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The GSCPI: A New Barometer of Global Supply Chain Pressures

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Abstract

We propose a novel indicator to capture pressures that arise at the global supply chain level, the Global Supply Chain Pressure Index (GSCPI). The GSCPI provides a new monitoring tool to gauge global supply chain conditions. We assess the index's capacity to explain inflation outcomes, using the local projection method. Our analysis shows that recent inflationary pressures are closely related to the behavior of the GSCPI, especially at the level of producer price inflation in the United States and the euro area.

Key words: global supply chain, inflation, transportation costs

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1 Introduction

The Covid-19 pandemic has thrown the functioning of the global economy into disarray, as never seen before supply chain disruptions hampered the trade of goods within and across borders. Shutdowns of factories (particularly in Asia), widespread lockdowns and mobility restrictions resulted in disruptions across logistic networks, increases in shipping costs and longer delivery times. These disruptions became particularly acute during the recovery phase of the pandemic as demand for commodities, intermediate inputs and goods outstripped their constrained supply.

The severity of production bottlenecks depends critically on the complex structure of supply chains within and across countries, where a disruption in one part of the supply network can resonate throughout the global production process. Monitoring this process has become important not only from the perspective of firms directly affected by disruptions, but also for policymakers for their assessment of potential demand/supply imbalances and the resulting inflationary pressures. Indeed, given the unprecedented shock that the global supply chains have witnessed, several measures have been proposed to capture potential disruptions. However, these measures, taken individually, tend to focus only on selected dimensions of global supply chains. For example, international shipping costs focus on the transportation dimension; supplier delivery times emphasizes the length of the delivery process, while backlogs indicators capture the delays in completing orders by firms possibly associated with capacity constraint.

Given the high-dimensional problem of measuring the functioning of the global supply chain, this paper's novel contribution is to construct a parsimonious high-frequency summary indicator, the *Global Supply Chain Pressure Index* (GSCPI), which combines information contained in a wide ranging set of (univariate) measures that are publicly available and that capture information at within and across countries.

More specifically, we build on Benigno et al. (2022c) and focus on seven interlinked countries[1] and a set of indicators coming from PMI and transportation costs. In the constructions of our index, we proceed in two steps. In the first one, we isolate the supply component from the underlying indicators, by using demand proxies at consumers' and firms' level coming from other sub-components of the PMI indexes. In the second step, we perform a principal component analysis on the *"depurated"* indicators to extract our index as their common component.

We plot our index in terms of standard deviation from its historical average on a monthly frequency starting from 1997 to the most recent observation. Recent readings

[1] The countries that we are considering are China, Euro-area, Japan, South Korea, Taiwan, United Kingdom, United States.

especially in the recovery phase of the pandemic indicates extreme strains on global supply chains with movements that exceed three standard deviations and peaked at above four standard deviations in November 2021. The Covid-19 pandemic has been an eye-opening example of how exogenous factors could influence the functioning of supply chains but climate related events (like floodings or earthquakes) and geopolitical developments (such as the recent Russia-Ukraine conflict) could also cause disruptions along regional and/or global supply chains.

While there are different measures that are used to proxy trade and financial market integration, our index provides a first measure to capture the status of global supply chains, a key aspect of the modern production process. In this way, the GSCPI could be used a monitoring tool to assess global supply chain conditions but also as a element of statistical model for understanding trade flows across countries or price movements.

As an example of a potential application, we adopt the local projection method as in Jordà (2005) to study the response of different measures of inflation in the Euro-area and United States to shocks to our GSCPI index along with global demand and supply components of oil prices changes (as in Groen et al. (2013)). The purpose of our analysis is to discuss how global supply factors have shaped recent inflationary pressures. Indeed, we show how the persistence of recent pressures at PPI and to a lesser extent CPI appears to be importantly related to the evolution of global supply factors, such as the one identified by the GSCPI.

In what follows we first describe the underlying components of our index and our method of its construction. We then describe its evolution, and we discuss one possible application related to its association with different measures of inflation (namely producer price inflation and consumer price inflation) for the U.S. and the Euro area.

2 Data Descriptions and Measures of Supply Chain Pressures

Several approaches have been used to assess supply chain problems. Such supply chain issues may arise within countries, such as back-ups at ports or a shortage of truck drivers, as well as internationally, such as a shortage of containers and port congestions. Our proposed measure therefore is built on variables that are meant to capture factors that put pressure on the global supply chain both domestically and arising from trade across countries.

The first set of indicators we draw from proxy for different measures of cross-border transportation costs. First, we use data on the Baltic Dry Index (BDI) that tracks the cost of shipping raw materials, such as coal or steel. Second, we also exploit the Harpex index, which tracks container shipping rate changes in the charter market for eight classes of all-container ships. Finally, the U.S. Bureau of Labor Statistics (BLS) constructs price indices that measure the cost of air transportation of freight to and from the U.S., and we use the inbound and outbound airfreight price indices for air transports to and from Asia and Europe.[2]

The second set of indicators rely on data from the manufacturing sector at the country level coming from IHS Markit's Purchase Manager Index (PMI) surveys. In terms of country coverage, we focus on those economies that have both a significant sample length and are substantially interlinked through global supply chains: China, Euro-area, Japan, Korea, Taiwan, the United Kingdom, and the U.S.[3]

From these PMI surveys, we use the following sub-components of the country-specific manufacturing PMIs. The 'Delivery Time' PMI sub-component, which captures the extent to which supply chain delays in the economy impact producers. This variable may be viewed as identifying a purely supply-side constraint. The 'Backlogs' PMI sub-component as this variable quantifies the volume of orders that firms have received but have yet to either start working on or complete. And, finally, we also use the 'Purchased Stocks' PMI sub-component, as this measures the extent of inventory accumulation by firms in the economy.[4]

3 The Global Supply Chain Pressure Index

In this section we describe the construction of our indicator and its evolution over time. Our focus is on building a global measure of supply chain pressure.

The previously discussed variables contain valuable information regarding the state of supply chains across the different regions. However, as emphasized above, each measure highlights different dimensions of potential disruptions in global supply chains. Furthermore, the emergence of global supply chains allowed industries across countries to become more interconnected, with air- and maritime freight transportation facilitating this interconnectedness. For example, final products of U.S. firms frequently end up being assembled out of components and parts produced in Asia and Europe. For these reasons, we will construct a supply chain pressure measure that combines data on country-specific supply chain measures with the global measures of transportation costs.

