INTERNATIONAL MONETARY FUND

Global Value Chains and Inflation Dynamics

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WP/24/62

2024
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WORKING PAPER

 WP/24/62

IMF Working Paper
Research and Western Hemisphere Departments

Global Value Chains and Inflation Dynamics
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Authorized for distribution by Nan Li and Ceyda Oner
March 2024

ABSTRACT: We study the inflationary impacts of pandemic lockdown shocks and fiscal and monetary stimulus during 2020-2022 using a novel harmonized dataset of sectoral producer price inflation and input-output linkages for more than 1000 sectors in 53 countries. The inflationary impact of shocks is identified via a Bartik shift-share design, where shares reflect the heterogeneous sectoral exposure to shocks and are derived from a macroeconomic model of international production network. We find that pandemic lockdowns, and subsequent reopening policies, were the most dominant driver of global inflation in this period, especially through their impact on aggregate demand. We provide a decomposition of lockdown shock by sources, and find that between 20-30 percent of the demand effect of lockdown/reopening is due to spillover from abroad. Finally, while fiscal and monetary policies played an important role in preventing deflation in 2020, their effects diminished in the recovery years.

RECOMMENDED CITATION: Chau, V., Conesa Martinez, M., Kim, T., & Spray, J. (2024). Global Value Chains and Inflation Dynamics. *IMF Working Papers, 2024/62*
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JEL Classification Numbers:	E31; F10; F41
Keywords:	Inflation; global value chains; network; pandemic; spillovers.
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* All authors are affiliated with the International Monetary Fund. The views in this paper are personal views of the authors and do not necessarily represent those of the IMF, its Executive Board, or IMF Management. We thank Chris Papageorgiou, Ceyda Oner, Prachi Mishra, Rodrigo Valdés, Filiz Unsal, Adrian Peralta-Alva, Rui Mano, Niels-Jakob Hansen, Yan Carriere-Swallow, Alasdair Scott, Abdoul Wane, Cian Ruane, Marco Arena, and parcipants at the IMF APD, WHD, RESDM Seminar Series for thoughtful comments and feedback.

WORKING PAPERS

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1 Introduction

The rise of global inflation after the COVID-19 pandemic caught the world by surprise and pushed inflation to its highest levels in decades. While traditional drivers of inflation, such as loose fiscal and monetary policies, have continued to be cited as the causes of high inflation, the recent inflationary period has also called into questions the vulnerabilities of the global value chains (GVCs) to disruptions (caused by lockdowns, disasters, and wars) and its role in transmitting shocks across countries.[1] To properly draw lessons from this inflationary period and ensure costly mistakes are not repeated in the future, it is important then to know the relative importance of different inflation drivers. In this paper, we provide a novel harmonized dataset of sectoral producer price, merged with input-output linkages and shocks, for more than 1000 sectors in 53 countries, and a framework to identify inflationary impact of different inflation drivers using the sectoral data.

Identifying the inflationary impact of shocks is empirically challenging. First, aggregate consumer price indices are functions of many concurrent shocks–demand and supply, domestic and foreign spillovers–and relying only on this data would not provide sufficient statistical power for identification. This is evident in the US inflation debate, where different policymakers and scholars attribute the high inflation rate to different drivers. Second, the same shock can appear to be both a "supply shock" and a "demand shock" that affect inflation in opposing ways. Lockdown policies can be a negative supply shock that increases the price level as limited production depletes inventories and makes goods scarce. At the same time, lockdowns can be thought of a negative demand shock that depresses prices, as workers receive lower income and demand less goods and services.[2] Furthermore, lockdowns can be predominantly a demand shock for one country and a supply shock for another, manifesting through higher imported input prices. Thus, studying the inflationary impact of pandemic lockdown requires taking a holistic, structured view of how lockdown can affect the units of observation of interest.

In this paper, we try to overcome the aforementioned empirical challenges and study the drivers of global inflation using a set of Bartik (1991) shift-share instruments derived from a general equilibrium model with international production network. Our empirical work has two components. First, we collect and harmonize PPI inflation data for a cross-section of 1134 international production sectors during the period 2020-2022, ensuring consistency with international input-output data and other relevant data sets. Second, we construct Bartik instruments of inflation drivers, leveraging the large changes in lockdown and fiscal policies worldwide during this period as *shifts* and the differential degrees of sectoral exposure to shocks through the trade network as *shares*. The "network exposure share" is derived from a macroeconomic model of international production in a networked supply

[1] See Elliott and Golub (2022); Carvalho et al. (2021); Acemoglu and Tahbaz-Salehi (2020)

[2] See Guerrieri et al. (2022) for how a shock can be both supply and demand in a multi-sector economy.

chain, which closely follows Baqaee and Farhi (2019).

In particular, identification of the impact of *supply-shocks* relies on the differential use of inputs in production: when a sector in a particular country enters lockdown (e.g. microchips in Thailand), a downstream sector that uses those inputs more extensively, either directly (e.g. automobile production in Mexico) or indirectly (e.g., automobile retail in the US), should see a larger increase in inflation. Symmetrically, identification of the impact of *demand-shocks* relies on the differential demand for products: a lockdown in the US will directly impact demand for automobiles from Mexico, and indirectly impact demand for microchips in Malaysia but will have a negligible impact on sectors with small bilateral trade shares (e.g. tobacco production from Cuba). The separate identification of the supply effect versus the demand effect of lockdowns comes from the fact that a production sector in a particular country might import intermediate goods from geographical locations that differ from where they export.

Using these instruments, we run Local Projection (LP) regressions à la Jordà (2005) to study the contemporaneous and dynamic effects of lockdowns and fiscal stimuli on producer prices. The aim of the baseline exercise is to study the impulse responses of various drivers of inflation. As an extension, we look at heterogeneity of these effects via allowing the impulse responses to differ depending on the stage of the pandemic, as well as own- versus network-effects.

Our main results are the following. *First*, lockdown (and reopening) policies are strong and persistent drivers of global inflation, both through supply and demand channels. Our estimates imply large economic impacts. On the supply side, the full lockdown of a major supplier that accounts for 50% of total expenditure raises a sector's PPI by 14.5%. On the demand side, a full lockdown of an economy that accounts for 50% of a sector's total output depresses its PPI by 15%. The inflationary effects of lockdown are large and persistent, peaking after 3 quarters and dissipating only after a year. All of our specifications include a full set of country, sector and time fixed effects. The results are qualitatively invariant to controlling for lagged inflation, changes in the exchange rate vis-a-vis the US dollar, and transportation costs.

Second, fiscal stimulus packages during the pandemics also had significant inflationary impact. Our estimates point to a fiscal multiplier of 0.75, i.e. a one dollar increase in fiscal spending would increase domestic demand by about 75 cents on impact. The inflationary impact on a sector's producer price depends on its "exposure" to the economy receiving the stimulus. To illustrate the potential magnitude, consider a stimulus package worth 10% of GDP and a sector that sells 50% of its value added domestically. The inflationary impact of the fiscal stimulus on this sector would be $0.75 \times 10\% \times 0.5 = 3.8\%$. However, fiscal shocks tend to be less persistent compared to lockdown shocks, peaking on impact and quickly dissipating after 2 quarters.

Third, in relative contribution, we find that pandemic lockdowns, and subsequent reopening policies, were the most dominant driver of global inflation in this period, especially through their impact on aggregate demand. While fiscal and monetary policies played an important role in preventing deflation in 2020, their effects diminished in the recovery years.

Fourth, the inflationary impacts of shocks are different in the beginning versus recovery phase of the pandemic. In particular, we find that the supply disruptions due to lockdown were more severe and long-lasting at the beginning of the pandemic than in the the recovery phase. By contrast, the demand effect of lockdown/reopening was the same in both phases. This suggests the possibility that firms were able to adapt to rising costs due to supply disruptions during the recovery phase, e.g. by switching to alternative sources. For fiscal policies, we find that fiscal stimulus had a much more persistent inflationary effect in the recovery phase, which suggests that while fiscal packages were helpful in supporting businesses and workers without a long-lasting inflationary impact at the trough of the pandemic, continuing to overheat the economy with fiscal stimulus when the economy has recovered could lead to very persistent inflation.

Finally, we find that global supply chains were important propagation channels of international shocks to producer prices. In the subsequent analysis, we decompose the impulse response into the one driven by the network effect and its own effect. The network effect–the impact of shocks to connected sectors–accounts for 50% of the total effect for "supply shocks" and almost the entire effect of "demand shocks." This result suggests that the production network is integral to the understanding of international spillover effects of a shock such as the pandemic.

Our identification leverages heterogeneous exposure of different industries to shocks. The identification assumption is that the exposure weights (pre-COVID network supply and demand shares) do not predict changes in sectoral inflation rates through channels other than the network of intermediate input trades as laid out in our theory.[3] While assuming that the network trade shares, which are endogenous objects, are uncorrelated with the levels of sectoral inflation rates might not be plausible, assuming that the shares are uncorrelated with the changes in inflation rates is a much weaker assumption (Goldsmith-Pinkham et al., 2020). The constructed Bartik instruments are applied as instrumental variables to the Local Projection framework (see Jordà (2023) for a literature summary).

A violation of the identification assumption would occur, for example, if two countries have high network supply and demand shares due to geographical proximity; however, being close also means that COVID infections—and the consequential supply disruptions—can spread across borders. A related concern is that trade shares were correlated with transport cost shocks induced by the pandemic. This could occur if COVID infections are passed along trade routes and lead to disruptions to transportation infrastructure. To address both of

[3]More formally, we assume that the initial period shares are not correlated with the structural error terms, i.e., changes in the outcome variable (PPI inflation).

these threat we run robustness tests controlling for the level and change of COVID infections in each country. We also control for route-sector-specific maritime transport costs. To do this we interact monthly route-specific maritime freight costs from Freightos Baltic Container Price Index with a measure of sector specific exposure to changes in transportation costs using data from the OECD Maritime Transport Cost dataset which contains bilateral ad valorem maritime transport costs for 43 importing countries from 218 countries of origin at a product level. In all instances, the results are robust to these controls and both the sign and magnitude of coefficients on the main explanatory variables remain largely unchanged.

These results have important implications for our understanding of international spillovers of policy through global supply networks. Firstly, we contribute to the inflation debate by showing that the rise in inflation across the world is indeed mostly demand-based. However, contrary to conventional wisdom we find this demand is stimulated via a general reopening of economies instead of fiscal stimuli. Secondly, in a world which is increasingly subject to supply-shocks and with the threat of economic fragmentation our results indicate that policy makers will a) need to consider the indirect impacts of economic policies in major trading partners, b) should internalize the global impact of their own economic policy through supply-networks, and c) should incentivize the building of resilient supply-chains, to minimize the impact of shocks.

Our paper is in the spirit of Acemoglu et al. (2016) and Baqaee and Farhi (2019), which study the transmission of macro-economic shocks through input-output production linkages. We extend this framework to the international setting and to the study of inflation dynamics. The use of the structural model here is necessary: as we are studying hundreds of different shocks (lockdown, fiscal, monetary shocks for 60+ countries), the model provides a parsimonious and intuitive way to combine those shocks into a few Bartik instruments. Furthermore, the model also allows us to decompose a shock, like lockdown, into different propagation channels. Another closely-related paper is Di Giovanni et al. (2023), which also studies the drivers of pandemic-era inflation using a multicountry model with input-output network. The model in that paper is slightly richer but is calibrated only to four large countries / areas, foregoing the richness of cross-country granular data. Our paper instead relies on the model to construct the Bartik instruments, applied to many more countries and sectors.

Our paper sheds light on supply chain disruptions caused by the COVID-19 lockdowns. Recent papers in the literature, which focus on the supply-chain issues of the pandemic, include Bonadio et al. (2021), Meier and Pinto (2022), Baqaee and Farhi (2022), Lafrogne-Joussier et al. (2022), Carrière-Swallow et al. (2023) and Alessandria et al. (2023). Laurence Ball and Mishra (2022) decomposes the post-pandemic inflation to the supply-side and demand side factors. On the theory front, Benigno and Eggertsson (2023) and Harding et al. (2023) attempt to explain the non-linearity of the Phillips Curve that was observed during the pandemic period. Our paper also contributes a large empirical literature on inflation.

In particular, our paper relates to a growing interest in the identification of inflation drivers via cross-sectional variations. For example, Fitzgerald and Nicolini (2014) and McLeay and Tenreyro (2019) show that using regional data helps disentangle demand- and supply-side shocks to inflation. Other papers such as Beraja et al. (2019) and Hazell et al. (2022) make use of state-level or city-level price indexes in the US to estimate the slope of the regional Phillips Curve. Deb et al. (2023) constructed a novel monetary policy shocks database to study the dynamics of the transmission of monetary policy on inflation and output, and the country characteristics that drive them.

Our paper builds on a literature using shift-share designs to identify the impact of macroeconomic shocks. Building from seminal applied work using differential exposure to shocks to identify causal relationships (Bartik, 1991; Card, 2001; Autor et al., 2013), a recent body of literature has made advances in understanding bias, inference and aggregation in shift share designs (Jaeger et al., 2018; Adao et al., 2019; Broxterman and Larson, 2020; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Our paper most closely relates to a literature using differential exposure to foreign market (Hummels et al., 2014; Berman et al., 2015; Aghion et al., 2018) and where different products are exposed to different types of consumers (Jaravel, 2019).

Our paper uses a model of international production networks to show a sector's exposure to demand and supply shocks are determined by the impact of up- and down-stream sectors direct and indirect exposure to the shock. Using this insight, we build a shift-share empirical framework which allows us to separately identify the impact of demand and supply shocks on PPI inflation and to independently identify the direct effect from indirect network effects. Unlike the previous works that integrate input-output linkages to a calibrated New Keynesian model (Rubbo, forthcoming; La'O and Tahbaz-Salehi, 2022), our focus is on constructing an empirical specification that enables measuring cross-sectional variations of a shock.

The remainder of the paper is organized as follows. Section 2 presents a model. Section 3 develops an empirical methodology and presents data description. Section 4 discusses the baseline results. Section 5 sheds light on additional issues including identification issues, robustness checks and geographic variations. Section 6 concludes.

2 Theoretical Framework

In this section, we write down a standard multi-country model featuring a global input-output network and derive the international inflationary response to various supply and demand shocks in closed-form. The model-based elasticities of country and sector-level inflation rates to shocks, which are functions of the underlying production network, will serve as the basis for the construction of our empirical Bartik instruments.

2.1 Environment

Our world economy has N countries, each with a representative consumer with some preference $u_i(C_i, L_i)$ over consuming a country-specific final good, denoted by C_i, and providing L_i units of labor.

There are N final consumption goods which are aggregators of S internationally produced intermediate goods under a constant returns to scale (CRS) technology:

$$D_i = \mathscr{D}_i(D_{i1}, \ldots, D_{iS}) \tag{1}$$

The final good output D_i is equal to total domestic demand, which includes private and public consumption:[4]

$$D_i = C_i + G_i \tag{2}$$

Let Q_i denote the price of final good i (consumer price index). As a simple way to analyze demand effect of fiscal and monetary policies on inflation, we assume that nominal public consumption $\widetilde{G}_i = Q_i G_i$ is given exogenously and financed via a lump-sum tax on households, while private consumption $\widetilde{C}_i = Q_i C_i$ is a choice variable set by the monetary authority.[5]

Each intermediate good s represents a specific country-sector–for example, Korean chemical manufacturing–in the data. An intermediate good once produced can be used either for the production of further intermediate goods or for final consumption. Good $s \in \{1, \ldots, S\}$ is produced using domestic value added L_s and other intermediate inputs under a CRS technology:

$$Y_s = \mathscr{F}_s\left(Z_s L_s, \{X_{sk}\}_{k=1}^S\right) \tag{3}$$

where L_s and X_{sk} are the amounts of labor and intermediate good k used in sector s, respectively. Z_s is the value added-augmented productivity in sector s.[6] Intermediate goods can be imported from another country. Labor is perfectly mobile between different sectors within a country but cannot move across countries. We assume the Law of One Price, which means the price of intermediate good s is the same in all countries.

