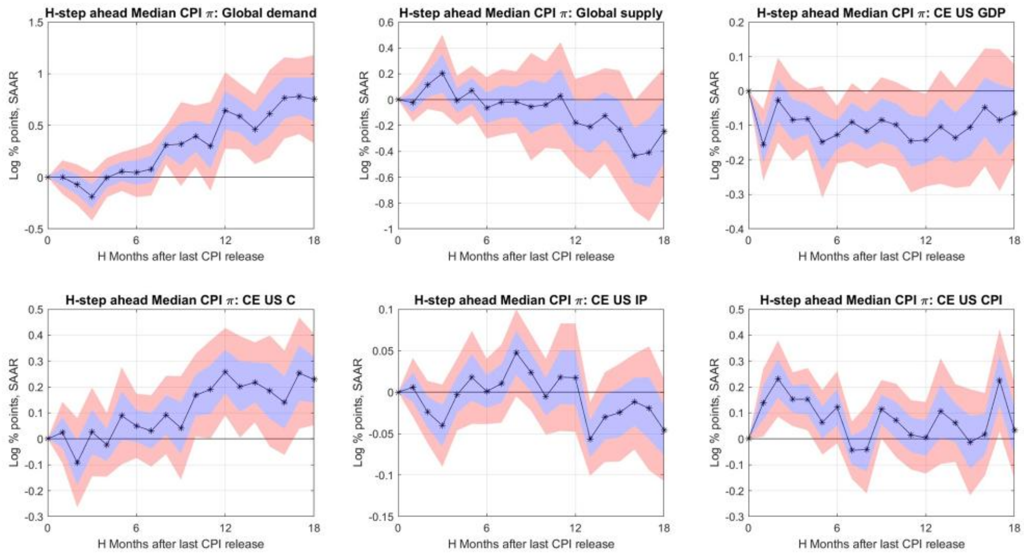
Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is h-step ahead annualized one-month log change in the core CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.

Figure A5: Local projections impulse responses of h-step ahead 1-month US trimmed mean CPI inflation to global and domestic CE forecast shocks.



Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is h-step ahead annualized one-month log change in the Cleveland Fed trimmed mean CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using “HAC” command in Matlab.

Figure A6: Local projections impulse responses of h-step ahead 1-month US median CPI inflation to global and domestic CE forecast shocks.



Note: The top chart left and middle charts are responses to one standard deviation global demand and supply shocks. The top right and bottom charts are one standard deviation CE nowcast error shocks to the US growth rates of real GDP, real personal consumption expenditures, industrial production, and the CPI, respectively. Dependent variable is h-step ahead annualized one-month log change in the Cleveland Fed trimmed mean CPI. The solid marked lines are mean responses while the blue and red shaded regions are one- and two-standard deviation error bands, respectively. Newey-West (1987) heteroscedasticity-and-autocorrelation-consistent standard errors computed using "HAC" command in Matlab.