There are two steps in the construction of the index. The first one relies on isolating

[2] In the Appendix we plot these measures of transportation costs showing how they have witnessed an enormous growth since the beginning of the global recovery of the COVID-19 pandemic.

[3] Note that in case of the U.S. the PMI data start only in 2007 so we combine the PMI data with those from the manufacturing survey of the Institute for Supply Management (ISM).

[4] In the Appendix we plot the GDP-weighted average of these 3 subcomponents of PMI.

the supply component from the indicators that we use as inputs in our index. The second one consists in the statistical procedure used to derive the index from the derived supply components.

3.1 Construction of Index

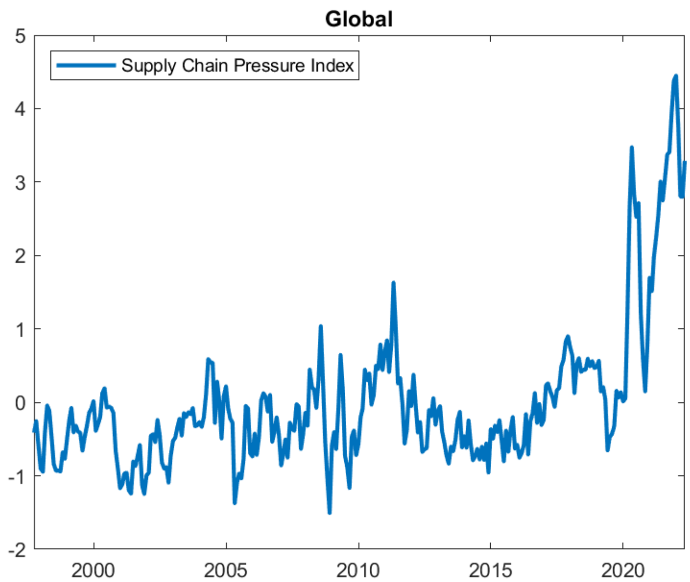
Movements in the country-specific PMI components as well as transportation cost series can be due to either changes in demand or supply factors. To better isolate the supply-side specific drivers of each data series we use additional information available from the PMI surveys for our set of seven economies. More specifically, we collect data on the 'New Orders' PMI sub-component, which captures the extent of customer demand for firms' products and regress the three country-specific supply chain PMI measures (delivery time, backlogs, and purchase stocks) on the contemporaneous value and two lags of this new orders component in an attempt to purge demand factors from these three supply chain PMI subcomponents. The residuals from these regressions for each country will then be used as inputs in constructing our global supply chain pressure index. In case of the transport cost variables, we use both a GDP-weighted average of the aforementioned 'New Orders' PMI sub-components as well as a similarly weighted average of the 'Quantities Purchased' PMI sub-components for our seven economies. The latter captures the extent of firms' demand for intermediate inputs (both domestic and foreign), to proxy for producers' input demand. In a similar vein as for the country-specific supply chain measures, we use regressions based on these two GDP-weighted demand proxies and their lags to cleanse our six global transport cost measures as much as possible from demand effects.

To estimate our GSCPI measure we thus have available a dataset of twenty-seven variables: the three country-specific supply chain variables for each of the Euro area, China, Japan, Korea, Taiwan, the U.K. and the U.S., the two global shipping rates, and the four price indices summarizing airfreight costs between the U.S., Asia and Europe. All these variables are as much as possible corrected for demand effects as described previously. This dataset is made up of monthly time series of uneven length: the advanced economies' supply chain variables all start in 1997, for Japan they start in 2001 and for the other Asian economies 2004, the Harpex index starts in 2001, the BDI goes back to 1985 and the BLS airfreight price indices go back to 2005 on a monthly frequency and are quarterly from 2005 to 1997. Our aim is to estimate a common or 'global', component from these time series. To be able to do that while also dealing with data gaps, we follow Stock and Watson (2002) and extract this common component for the 1997-2021 period through a principal component analysis while simultaneously filling the data gaps using this estimated common component.

The benefit of using the principal component analysis is its ability to determine the individual relevance of the used indicators so that the weight each receives is consistent with its historical importance to fluctuations in global supply chains as we characterize them. One of the desirable features of this approach is that the more correlated a component is with its peers, the higher the weights it receives. This implies that a small deterioration in a heavily weighted component is more relevant for capturing pressures in the global supply chain index than a large worsening of little weight.

Figure 1 presents the evolution of the resulting Global Supply Chain Pressure Index (GSCPI) on a monthly basis since 1997. The index is normalized such that a zero indicates that the index is at its average value with positive (negative) values representing how many standard deviations the index is above (below) this average value.

Figure 1: Evolution of the Global Supply Chain Pressure Index



The GSCPI oscillates over time, with several episodes that are noteworthy. We note a fall and then rebound of the index during the Global Financial Crisis (GFC). While our empirical methodology attempts to purge demand factors before constructing the GSCPI, it is not a perfect measure and its dynamics during the GFC likely still capture some demand components. The variation in the index is not as large as in later periods, which arguably captures stronger supply-side factors. First, we see a substantial rise in the index in 2011. This can be explained by two natural disasters. The first is the Tōhuku earthquake and resulting tsunami, which hit Japan and had an impact on both domestic and foreign production given that the regions struck by the disaster specialized in automobile manufacturing. The second event involved flooding that hit Thailand, which led to seven of the country's largest industrial estates being awash, which impacted the global production chains of the auto and electronics industries. Next, we see that the index rises again during the 2017-2018 China-U.S. trade disputes, as firms had to adjust their global sourcing strategies.