[4] Our framework does not include investment and thus might not adequately capture intertemporal channels of demand and supply effects on inflation (for example, if an increase in investment this period raises demand and inflation today, but will lead to more goods being available and thus cheaper prices in the longer terms).

[5] On fiscal policy, we follow Acemoglu et al. (2016) in using exogenous variation in domestic demand (our term G_i) as a tool to trace out the network impact of demand shock. On monetary policy, the assumption that the monetary authority directly set nominal demand, which we follow Lucas (1973), might appear ad-hoc, but one can give a model with more micro-foundation, e.g. with cash-in-advance constraints, and back out the path of money supply or interest rate that would implement the desired consumption path.

[6] The assumption that productivity is value added-augmenting is without loss of generality. The model economy is identical to one with only Hicks-neutral TFP, with value added being first produced in one sector before being supplied to the intermediate-good producing sectors.

The market clearing conditions for intermediate goods and labor are given by:

$$\sum_{i=1}^{N} D_{is} + \sum_{k=1}^{S} X_{ks} = Y_s, \qquad s = 1,2,...,S \tag{4}$$

$$\sum_{s\in\mathscr{S}_i} L_s = L_i, \qquad i = 1,2,...,N \tag{5}$$

where $\mathscr{S}_i$ denote the set of intermediate goods produced in country i.

2.2 Equilibrium Inflation

Let W_s be the wage that sector s has to pay for its labor, and P_s the price of good s. Throughout the paper, we use lowercase notations to denote the log of corresponding uppercase variables $x = log(X)$, and hats indicate deviation from the steady state: $\widehat{x} \equiv x - \overline{x}$.

The cost minimization problem in sector s is:

$$MC_s(Z_s, W_s, \{P_k\}_{k=1}^S) = \min_{L_s^*, \{X_{sk}^*\}_{k=1}^S} \left\{ W_s L_s^* + \sum_{k=1} P_k X_{sk}^* \right\} \quad \text{s.t.} \quad \mathscr{F}_s\left(Z_s L_s^*, \{X_{sk}^*\}_{k=1}^S\right) = 1 \tag{6}$$

Applying Shephard's Lemma, we obtain a well-known optimal equilibrium condition that the expenditure share of an input in marginal cost is equal to the output elasticity of that input:

$$\frac{\partial \log MC_s}{\partial \log W_s} = \frac{W_s L_s}{MC_s Y_s} = \theta_s \qquad \frac{\partial \log MC_s}{\partial \log P_k} = \frac{P_k X_{sk}}{MC_s Y_s} = \omega_{sk}$$

We denote by θ_s and ω_{sk} the share of value added and intermediate input k in total cost, respectively. These shares are key objects that describe input-output relationships and satisfy $\theta_s + \sum_k \omega_{sk} = 1$ by construction.

Using this equilibrium condition, we can approximate the marginal cost function of each sector to the first order:

$$\begin{aligned} d\log MC_s &\approx \frac{\partial \log MC_s}{\partial \log W_s} \cdot (d\log W_s - d\log Z_s) + \sum_{k=1}^{S} \frac{\partial \log MC_s}{\partial \log P_k} \cdot d\log P_k \\ &= \theta_s (d\log W_s - d\log Z_s) + \sum_k \omega_{sk} d\log P_k. \end{aligned}$$

The input shares are evaluated at the point of approximation, which can be the input-output matrix of a particular year or its long-term average. We assume that markup is time-invariant, so that changes in marginal costs are linked one-to-one with changes in prices:[7]

$$d\log P_s = \theta_s(d\log W_s - d\log Z_s) + \sum_k \omega_{sk} d\log P_k \tag{7}$$

Equation (7) can be written in matrix form:

$$d\log \mathbf{P} = \Theta(d\log \mathbf{W} - d\log \mathbf{Z}) + \Omega d\log \mathbf{P} \tag{8}$$

where $\Theta = (\{\theta_s\}_s)$ and $\Omega = (\{\omega_{sk}\}_{s,k})$. Solving for equilibrium inflation $d\log \mathbf{P}$, we get:

$$d\log \mathbf{P} = [I-\Omega]^{-1}\Theta(d\log \mathbf{W} - d\log \mathbf{Z}) \tag{9}$$

Equation (9) has not yet described inflation as a function of exogenous drivers, but is nonetheless useful to explain the mechanisms at play. The equation says that the PPI inflation rate for intermediate goods, $d\log \mathbf{P}$, is a weighted average of the changes in value added unit cost, $d\log W - d\log Z$, across all sectors.[8] The weight that sector s places on sector k is given by the Leontief inverse $[I-\Omega]^{-1}$, scaled by the value added share, and describes the importance of sector k as an upstream input producer. If sector s does not use intermediate input, it has a 100% weight on its own value added, and its output price is only affected by the value added cost in its own sector. However, a sector that uses more intermediate inputs will also be affected by input price changes, which are dependent on cost conditions in the upstream sectors.

In equation (9), wages are endogenous objects and determined by underlying exogenous shocks. In a closed economy, we can think of wages as being the direct choice variable for monetary policy (Baqaee et al. (2021)). In an international setting, wages will be determined by international shocks and policies as well, so it is important to capture international linkages.

For ease of exposition, we assume that in the short run, labor is perfectly inelastic within each sector: $L_s = \overline{L}_s$.[9] If the production function is Cobb-Douglas with respect to labor,

[7] In the case of variable markup, the equilibrium condition simply becomes:

$$d\log P_s \approx d\log \mu_s + (1-\gamma_s) d\log W_s + \sum_k \gamma_s \omega_{sk} d\log P_k$$

One can formulate a model of variable markup and study its implication for inflation, which we do not attempt in this paper.

[8] We can show that the pre-multiplied matrix $(I-\Omega)^{-1}\Theta$ in equation (9) is indeed a weight matrix. Let $\mathbf{1}$ denote a vector of 1. We have:

$$[I-\Omega]^{-1}\mathbf{1} = \left(\sum_{i=0}^{\infty}\Omega^i\right)\mathbf{1} = \mathbf{1} + \sum_{i=1}^{\infty}\Omega^i\mathbf{1} = \mathbf{1} + \sum_{i=0}^{\infty}\Omega^i(I-\Theta)\mathbf{1} = \mathbf{1} + [I-\Omega]^{-1}(I-\Theta)\mathbf{1}$$

where we have used the identity $\Omega\mathbf{1} = I-\Theta$. Re-arranging, we have $[I-\Omega]^{-1}\Theta 1 = 1$, i.e., each row of the matrix $[I-\Omega]^{-1}\Theta$ sums to one.

[9] We also have general results for the case of endogenous labor supply, where the wage response will be jointly determined by the labor demand and supply curves, which require more structural assumptions such

the wage bill is always a constant fraction of nominal output: $W_s L_s = (1-\gamma_s)\widetilde{Y}_s$, where $\widetilde{Y}_s = P_s Y_s$. In this special case of perfectly inelastic labor supply, fluctuations in nominal output translate one-to-one into nominal wage changes: $d\log W_s = d\log(\widetilde{Y}_s)$.

Finally, we relate nominal output to expenditures. Nominal output or sales of a sector is equal to the spending on that good from all intermediate good purchasers and final consumers:

$$\widetilde{Y}_s = \sum_{i=1}^{N} \widetilde{D}_{is} + \sum_{k=1}^{S} \widetilde{X}_{ks} \tag{10}$$

where we remind that D notates total domestic demand, which includes private and public consumption. Let $\Xi_{is} \equiv \widetilde{D}_{is}/\widetilde{D}_i$ be the share of good s in country i final consumption expenditure. We can rewrite the equation above in matrix form:

$$\widetilde{\mathbf{Y}} = \Xi' \widetilde{\mathbf{D}} + \Omega' \widetilde{\mathbf{Y}} \tag{11}$$

Re-arrange, we have:

$$\widetilde{\mathbf{Y}} = \left[I - \Omega'\right]^{-1} \Xi' \widetilde{\mathbf{D}} \tag{12}$$

Let $\Phi_Y = (\widetilde{Y}_1, \ldots, \widetilde{Y}_S)$ and $\Phi_D = (\widetilde{D}_1, \ldots, \widetilde{D}_N)$ be diagonal matrices of total output and expenditure values at the steady state (or another point of approximation). We can relate changes in output to changes in expenditure as:

$$d\log \widetilde{\mathbf{Y}} = \Phi_Y^{-1} [I - \Omega']^{-1} \Xi' \Phi_D \, d\log \widetilde{\mathbf{D}} \tag{13}$$

Using all results, we summarize the impact of supply and demand forces on inflation rate in the Proposition 1.

Proposition 1. *Suppose that labor supply is perfectly inelastic in the short-run. Conditional on changes to sectoral TFP* $\mathbf{Z}$ *and country demand* $\widetilde{\mathbf{D}}$*, the PPI inflation rate in the network economy is given by:*

$$d\log \mathbf{P} = \Phi^D d\log \widetilde{\mathbf{D}} - \Phi^S d\log \mathbf{Z}$$

where $\Phi^D \equiv [I-\Omega]^{-1} \Theta \Phi_Y^{-1} [I-\Omega']^{-1} \Xi' \Phi_D$ *captures inflation elasticity to demand shocks and* $\Phi^S \equiv [I-\Omega]^{-1}\Theta$ *captures inflation elasticity to supply shocks.*

While much of our empirical analysis focuses on PPI inflation, for completeness, let us state an equivalent proposition for CPI inflation. Note that the final good is simply a basket of intermediate goods with shares described by the matrix Ξ. We can show then that CPI inflation is simply a weighted average of corresponding changes of PPI inflation, appropriately

as the elasticity of labor supply.

weighted: $d\log CPI = \Xi d\log \mathbf{P}$.

Proposition 2. *Conditional on changes to sectoral TFP* $\mathbf{Z}$ *and country demand* $\widetilde{\mathbf{D}}$*, the CPI inflation rate in the network economy is given by:*

$$d\log \mathbf{CPI} = \Phi^D_{CPI} d\log \widetilde{\mathbf{D}} - \Phi^S_{CPI} d\log \mathbf{Z}$$

where $\Phi^D_{CPI} \equiv \Xi[I-\Omega]^{-1}\Theta\Phi_Y^{-1}[I-\Omega']^{-1}\Xi'\Phi_D$ *captures inflation elasticity to demand shocks and* $\Phi^S_{CPI} \equiv \Xi[I-\Omega]^{-1}\Theta$ *captures inflation elasticity to supply shocks.*

2.3 Operationalize theoretical framework

Let us briefly describe how we operationalize Proposition 1 in our empirical analysis.

Supposed we want to study the impact of COVID-19 lockdown on inflation. We explore the possibility that lockdown could affect inflation both through a demand channel (reduced consumption) and supply channel (intermediate input shortage), and use our framework to delineate the two effects. To be concrete, let $\Lambda_s \in [0,1]$ (respectively, Λ_i) denote the stringency of lockdown in sector s (respectively, country i), with 1 being a full shutdown of the sector and 0 being completely unrestricted.

We suppose lockdown in sector s directly reduces the value added productivity of that sector by β^S percent, while lockdown in country i reduces its domestic aggregate demand by β^D percent. Using our Proposition 1, we obtain the sectoral inflation response of sector s to lockdown shocks in all countries and sectors:

$$d\log P_s = -\sum_{k=1}^{S} \Phi^S_{sk} d\log Z_k + \sum_{i=1}^{N} \Phi^D_{si} d\log \widetilde{D}_i = \beta^S \left(\sum_{k=1}^{S} \Phi^S_{sk} d\log \Lambda_k\right) - \beta^D \left(\sum_{i=1}^{N} \Phi^D_{si} d\log \Lambda_i\right) \quad (14)$$

Finally, let us define our shift-share Bartik instruments, where shifts are lockdown shocks and shares are network supply and demand relationships:

$$B^S_s \equiv \sum_{k=1}^{S} \Phi^S_{sk} d\log \Lambda_k$$
$$B^D_s \equiv -\sum_{i=1}^{N} \Phi^D_{si} d\log \Lambda_i$$

This gives us a succint equation that we can use for empirical analysis:

$$d\log P_s = \beta^S B^S_s + \beta^D B^D_s \quad (15)$$

We repeat the procedure for fiscal and monetary shocks by assuming that each of those policies will change aggregate demand, albeit with different elasticities to be informed by the data.

3 Mapping the Model to Data

3.1 Data

To map the model to data, we gather PPI inflation data for 1143 production sectors in 53 countries, including 31 advanced economies (AEs) and 22 emerging markets (EMs), for the period 2019-2022. We harmonize inflation data by reclassifying sectors to accord with the 45 industries in the OECD World Input-Output Table (WIOT). In order to evaluate the impacts of shocks on global inflation we merge the harmonized inflation data with various data sets on shocks: lockdown stringency, COVID-19 fiscal stimulus packages, monetary policy (policy rates and central bank balance sheet). Finally, our shift-share empirical design requires interacting the shock series (shifts) with exposure matrices (shares) computed from the OECD WIOT. Table 5 and Table 6 in the appendix list all the countries and sectors in the sample.

Harmonizing PPI Inflation Data

First, we put together data on our main dependent variable —PPI inflation— at the month, country, and sector-level. To do this, we first obtain sectoral inflation data for 1143 sectors in 53 different countries. The data comes from national statistical agencies and HAVER. Because countries have different sectoral classifications, we harmonize the data by manually assigning sectors to the corresponding WIOT sectors based on their respective definitions. To give some examples, the sector in the OECD Input-Output Tables (IOT) described as "Textiles, textile products, leather and footwear" is merged to Germany's sector "Manufacture of Textile, Apparel, Leather Related", Thailand's sector "Textiles Textile Products", or Costa Rica's sector "Leather and Products; Footwear". To our knowledge, ours is the first harmonized dataset that contains sectoral PPI at monthly frequency for different countries. Our panel is unbalanced and skewed towards manufacturing sectors due to services data being unavailable in many emerging markets.[10] For our regression analysis, we winsorize the inflation data at the 1% level to account for outliers. Our results are robust when using the original non-winsorized inflation variable, which we will discuss in detail later.

Construction of Monthly Country-Sector Level Shocks

Second, we gather data on lockdown, fiscal, and transport shocks at the country-sector-month level.

Lockdown intensity at the country level comes from the lockdown stringency index in the Oxford COVID-19 Government Response Tracker database (Hale et al., 2020). This

[10] We define as service sectors all those including and below the OECD IOT sector "Electricity, gas, steam and air conditioning supply" in the list of Table 6 In the end, services sectors comprise of 21 percent of our sample.

measure ranges from 0 to 1, with 1 representing a full lockdown.

Figure 1 plots the average lockdown stringency for each region of the world. Lockdown stringency is highly synchronized across the world, yet also exhibits sufficient heterogeneity. East Asia, for example, had an early spike in January 2020, and maintained a relatively high level of lockdown all the way until the end of 2022. Europe, on the other hand, oversaw a steeper lockdown early on, but was among the quickest to loosen restrictions. While Latin America had seen a steady reopening throughout the pandemic years, South Asia saw a much more bumpy road, with clear spikes associated with the Delta and Omicron waves of the virus.

It is important for us to have lockdown data not only at the country level, but also at the sector-level. National lockdown measures may not be representative of the sector-level data because different sectors have varying abilities to work from home. To address this problem, we construct a sector-level lockdown measure by interacting the country-wide variable with each sector's ease of work from home, provided by Dingel and Neiman (2020) using information from the Occupation Information Network (O*NET) database.[11] Figure 16 in the Appendix shows the sectors with the lowest suitability for remote work (e.g., accommodation, agriculture, fishing, mining) and the highest (e.g., IT, finance, education).

For our *fiscal shock*, we use data on COVID-19 fiscal stimulus packages announced by national governments from the OxCGRT dataset.[12] We plot the time series of fiscal stimuli (in percents of GDP) by region in Figure 2. A potential difficulty is that the dataset assigns each fiscal package to the announcement date, and we do not have information about when the money is actually disbursed or used. We attempt to overcome this problem in two ways. First, we include a detailed set of monthly lags for fiscal variables in the baseline regression, which "allows the data to speak" regarding how long after announcement we will start to observe macroeconomic impacts of fiscal stimuli. Second, we perform a robustness check where we employ a smoothed version of the fiscal series instead of the raw data where we observe spikes on announcement dates. We explore various smoothing techniques, including uniform smoothing (e.g., assuming that the package is disbursed in equal amounts over the next m months) and geometric decay (e.g., assuming that only a fraction α of the remaining amount of the package is disbursed). For the baseline, we calibrate α so that each package has a half-life of 3 months, i.e. half of the fiscal impact will be concentrated to the first three months from the date of announcement. Regression results are robust to various specification of disbursement assumptions.

For *monetary policy*, because Central Banks took broad measures to support the economy during the pandemic, it is important for us to capture not only traditional but also unconventional monetary policy. To this end, we employ two measures of monetary policy

[11] A caveat to consider is that their measure is based on U.S. data and the nature of occupation might differ across countries.

[12] This measure is highly correlated with the size of announced fiscal measures in Kirti et al. (2022).

stance across country: policy rate and changes in Central Bank balance sheet sizes. The latter was especially important during the pandemic, as interest rates were often near or at the zero lower bound.

Finally, we also consider shocks to maritime *transport costs*. We obtain the route-specific transport cost shocks at the monthly frequency from the Freightos Baltic Container Price Index. Data is available for 11 major maritime transport routes. However, different sectors are more or less exposed to transport costs, for instance, because the products are particularly bulky but low value (e.g. cement). We, therefore, construct sector-route-month specific transport cost shocks by interacting the transport cost index with the bilateral ad valorem maritime transport costs from the OECD Maritime Transport Cost dataset. Data is available for 43 importing countries from 218 countries of origin at a product level in a cross-section. The interacted dataset contains the ad-valorem estimate for the cost of shipping a particular product on a given route in a given period e.g. cement from China to Europe in December 2023. For each sector, we then aggregate up the transport cost for all inputs using the input-output database described above. This yields a sector-time specific measure of transport costs.

Construction of Bartik Instruments

We gather data on global production networks from OECD IOT for 2018 to construct the exposure of each sector to lockdown and fiscal shocks. These data are available for 45 sectors in 64 countries. The exposure shares are informed by the theoretical model of international production network laid out in Section 2. Figure 17 in the Appendix shows that cross-sector linkages are sizable, as the median sector sources only 8 percent of its intermediate inputs from within sector (and 92 percent from outside). However, the network is also sparse, as the majority of sectors buy from and sell intermediate inputs to only 4-5 other sectors (Figures 18 and 19).

The four primary Bartik-instruments that we generate are:

- **Lockdown-supply** B^S: this captures the supply disruptions induced by changes in lockdown conditions. For a given sector s, the lockdown-supply Bartik instrument is given by the inner product of changes in lockdown conditions of counterpart sectors and the exposure of sector s *through a supply relationship*: $B^S_{s,t} = \sum_k \Phi^S_{sk} d\log\Lambda_k$. The supply exposures Φ^S is given in Proposition 1.

- **Lockdown-demand** B^D: this captures the demand disruptions induced by changes in lockdown conditions at the country level. For a given sector s, the lockdown-demand Bartik instrument is given by the inner product of changes in lockdown conditions of counterpart countries and the exposure of sector s *through a demand relationship*: $B^D_{s,t} = \sum_i \Phi^D_{si} d\log\Lambda_i$, where the demand exposures Φ^D is given in Proposition 1.

- **Fiscal** B^{fiscal}: this captures the demand effects of fiscal stimulus packages, spilling over to production sectors through global input-output linkages. For a given sector s, the fiscal Bartik instrument is given by the inner product of changes in fiscal stimulus and demand exposure: $B_{s,t}^{\text{fiscal}} = \sum_i \Phi_{si}^D d\log F_i$. For fiscal stimulus, we use the COVID-19 specific fiscal packages from Oxford CGRT database. To potentially account for the situation where the money does not get disbursed on the date of the announcement, we consider an alternative measure where any given fiscal package has an exponentially decaying effect on the economy.

- **Monetary** B^{Monetary}: this Bartik instrument captures the impact of monetary policy, again interacting the demand exposure by country with the country-level monetary policy changes: $B_{s,t}^{\text{monetary}} = \sum_i \Phi_{si}^D d\mathscr{M}_i$, where $\mathscr{M}_i$ is a measure of monetary policy. We use the 3-month changes in the Central Bank assets in the balance sheet as a proxy for monetary policy stance.

As is conventional in the shift-share study design, we use the 2018 World Input-Output Table (pre-pandemic) to calculate the exposure shares to avoid endogeneity. These exposure matrices capture both the impact through direct trade links as well as indirectly through one or more links. The "shifts" in our Bartik instruments are calculated as 3-month changes, and four quarterly changes are included in the regression to capture yearly impact of shocks.

Correlation between network linkages and between shocks

Our identification relies on having substantial variation in the supply and demand relationships, which are key to distinguish supply- versus demand-channel of the same shocks, as well as between the different types of shocks. In our data, the correlation between the upstream and downstream exposure between any two sector pair is 0.47. The correlations between lockdown and monetary shocks, between lockdown and fiscal shocks, and between monetary and fiscal shocks are 0.34, 0.15, and 0.36, respectively. Thus, this assuages concerns regarding our network linkages or shocks being too correlated.

4 Baseline Regression

To study the dynamic response of inflation to various shocks, we run the following Local Projection regressions (following Jordà (2005)) as our baseline:

$$\begin{aligned}\text{PPI inflation}_{s,t+h} = &\sum_{l\in\{0,3,6,9\}} \beta_l^{\text{S}} B_{s,t-l}^S + \sum_{l\in\{0,3,6,9\}} \beta_l^{\text{D}} B_{s,t-l}^D + \sum_{l\in\{0,3,6,9\}} \beta_l^F B_{s,t-l}^{\text{fiscal}} \\ &+ \sum_{l\in\{0,3,6,9\}} \beta_l^M B_{s,t-l}^{\text{monetary}} + \text{controls}_{s,t} + u_{s,t} \qquad (16)\end{aligned}$$

The subscript s denotes sector (e.g., Australian mining) and t indexes time. We run the regression separately for each shock as well as jointly together. All specifications include a full set of country, sector, and time fixed effects to avoid omitted variables that are specific to countries, sectors, and time periods. Depending on specifications, our controls will include a subset of the following variables: lagged inflation, exchange rate depreciation, transport costs, and oil price shocks. Standard errors are clustered at the country-sector level, and we use the Driscoll-Kraay standard errors to address the potential problem of auto-correlated errors. Equation (16) is our most comprehensive regression; in the following section, we will report results when shocks appear separately and jointly together. Finally, for each shock, we will also report results for specifications with only year-over-year changes (β_l is the same for all l) versus when the four quarterly changes have different coefficients, which could shed light on the response time of inflation to shocks within a year.

4.1 Simplified Setup

We begin by considering a simplified sub-specification of equation (16). This sub-specification includes the two Bartik instruments related to lockdown, $B^S_{s,t-l}$ and $B^D_{s,t-l}$, where $l = 0$, along with country, time, and sector fixed effects. Our initial focus is on the contemporaneous inflationary impact of the Covid-19 lockdown, specifically examining the case where $h = 0$. In the subsequent subsections, we will examine the full specification to address potential confounding effects, time lags, and auto-regressive factors.

The first column in Table 1 reports the coefficient estimates for this specification. We observe that an increase in lockdown tends to elevate sectoral PPI inflation through supply links (lockdown makes intermediate inputs scarce and increases production costs) while lowers inflation through demand links (lockdown depresses aggregate demand and lowers equilibrium factor costs (e.g., wage)). The coefficient for the lockdown supply shock is 0.295, which according to Proposition 1 can be interpreted as the elasticity of value-added productivity due to lockdown. In other words, the complete lockdown of a sector lowers that sector's productivity by 29.5 percent. Translating this estimate to "inflationary impact" depends on the sector's value added share. If the sector is 100% value added and does not use intermediate inputs, then a full lockdown increases PPI inflation by 29.5 percent. Alternatively, if only a fraction θ of sales comes from value added, then the direct inflationary impact is 0.295θ.

Turning to demand effects of lockdown, again referring back to Proposition 1, the coefficient -0.355 can be interpreted as the elasticity of aggregate demand to lockdown changes: locking down a country completely depresses aggregate demand by about 35.5 percent. Again, translating this into inflationary impact requires knowing more about the country-sector specific demand linkages. For example, locking down a country whose spending accounts for 50 percent of a sector's revenue will lead to a direct-impact sectoral deflation of

$35.5 \times 0.5 = 17.8$ percent, plus second-round effects through the input-output network.

One may be concerned that local lockdown might be correlated with other local inflation drivers, and the effect we identified in the first column of Table 1 may not really be the caused by lockdown and supply chains. This concern is valid as the diagonal elements of the input-output matrix tend to be large (see Figure 17). To address this issue, we follow Acemoglu et al. (2016) and include only foreign lockdown shocks when constructing the Bartik instruments, while controlling for local lockdown separately. Column (2) of Table 1 reports the results of this exercise, and shows that the coefficients on lockdown supply and demand shocks change slightly but are similar in magnitudes, signs, and significance. The within-sector lockdown control variable is only significant at the 10 percent level, which could be due to the demand and supply effects cancelling each other out.

Fiscal Stimulus We now turn to studying the contemporaneous inflationary impact of COVID-19 fiscal stimulus measures. Similar to the previous specification, we regress PPI inflation at the country-sector-month frequency against the Bartik instrument related to fiscal constructed in Section 3.1. Again, we include a full set of country, time, and sector fixed effects. Since our data includes fiscal stimulus on the date of the announcement, we include 12 monthly lags of the fiscal shock variable to allow the data to "speak" regarding when, on average, inflationary impact of a fiscal stimulus appears after announcement. Furthermore, we also assume that only a fraction of the remaining amount is disbursed each month, calibrated to have a half time of 3 months.

Table 2 reports the result. We see that most of the inflationary impact occurs on the month of the announcement, and some from one or two months prior. The coefficient for contemporaneous impact is 0.754, which can be read as the fiscal multiplier: a 1 dollar increase in fiscal spending increases domestic aggregate demand by almost 75 cents on impact.

Again, it is worth noting that this coefficient does not yet represent inflationary impact. To demonstrate how to convert this estimate to inflationary impact, consider a stimulus package in a country that accounts for 50 percent of a sector's total revenue *through both final and intermediate good trades*. Suppose also the sector has a 40% value added share. Then, the direct inflationary impact will be $0.754 \times 0.5 \times 0.4 = 0.15$, or 15 percent. The total impact will have to account for second-round effects (and so on) through the input-output network. Notably, the coefficient for the 11-month lag is also significant, indicating that changes of fiscal stimuli are perhaps more important than the levels. As a consequence, withdrawing fiscal stimuli from a currently high level would make inflation converge back to its lower levels.

4.2 Full Specification

We now turn to the full specification presented in equation (16), which includes all shocks and controls. Table 3 presents the regression results for the contemporaneous coefficients ($h = 0$). Every column includes a full set of country, sector, and time fixed effects. Column (1) features only the previously mentioned inflation drivers. Starting from Column (2), we progressively introduce controls such as inflation persistence, currency effects, maritime transportation inflation, and oil price shocks, which we will discuss in more detail later. To mitigate outlier issues, sectoral inflation is winsorized at the 1 percent level at the moment.

Column (1) of Table 3 shows that Covid-19 lockdowns, and the subsequent re-openings, were significant drivers of inflation during our sample period (June 2019- December 2022). In terms of magnitude, starting from column (1), the coefficient on contemporaneous effect of lockdown on inflation through supply links is 0.291, implying that the full lockdown of a major supplier that accounts for 50% of input costs (through both direct and indirect trade links) would lead to a 14.5% PPI inflation (0.291 times 0.5) in the affected sector.[13] The demand channel of lockdown is also significant. The estimated contemporaneous coefficient is -0.302, which implies that the estimated reduction in aggregate demand due to lockdown is about 30%. In terms of inflationary impact, a sector that sells entirely to the domestic market (thus being fully exposed to domestic aggregate demand) and whose value-added share is 50% will experience a deflationary impact of 15%. Fiscal stimulus packages and monetary policies are also statistically significant and important drivers of inflation. An estimated contemporaneous coefficient of 0.561 for fiscal implies that a fiscal stimulus package that equal 10% of GDP raises each industry's PPI inflation by 5.6%. Finally, an estimated coefficient of 0.042 for monetary policy implies that an expansion of the central bank balance sheet that doubling central bank assets raises PPI inflation by about 4%. The result is robust to including lagged inflation and currency depreciation of a country.

To investigate the dynamic impacts of these shocks, we plot the results of local projection regressions in Figure 3 for different forward horizons of PPI inflation on the three Bartik instruments respectively. Each regression uses the most comprehensive set of controls as in column (4) of Table 3. The impulse response shows that an increase in lockdown stringency increases inflation due to the disruptions it causes to the supply chains. However, an increase in lockdown can also lead to deflation, as it leads to diminished aggregate demand. The effects are also quite persistent, lasting for about 10 months and diminishing gradually over time. Fiscal stimuli also tend to increase inflation, but the effects at longer horizons are only estimated imprecisely under this specification. After half a year, the effect of fiscal stimulus is not distinguishable from zero. Monetary shocks, as shown in Panel (d) of Figure 3, have most persistent impacts on producer producer inflation among the four channels, though the effects at longer horizons are less statistically significant.

[13]Recall that lockdown stringency is scaled to take real values from 0 to 1, with 1 being complete lockdown.

Robustness The general Bartik identification assumption is that shares do not predict outcomes through channels other than those laid out by the researcher and there are no spillovers from treatment to control groups through general equilibrium effects. For the identification assumption to be violated there would need to be a time varying omitted variable which is correlated with pre-Covid trade shares and which impacts inflation through a channel unrelated to our measures of supply and demand. Our main concern is that some other factor is correlated with both the Domar weights and the change in prices.

First, we contemplate the scenario where transport costs were impacted by the pandemic, given the substantial disruptions at ports and along trade routes. These costs might also correlate with pre-shock trade shares. This concern is visualised in Figure 15 which demonstrates a pronounced surge in trade costs during the pandemic, particularly from Asia to Europe and North America. To address this concern, we construct a sector-specific measure of maritime transport at the monthly frequency by interacting the route-specific cost with the product specific transportation cost.

$$\text{PPI inflation}_{s,t+h} = \sum_{l\in\{0,3,6,9\}} \beta^{\mathrm{S}} B^{S}_{s,t-l} + \sum_{l\in\{0,3,6,9\}} \beta^{\mathrm{D}} B^{D}_{s,t-l} + \sum_{l\in\{0,3,6,9\}} \beta^{F} B^{\text{fiscal}}_{s,t-l} + \sum_{l\in\{0,3,6,9\}} \text{controls}_{s,t-l} + u_{s,t} \tag{17}$$

Specifically, we interact monthly route-specific maritime freight costs from Freightos Baltic Container Price Index. with a measure of sector specific exposure to changes in transportation costs using data from the OECD Maritime Transport Cost dataset.[14]

As shown in column (3) of Table 3, the inclusion of the shipping costs does not materially change the main coefficients. The point estimates for the impact of shipping cost inflation on PPI inflation ranges from 0.059 to 0.035 and is statistically significant at the 1 percent level. Interpretation of the magnitudes depends on the extent of transport cost inflation across the full input basket. For instance, a coefficient of 0.035 implies transport cost inflation of 10 percent on 100 percent of inputs would increase PPI inflation by 0.35 percent. This is slightly lower than the elasticity found in Carrière-Swallow et al. (2023) who estimate transport cost inflation of 1 percent will raise PPI inflation approximately 0.15 percent. The lower elasticity found in this paper is to be expected given we include a rich set of additional variables which capture supply-disruptions which may be correlated with transport costs.[15]

Second, we consider the oil price shock as presented in column (4) of Table 3. The oil price shock variable is used as a control due to the high volatility of commodity prices during

[14]The sector-specific measure of transport costs over time provides a particularly fine level of detail and goes beyond some previous literature Carrière-Swallow et al. (2023). We also obviate the concern that the transport cost shocks may be endogenous because the product-specific ad-valorem trade costs data we use comes from pre-pandemic estimates.