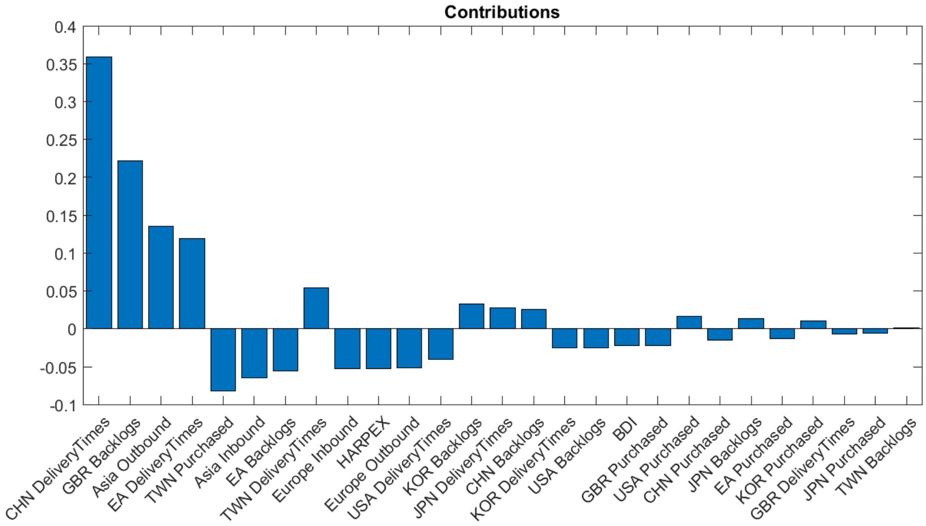
The GSCPI pressure rises for the aforementioned events pale in comparison to what has been observed since the Covid-19 pandemic began. First, we observe that the GSCPI jumps at the beginning of the pandemic period when China shut down its economy. The global supply chain pressure gauge then fell briefly as world production started to get back on-line around the Summer of 2020 before rising at a dramatic pace during the 2020 Covid Winter waves and the subsequent recovery period. More recently, the GSCPI seems to suggest that global supply chain pressures, while still historically high, have peaked and started to moderate from the end of 2021. The recent geopolitical developments and further lockdown measures in China have partially reverted this trend and looking ahead it would be interesting how these events will unfold and affect the global production network.

In interpreting the movements of the index, it is useful to monitor how the different components have contributed to its change over time. So, for example an improvement in the index associated with a large decline in transportation costs would be less indicative of a general improvement than a more widespread improvement in several sub-indicators.

In Figure 2, we focus on the change between March and April 2022. Each column represents the contribution in standard deviation of each component of our index toward its overall change. As the chart indicates, the worsening of global supply chain pressures in April was predominantly driven by the Chinese 'delivery times' component, the increase in airfreight costs from the U.S. to Asia and the Euro-area 'delivery times' component, while other components have eased over the month. These developments could be associated with the stringent Covid-19 related lockdown measures adopted in China, as well as the consequences of the Ukraine-Russia conflict for supply chains in Europe.

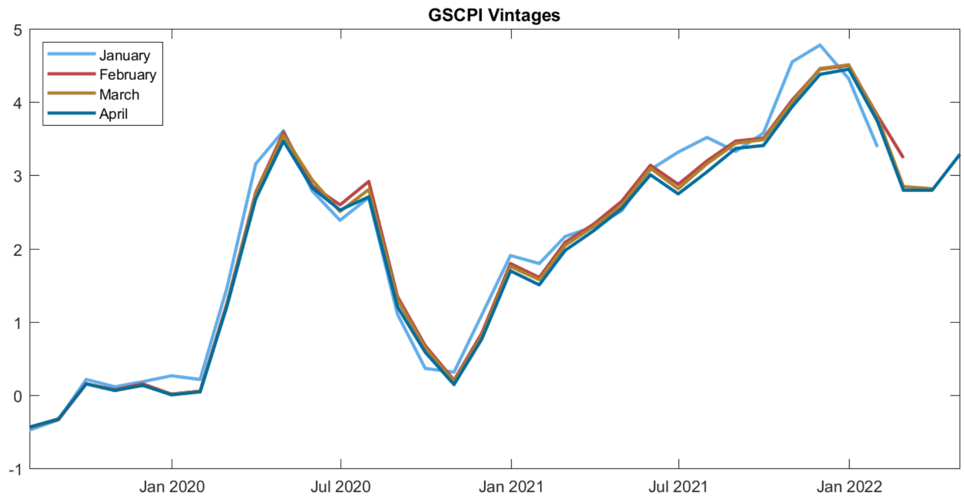
Finally, the other aspect to keep into account is related that in constructing the GSCPI between 1997 and the present, some of our underlying data start later than 1997, whereas other series are published with a one-month lag. Consequently, we have data gaps both early in the sample as well as at the end. As discussed above, we take that into account when estimating the common component across the series by means of principal component analysis and in the process impute estimated values into these data gaps, as suggested by Stock and Watson (2002a,b). This implies that GSCPI levels of the most recent months can be revised as realized data become available and replace these imputed values. In addition, for some of the series, mainly the BLS airfreight cost indices, each new release

Figure 2: Contributions to the GSCPI decline between March-April 2022



comes with revisions to up to twelve months of previous data. Figure 3 compares the current release of the GSCPI with the previous three releases, and it shows that revisions can have an impact up to a year back in time.

Figure 3: Data Vintages and the Evolution of the GSCPI



The figure furthermore shows that the current vintage of the GSCPI indicates that the decrease in global supply chain pressures through April occurred at a slighter faster pace than prious GSCPI estimates had suggested.

4 The Global Supply Side of Inflationary Pressures

In this section, we present one example of how to use our index not only as a monitoring but also as an analytical tool. We present an application for assessing the impact of movements in the pressure index on inflation.

U.S. inflation has surged as the economy recovers from the Covid-19 recession. This phenomenon has not been confined to the U.S. economy, as similar inflationary pressures have emerged in other advanced economies albeit not with the same intensity. Developments on the supply side of economies are often highly correlated across countries and in this section we expand on Benigno et al. (2022b) and use global proxies for these supply side developments to uncover which common cross-country forces have been driving observed inflation.

One of these global supply side factor is our newly constructed Global Supply Chain Pressure Index (GSCPI). Another key potential global supply side variable is the price of energy, for which we focus on oil, and we back out components of oil price fluctuations in terms of a global demand factor and an oil supply factor, as is published weekly in the Federal Reserve Bank's Oil Price Dynamics Report. The underlying methodology is explained in Groen et al. (2013) and Groen and Russo (2015), and it uses a common factor model on a large number of financial variables to decompose weekly Brent crude oil price changes into demand effects, supply effects, and an unexplained residual. Figure 4 depicts the resulting oil price decomposition over a recent period, cast in year-over-year changes to make it in line with the empirical analysis in this section.