[15]We also run very different specifications over different time periods. Our model include not only transport cost inflation, but also the interaction with the transport cost exposure at the sectoral level. This yields a sector specific transport cost measure capturing the extent of transport cost inflation of all input products given the route they travel and the proportion of transport costs in the final sales price.

this period. This variable was constructed by interacting the changes in global oil prices with a sector's exposure to oil shocks, derived from the input-output table in the same way as the exposure to lockdown shocks. Including this variable does mitigate the size of our main effects; however, the direction of the coefficients and the statistical significance remain intact. Our interpretation of this result is that there might be a common factor driving both the oil price variations and lockdown measures. However, controlling for the former does not qualitatively change our results.

Third, we incorporate the number of countrywide COVID cases per capita. Consider, for instance, that the change in inflation in a country is influenced by a shift in COVID infections within that nation. If these infections are positively correlated with COVID cases in its trading partners, then the alteration in price may appear to be driven by a supply or demand channel when, in fact, it is primarily influenced by an increase in COVID cases

Finally, in Table 4 we test the robustness of results to different cleaning assumptions and fixed effects. Column 3 shows that results are largely unimpacted by winsorizing PPI inflation. Where differences exist in the magnitude of coefficients it tends to be the case that both lockdown-demand and lockdown-supply shocks have larger impacts, suggesting our approach to winsorize at the 1 percent level is conservative. In Column 4 and 5, we experiment with different fixed effects. Column 4 drops the time fixed effects while Column 5 replaces the separate country, sector, and time fixed effects with country-sector fixed effects. There are no large differences in coefficient magnitude or significant. The high level of stability across all specifications, helps to bring confidence that our model is highly robust.

We acknowledge that several other drivers of inflation could potentially be important but are not included in our framework primarily because of a lack of good cross-country data. Firstly, labor market tightness is likely to have been an important driver of inflation during the pandemic. Our model makes a number of simplifying assumptions on the labor market which help ensure tractability but in practice there maybe important forces that we miss. Secondly, our framework assumes that market power is constant over time, whereas the pandemic could have changed the distribution of market power across firms or sectors. Thirdly, our framework is silent on the roll of inventories or storage. While one should be concerned that these maybe important drivers of inflation, unless they are systematically correlated with pre-pandemic trade shares they should not introduce bias into our estimates but instead increase noise. One reassuring fact in this regard is that despite not including these measures in our main specification, we still are able to obtain an extremely strong fit for the data.

4.3 Relative Contributions of Inflation Drivers

Next, we investigate the relative contribution of these channels in driving inflation during 2020-2022. In Figure 4, we plot the predicted PPI inflation (outcome variable) due to subgroups of variables (contemporaneous and lags): lockdown-supply, lockdown-demand, fiscal, monetary and other controlling factors. For example, the inflation contribution coming from Covid-19 fiscal stimulus at month t is given by

$$\sum_{l\in\{0,3,6,9\}} \hat{\beta}_l^F B_{s,t-l}^{\text{fiscal}}.$$

In each subplot, each variable is aggregated by taking a weighted mean across sectors, with weights proportional to sectoral size (output). In Figure 5, we plot the same figure for United States, Germany, China and India to investigate the cross-country variations.

One can immediately observe that the model explains inflation dynamics very well at the global level and at the country level for major nations. The biggest contributor to inflation dynamics during the pandemic and its aftermath is the effect of lockdown / reopening on demand. At the beginning of the pandemic, the downward pressure on prices due to lost demand overwhelms the upward price pressure due to supply chain disruptions, leading to a deflationary force. However, decisive accommodative monetary policy at the beginning of the pandemic played a significant role in preventing deflation. The model successfully explains why inflation was relatively low, but above zero, during the first year of the pandemic.

In the later period, the simultaneous reopening of economies leads to a surge in demand that drives inflation higher. This effect overwhelms the benefit of supply chain normalization, which eases price pressure. Interestingly, we find some inflationary effect from the delayed re-normalization of monetary policy, but the effect is relatively small compared to that of demand recovery.

4.4 Differential Impacts of Shocks in Beginning versus Recovery Phase of Pandemic

We now explore the possibility that the impulse response functions may differ between the initial and recovery phases of the pandemic, potentially due to changes in the structure of the economy. To investigate this idea, we perform the local projection regressions for various forward horizons of PPI inflation on the four Bartik instruments as before, but we now allow the coefficients to vary between the two phases of the pandemic — specifically, we compare the coefficient estimates from the first 12 months of the global pandemic to those from later months:[16]

$$\text{PPI inflation}_{s,t+h} = \sum_{l\in\{0,3,6,9\}} \beta^{\text{S}}_{l,t} B^{S}_{s,t-l} + \sum_{l\in\{0,3,6,9\}} \beta^{\text{D}}_{l,t} B^{D}_{s,t-l} + \sum_{l\in\{0,3,6,9\}} \beta^{F}_{l,t} B^{\text{fiscal}}_{s,t-l} \tag{18}$$

$$+ \sum_{l\in\{0,3,6,9\}} \beta^{M}_{l,t} B^{\text{monetary}}_{s,t-l} + \text{controls}_{s,t} + u_{s,t} \tag{19}$$

where for a given shock $x \in \{S, D, F\}$ the coefficient is expanded to:

$$\beta^{x}_{l,t} = \beta^{x}_{l,\text{beginning}} \cdot 1_{t\leq 2020m12} + \beta^{x}_{l,\text{recovery}} \cdot 1_{t>2020m12}$$

As before, we include a full set of fixed effects as well as lagged inflation, exchange rate depreciation, and maritime transport cost inflation for controls.

We plot the IRFs with time-dependent effects in Figure 6. In the top panel, we observe that the inflationary impact of supply disruptions due to lockdown was more severe and long-lasting at the beginning of the pandemic than in the recovery phase. The IRFs for demand, presented in the second panel, are almost identical for the two phases of the pandemic. The recovery through the demand channel appears to be just as rapid as its initial drop when the lockdowns began in early 2020. A possible interpretation of these results is that, in the recovery phase of the pandemic, firms find it easier to adapt to rising costs by switching to alternative input sources.[17] However, they seem less capable of adapting when confronted with increased customer demand.

In a similar vein, the IRFs for fiscal measures (bottom panel) indicate a substantial difference in the inflationary impact of fiscal stimulus in the initial versus recovery phases of the pandemic. The inflationary impact of fiscal stimulus became much more persistent in the recovery phase of the pandemic. This suggests that fiscal packages at the early stage of the pandemic were perhaps helpful in supporting businesses and workers without a long-lasting inflationary impact. However, over-doing it when the economy has recovered to its normal level could lead to very persistent inflation. This finding augments the view that the impact of fiscal policy varies across business cycles.[18]

[16] We divide the data into two periods, 2020 and from 2021 onward because many countries began reopening their economies and lifting emergency restrictions most pronouncedly in 2021.

[17] Empirical evidence on supply chain diversification in the aftermath of COVID-19 is still limited, but several studies such as Lin et al. (2021) and Polyviou et al. (2023) show its mitigating effect at the regional level.

[18] See, for example, Auerbach and Gorodnichenko (2012), Riera-Crichton et al. (2015) and Ramey and Zubairy (2018) for works discussing state-dependent impacts of fiscal policy on output and Tagkalakis (2008) on private consumption. On a theory front, this relates to the non-linear nature of the Phillips Curve, which exhibits a flat slope between output shocks (induced by fiscal measures) and price changes under subdued inflationary pressures and steepens as inflationary pressures intensify due to reopening (Harding et al., 2023).

4.5 The Role of Network in Propagating Shocks

In this subsection, we investigate whether the global value chain is an important propagation channel of shocks across countries and shed light on how the relative strength of the network effect evolves over time and differs across shock types.

Decomposition of direct versus network effects. Let us start with supply shocks. We constructed our lockdown-supply shock Bartik instrument by multiplying the lockdown exposure matrix Φ^S with the vector of lockdown "shifts" Λ. The lockdown exposure matrix, by construction, captures both the direct and indirect effects:

$$\Phi^S = [I-\Omega]^{-1}\Theta = \left[I+\Omega+\Omega^2+...\right]\Theta = \underbrace{(I+\Omega)\Theta}_{\text{direct}} + \underbrace{\left(\sum_{i=2}\Omega^i\right)\Theta}_{\text{indirect}} \tag{20}$$

We define "direct effect" as the effect of shocks that originate either in that industry or in the direct suppliers. Similarly, the "indirect effect" is defined as the effect of shocks that are transmitted from an industry that is at least two steps away in the production chain. We then use these matrices to form the direct and indirect lockdown-supply Bartik instruments:

$$B^{S,dir}_{s,t} = \sum_k \Phi^{S,dir}_{sk}\, d\log\Lambda_k, \qquad B^{S,ind}_{s,t} = \sum_k \Phi^{S,ind}_{sk}\, d\log\Lambda_k \tag{21}$$

where $\Phi^{S,dir} = (I+\Omega)\Theta$ and $\Phi^{S,ind} = \Phi^S - \Phi^{S,dir}$ as explained above.

We perform similar decomposition for demand shocks. The demand exposure matrix Φ^D can also be separated into a direct and indirect components, albeit the process is more complicated. Recall that $\Phi^D = [I-\Omega]^{-1}\Theta\Phi_Y^{-1}[I-\Omega']^{-1}\Xi'\Phi_D$. The rightmost elements of this matrix $\Phi_Y^{-1}[I-\Omega']^{-1}\Xi'\Phi_D$ relates to the calculation of "trade in value-added." Even though this also involves network considerations, for the purpose of calculating inflationary pressure, we assign it to be the "direct effect" of demand shock since it indicates how much a rise in demand for a sector's output, either directly or through the supply chain, puts upward pressure on the marginal cost of that very sector. The remainder of the effect then captures how that cost pressure propagates through the network, which we term the "network effect" of demand. In summary, the Bartik instruments for lockdown-demand shocks will be calculated as:

$$B^{D,dir}_{s,t} = \sum_k \Phi^{D,dir}_{sk}\, d\log\Lambda_k, \qquad B^{D,ind}_{s,t} = \sum_k \Phi^{D,ind}_{sk}\, d\log\Lambda_k \tag{22}$$

where $\Phi^{D,dir} = \Theta\Phi_Y^{-1}[I-\Omega']^{-1}\Xi'\Phi_D$ and $\Phi^{D,ind} = \Phi^D - \Phi^{D,dir}$.

Results After calculating the direct and network Bartik instruments, we run a regression similar to the baseline regression (16), but now we allow for the coefficients to differ for the direct and network variables for each type of shocks. We normalize each shock by its standard deviation, so the coefficients correctly capture the strength of the direct versus network effects (as opposed to capturing elasticities in the IRFs in other sections).

Figure 7 plots the estimated strength of direct versus network effect for our lockdown-supply and lockdown-demand shocks. We see that for the lockdown-supply shock, the direct effect is higher on impact but not as persistent, while the indirect effect builds up over time and takes longer to converge to zero. This is consistent with the temporal profile of shock propagation: lockdown in a country affects the sectors in that country first, but the inflationary effect slowly propagates over time to neighboring sectors, reaching a peak in about two quarters. It is worth noting that while the direct effect dissipates after three quarters, the indirect effect is still significant after a year. For the lockdown-demand shock, the network effect is overwhelmingly dominant. This indicates that most sectors would see the inflationary pressure via higher input costs rather than the direct pressure on its own labor cost.

5 Further Discussions

5.1 Unpacking Lockdown Shocks

While the primary focus of this paper is to estimate the effects of lockdown shocks on a global scale, our approach is versatile enough to be implemented in a variety of contexts. Specifically, it can be used in situations where a shock event impacts different country-industry pairs to varying degrees. Using this approach, we decompose the lockdown shocks according to their input of origin, allowing us to measure the relative contribution of each region. Recall that the Bartik instrument in the previous section was formed by summing across destination sector. We now focus on summing by region to identify which region contributed more to the shocks.

Panel (a) of Figure 8 plots the decomposition of the lockdown supply shock by input of origin. The same graph for demand, shown in Panel (b), is simply a mirror image. These results indicate that supply disruptions initially emerged in Asia, persisting through the first 6 months of 2020. By March 2020, North America and Europe became significant contributors, each affecting the supply chain in comparable magnitudes. A minor surge occurred at the close of 2020 and the onset of 2021, primarily due to Europe's second wave of lockdowns. During 2021-2022, the easing of supply disruptions has been largely attributable to reopenings in Europe and North America, while Asia continued to experience ongoing lockdowns. It is also worth noting that, between Europe and North America, Europe as a whole contributed more to the reopening force.

In Figure 9, we examine each country affected by supply disruptions to determine what proportion of these disruptions can be attributed to lockdowns in other countries versus domestic lockdowns. Specifically, we calculated the foreign share for supply disruptions for each country by month, and plot the distribution for each country using a boxplot. Several key observations emerge from this chart. First, the United States, being a relatively closed economy, shows a negligible foreign contribution to its supply disruptions. Second, Asian manufacturers, as the center of global supply chains, are considerably more affected by foreign lockdowns. In a median month, 10 percent of the supply disruptions in Taiwan Province of China and Korea originate from abroad, with peaks reaching up to 30 percent for Taiwan Province of China and 50 percent for Korea in our data sample. Finally, Latin American countries, with the exception of Chile, appear to be relatively insulated from supply chain disruptions originating from abroad, as the foreign share is less than 5 percent in most months. This trend aligns with these nations having low global value chain participation, which may be attributed to their roles as commodity exporters (e.g., Colombia).

On the demand side, Panel (b) of Figure 9 reveals that the foreign share is substantially higher across all regions. For Latin American countries, the average foreign share is close to 20 percent — nearly four to five times higher than the numbers from the supply side. A similar trend is observed for the US. For Asian manufacturers, foreign share is around 50 percent in a median month, highlighting the region's high susceptibility to global demand conditions. To unpack the demand shock further, recall that there are two channels through which higher demand can drive inflation. One is "Pure Demand"; increased demand within a specific sector, whether caused by reopening or expansionary policies, leads to a rise in that sector's prices. The other channel is "Network Cost" — namely a surge in demand within a country inflates the prices of intermediate goods, affecting sectors that may not necessarily sell directly to that destination but are still impacted via elevated input costs.

In Figure 10, we calculate the share of the total demand effect that operates through the network cost channel for each country. Our results show that, for the majority of countries, 90 percent of the demand shock manifests through higher input costs. The magnitude of this network propagation is large, which again highlights the importance of incorporating the input-output network into analysis when a shock is global in nature.

5.2 Inflation in Asia

In this subsection, we turn our attention towards a comparative analysis between Asia and the rest of the world during and post the pandemic period, investigating the disparities in their respective inflation trends. We focus on Asia for two main reasons: first, the inflation dynamics in Asia were distinct from the rest of the world, with considerably lower inflation rates (as depicted in Figure 11) and second, Asia plays a disproportionately influential role in global value chains.

Within the context of our framework, we consider two hypotheses which could explain this divergence: (i) slower re-opening and quick withdrawal of large stimulus packages (ii) structural differences in the effects of shocks.

In support of the first hypothesis, Figure 1 shows the evolution of lockdown stringency over time which demonstrates that Asian countries did not have the same rapid reopening observed for much of the rest of the world. The smaller inflationary impact from the gradual re-opening can be observed for two major Asian economies - China and India - in Figure 5. The inflation decomposition shows that, relative to Germany and the USA, the inflationary impacts from lockdown-demand in China and India was small in 2021 and 2022. This is consistent with the USA and Germany reopening from relatively stricter lockdowns more rapidly and hence stimulating demand to a greater degree. A second key factor for Asia was the relatively fast withdrawal of smaller fiscal stimulus packages in 2021 and 2022. Figure 12 presents a scatter plot of all the countries in our sample, highlighting the variation attributable to these two factors. The y-axis represents the magnitude of fiscal inflationary impact, while the x-axis signifies the lockdown supply-chain inflation impacts, which sum the effects of demand and supply during lockdown. These values are derived from the accumulated impacts over the 2021-2022 period, as per the local projection methods. The scatter plot reveals that during 2021-22, Asian countries (shown in red) typically experienced a slower pace of reopening alongside a rapid withdrawal of stimulus packages, both leading to lower inflation.

In support of the second hypothesis, we separately estimate our framework for a sample of Asian countries to see if shocks had a differential impact. Figure 13 and 14 illustrate the impulse responses to various shocks, providing a comparison between Asian countries and the full sample. These figures reveal that the lockdown-supply shocks typically had similar impacts over a similar time frame among Asian countries and among the rest of the world, while the lockdown-demand shocks resulted in smaller effects in Asia. Importantly, a smaller demand coefficient would help explain Asia's lower inflation during the second half of the pandemic as not only was the reopening more gradual, the predicted impact would be smaller. The impacts of fiscal and monetary interventions on inflation in Asia were smaller in magnitude than for the full sample and not statistically significant in Asia, unlike the full sample. This disparity suggests the presence of structural differences in the way these regions respond to shocks. While our methodology does not allow us to identify the route cause of the differential response to shocks among Asian countries, one potential explanation is the smaller proportion of services in GDP among Asian countries. It is possible that these sectors played a particularly large role in driving inflation in the rest of the world during reopening given they were particularly highly impacted by a preference for consumers to avoid human interaction during the pandemic and hence experienced a disproportionate rebound. An alternative possibility is that Asian countries implemented policies to regulate prices in some key sectors which artificially lowered prices. However, this is speculative and an area which deserves further investigation in future research.

This section suggests that both (i) a more gradual reopening and faster withdrawal of large stimulus packages and (ii) a structurally smaller inflation response to shocks contributed to why Asian countries have experienced comparatively moderate inflation. It also speaks to the important heterogeneity globally in inflation response to supply-chain shocks even during a very large and global pandemic.

6 Conclusion

The integration of the global economy over the last few decades has led to increasingly complex supply-chains which span multiple borders. As a consequence, local shocks can have far-reaching effects on prices across the globe via supply and demand channels. The government response to the COVID-19 pandemic represents a valuable natural experiment to study this phenomena given fiscal stimuli, monetary stimuli, and lockdowns had large impacts on supply and demand and were implemented by each country, with different magnitudes at different times.

We proposed a new empirical framework to estimate the impact of a disruptions in segments of the supply chain to producer inflation. Our approach merges the Bartik-style shift share design with the local projection method to investigate time-varying effects of a production shock to inflation. The framework relies on the pre-shock differential use of inputs in production to derive causal estimates of the shock impact on prices via supply and demand channels. We apply this framework to study the price impacts from pandemic policies. Using a new panel dataset of sectoral PPIs and input-output linkages for 53 countries, we investigate the impact of pandemic-lockdown shocks. We find that (i) pandemic lockdowns had large, significant and persistent effects on inflation via both supply and demand channels contributing 36 percent of global inflation drivers over the sample period; (ii) fiscal stimuli had a statistically significant but smaller impact on inflation (5 percent of global inflation); (iii) demand recovery was the primary driver of 2021 producer inflation (15 percent of 2021-2022 global inflation); and (iv) that network effects constitute at least 50 percent of the impact from supply and demand shocks. Finally, we run an application of our framework for a sub-region showing that our model can explain lower inflation in Asia.

From a broader perspective, our paper is one of the first attempts to identify the impact of a global shock by leveraging input-output linkage data. One potential venue for future research is to study the impact of other global shocks including the commodity price increases following Russia's war in Ukraine, the impact of global energy price movements, or global spillovers from monetary policy along trade routes. Another potential opportunity from this research is to identify which country-sector pairs are most important for determining global movements in producer prices. This could help policy makers to identify systemically important sectors and supply links and to help build future resilience to shocks.

References

Daron Acemoglu and Alireza Tahbaz-Salehi. Firms, failures, and fluctuations: the macroeconomics of supply chain disruptions. Technical report, National Bureau of Economic Research, 2020. 1

Daron Acemoglu, Ufuk Akcigit, and William Kerr. Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, 30:273–335, 2016. 1, 5, 4.1, 1

Rodrigo Adao, Michal Kolesár, and Eduardo Morales. Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010, 2019. 1

Philippe Aghion, Antonin Bergeaud, Matthieu Lequien, Marc J Melitz, et al. The impact of exports on innovation: Theory and evidence. 2018. 1

George A Alessandria, Shafaat Y Khan, Armen Khederlarian, Carter B Mix, and Kim J Ruhl. The aggregate effects of global and local supply chain disruptions: 2020–2022. Technical report, National Bureau of Economic Research, 2023. 1

Alan J. Auerbach and Yuriy Gorodnichenko. Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2):1–27, May 2012. 18

David Autor, David Dorn, and Gordon H Hanson. The geography of trade and technology shocks in the united states. *American Economic Review*, 103(3):220–25, 2013. 1

David Baqaee and Emmanuel Farhi. Networks, barriers, and trade. Working Paper 26108, National Bureau of Economic Research, July 2019. 1

David Baqaee and Emmanuel Farhi. Supply and demand in disaggregated keynesian economies with an application to the covid-19 crisis. *American Economic Review*, 112 (5):1397–1436, May 2022. 1

David Baqaee, Emmanuel Farhi, and Kunal Sangani. The Supply-Side Effects of Monetary Policy. NBER Working Papers 28345, National Bureau of Economic Research, Inc, January 2021. 2.2

Timothy J Bartik. Who benefits from state and local economic development policies? 1991. 1

Pierpaolo Benigno and Gauti B Eggertsson. It's baaack: The surge in inflation in the 2020s and the return of the non-linear phillips curve. Technical Report 31197, National Bureau of Economic Research, April 2023. 1

Martin Beraja, Erik Hurst, and Juan Ospina. The aggregate implications of regional business cycles. *Econometrica*, 87(6):1789–1833, 2019. 1

Nicolas Berman, Antoine Berthou, and Jérôme Héricourt. Export dynamics and sales at home. *Journal of International Economics*, 96(2):298–310, 2015. 1

Barthélémy Bonadio, Zhen Huo, Andrei A. Levchenko, and Nitya Pandalai-Nayar. Global supply chains in the pandemic. *Journal of International Economics*, 133:103534, 2021. 1

Kirill Borusyak, Peter Hull, and Xavier Jaravel. Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213, 2022. 1

Daniel A Broxterman and William D Larson. An empirical examination of shift-share instruments. *Journal of Regional Science*, 60(4):677–711, 2020. 1

David Card. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64, 2001. 1

Yan Carrière-Swallow, Pragyan Deb, Davide Furceri, Daniel Jimenez, and Jonathan D Ostry. Shipping costs and inflation. *Journal of International Money and Finance*, 130: 102771, 2023. 1, 4.2, 14

Vasco M Carvalho, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321, 2021. 1

Pragyan Deb, Julia Estefania Flores, Melih Firat, and Davide Furceri. Monetary policy transmission heterogeneity: Cross-country evidence. 2023. 1

Julian Di Giovanni, ebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yildirim. Pandemic-era inflation drivers and global spillovers. Technical report, National Bureau of Economic Research, 2023. 1

Jonathan I. Dingel and Brent Neiman. How many jobs can be done at home? *Journal of Public Economics*, 189:104235, 2020. 3.1

Matthew Elliott and Benjamin Golub. Networks and economic fragility. *Annual Review of Economics*, 14:665–696, 2022. 1

Terry J. Fitzgerald and Juan Pablo Nicolini. Is there a stable relationship between unemployment and future inflation? evidence from us cities. *Working Paper, Federal Reserve Bank of Minneapolis*, 2014. 1

Paul Goldsmith-Pinkham, Isaac Sorkin, and Henry Swift. Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624, 2020. 1

Veronica Guerrieri, Guido Lorenzoni, Ludwig Straub, and Iván Werning. Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? *American Economic Review*, 112(5):1437–74, May 2022. 2

Thomas Hale, Sam Webster, Anna Petherick, Toby Phillips, and Beatriz Kira. Oxford covid-19 government response tracker. Blavatnik School of Government, 2020. 3.1

Martín Harding, Jesper Lindé, and Mathias Trabandt. Understanding post-covid inflation dynamics. *Journal of Monetary Economics*, 2023. 1, 18

Jonathon Hazell, Juan Herreño, Emi Nakamura, and Jón Steinsson. The Slope of the Phillips Curve: Evidence from U.S. States*. *The Quarterly Journal of Economics*, 137 (3):1299–1344, 02 2022. 1

David Hummels, Rasmus Jørgensen, Jakob Munch, and Chong Xiang. The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, 104(6):1597–1629, 2014. 1

David A Jaeger, Joakim Ruist, and Jan Stuhler. Shift-share instruments and the impact of immigration. Technical report, National Bureau of Economic Research, 2018. 1

Xavier Jaravel. The unequal gains from product innovations: Evidence from the us retail sector. *The Quarterly Journal of Economics*, 134(2):715–783, 2019. 1

Òscar Jordà. Local projections for applied economics. *Annual Review of Economics*, 15: 607–631, 2023. 1

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182, March 2005. 1, 4, 3, 6, 13, 14

Mr Divya Kirti, Yang Liu, Soledad Martinez Peria, Ms Prachi Mishra, and Jan Strasky. *Tracking Economic and Financial Policies During COVID-19: An Announcement-Level Database*. Number 17879. International Monetary Fund, 2022. 12

Raphael Lafrogne-Joussier, Julien Martin, and Isabelle Mejean. Supply shocks in supply chains: Evidence from the early lockdown in china. *IMF Economic Review*, 2022. 1

Jennifer La'O and Alireza Tahbaz-Salehi. Optimal monetary policy in production networks. *Econometrica*, 90(3):1295–1336, 2022. 1

Daniel Leigh Laurence Ball and Prachi Mishra. Understanding u.s. inflation during the covid era. *IMF Working Paper*, 2022. 1

Yongjia Lin, Di Fan, Xuanyi Shi, and Maggie Fu. The effects of supply chain diversification during the covid-19 crisis: Evidence from chinese manufacturers. *Transportation Research Part E: Logistics and Transportation Review*, 155:102493, 2021. 17

Robert E. Lucas. Some international evidence on output-inflation tradeoffs. *The American Economic Review*, 63(3):326–334, 1973. 5

Michael McLeay and Silvana Tenreyro. *Optimal Inflation and the Identification of the Phillips Curve*, pages 199–255. University of Chicago Press, June 2019. 1

Matthias Meier and Eugenio Pinto. Covid-19 supply chain disruptions. 2022. 1

Mikaella Polyviou, Robert Wiedmer, Sangho Chae, Zachary S. Rogers, and Carlos Mena. To concentrate or to diversify the supply base? implications from the u.s. apparel supply chain during the covid-19 pandemic. *Journal of Business Logistics*, 44(3):502–527, 2023. 17

Valerie A. Ramey and Sarah Zubairy. Government spending multipliers in good times and in bad: Evidence from us historical data. *Journal of Political Economy*, 126(2):850–901, 2018. 18

Daniel Riera-Crichton, Carlos A. Vegh, and Guillermo Vuletin. Procyclical and countercyclical fiscal multipliers: Evidence from oecd countries. *Journal of International Money and Finance*, 52:15–31, 2015. Adjustment in the Aftermath of the Global Crisis 2008-09: New Global Order? 18

Elisa Rubbo. Networks, phillips curves, and monetary policy. *Econometrica*, forthcoming. 1

Athanasios Tagkalakis. The effects of fiscal policy on consumption in recessions and expansions. *Journal of Public Economics*, 92(5):1486–1508, 2008. 18

A Main Tables

Table 1: Contemporaneous Inflationary Effects of Lockdown Shocks

	Dependent variable: Sectoral PPI Inflation (y/y)	
	All shocks	Foreign shocks only
Lockdown supply shock	0.295***	0.375**
	(0.028)	(0.131)
Lockdown demand shock	-0.355***	-0.257***
	(0.036)	(0.070)
Within-sector lockdown shock		0.054*
		(0.032)
Time effects	Yes	Yes
Industry effects	Yes	Yes
Country effects	Yes	Yes
Observations	48387	48387

Notes: This table reports coefficients of the panel regression (16) when only the contemporaneous effects of lockdown supply and demand shocks are considered ($h = 0$). Lockdown supply and demand shocks are Bartik instruments defined in section 3.1. Inflation and shocks are measured as one-year changes. Observations are at monthly frequency. In the first column, the Bartik instruments are summation over lockdown shocks in all countries and sectors, while in the second column, only foreign shocks are included. The second column controls for lockdown shock from within sector separately, as in Acemoglu et al. (2016). Driscoll-Kraay standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Contemporaneous Inflationary Effects of Fiscal Shock

		Dependent variable: Sectoral PPI Inflation (y/y)	
		(1)	(2)
Fiscal shock, annual change		0.754^{***}	
		(0.170)	
Fiscal shock, quarterly change	Lag 0		0.769^{***}
			(0.098)
Fiscal shock, quarterly change	Lag 3		0.803^{***}
			(0.147)
Fiscal shock, quarterly change	Lag 6		0.794^{***}
			(0.185)
Fiscal shock, quarterly change	Lag 9		0.662^{**}
			(0.265)
Time effects		Yes	Yes
Industry effects		Yes	Yes
Country effects		Yes	Yes
Observations		48387	48387

Notes: This table reports coefficients of the panel regression (16) when only the contemporaneous effects of fiscal shocks are considered ($h = 0$). Fiscal shock is the Bartik instrument defined in section 3.1. The first column measures year-over-year changes in fiscal shock, while the second column uses four lags of quarterly changes. Inflation is measured as one-year changes. Observations are at monthly frequency. Driscoll-Kraay standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Full specification: Inflationary Effects of All Shocks

		Dependent variable: Sectoral PPI Inflation (y/y)			
		(1)	(2)	(3)	(4)
Lockdown-supply	Lag 0	0.291***	0.326***	0.325***	0.088**
		(0.041)	(0.037)	(0.036)	(0.030)
	Lag 3	0.322***	0.355***	0.353***	0.166***
		(0.048)	(0.058)	(0.059)	(0.032)
	Lag 6	0.334***	0.359***	0.357***	0.174***
		(0.047)	(0.051)	(0.053)	(0.023)
	Lag 9	0.242***	0.267***	0.264***	0.112***
		(0.058)	(0.053)	(0.055)	(0.027)
Lockdown-demand	Lag 0	-0.302***	-0.368***	-0.369***	-0.165***
		(0.050)	(0.035)	(0.035)	(0.034)
	Lag 3	-0.371***	-0.429***	-0.431***	-0.274***
		(0.034)	(0.057)	(0.058)	(0.033)
	Lag 6	-0.430***	-0.473***	-0.474***	-0.319***
		(0.037)	(0.048)	(0.050)	(0.031)
	Lag 9	-0.324***	-0.354***	-0.352***	-0.220***
		(0.077)	(0.047)	(0.047)	(0.028)
Fiscal	Lag 0	0.561***	0.578***	0.585***	0.656***
		(0.113)	(0.150)	(0.149)	(0.135)
	Lag 3	0.592***	0.479**	0.482**	0.588***
		(0.148)	(0.198)	(0.196)	(0.173)
	Lag 6	0.474**	0.459***	0.462***	0.540***
		(0.168)	(0.134)	(0.116)	(0.123)
	Lag 9	0.345*	0.269**	0.261**	0.319**
		(0.204)	(0.110)	(0.101)	(0.127)
Monetary	Lag 0	0.042***	0.025	0.026	0.003
		(0.010)	(0.022)	(0.022)	(0.021)
	Lag 3	0.077**	0.057***	0.057***	0.044**
		(0.032)	(0.013)	(0.013)	(0.015)
	Lag 6	0.062*	0.040***	0.040***	0.027**
		(0.037)	(0.008)	(0.009)	(0.012)
	Lag 9	0.074	0.042**	0.042**	0.043**
		(0.050)	(0.017)	(0.017)	(0.022)
Transport cost				0.059***	0.035***
				(0.014)	(0.010)
Oil price inflation					0.517***
					(0.056)
FX depreciation			0.297***	0.288***	0.303***
			(0.043)	(0.042)	(0.038)
FX depreciation*EM dummy			0.079**	0.093**	0.068**
			(0.033)	(0.036)	(0.030)
Lagged inflation			0.160	0.161	0.164
			(0.165)	(0.165)	(0.132)
Full fixed effects		Yes	Yes	Yes	Yes
Observations		48387	40177	40177	40177