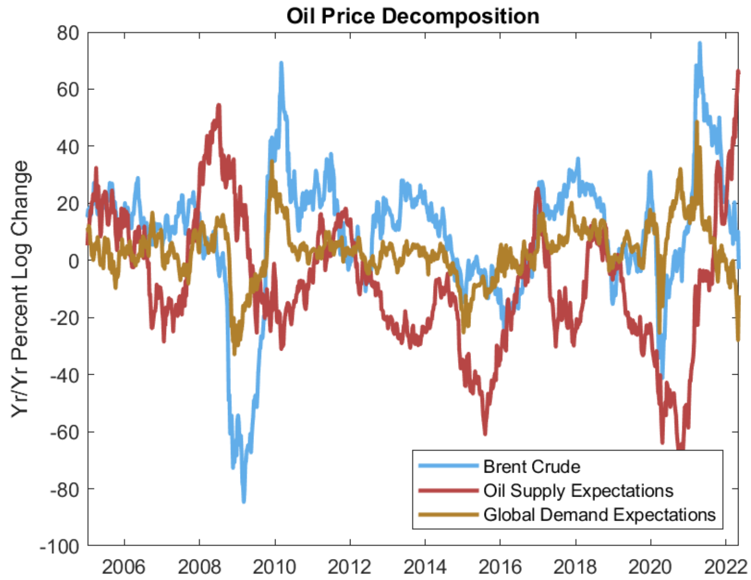
In our analysis we focus on the U.S. as well as the euro area as the representative 'country' for inflation developments in major advanced economies outside the United States. In terms of inflationary measures, we focus on inflation at the firm level, as summarized by PPI inflation, as well as inflation at the retail level, and in that case we focus on CPI inflation.

4.1 Methodology

Our methodology exploits the local projection method of Jordà (2005) and use this approach to trace out the response of inflation rates to shocks to either our GSCPI as well as the demand and supply components of oil price changes. Given the relatively short sample it might be challenging to specify and estimate an appropriate underlying multivariate system. The local projection method allows us to be agnostic about such a system and to approximate the impulse response function (IRF) of a shock by means of a set of direct, linear regressions.

To approximate the implied IRFs of shocks to the GSCPI and oil price changes for

Figure 4: Decomposing Brent Crude Oil Prices in Demand and Supply Components



inflation, we use the following regression model:

$$y_{t+h} = \alpha_h + \beta_h x_t + \sum_{l=1}^{p} \delta_l' \mathbf{w}_t + \varepsilon_{t+h} \quad \text{for } h = 1, \dots, H, \tag{1}$$

where y_t is a year-over-year inflation rate, x_t is either the GSCPI, the demand component of year-over-year oil price changes op_t^d or the supply component of year-over-year oil price changes op_t^s, and $\mathbf{w}_t$ is vector of control variables including lags of y_t and x_t. The estimated β_h from (1) for $h = 1, \dots, H$ reflect the response of y_t up to H months out to a standard deviation innovation in x_t now.

The model in (1) can simply be estimated by means of OLS for h separately and Newey and West (1987) based standard errors for β_h can be used to quantify the uncertainty around these implied impulse response functions. However, as h in (1) becomes larger the estimates of β_h's becomes more susceptible to higher variance, especially in the sample sizes that we are employing here. To address this issue Barnichon and Brownlees (2019) propose to approximate the sequence of β_h in (1) across the different horizons h as a linear combination of K B-spline basis functions

$$\beta_h \approx \sum_{i=1}^{K} b_k B_k(h), \tag{2}$$

where B_k for $k = 1, \dots, K$ are the set of B-spline functions and b_k for $k = 1, \dots, K$ is a set of scalar parameters. The set b_k of scalar parameters in (2) can be estimated by means of a penalized estimator that shrinks (2) towards a quadratic polynomial in h.[5]

The choice of control variables $\mathbf{w}_t$ in (1) are crucial for controlling the error term ε_{t+h}, and to that end, lags of y_t, x_t and other variables of interest are included in w_t. We also include a monthly proxy for year-over-year GDP growth, denoted as ry_t, in w_t to control for the impact of real activity on inflation not accounted for by x_t, using the approach of Groen et al. (2020).[6] Finally, the control variables w_t are also used to identify the implicit independent shocks to the GSCPI and the oil price components to facilitate the estimation of the corresponding IRFs β_h for $h = 1, \ldots, H$. Following Shapiro and Watson (1988) and Barnichon and Brownlees (2019), the timing restrictions implied by recursive identification can be imposed for each x_t with a specific choice of control variables w_t and whether to start the estimation at $h = 0$ or $h = 1$. In a recursive shock identification, identification can be achieved by controlling for the contemporaneous values of the variables ordered before the shock variable of interest (x_t in (1)). Within our setting

$$\begin{aligned} w_t^{GSCPI} = (&y_t, y_{t-1}, \ldots, y_{t-p}, ry_t, ry_{t-1}, \ldots, ry_{t-p}, \\ &GSCPI_{t-1}, \ldots, GSCPI_{t-p}, op_{t-1}, \ldots op_{t-p}),' \end{aligned} \tag{3}$$

and

$$\begin{aligned} w_t^{op^d} = w_t^{op^s} = (&y_t, y_{t-1}, \ldots, y_{t-p}, ry_t, ry_{t-1}, \ldots, ry_{t-p}, \\ &GSCPI_t, GSCPI_{t-1}, \ldots, GSCPI_{t-p}, op_{t-1}, \ldots op_{t-p})', \end{aligned} \tag{4}$$

where $op_t = (op_t^d \ op_t^s)'$. The recursive ordering implied by (3) and (4) equals y_t, ry_t, $GSCPI_t$, op_t^d and op_t^s, and thus imposes that inflation does not respond contemporaneously to innovations in the other variables, GSCPI is allowed to respond to innovations in y_t and ry_t but not to those hitting the oil price components, and both oil price components can respond immediately to shocks to y_t, ry_t and $GSCPI_t$ and are by construction uncorrelated with each other.

4.2 Results

The framework outlined in the previous subsection can now be used to assess how, on average, PPI and CPI inflation responds to independent innovations to the GSCPI and both the demand and supply components driving yearly oil price changes. To recap, using monthly data from January 1997 upto February 2022 we estimate the local projections for each of the shock variables GSCPI, oil price demand component and oil price supply

[5] Li et al. (2021) show in an extensive simulation exercise that such a penalized estimation of the local projection IRF substantially decreases its variance.

[6] Groen et al. (2020) use monthly data on industrial production, real retail sales, real exports and real imports to interpolate quarterly GDP data to the monthly frequency.

component across $h = 1, \ldots, H$ monthly horizons, where we set $H = 16$ for the IRFs and use the Aikaike Information Criterion (AIC) to determine the lag order of the lagged variables included in the control variable set for the three shock variables. We also compute the corresponding 90% confidence intervals for the IRFs based on the Newey-West type variance estimator described in Barnichon and Brownlees (2019, p. 525). The local projection-based IRFs are estimated for both year-over-year PPI inflation as well as CPI inflation.