Notes: This table presents the regression coefficients of sectoral PPI inflation on Bartik instruments for the supply effect of lockdown shocks, demand effect of lockdown shocks, and fiscal shocks.Inflation, transport cost, oil inflation, and exchange rate depreciation are measured as year-over-year changes, while supply, demand, fiscal, and monetary shocks are included as 4 quarterly changes. Observations are at the monthly frequency. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

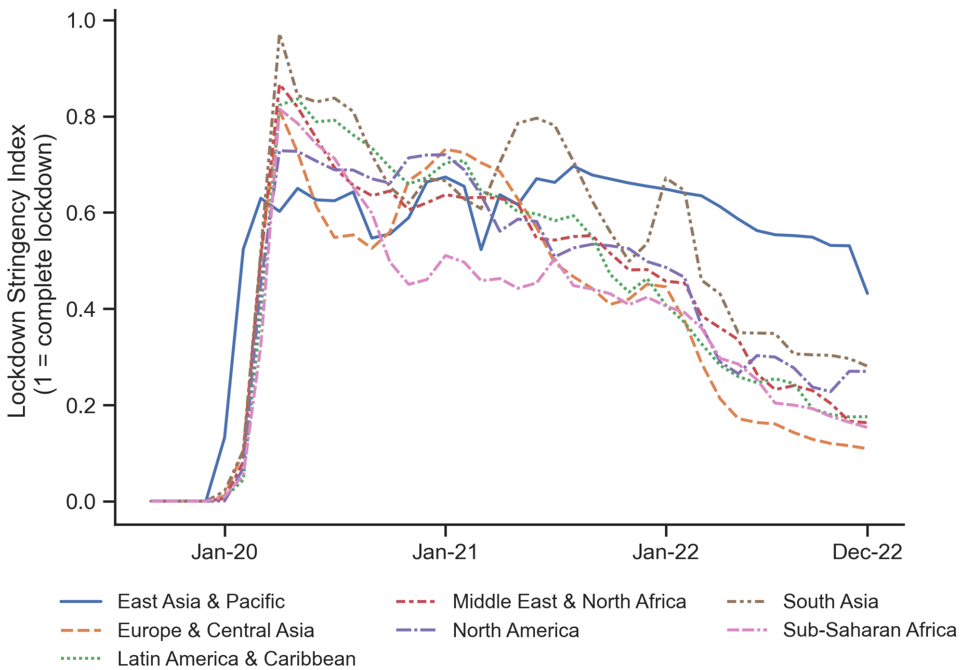
Table 4: Full specification: Inflationary Effects of All Shocks

		Dependent variable: Sectoral PPI Inflation (y/y)				
		(1)	(2)	(3)	(4)	(5)
Lockdown-supply	Lag 0	0.088**	0.084**	0.173***	0.129**	0.086**
		(0.030)	(0.031)	(0.045)	(0.049)	(0.040)
	Lag 3	0.166***	0.161***	0.266***	0.177***	0.171***
		(0.032)	(0.033)	(0.052)	(0.046)	(0.051)
	Lag 6	0.174***	0.169***	0.253***	0.087**	0.186***
		(0.023)	(0.025)	(0.050)	(0.032)	(0.048)
	Lag 9	0.112***	0.109***	0.170***	0.061	0.126***
		(0.027)	(0.030)	(0.035)	(0.046)	(0.026)
Lockdown-demand	Lag 0	-0.165***	-0.159***	-0.284***	-0.209***	-0.156***
		(0.034)	(0.032)	(0.053)	(0.038)	(0.034)
	Lag 3	-0.274***	-0.265***	-0.427***	-0.266***	-0.273***
		(0.033)	(0.032)	(0.050)	(0.042)	(0.046)
	Lag 6	-0.319***	-0.309***	-0.478***	-0.186***	-0.326***
		(0.031)	(0.033)	(0.061)	(0.030)	(0.049)
	Lag 9	-0.220***	-0.212***	-0.344***	-0.122***	-0.230***
		(0.028)	(0.026)	(0.061)	(0.025)	(0.041)
Fiscal	Lag 0	0.656***	0.637***	0.818***	0.504***	0.609***
		(0.135)	(0.139)	(0.216)	(0.140)	(0.155)
	Lag 3	0.588***	0.575**	0.770**	0.424	0.569**
		(0.173)	(0.177)	(0.282)	(0.272)	(0.200)
	Lag 6	0.540***	0.526***	0.741**	0.615***	0.542***
		(0.123)	(0.131)	(0.245)	(0.154)	(0.158)
	Lag 9	0.319**	0.320**	0.485**	-0.118	0.352**
		(0.127)	(0.126)	(0.198)	(0.179)	(0.136)
Monetary	Lag 0	0.003	0.010	0.008	0.040*	0.002
		(0.021)	(0.020)	(0.034)	(0.023)	(0.023)
	Lag 3	0.044**	0.047**	0.071**	0.090**	0.045**
		(0.015)	(0.016)	(0.028)	(0.035)	(0.015)
	Lag 6	0.027**	0.028**	0.052**	0.068*	0.028**
		(0.012)	(0.011)	(0.017)	(0.038)	(0.013)
	Lag 9	0.043**	0.042**	0.091**	0.066	0.044**
		(0.022)	(0.021)	(0.044)	(0.042)	(0.021)
Transport cost		0.035***	0.032***	0.049**	0.078**	0.025**
		(0.010)	(0.010)	(0.020)	(0.033)	(0.011)
Oil price inflation		0.517***	0.517***	0.665***	0.517***	0.520***
		(0.056)	(0.056)	(0.077)	(0.060)	(0.068)
FX depreciation		0.303***	0.259***	0.326***	0.288***	0.297***
		(0.038)	(0.037)	(0.057)	(0.026)	(0.039)
FX depreciation*EM dummy		0.068**	0.114**	0.279***	0.085*	0.073**
		(0.030)	(0.035)	(0.067)	(0.047)	(0.028)
Lagged inflation		0.164	0.162	0.181	0.157	0.040
		(0.132)	(0.132)	(0.176)	(0.127)	(0.145)
Covid Cases per Capita		No	Yes	No	No	No
Winsorized 1 percent		Yes	Yes	No	Yes	Yes
Time FE		Yes	Yes	Yes	No	Yes
Country Sector FE		Yes	Yes	Yes	Yes	No
Country-Sector FE		No	No	No	No	Yes
Observations		40177	40177	40177	40177	40177

Notes: This table presents the regression coefficients of sectoral PPI inflation on Bartik instruments for the supply effect of lockdown shocks, demand effect of lockdown shocks, and fiscal shocks, under different robustness test exercises.Inflation, transport cost, oil inflation, and exchange rate depreciation are measured as year-over-year changes, while supply, demand, fiscal, and monetary shocks are included as 4 quarterly changes. Observations are at the monthly frequency. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

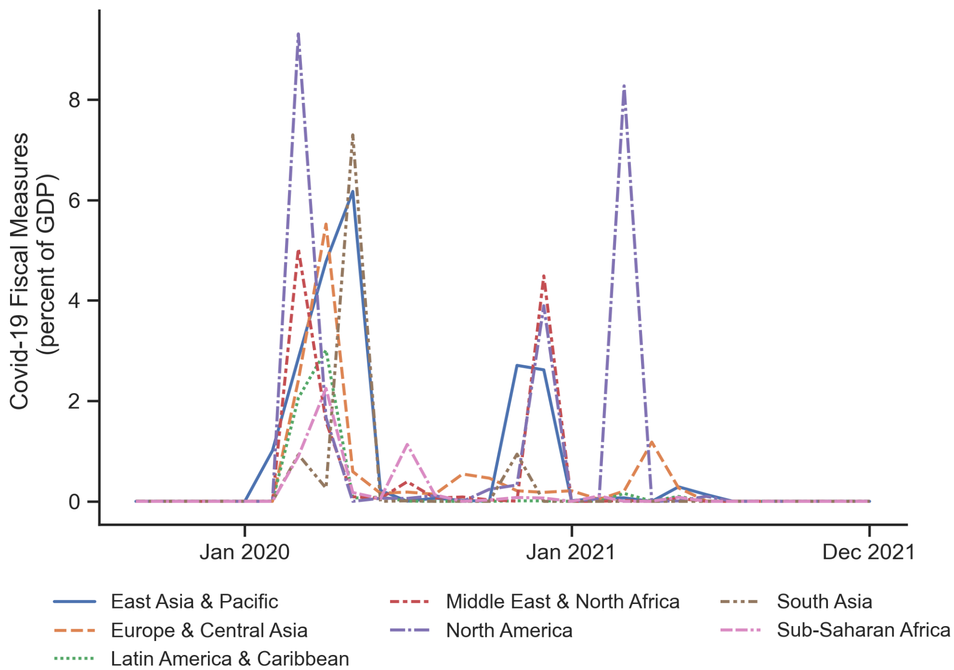
B Main Figures

Figure 1: Lockdown Stringency by Region



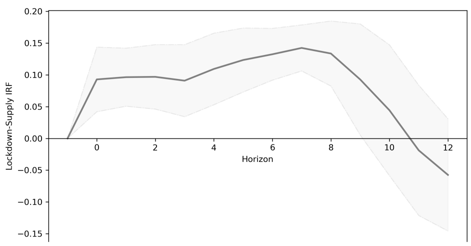
Sources: Oxford CGRT; authors' elaboration. This figure plots the average national lockdown stringency for different regions of the world. Lockdown stringency is an index ranging from zero to one, with one representing a full lockdown. Daily data is aggregated to monthly frequency, and regional indices are averages of national indices weighted by pre-sample GDP levels.

Figure 2: COVID-19 Related Fiscal Stimulus by Region

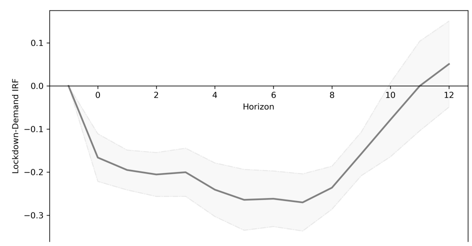


Sources: Oxford CGRT; authors' elaboration. This figure plots the COVID-19 fiscal stimulus package (as a share of GDP) announced by national governments stringency for different regions of the world. The raw data has been aggregated up to the monthly frequency.

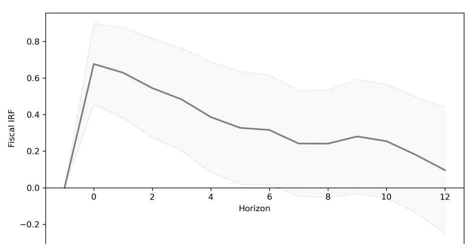
Figure 3: Local Projection Impulse Response Functions



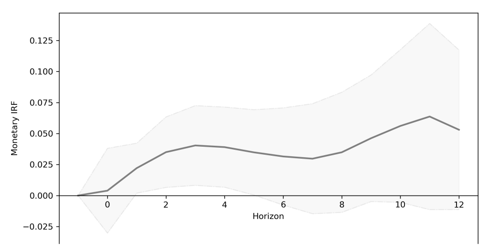
(a) Lockdown-Supply



(b) Lockdown-Demand



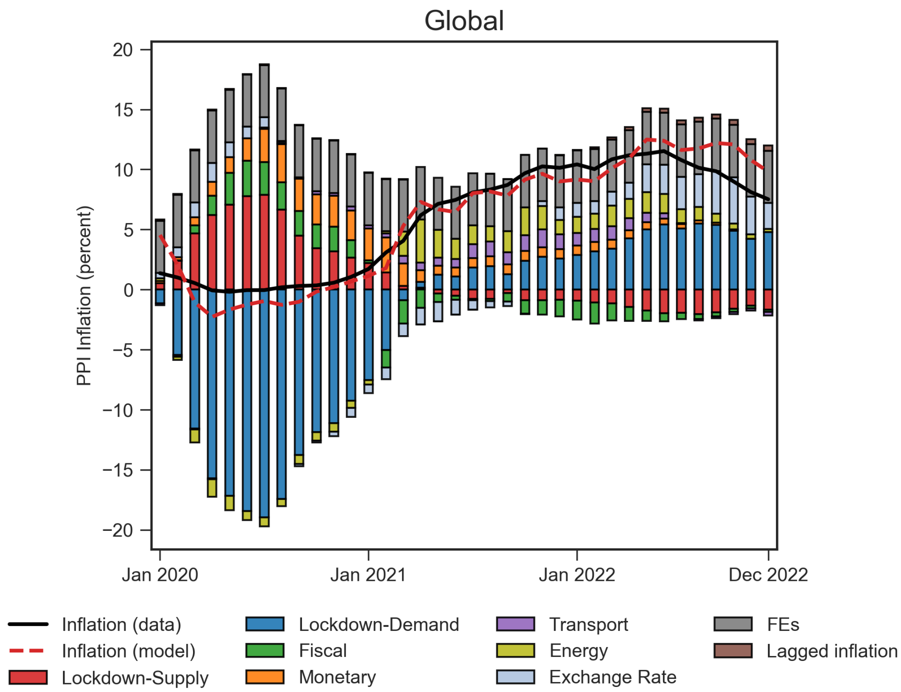
(c) Fiscal Shocks



(d) Monetary Shocks

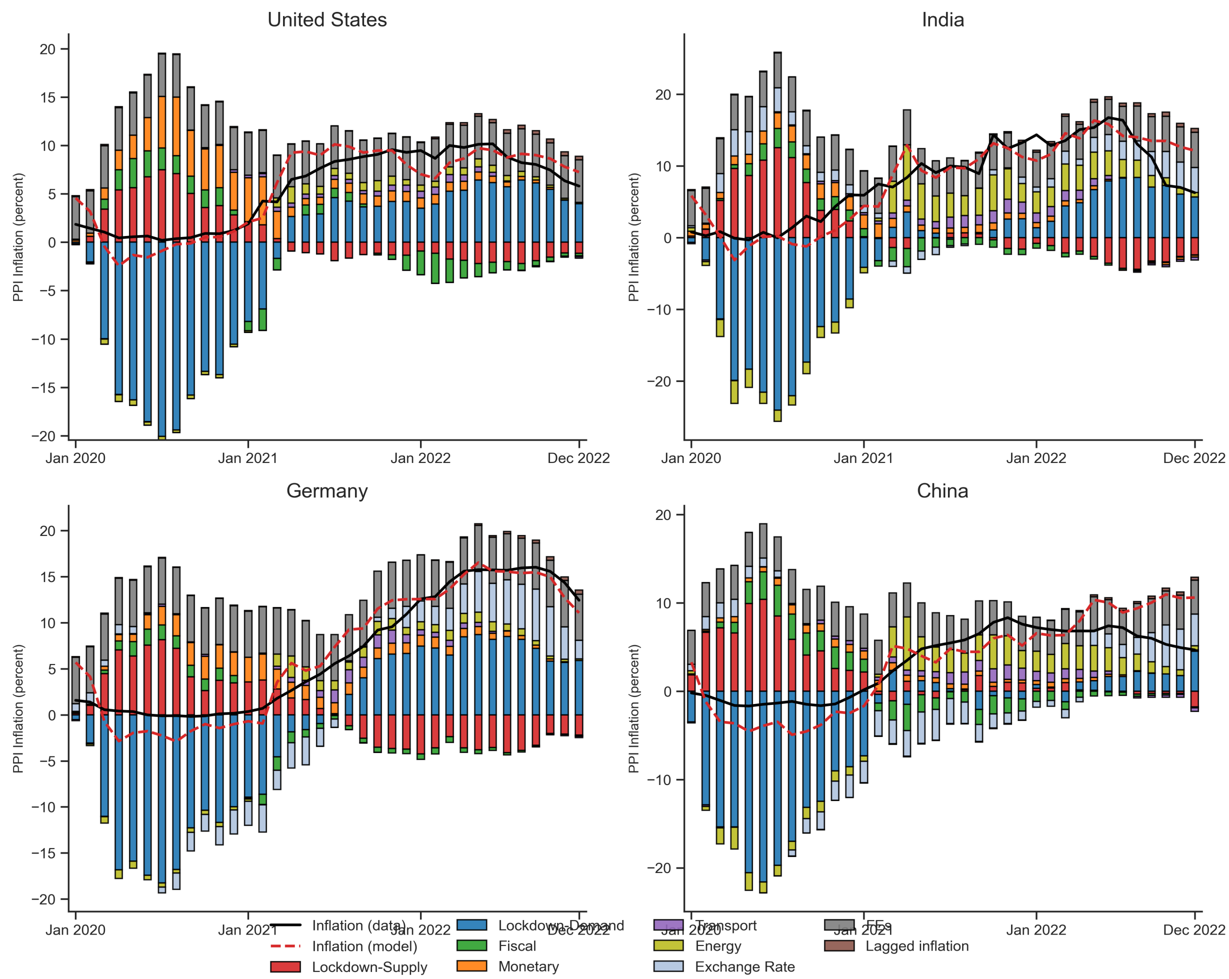
Notes: This figure plots the results of local projection regressions (à la Jordà (2005)) for different forward horizons of PPI inflation on the four Bartik instruments for the supply effect of lockdown, demand effect of lockdown, fiscal and monetary shocks, respectively. This figure shows that lockdown increases inflation due to supply disruptions, but decreases inflation due to diminished demand at the same time. The effects are strong and last for about 10 months. It also showsthat fiscal stimuli increase inflation, but the effects at longer horizons are only estimated imprecisely. Monetary shocks have more persistent impacts on inflation than the other channels.