We start by first discussing the PPI inflation results. Fig 5 describe the PPI inflation response to one standard deviation shocks to the GSCPI, the oil price demand component, and the oil price supply component for the U.S. and the Euro-area, respectively.[7] Compared to the PPI inflation responses to GSCPI shocks, the PPI inflation responses to the oil price component shocks are swifter with the impact of supply driven oil price shocks somewhat larger in magnitude than those of demand driven oil price shocks. The PPI inflation response in case of GSCPI shocks, in contrast, build over time reflecting the cumulative impact of a disruption that works itself through the different layers of global supply chains.

Figure 6 presents the CPI inflation results for the U.S. and the euro area. Qualitatively, the responses across the three shocks are similar to those documented in case of PPI inflation. The magnitude of the responses, however, are substantially smaller for CPI inflation. This is not surprising given that a multitude of factors may drive a wedge between producer and retail pricing.

The aforementioned discussion of IRFs focused on the average response of inflation rates to shocks to global supply chains and oil prices. Although the magnitudes of the responses across the shocks seems fairly similar for each inflation measures, this discussion did not touch upon the fact that (a) oil price shocks are on average more volatile than shocks to the GSCPI, and (b) the post Covid-2019 period experienced shocks to supply chains and energy prices that were larger than in the 1997-2019 period. Indeed, during 2020-2022 independent shocks to the GSCPI reached sizes up to three times the full-sample standard deviation of GSCPI innovations, whereas shocks to both components of oil price changes in 2020-2022 were up to two times the full-sample standard deviations. To quantify this in more detail for the post Covid-19 period, we use the IRF estimation approach described in Section 4.1 to decompose the realized inflation moves since late 2019. We operationalize this by means of

$$y_t = \delta_0 + v_t^R + \sum_{h=1}^{\infty} \hat{\beta}^h_{GSCPI} \hat{\epsilon}^{GSCPI}_{t-h} + \sum_{h=1}^{\infty} \hat{\beta}^h_{po^d} \hat{\epsilon}^{po^d}_{t-h} + \sum_{h=1}^{\infty} \hat{\beta}^h_{po^s} \hat{\epsilon}^{po^s}_{t-h}, \tag{5}$$

[7] Given that global crude oil prices are quoted in U.S. dollars, we transform in the following our oil price component series in local currency terms for the euro area analyses.