Figure 4: Relative Contributions of Lockdown-Supply, Lockdown-Demand, and Fiscal Shocks on Inflation at the Global Level



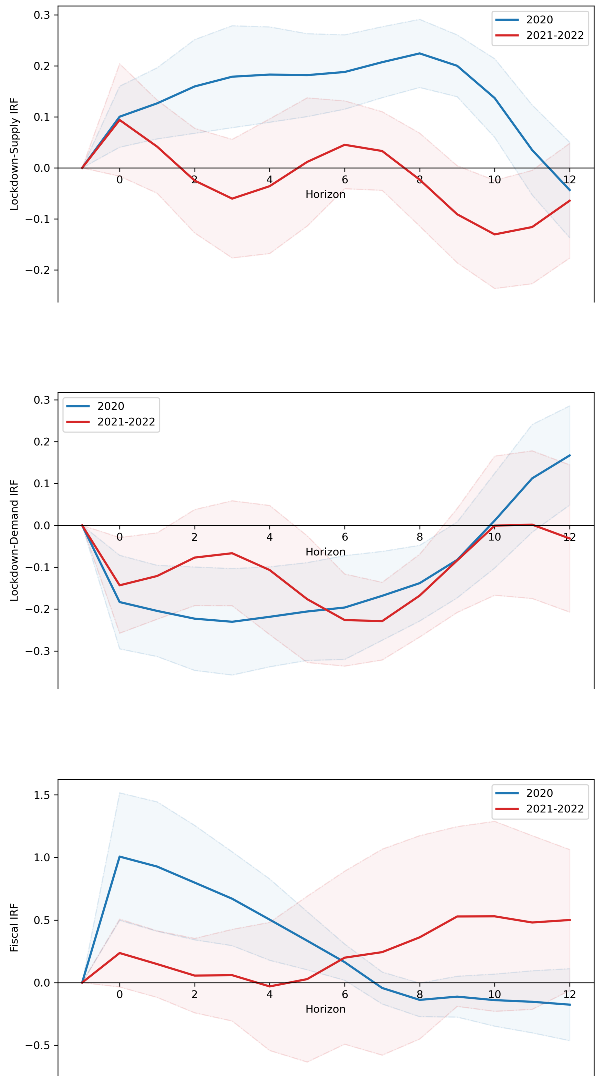
Notes: This figure plots the predicted PPI inflation (outcome variable) due to subgroups of variables (contemporaneous and lags): lockdown-supply, lockdown-demand, and fiscal. In each subplot, each variable is aggregated by taking a weighted mean across sectors, with weights proportional to sectoral size (sales). The regression does not include time FE. This figure shows that lockdown reopening has a strong impact and is the overwhelming driver of high inflation in the recovery from the pandemic.

Figure 5: Relative Contributions of Lockdown-Supply, Lockdown-Demand, and Fiscal Shocks on Inflation for Major Nations



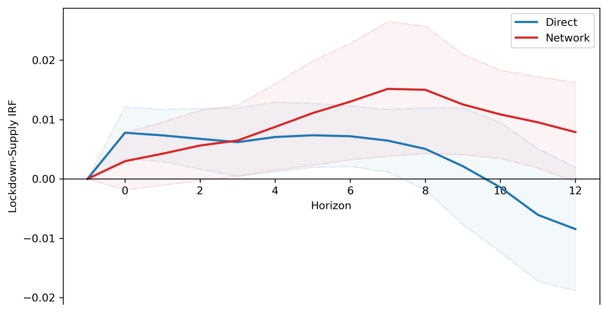
Notes: This figure plots the predicted PPI inflation (outcome variable) due to subgroups of variables (contemporaneous and lags): lockdown-supply, lockdown-demand, and fiscal. In each subplot, each variable is aggregated by taking a weighted mean across sectors, with weights proportional to sectoral size (sales). This figure shows that lockdown reopening has a strong impact and is the overwhelming driver of high inflation in the recovery from the pandemic.

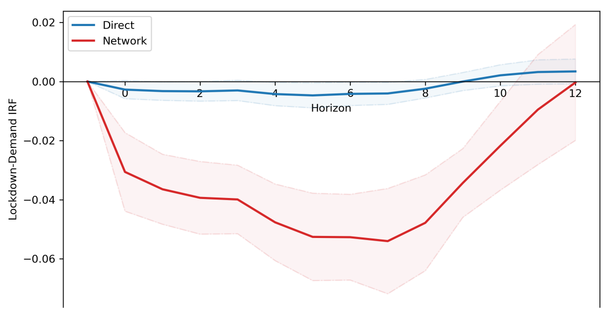
Figure 6: Differential Effects of Shocks on Inflation in at the Beginning versus End of the COVID-19 Pandemic (Local Projection IRF)



Notes: This figure plots the results of local projection regressions (à la Jordà (2005)) for different forward horizons of PPI inflation on the three Bartik instruments for the supply effect of lockdown, demand effect of lockdown, and fiscal shocks, respectively. Importantly, the coefficients are allowed to differ for the two phases of the pandemic (2020 versus 2021 and later). Each regression includes four quarterly lags of all Bartik variables, as well as lagged inflation, exchange rate depreciation, maritime transport cost inflation, and a full set of fixed effects (country, sector, time) as controls. This figure shows that the inflationary impact of lockdown via supply channels becomes unimportant in the recovery phase of the pandemic (top panel), while the opposite is true for fiscal stimuli (bottom panel).

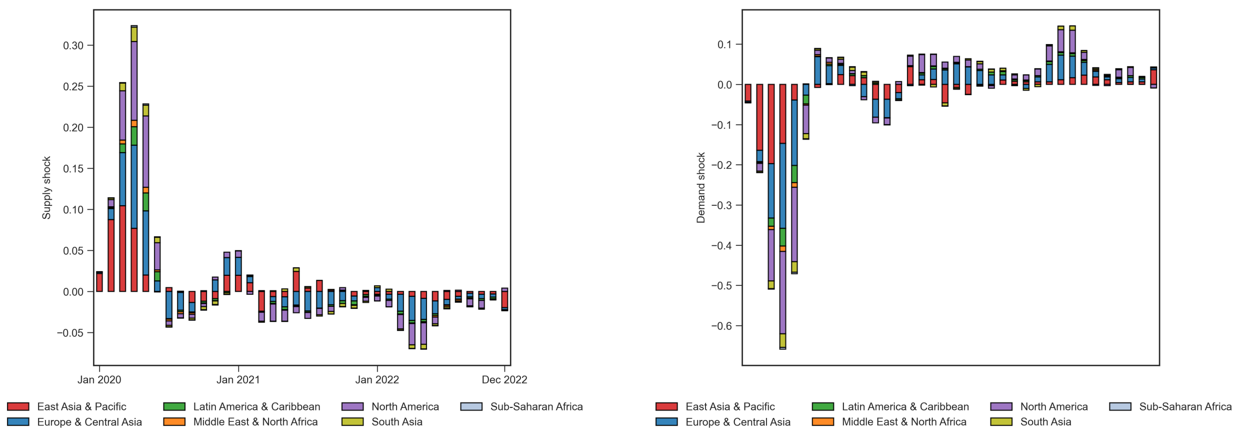
Figure 7: The role of network in propagating shock





Notes: This figure plots the magnitudes of the direct and network effects for the lockdown-supply, lockdown-demand, and fiscal shocks for an average sector. Each line is constructed by multiplying the estimated coefficient for the respective Bartik instrument by the standard deviation of the variable (across all sectors and time).

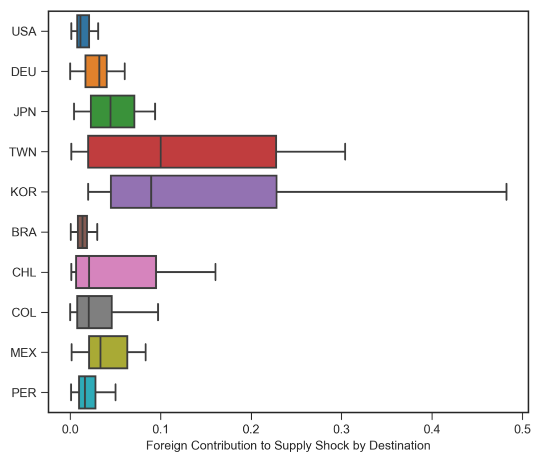
Figure 8: Unpacking lockdown shocks: inflation contribution by origin



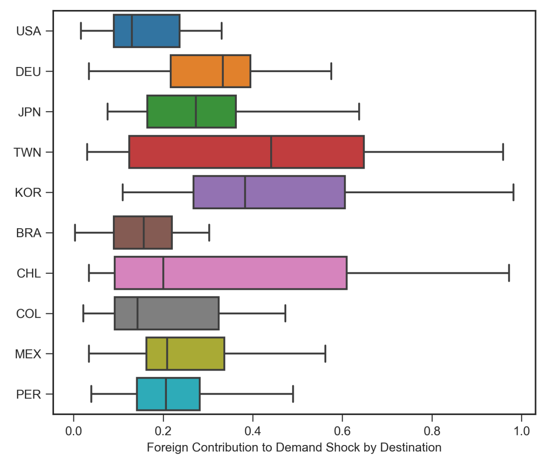
(a) Supply (b) Demand

Notes: East Asia lockdown important at the onset of the pandemic, but soon dominated by lockdown reopening policies in Europe and US.

Figure 9: Unpacking lockdown shocks: foreign contribution of shocks



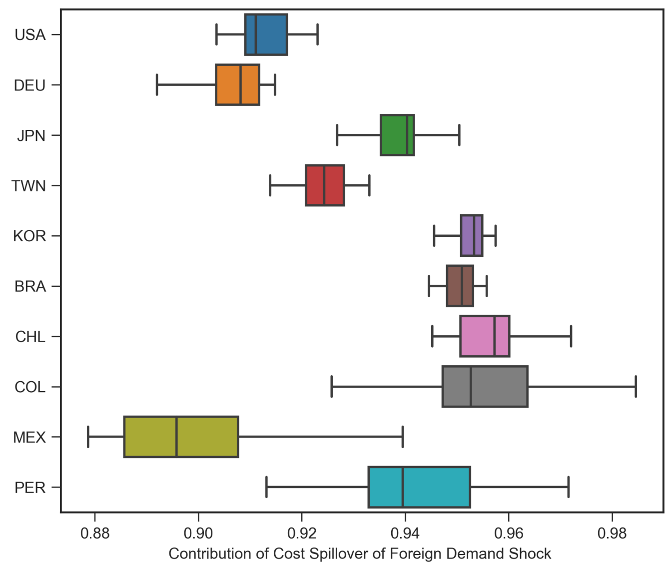
(a) Supply



(b) Demand

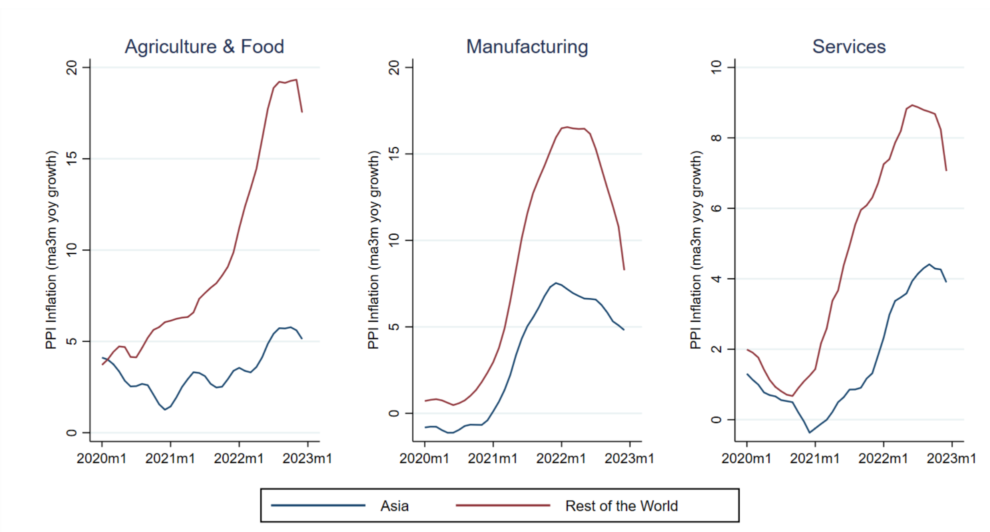
Notes: US and LAC less vulnerable to foreign supply disruptions than "Asian manufacturers" e.g. TWN and KOR. Countries are 4-5 times more prone to foreign demand shocks than supply shocks. LAC: about 20-30 percent of demand shock is spillover from foreign lockdown/reopening policies.

Figure 10: Demand shock operates through indirect network effect



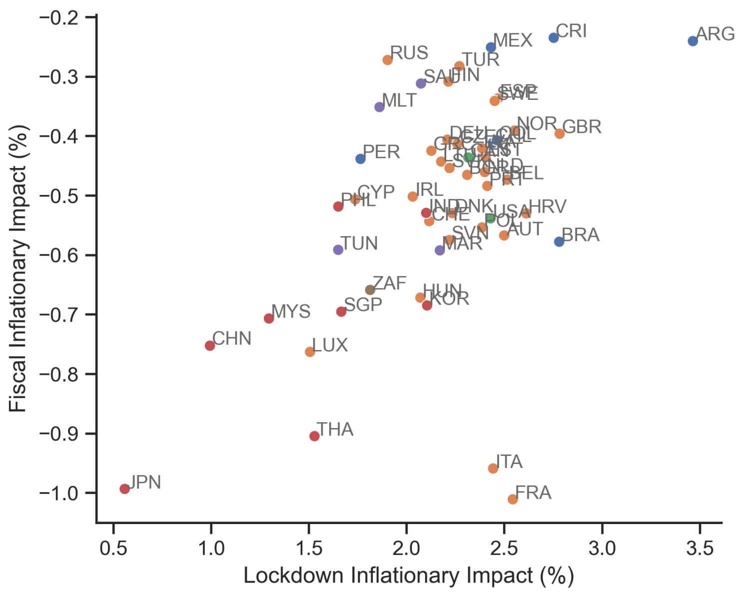
Notes: Two channels through which demand raises a sector's PPI inflation. Higher demand for a good raises its price ("pure demand" channel). Higher demand for other goods raises the price of intermediate goods that are inputs to production ("cost" channel that operates through the network) 90 percent of demand shock is via the "cost" channel.