Figure 5: Impulse Responses: PPI Inflation

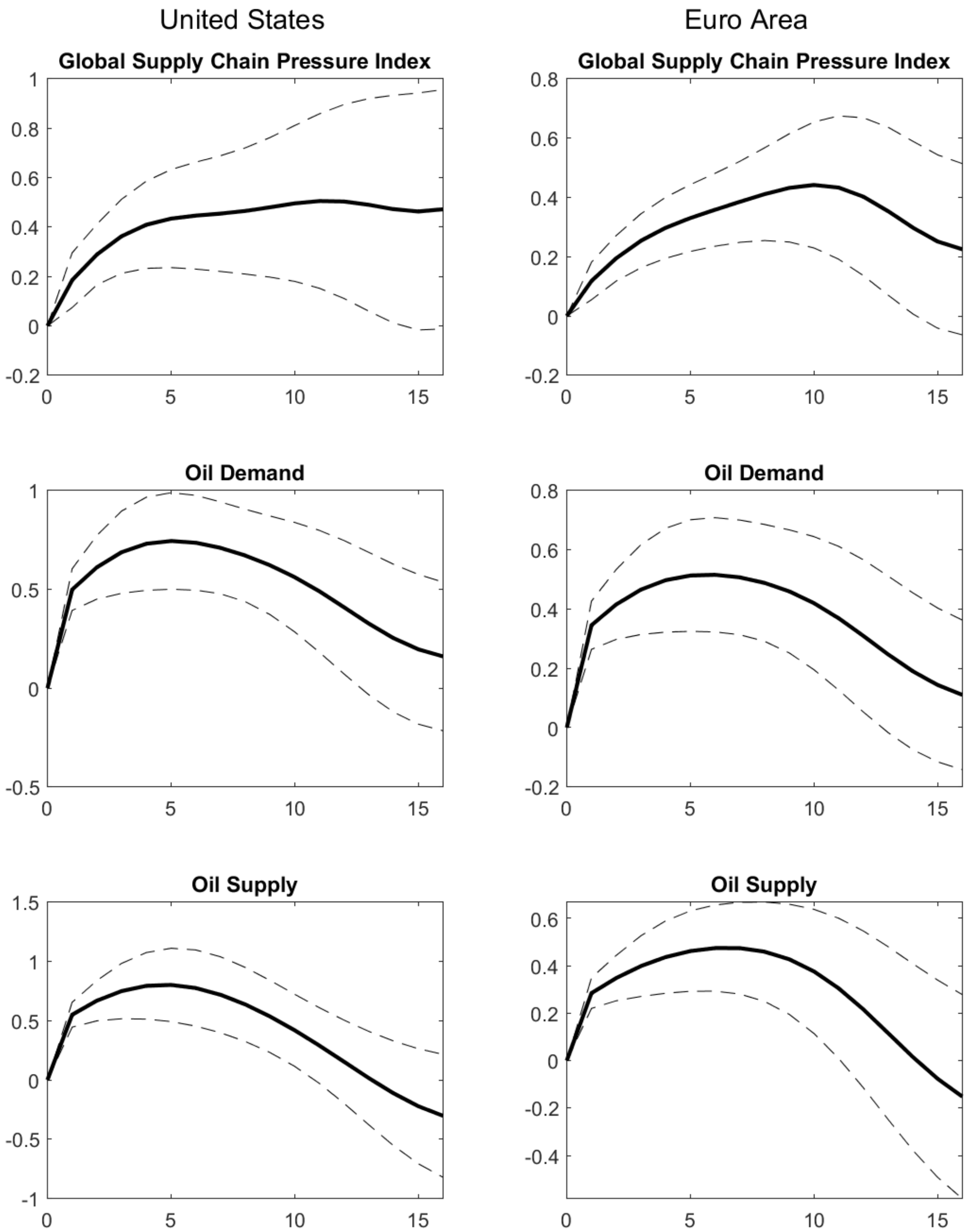
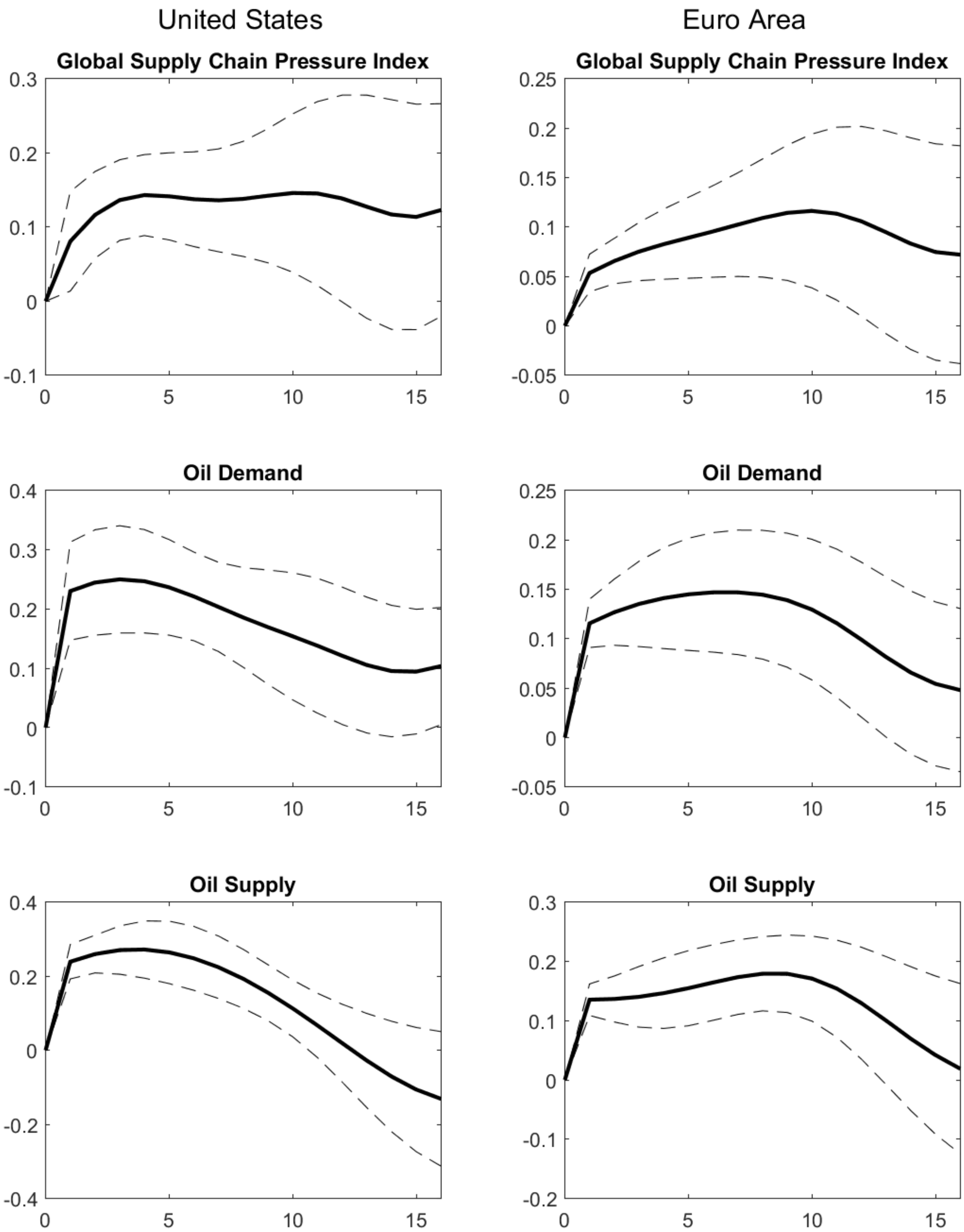


Figure 6: Impulse Responses: CPI Inflation



with δ_0 is the historical mean of the year-over-year inflation rate y_t, and $\hat{\epsilon}_t^{GSCPI}$, $\hat{\epsilon}_t^{po^d}$ and $\hat{\epsilon}_t^{po^s}$ are residuals of regressions of, respectively, GSCPI, the oil price demand component and the oil price supply component on an intercept and their respective set of control variables set out in (3) and (4). At this stage it is useful to remind the reader that we use the control variables to impose the timing restrictions of the recursive identification scheme, and the residuals used in (5) therefore reflect the independent innovations to the GSCPI and the oil price components. In (5) the empirically identified shocks to the GSCPI and the oil price components are combined with their corresponding IRFs estimated through (1) and (2) to quantify the inflation contribution of present and past shocks to global supply chains and oil prices. Finally, v_t^R represents the part of inflation not explained by its mean as well as the shocks to GSCPI and oil prices, and it is due to initial conditions and inflation-specific shocks unrelated to shocks to supply chains and oil prices.

In case of the U.S. we report the historical decomposition of PPI and CPI inflation rates for the post-2019 period using (5). For both inflation rates we notice that deteriorating global supply chain conditions from Spring 2020, then initially reaching a plateau in Fall 2020, followed by a renewed upwardly inflation push due to heightened global supply chain pressures from Summer 2021 onwards, and this appears to top out in early 2022. Oil price shocks played a key role in keeping inflation in check during 2020, especially for PPI inflation, on the back of falling global demand and oversupply in terms of oil production. As economies recovered from the initial Covid-19 shock rising oil prices then became a major impetus behind accelerating inflation throughout 2021. We uncover similar patterns for the euro area in Figure 8 with maybe a somewhat larger impact of supply chain pressures and oil price changes in that economy. Hence, the persistence of recent inflationary pressures at the CPI and PPI levels appears to be importantly related to the evolution of global supply factors such as production or shipping bottlenecks and input prices.