Figure 11: PPI Inflation in Key Sectors in Asia and Rest of the World



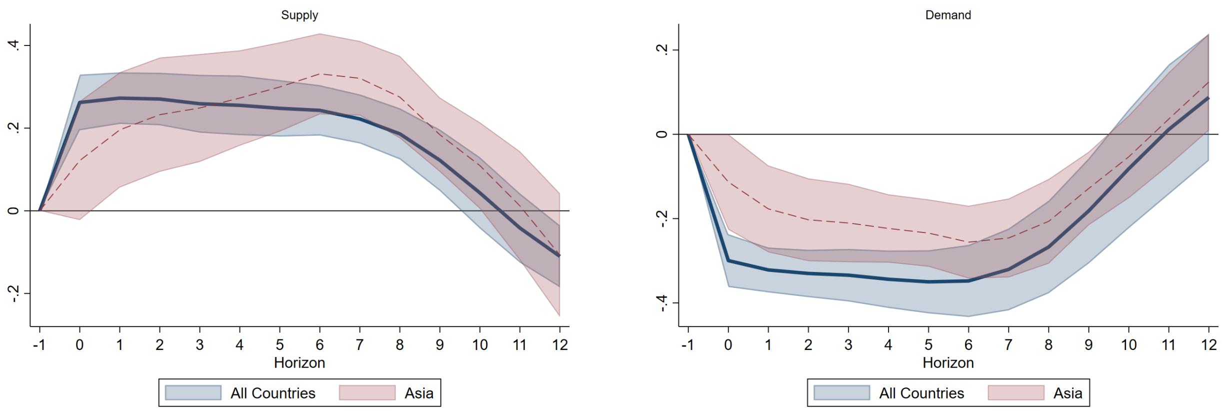
Notes: This figure plots the average three month moving average for PPI inflation in three key sectors separately for 8 Asian economies (Japan, Singapore, Korea, Taiwan Province of China Province of China, China, India, Malaysia, Thailand) and the 45 remaining countries in the sample.

Figure 12: Re-opening and withdrawal of Fiscal Spendings



Notes: This figure plots the cross-country variations in the inflationary impacts of lockdown and fiscal spending during the 2021-22 period. The scatter plot indicates that Asian countries had relatively slower re-opening and quick withdrawal of large stimulus packages

Figure 13: Local Projection Impulse Response Functions for Asian Countries (Part 1)

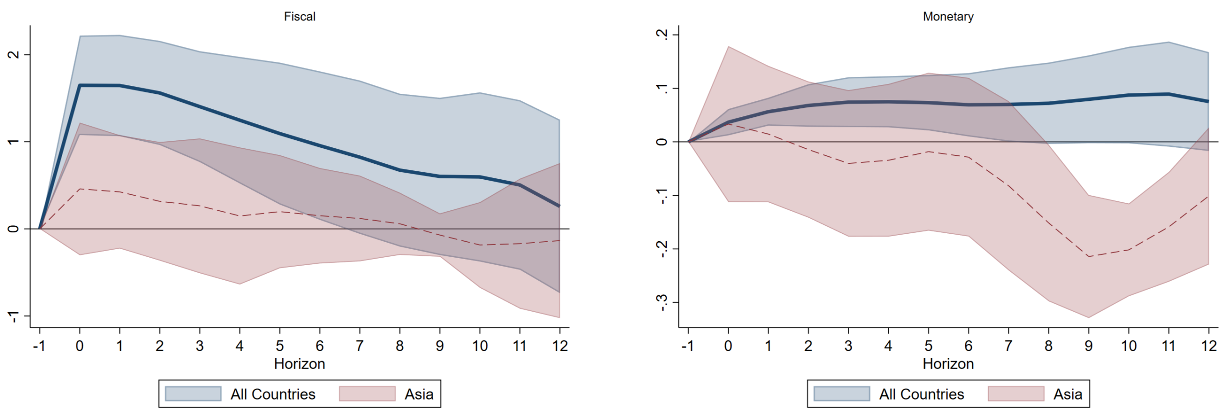


(a) Lockdown-Supply

(b) Lockdown-Demand

Notes: Restricting the sample to Asian countries, this figure plots the results of local projection regressions (à la Jordà (2005)) for different forward horizons of PPI inflation on the three Bartik instruments for the supply effect of lockdown, demand effect of lockdown, fiscal shocks and monetary shocks, respectively. Each regression includes four quarterly lags of all Bartik variables, as well as lagged inflation, exchange rate depreciation, maritime transport cost inflation, and a full set of fixed effects (country, sector, time) as controls.

Figure 14: Local Projection Impulse Response Functions for Asian Countries (Part 2)



(a) Fiscal Shocks

(b) Monetary Shocks

Notes: Restricting the sample to Asian countries, this figure plots the results of local projection regressions (à la Jordà (2005)) for different forward horizons of PPI inflation on the three Bartik instruments for the supply effect of lockdown, demand effect of lockdown, fiscal shocks and monetary shocks, respectively. Each regression includes four quarterly lags of all Bartik variables, as well as lagged inflation, exchange rate depreciation, maritime transport cost inflation, and a full set of fixed effects (country, sector, time) as controls.

C Supplementary Materials for Data Description

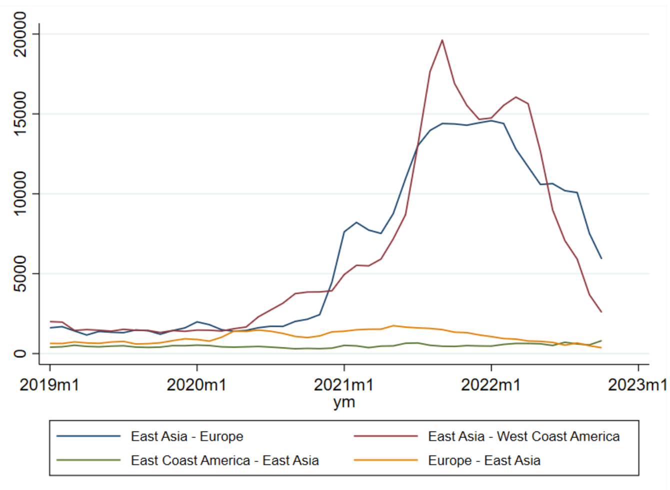
Table 5: Sample of Economies

Advanced Economies	Emerging Economies
Austria	Argentina
Australia	Brazil
Belgium	Bulgaria
Canada	Chile
Cyprus	China
Czech Republic	Colombia
Denmark	Costa Rica
Estonia	Croatia
Finland	Hungary
France	India
Germany	Malaysia
Greece	Mexico
Ireland	Morocco
Italy	Peru
Japan	Philippines
Latvia	Poland
Lithuania	Russia
Luxembourg	Saudi Arabia
Malta	South Africa
Netherlands	Thailand
New Zealand	Tunisia
Norway	Türkiye
Portugal	
Singapore	
Slovakia	
Slovenia	
Korea	
Spain	
Sweden	
Switzerland	
Taiwan Province of China	
United Kingdom	
United States	

Table 6: Sector (OECD IOT)

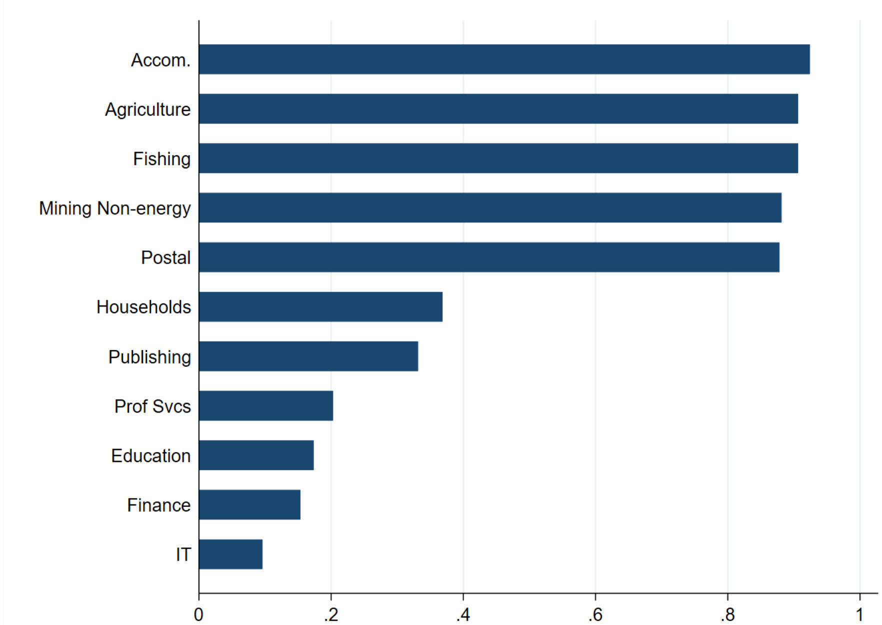
Agriculture, hunting, forestry
Fishing and aquaculture
Mining and quarrying, energy producing products
Mining and quarrying, non-energy producing products
Mining support service activities
Food products, beverages and tobacco
Textiles, textile products, leather and footwear
Wood and products of wood and cork
Paper products and printing
Coke and refined petroleum products
Chemical and chemical products
Pharmaceuticals, medicinal chemical and botanical products
Rubber and plastics products
Other non-metallic mineral products
Basic metals
Fabricated metal products
Computer, electronic and optical equipment
Eletrical equipment
Machinery and equiment, nec
Motor vehicles, trailers and semi-trailers
Other transport equipment
Manufacturing nec; repair and installation of machinery and equipment
Eletricity, gas, steam and air conditioning supply
Water supply; sewerage, waste management and remediation activities
Construction
Wholesale and retail trade; repair of motor vehicles
Land transport and transport via pipelines
Water transport
Air transport
Warehousing and support activities for transportation
Postal and courier activities
Accommodation and food service activities
Publishing, audiovisual and broadcasting activities
Telecommunications
IT and other information services
Financial and insurance activities
Real estate activities
Professional, scientific and technical activities
Administrative and support services
Public administration and defence; compulsory social security
Education
Human health and social work activities
Arts, entertainment and recreation
Other service activities
Activities of households as employers

Figure 15: Evolution of Trade Costs by Route



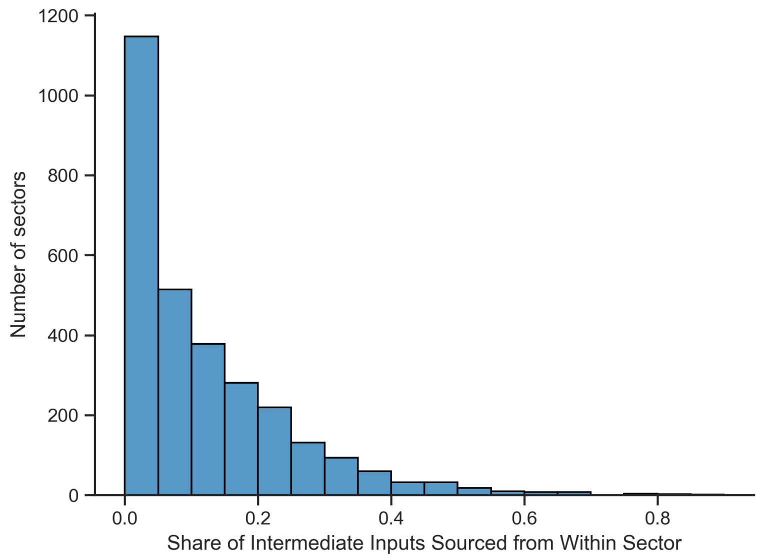
Notes: This graph shows the monthly Baltic Container Price Index sourced from the Freightos. It captures the transport cost for different routes.

Figure 16: Sectoral Lockdown



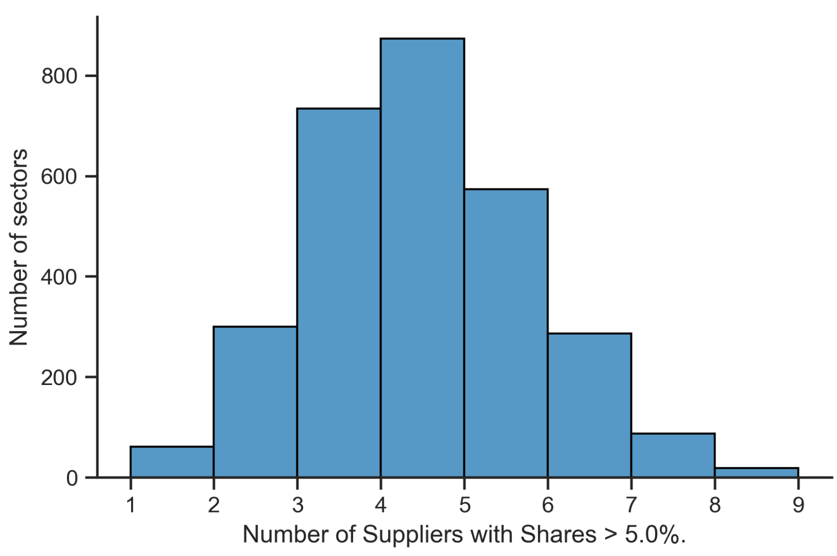
Notes: This graph shows the top and bottom sectors in terms of sectoral lockdown according to the Occupation Information Network (ONET) database.

Figure 17: Distribution of Self-Sourced Intermediate Input Share



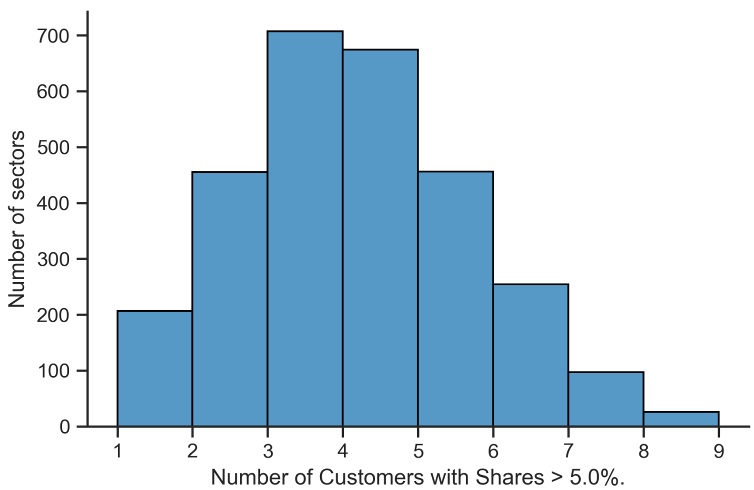
Sources: OECD WIOT; authors' elaboration. This figure plots the distribution of the share of intermediate input that a sector sources from within its own sector. It shows that most sectors source intermediate inputs primarily from other sectors, with the median sector sources only about 8 percent of total intermediate inputs from within sector.

Figure 18: Distribution of Number of Significant Suppliers



Sources: OECD WIOT; authors' elaboration. This figure plots distribution of the number of significant suppliers, defined as those accounting for more than 5 percent of total intermediate inputs, across production sectors in the WIOT data. The figure shows that intermediate input supply tends to be concentrated within a few upstream sectors, with the majority of sectors sourcing from 4-5 supplying sectors.

Figure 19: Distribution of Number of Significant Buyers



Sources: OECD WIOT; authors' elaboration. This figure plots distribution of the number of significant buyers, defined as those accounting for more than 5 percent of total sales, across production sectors in the WIOT data. The figure shows that intermediate input sales tend to be concentrated within a few downstream sectors, with the majority of sectors selling to about 4-5 downstream buyers.

PUBLICATIONS

Global Value Chains and Inflation Dynamics

Working Paper No. WP/2024/062