5 Conclusion

In this paper we present a novel indicator aimed at gauging global supply chain pressures. Our goal in constructing the GSCPI is to build a parsimonious measure of these pressures that keep into account different dimensions along which supply chain factors could constraint the global production network. We have used our index for assessing its role in explaining recent inflationary pressures as one example of its potential applications. There are two directions along which we could further develop this product: the first one consists in developing regional indicators (as in Benigno et al. (2022a)). The second one could exploit other data with more granular information (truck and port data for exam-

Figure 7: Decomposing U.S. Inflation Post-2019

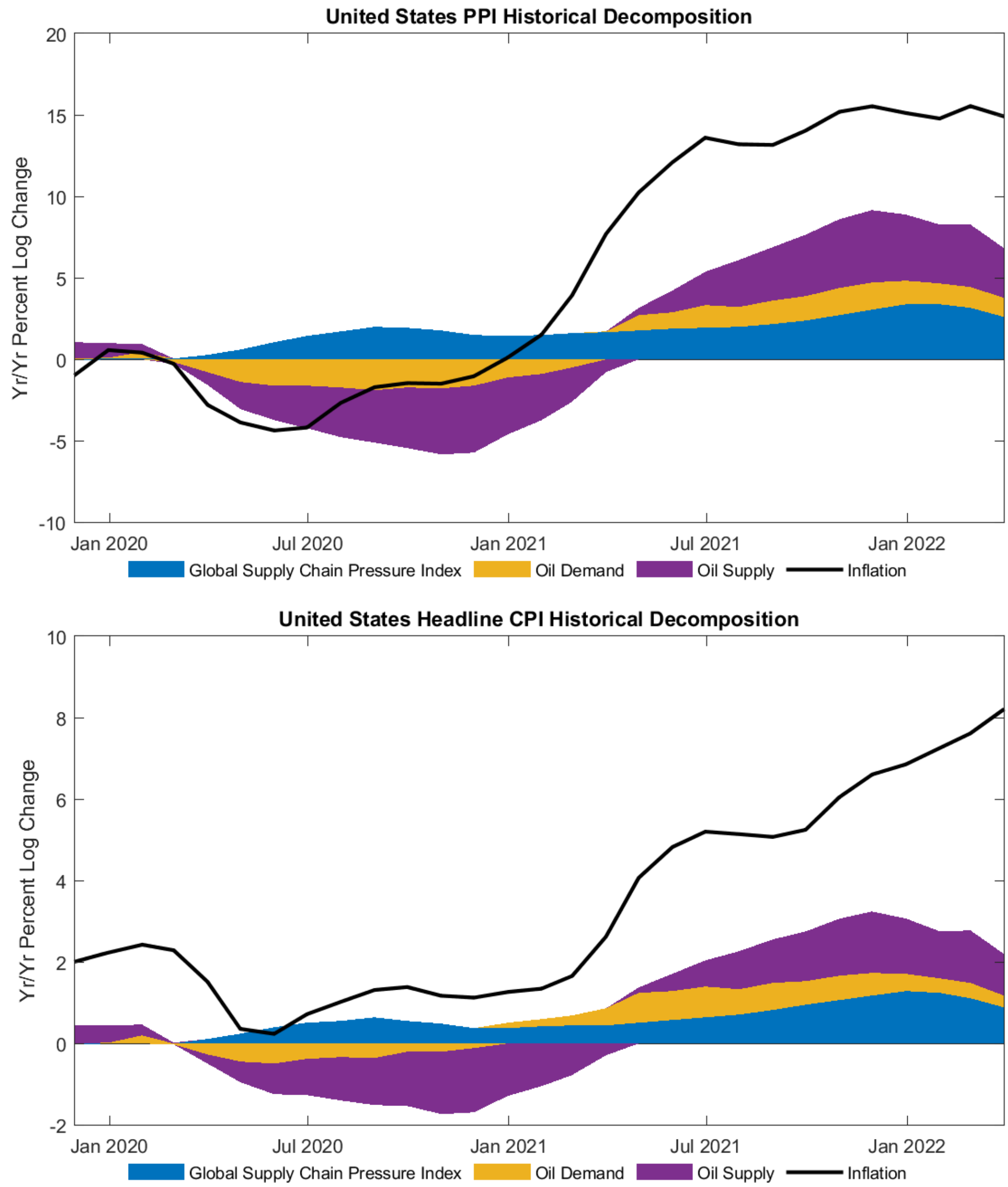
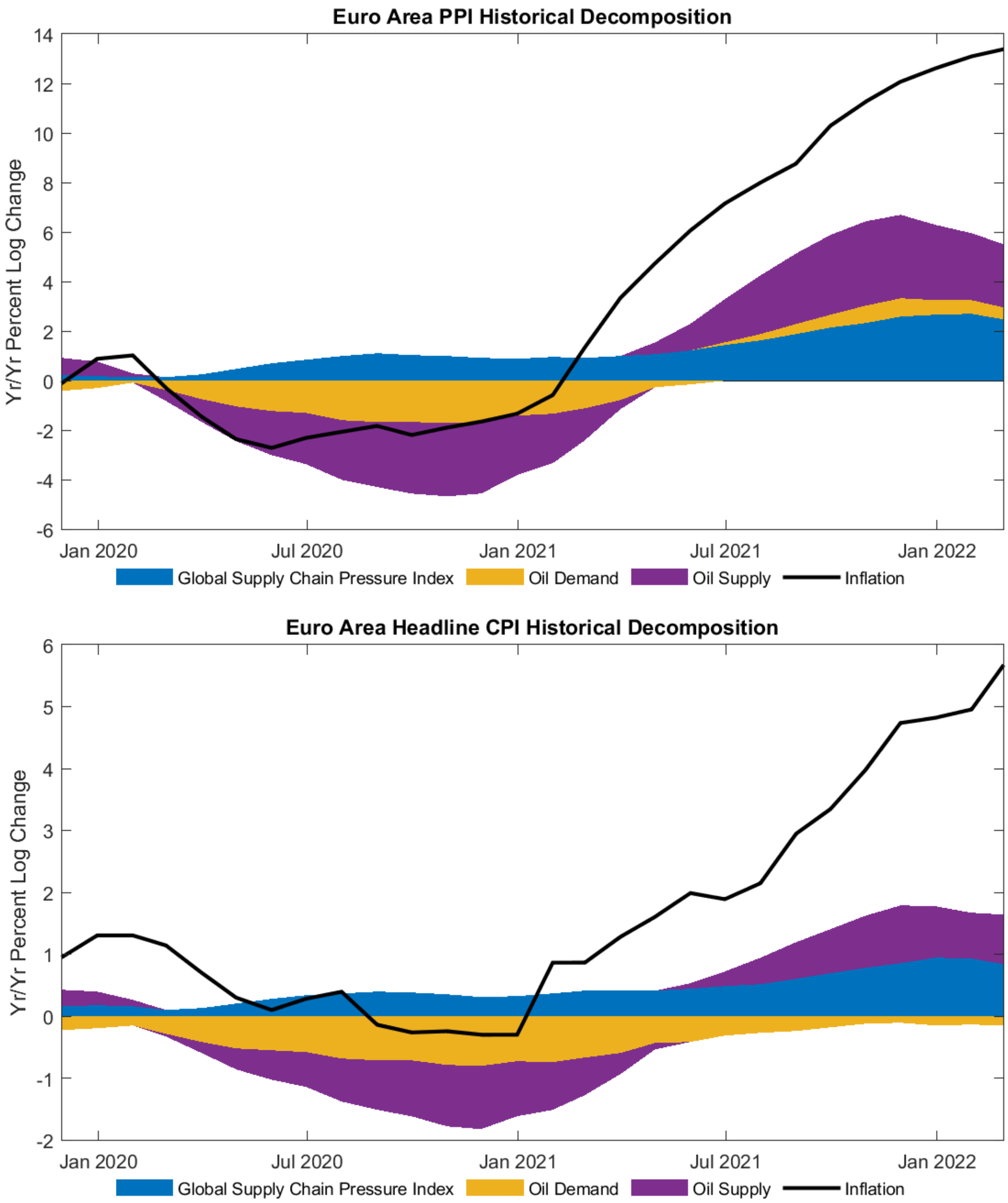


Figure 8: Decomposing Euro Area Inflation Post-2019



ple). Furthermore different analytical and empirical frameworks could use our index for the understanding of other aspects of interest in the economy.

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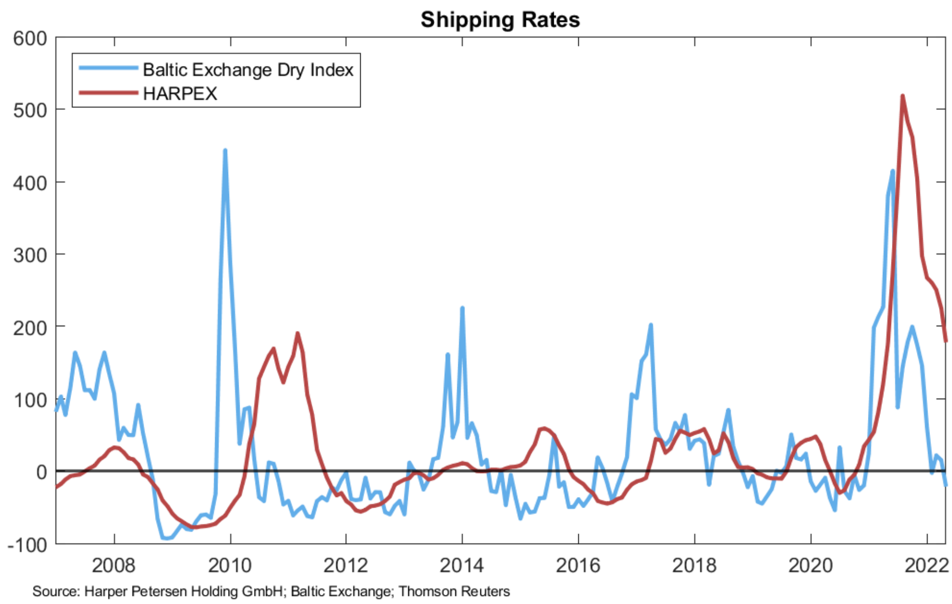
Appendix
for
“A New Barometer of Global Supply Chain Pressures”

A Components of the GSCPI

We show our measures of transportation costs in the two charts below. In A.0 we notice that both shipping cost indices have witnessed enormous growth since the beginning of the global recovery from the troughs of the Covid-19 pandemic, although the BDI has begun to slow in recent months. It is interesting to note that the Harpex container shipping cost measure increased considerably more relative to what was observed during recovery from the Global Financial Crisis (GFC), while the BDI rise has been on par. A.0 plots the inbound and outbound costs of airfreight from or to the U.S. from or to Asia and Europe. Especially airfreight costs from Asia and Europe to the U.S. accelerated sharply in 2020, as airlines dramatically cut airfreight capacity in response to the pandemic.

Figure A.0: Evolution of Shipping Rates



In A.0, we plot GDP-weighted averages of the sub-components of our countries' manufacturing PMIs. The measures of supply bottlenecks have risen dramatically during the recent recovery period, and this rise has been most notable for the 'Delivery Time' component of the PMIs across our seven economies.

Figure A.0: Evolution of Air Freight Rates

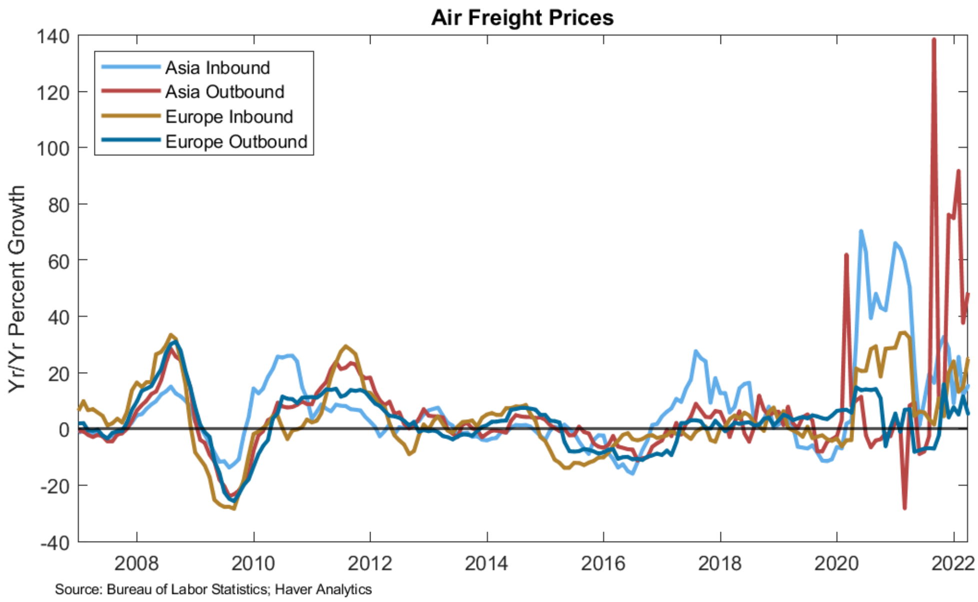


Figure A.0: GDP-weighted Sub-components of Countries' Manfufaturing PMIs